Turbocharging Profits?
Contract Gaming and Revenue Allocation in Healthcare*

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Abstract

Firms often exploit loopholes in government contracts to boost revenues. The welfare consequences of this behavior depend on how firms use the marginal windfall dollar, yet little evidence exists to guide policymakers. This paper studies how hospitals allocated over $3 billion obtained from gaming a Medicare payment loophole. The average gaming hospital increased both Medicare and total revenue by around 10%, implying large spillovers on other payers. Consistent with theories of organizational behavior, nonprofit hospitals deployed most of the windfall toward operating costs, while for-profits deducted the entire amount off their balance sheet, distributing a substantial portion to executives and shareholders. Accordingly, we detect modest reductions in mortality rates at nonprofits but no changes at for-profits. Our results imply that the consequences of such engineered windfalls vary substantially by hospital ownership.

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1 Introduction

Governments frequently contract with private firms to deliver goods and services. Design flaws or ambiguities in contracts provide opportunities for firms to exploit loopholes and increase revenue beyond the intention of policymakers. This behavior, in which firms "engineer" windfalls, is estimated to cost the U.S. government hundreds of billions of dollars annually (Government Accountability Office, 2023). Fraud and abuse in public contracting is also a major fiscal and policy concern in other countries (Hafner et al., 2023). Despite the prevalence and significant costs associated with the gaming of government contracts, little research exists on how firms utilize funds obtained from engineered windfalls. The welfare consequences of this behavior depend on how firms allocate the marginal dollar of excess revenue.

These issues are particularly acute in the U.S. healthcare sector, which represents one-fifth of the economy, features an outsized government presence, and is rife with information frictions and agency problems (Arrow, 1963). Medicare and Medicaid account for a quarter of federal expenditures, but more than half of all estimated improper federal payments (Government Accountability Office, 2023). Payment system design is one common contracting challenge in this setting. Policymakers' efforts to design an efficient system can be frustrated by the actions of providers and insurers to maximize their own revenue through "gaming" (Dafny, 2005; Decarolis, 2015; Duggan, 2000; Geruso and Layton, 2020). If providers direct gaming revenue to patient care, policymakers may have less to fear from payment system weaknesses. However, if excess revenue has limited benefits for patients, it would support devoting greater resources to contract design and payment oversight (Leder-Luis, n.d.; Shi, 2024).

In this paper, we study how hospitals allocate the revenue obtained from exploiting a loophole in the Medicare 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 modify that contract to pay hospitals for some of the 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 hospital gaming and its consequences. First, turbocharging involves a top-down administrative decision by hospital managers to inflate charges across all patients via a simple change in hospital bookkeeping. Second, turbocharging appears to have been driven by geographic coincidence. 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 in 2002.

We first show 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 type of ownership is highly predictive of turbocharging. Government-owned hospitals have little incentive to exploit loopholes to increase revenue because they operate under soft budget constraints (Kornai, Maskin and Roland, 2003). In contrast, managers of for-profit hospitals have more incentive to maximize profits since they can distribute profits to themselves (Hansmann, 1980). Consistent with these theories, we find that for-profit hospitals are heavily over-represented among gamers, while almost no government hospitals engaged in turbocharging.

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 its downstream effects on patients. We match on BBA97 payment cut parameters to compare gamer hospitals to those that had a similar motive to engage in manipulation but did not do so. Our analytic sample includes 120 gamers and 1,396 matched comparator hospitals.

We find that, on average, hospitals that game Medicare by turbocharging obtain nearly $17 million in excess outlier payments, which translates to a 10% increase in total Medicare inpatient revenue between 1998 and 2003. The rapid growth in hospital list prices 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, Gottlieb and Molnár, 2017; Clemens and Gottlieb, 2017). Indeed, we detect large spillover effects on other insurers: Total hospital revenue increases by $67 million, 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 nearly half of the revenue obtained from turbocharging flowed toward operating costs, though the estimate is

[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.

imprecise. Second, we study changes in net worth (defined as assets less liabilities) and find minimal effects here, 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 often flow to a hospital's parent organization, where they could be used for various purposes, such as executive compensation or, in the case of for-profit hospitals, paid out to shareholders. We find nearly $40 million per hospital flows off the balance sheet or over half of the estimated total revenue obtained from turbocharging.

These findings obscure economically meaningful and statistically significant differences between the way nonprofit and for-profit hospitals allocate this revenue. Among nonprofits – but *not* at for-profits – revenues flow predominantly to operating costs. In particular, nonprofits increase spending on non-labor direct operating costs, which could enhance care delivery. Given these differences in behavior, we find a modest improvement in mortality rates at nonprofit hospitals but no changes at for-profit hospitals. Our estimates imply that nonprofit gamers reduce mortality rates by 3% following an 8% increase in Medicare spending. This is lower than the return on hospital spending reported by prior studies but aligns remarkably well once we account for the fact that a quarter of the revenue was not directed to patient care (Doyle et al., 2015; Silver, 2021).

For-profit hospitals transfer all of the excess revenue off their balance sheets. We, therefore, trace the funds to the hospital's parent organization. Via SEC filing data, we show that Tenet Corporation, whose hospitals account for three-fourths of the for-profits engaging in turbocharging, dramatically increased compensation for its highest-paid executives during the gaming period. The system also engaged in stock buybacks, which resulted in millions paid to shareholders. Back-of-the-envelope calculations suggest that roughly a billion dollars were funneled toward their executives and shareholders.

This paper contributes to several strands of literature. First, we extend research studying how firms respond to windfall gains. Much of this literature has focused on firm responses to winning lawsuits, grants, or bonuses (Blanchard, Lopez-de Silanes and Shleifer, 1994; Howell and Brown, 2022; Cespedes, Huang and Parra, 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, Geruso and Mahoney, 2018; Gross et al., n.d.; Cooper et al., 2017). Some prior studies have examined how firms exploit loopholes, for example, by "upcoding" patient or beneficiary risk to increase their revenue (Dafny, 2005; Sacarny, 2018; Silverman and Skinner, 2004; Cook and Averett, 2020; Geruso and Layton, 2020).

However, little is known about how firms allocate revenue obtained from exploiting loopholes. Managers may view revenue derived from loopholes as less legitimate and less permanent than revenue obtained from intended policy changes (Wang, Stuart and Li, 2021). Such compartmentalization of revenue into separate "mental accounts" may lead managers to spend engineered windfalls differently (Thaler, 1985). For example, while several studies on policy-driven windfalls find that the cash is invested into the firm or to benefit employees (Saez, Schoefer and Seim, 2019; Howell and Brown, 2022), we find minimal evidence of such behavior. For-profit hospitals invest no revenue in the hospital and instead transfer the majority of funds off the balance sheet. Even among nonprofit hospitals, no excess revenue is spent on long-term commitments such as fixed capital, additional staff, or higher wages; instead, it is spent on more immediate operating needs.

Second, we contribute to the literature on 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, Carlton and David, 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, how they allocate the excess revenue (Newhouse, 1970; Rose-Ackerman, 1996; Glaeser and Shleifer, 2001; Garthwaite, Gross and Notowidigdo, 2018). In particular, we find that nonprofit hospitals appeared to increase quality and admit sicker patients, while for-profits admit healthier patients with no detected improvements in quality. These results highlight that payment loopholes can influence quality and reallocate patients across hospitals.

Third, our results demonstrate the potential for large spillover effects of loopholes in government payment contracts onto other payers (Clemens and Gottlieb, 2017; Clemens, Gottlieb and Molnár, 2017; Einav et al., 2020). Benevolent policymakers would internalize these spillovers when considering investments in contract design or provider oversight. 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 in insurer-provider surprise billing disputes (Gordon et al., 2022) and among nursing homes aiming to appear less profitable to raise reimbursements from public payers (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 also demonstrates the value of improving payment design and investing in disciplinary mechanisms to curb fraud and abuse (Howard and McCarthy, 2021; Leder-Luis, n.d.; Perez and Wing, 2019; Shi, 2024). These studies typically quantify how providers respond to specific disciplinary mechanisms, assuming that the targeted behavior is socially undesirable. We complement these studies by showing that the social value of such healthcare spending is not uniformly high or low and varies significantly by provider ownership type.

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. 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

[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.

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 for-profit chain Tenet relied much more heavily on outlier payments than was previously known (Galloro, 2002). At roughly the same time, a whistleblower suit was filed in federal court alleging that Tenet and several other hospitals, including many nonprofit facilities, had fraudulently manipulated the outlier payment system (Leder-Luis, n.d.; U.S. v. Tenet et al., 2002). News stories in the ensuing period highlighted that several hospitals and hospital systems were receiving surprisingly high outlier payments, including clusters around Philadelphia and New Jersey

(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 them. 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 hospital systems for fraudulent billing under the False Claims Act. Tenet, in particular, agreed to pay $788 million to settle the allegations on outlier payments (U.S. Department of Justice, 2006). While federal agencies called turbocharging fraud, hospitals claimed it was "flawed public policy, not fraud or illegal activity" (United States Senate, 2003). This dispute, therefore, perfectly illustrates the type of "gray" area frequently encountered in government contracts, which is exploited by firms to their advantage. Given the legal uncertainty, federal agencies mainly sued hospitals where whistleblowers stepped forward with evidence of payment manipulation. In the analysis that follows, we provide systematic evidence that the scope of gaming went far beyond the hospitals that were sued.

3 Theoretical Background

In this section, we draw on economic theory to generate predictions on which types of firms are more likely to exploit loopholes and, conditional on doing so, differences in how firms may use these funds.

3.1 Incentive to Game

A hospital's governance structure varies by whether it is owned by a nonprofit, for-profit, or government organization. Nonprofits are exempt from paying most income and property taxes. In return, they must provide some charity care or services to the local community. Nonprofits cannot disburse surplus revenue to private shareholders or individuals, including managers.[4] For-profits pay corporate taxes and can distribute profits to managers and shareholders. 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

[4]However, nonprofits can make salary adjustments to increase executive compensation, where according to IRS rules, compensation must be reasonable and not excessive relative to peer organizations.

charitable mission, and in for-profits, it is often perceived as maximizing shareholder returns. Government-owned hospitals are subsidized by taxpayers and primarily aim to provide services to underserved populations, including low-income and uninsured patients.

These differences in governance inform theories of hospital and nonprofit behavior more broadly (see Sloan 2000 and David, Philipson and Malani 2007 for a review). For example, the altruist model views nonprofits and government firms as maximizing social welfare and, therefore, more focused on maximizing quality. These organizations are more likely to attract altruistic decision-makers who prioritize the organization's mission and societal welfare over personal gain (Rose-Ackerman, 1996; Besley and Ghatak, 2005). However, managers of government entities may have less incentive to maximize revenue than nonprofits because they face a "soft" budget constraint: the government subsidizes their losses but also taxes away their surplus (Kornai, Maskin and Roland, 2003; Baicker and Staiger, 2005).

A related model considers how nonprofit status can be a signal of noncontractible quality: since patients cannot easily observe hospital quality, and nonprofits do not face pressure to distribute profits to owners, patients may trust nonprofits more than for-profits to prioritize quality over profits (Arrow, 1963; Hansmann, 1980; Glaeser and Shleifer, 2001; Jones, Propper and Smith, 2017). Nonprofits may commit to the norms and expectations of their institutional environment to maintain their legitimacy. Alternatively, nonprofits may operate as "for-profits in disguise," seeking to maximize profits while disguised as charitable organizations (Weisbrod, 1988). In practice, nonprofits are likely neither pure profit nor pure welfare maximizers (Newhouse, 1970).

Drawing on this literature, for-profits may be more likely to engage in potentially improper behavior, such as exploiting loopholes in payment contracts, than nonprofit or government-owned hospitals. In particular, for-profit managers have more to gain from such behavior since they can distribute profits to themselves. Nonprofits may have more taste to engage in such profit-maximizing schemes than government hospitals but less taste to do so than for-profits. Consistent with this hypothesis, Horwitz (2005) finds that for-profit hospitals are more likely to offer profitable medical services, government hospitals are more likely to offer unprofitable services, and nonprofits fall in the middle.

3.2 Use of Excess Revenue

These theories of hospital ownership provide insights into how hospitals may allocate excess revenue obtained from a loophole. For example, nonprofits have implicit constraints based on their reputation as providers of charity care and explicit constraints on their use of funds that may motivate them to spend excess revenue on patient care. More altruistic managers may also be more aligned with furthering nonprofit goals, such as expanding access to care or improving quality. 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.

Hospitals may also spend profits differently based on the source and permanence of funds. Individuals, for example, often deviate from a standard consumption model and instead tend to compartmentalize their finances into separate "mental accounts", influencing their decisions on spending, saving, and investing (Thaler, 1985). Applying this logic to hospital managers, they may view funds obtained from exploiting loopholes as less legitimate than those obtained from an intended policy change and, therefore, hold them in a separate mental account. Accordingly, managers may choose to immediately spend the unearned windfall rather than increase reserves or invest in capital projects (Wang, Stuart and Li, 2021). Managers may also view funds obtained from loopholes as temporary, whereas budgetary and other policy changes can lead hospitals to experience more permanent changes in reimbursement. Hospitals may be reluctant to spend revenue from temporary sources on long-term commitments and instead spend it on more immediate operating needs. Indeed, the loophole studied in this setting proved to be transitory.

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). The flypaper effect could be interpreted as an application of mental accounts to the use of funds by organizations (Thaler, 1990). In our setting, since hospitals receive outlier payments as reimbursements for care provided during costly inpatient stays, hospitals may deploy the excess revenue toward inpatient care, even though other uses may be more optimal. Such a finding may be more likely to manifest in nonprofits than for-profits, given their non-distribution constraints and the implicit contract to provide community benefits for tax subsidies. To the extent that nonprofits view these funds as unearned via gaming, they may also justify this "improper" behavior by using funds obtained from the outlier payments program for their intended purpose.

4 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. 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.[5] To observe hospital characteristics, we link this file with CMS Providers of Services data and American Hospital Association survey data.

We directly observe the parameters that CMS contractors used to calculate payments through the CMS Impact file and Provider-Specific File. We use hospital cost report data rebased to calendar years to track financial information, including revenues and expenses. Because cost reports occasionally contain extreme values that are likely errors, we winsorize all cost report variables 1% on each side within year. For all-payer revenue and operating costs, where transient changes are particularly common, we suppress values that are more than double the average of the previous and next year. 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. We assemble a cohort of Medicare patients hospitalized for non-deferrable conditions via the emergency department (Card, Dobkin and Maestas, 2009; Doyle et al., 2015). The data includes rich patient covariates, including demographics, diagnosis histories, and the diagnosis for which the patient was admitted.[6] 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, Dobkin and Maestas, 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, Graves and Gruber, 2019; Hull, 2020).

Lastly, we use SEC filing data available through Compustat to determine executive compensation and shareholder payouts for publicly traded hospital systems. Specifically, we present the total salary and bonus for the top five highest-paid executives. We also present a measure of total compensation realized 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,

[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]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, Kakani and Sacarny (n.d.) and Gaynor et al. (n.d.). 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.

directors, trustees, and other key employees.[7]

5 Research Design

5.1 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 focusing on growth in charges and outlier payments, drawing on the methods CMS used while addressing their weaknesses.[8] Our algorithm uses a simulated payments strategy that holds 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 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:

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

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.

[7] To link our individual hospital sample to the 990 data, we identified the tax EIN of hospitals using information from https://www.communitybenefitinsight.org, when available. If not, we matched hospitals to the 990 data based on their name and location.

[8] 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.

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. Appendix Figure D.1 illustrates the joint distribution of $\hat{d}_h$ and superimposes this classification scheme. Panels (a) and (b) plot the joint distributions of log growth in percentiles and absolute values, respectively. We flag 180 hospitals as gamers, 2,530 as non-gamers, and 533 as indeterminate.

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 remainder were in the indeterminate range.[9] 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.

5.2 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 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. While for-profit hospitals comprise about 15% of all hospitals, they are nearly 40% of hospitals in the top decile. Nonprofit hospitals are represented across 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 3 about hospital ownership

[9] This omits Tenet hospitals because the Tenet lawsuit was against the entire corporation rather than a specific facility. However, of the 94 hospitals affiliated with Tenet between 1998-2001, we classify 60 (64%) as gamers.

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.

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 scores, suggesting they may serve a higher-risk patient population. 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).

5.3 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 ever affiliated with Tenet from the non-gamer group since the chain gamed heavily, and the excess revenue may have been diverted to these facilities. 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.2). 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, Heggeness and Kao, 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 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.[10] We use these parameters at their 1997 values, which were set 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, King and Porro, 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 and 1,396 non-gamer hospitals. Table 1 provides summary statistics on the gaming hospitals and 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 that both were and were not directly matched upon. Appendix Table D.3 presents descriptive statistics for hospitals in the final analysis sample by type of ownership.

[10] 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.

5.4 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 engaged in 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.

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

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.[11] X_{ht} is a time-varying control for Medicare Advantage penetration in the hospital's market.[12] 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, the analysis assumes that outcomes for gamers and comparators would have progressed on similar trends as in the 1994–1997 period, absent the gaming behavior observed over 1998–2003. This "parallel trends" assumption is standard in D-D research designs and is untestable. However, an event study can provide suggestive evidence on the assumption by showing whether the groups were on differential trends prior to the gaming episode. It also helps to study effect dynamics. We therefore estimate the following model:

[11] Appendix Tables D.5 and D.6 report β_3, the effect during the post-gaming period.

[12] 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).

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

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 re-converge after CMS closes the loophole. While the post-gaming period is complicated by legal uncertainty and settlements, this convergence further suggests the groups would have been on similar trends absent the gaming.

6 Results

This section presents our main results on the excess revenue hospitals generated by exploiting the loophole and how they allocated this revenue. Figures 4 and 5 present event studies using 1997 as the reference year and demarcate the gaming period (1998–2003) with vertical dashed lines. Table 2 presents the corresponding D-D estimates distinguishing between the early (1998–2000) and late (2001–2003) periods.

6.1 Excess revenue

We begin by confirming that hospital charges increase differentially at hospitals identified as gamers by our algorithm. Appendix Figure D.3 Panel (a) shows the divergence in mean charge per inpatient stay between gamers and the matched comparators. Panel (b) presents the corresponding event study plot. Table 2 presents the corresponding estimated effects on log charge per patient stay. We find that gamers increase their charges by 96% at the height of gaming relative to the comparators.

We then quantify the excess outlier payment revenue gained by the gamers due to turbocharging. Figure 4 Panel (a) presents the event study for total outlier payments in millions of dollars. Gamers and non-gamers have similar trends until 1998 when revenue increases differentially for gamers. Excess outlier revenue peaks for gamers in 2002. As expected, there was a sharp drop in 2004, the first full year in which the loophole was closed. Payments return to baseline and stay there through 2006. Table 2 presents the corresponding coefficients of interest from Equation 2 and shows that the hospitals gain \$1.3M in outlier payments per year in the early period and \$4.4M per year in the late period. Relative to the pre-gaming average of \$1.7M per year, gaming hospitals more than double their outlier payments at the height of turbocharging. Summing over the six years, the average gamer obtains over \$17M in excess outlier payment revenue. We therefore can estimate that gamers obtained over \$3 billion in excess outlier payments by multiplying 180 (the full set of gamers) by \$17M.

Figure 4 Panel (b) plots the event study for Medicare inpatient revenue, a broader measure of income that includes DRG payments. It shows a strikingly similar pattern to that seen for outlier payments. The corresponding coefficients in Table 2 are very similar in magnitude to those estimated for outlier payments. A comparable increase in total Medicare inpatient revenue and outlier payments is expected, since increasing charges should not affect DRG payments. This pattern also implies that significant changes on other margins, such as increasing the volume of Medicare patients, are unlikely. 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. Using the Poisson analog of equation 2, we find that gaming raises rates by 7.6% in the early period and 21.8% in the late gaming period (Table 2).

We next 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, a practice that remains common today (Cooper et al., 2019). Another potential channel would be if other insurers mimic Medicare's payment systems and also make outlier payments.[13]

Figure 4 Panel (c) presents the event study plot for all-payer revenue and finds a trajectory similar to Medicare payments, with a peak in 2002; excess revenue subsequently falls and becomes statistically insignificant by 2004. Table 2 shows that the increase in total revenue is about triple the increase in Medicare inpatient revenue, just as baseline total revenue is about triple baseline Medicare inpatient revenue, suggesting similar Medicare and non-Medicare effects. The \$11.2M per year effect aggregates to \$67.3M over the whole period. Unlike the patterns in outlier payments and Medicare revenue, we find that some

[13] 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 decline precipitously (Tenet Healthcare Corporation, 2003, 2004).

increase in all-payer revenue persists beyond 2003. This might reflect the persistent increase in charges discussed above since hospital chargemaster rates are frequently used to set commercial insurance prices. Our results, therefore, imply large and persistent spillover effects of turbocharging to private insurers and, consequently, to employers and employees that fund private health insurance plans.

6.2 Use 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 (often referred to as surplus in the case of nonprofits). We begin by examining the effect on operating costs. Figure 4 Panel (d) presents the corresponding event study plot. The groups follow similar pre-trends and trends through the early period, then gamers experience an uptick in the late period. The costs subsequently decline, in relative terms, after the loophole is closed. Table 2 presents the D-D coefficients. We estimate a differential increase in operating cost of \$10.8M per year during the late period. Aggregated over the whole gaming episode, operating costs increase by \$32.3M (not statistically significant) or 48 cents for every incremental dollar of all-payer revenue. The statistically insignificant effect on total costs reflects the average of increases observed among nonprofit gamers and decreases observed among for-profit gamers, which we explore in Section 6.3. By construction, the remaining half of excess revenue flows toward increasing profits.

Hospitals can use greater profits for two purposes. First, they could be used to increase a hospital's net worth, which represents a hospital's total assets net of the change in liabilities. Hospitals could increase short-term or long-term assets like cash reserves or fixed capital (e.g., purchase new equipment) or pay down short-term or long-term debt to reduce their liabilities. Second, profits can be transferred by 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.

Figure 4 Panel (e) presents the event study plot for changes in 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.[14] The D-D results confirm an early decline in net worth that is later partially reversed (Table 2). The overall effect is essentially zero and

[14]Figure D.4 presents event study plots for the change in assets and liabilities separately. They suggest an increase in liabilities over 1998–2000, which was offset by a similar-sized increase in assets later in the period. The coefficients in Table 2 also exhibit this pattern.

is statistically insignificant. The estimated confidence interval allows us to reject an increase of more than $12.5M in net worth for the average gamer hospital during this episode, which is one-sixth of the estimated inflow in revenue. This result suggests that excess revenue is not used to pay down liabilities or increase assets.

The lack of a meaningful change in net worth for gamer hospitals leaves only one possible avenue for the remaining excess profits: net deductions. Table 2 shows that net deductions increase by $6.6M per year or nearly 60 cents for every incremental dollar of revenue. In Section 6.3, we show that this increase in net deductions is predominantly driven by for-profit hospitals.

Figure 4 Panel (f) presents the associated event study plot, which confirms similar trends before 1998 and a sharp increase in deductions that closely tracks the increase in revenue. This result implies that over half of the revenue obtained by turbocharging is transferred off hospital balance sheets. 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.[15] While the cost report data alone does not permit us to examine the ultimate uses of these deductions, Section 6.3 explores whether the revenue is transferred to executives and shareholders at for-profit hospitals.

Taken together, we find that during the 6-year gaming period, the average turbocharging hospital increases operating costs by $32.3M, increases net balance deductions by $39.5M, and decreases net worth by $3.8M. These changes roughly sum up to the total of 67.3M increase in all-payer revenue.[16] These results are consistent with the mental accounting hypotheses discussed in Section 3 since hospitals fail to invest the revenue in new capital or in growing net worth and instead direct most funds towards operating costs or send them off the hospital balance sheet.

6.2.1 *Inputs to care*

The results in the previous section imply that about 60% of the funds obtained by turbocharging were transferred outside the hospital. We also find some signs that funds were directed to operating costs, though the results are imprecise. We now directly explore the effect on measures of care inputs to assess whether patients or hospital staff may have

[15] 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.

[16] The two sides are not exactly equal due to variable-specific data cleaning like winsorizing; the use of slightly different samples for net balance deductions and change in net worth, since we do not observe these values for 1994; and our use of all-payer revenue rather than total income, which also includes investment income but yields essentially identical results.

benefited from the revenue windfall.

We first examine changes in three measures of care inputs. Figure 5 Panels (a), (b), and (c) present the event study plots for total inpatient volume, hospital FTE, and total spending on salaries, respectively. Reassuringly, each has flat pre-trends. Gamer hospitals also do not appear to differentially serve more patients, employ more staff, or increase spending on personnel during 1998–2003. In fact, the FTE series implies a slight decline in staff during this period and a larger decline after the outlier payment loophole is closed.

Table 3 Panel A presents the corresponding coefficients on patient volume and hospital FTE. The point estimate on patient volume is close to zero and is statistically insignificant. The confidence intervals allow us to reject an increase of more than 3.4%. Similarly, the coefficients on staff FTE imply, if anything, a decline in staffing during the gaming period. Averaging over the entire episode, we can reject an increase of more than 0.8%.

Since the spending on salaries is a component of total operating cost, we prefer to report the coefficient on salaries in Table 2 Panel B. By this measure, the average effect over the entire period is small and statistically insignificant and implies an increase of $4.2M. This is disproportionately small relative to the estimated increase in operating cost ($32M) given that salaries account for more than 40% of total costs. Taking the results on FTE and salaries together, however, we conclude there is no consistent evidence of gamers deploying the excess revenue toward labor inputs. This finding is consistent with the hypothesis discussed in Section 3 that hospitals would be reluctant to use these funds to enter into longer-term commitments due to their transience.

6.2.2 *Quality of care*

Finally, we directly investigate whether patient health outcomes improve at gamer hospitals. As discussed in Section 4, we examine changes in standard measures of quality used by Medicare and other payers in performance pay incentive programs to improve hospital quality. These analyses focus on patients hospitalized through the emergency department for any of 29 non-deferrable conditions (Doyle et al., 2015). We observe patients' 30-day mortality and readmission as well as key covariates that might affect their risk of experiencing these outcomes: their demographics, their illness histories (derived from previous hospitalizations), and their principal diagnosis category.

We begin by looking for signs of patient selection. To do so, we model the risk of mortality and/or readmission among the non-deferrable patients as a function of their key covariates.[17] Then, we calculate the average observable mortality and readmission risk of non-deferrable patients in each hospital in each year and study it as an outcome. Table 3 Panel B presents the estimated effects. The results show an (insignificant) decline in predicted mortality risk matched by a small but significant increase in predicted readmission risk; we detect no change in the composite risk of mortality *or* readmission.

Then, we test whether patient outcomes improved. We assemble yearly cohorts of the non-deferrable patients and run the following first-step regression:

$$mr_{iht} = \gamma_{ht} + Z_{iht}\Phi + \eta_{iht} \quad t \in 1994, \ldots, 2006 \tag{4}$$

Where i indexes patients and mr_{iht} is an indicator for patient endpoint (mortality, readmission, or a composite of both). The γ_{ht} are hospital-year fixed effects, and the Z_{iht} are patient covariates. We extract the fixed effects, which can be interpreted as the hospital's risk-adjusted mortality rate (Chandra et al., 2016). These fixed effects become the outcome variables in the hospital-level event study or D-D model.

Table 3 Panel C presents the coefficients on these three patient health endpoints. There are no detected improvements. We find a small and statistically insignificant decline in mortality. We detect an increase in readmissions of 0.3 percentage points, about 3% of the baseline mean.[18] When we consider the composite outcome of mortality or readmission, we cannot detect an effect. Event studies reaffirm these findings, with no clear pre-trends and no clear signs of improvement during or after the gaming period (Figure 5 Panels d–f).

Overall, there is an insufficient signal here to conclude that the quality of care changes at gamer hospitals during this episode. The coefficients are estimated precisely enough to allow us to rule out an average decline in mortality of more than 0.55 percentage points (4% relative to the baseline mean), and we can nearly rule out any decline in readmissions. Thus, in addition to detecting no statistically significant gains in patient outcomes, we can also statistically reject moderate improvements in quality.

[17] Specifically, we regress an indicator for mortality, readmission, or a composite of both on patient demographics, illness histories, and principal diagnosis categories. This regression is run only for patients at the comparator hospitals. Then, using the coefficients from the regression, we predict the probability of mortality, readmission, or the composite for all non-deferrable patients.

[18] Medicare did not penalize high readmission rates during this period, and they were not a topic of policy debate. It is also worth noting that reducing mortality opens the potential for readmission.

6.3 Heterogeneity by hospital ownership

We now test whether hospitals under for-profit and nonprofit ownership make different choices about how to allocate revenue from gaming, as predicted by economic theory.[19] Our findings are consistent with theories of altruism and non-contractible quality that predict different behavioral responses from nonprofit compared to for-profit firms.

As seen in Table 4, for-profit and nonprofit gamer hospitals experience comparable increases in outlier payments and Medicare inpatient payments. Both sets of gamers also obtain a similar increase in all-payer revenue relative to the baseline of about 10%. This suggests spillovers to other payers in both types of hospitals. The key difference between the two groups appears in the use of incremental revenue. Nonprofit hospitals primarily allocate excess revenue to operating costs: the average nonprofit increases operating costs by $56.7M over the 6-year gaming period, approximately 75% of the incremental all-payer revenue. The remainder of the revenue is mostly transferred off their balance sheet with little impact on net worth.

In contrast, for-profit hospitals mainly transfer funds off the balance sheet, presumably to their parent company: net deductions increase by $78.4M over the 6-year gaming period. This estimate appears puzzling at first since it represents 145% of the estimated increase in their all-payer revenue. This is made possible by reducing operating costs and net worth and using these proceeds to increase net deductions. Figure 6 provides the accompanying event studies for these subgroup analyses. We can reject the null hypotheses that the effects on change in net worth and net deductions are the same at the 5% level, and we reject that null for operating costs at the 10% level. Hence, nonprofits and for-profits allocate the excess revenue differently in an economically meaningful and statistically significant way.

We examine the effects on operating costs for nonprofit gamers in more detail to determine where they allocated the excess funds. Appendix Table D.4 presents the associated results. We continue to find no significant increase in salaries even among nonprofit gamers. The increase in costs is mainly driven by "other direct" costs, which account for approximately half of the total cost base. We estimate a statistically significant increase of about $6.5M per year during the gaming period in other direct costs, more than two-thirds of the total increase in costs and disproportionately larger than its share of the cost base.

This category of other direct costs includes general, inpatient, and ancillary services. However, we have less statistical power to detect the effects on these smaller spending items. We detect a statistically significant increase only in non-salary hospital inpatient services of

[19]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 3 and 2 using this sample. Next, we repeat the method for nonprofit gamers.

about \$0.6M per year, a disproportionately large increase of about 25% relative to baseline. The coefficients also suggest an increase in spending on non-salary general services, though it is not statistically significant. Taken together, these results suggest that nonprofits invest at least some of the excess funds into clinical inputs, yielding higher spending even as patient volume is flat or falling. These results are consistent with the flypaper effect discussed in Section 3 since we find that the funds are used disproportionately for inpatient care, which is service the funds pay for in the first place.

Table 4 Panels D and E present the effects on patient risk and health outcomes. The coefficients in Panel D show that nonprofit gamers treated a 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. In contrast, for-profit gamers treated a much lower-risk patient population. The predicted mortality dropped by 0.86 percentage points or 6% of baseline risk. These results suggest the possibility of some reallocation of patients across hospitals due to this episode.

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. 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 hospitals. This is not surprising since only 75% of the revenue is used directly for patient care. If we account for this diversion, the mortality improvement relative to spending is perfectly in line with previous estimates. We also detect a modest increase in readmission rates at nonprofit gamers of 0.6 percentage points.

For-profit hospital outcomes reveal a different pattern. There are statistically significant reductions in hospital FTE and total spending on salaries among for-profit gamers. Accordingly, operating costs decline, though this decline is not statistically significant. Since little of the income is invested into the hospital and the majority is sent off the balance sheet, it is perhaps unsurprising that there are no changes in quality outcomes among for-profit gamers.

6.3.1 *Executive compensation and shareholder payouts*

We now investigate whether hospitals used some of the excess 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) 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. In contrast, compensation to hospital-level executives represents a part of hospital operating costs, though the cost report data does not disaggregate executives from non-executive salaries.

Unfortunately, data on executive compensation is not systematically collected or made available for research, as discussed in Section 4. Because of how the data is organized, 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. Since few health systems are publicly traded during our sample period, we can only study compensation at a single for-profit firm that gamed – Tenet Corporation.[20] 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 similar pattern to that of outlier payments. Figure 7 Panel (a) shows total executive salary and bonus at Tenet reaching a peak of $13.4M in 2001 before falling in the year the Tenet scandal broke. This is about double the compensation level of $6M observed in 1998. The pattern is even more striking in Panel (b), which expands the measure to include stock options exercised. By this metric, Tenet executives received $92.5M in 2001. No such patterns are observed among the non-Tenet systems. Moreover, we are likely underestimating the true amount distributed to executives since only compensation for the five highest-paid executives is reported.

Publicly traded firms can also disburse profits to shareholders. As seen in Figure 7 Panel (c), Tenet shareholder payouts also coincide with the gaming period, with shareholders receiving $923M between 2000 and 2004. While 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

[20] There are also a few gamer hospitals owned by other publicly traded firms, but they account for negligible fractions of bed capacity or patient volume of those firms, so we do not tag these firms as gamers.

revenue was disbursed to the five highest-paid executives and 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. Table 4 Panel (b) reports the D-D estimates, and Figure 7 Panel (d) presents the corresponding event study plot. In complete contrast to the patterns observed for Tenet, we do not observe any increase in compensation during 1998–2003. These results strongly suggest divergence with regard to the use of funds for executive pay between for-profit and nonprofit firms. These results support the organization theories discussed in Section 3 that managers at nonprofit and for-profit firms may use surplus funds differently.

6.4 Robustness checks

This section describes results from robustness checks testing the sensitivity of our key results to changing important assumptions or methods. The estimates obtained from these robustness checks are presented in Appendix Figure D.5, which focuses on the six key outcomes representing the flow of funds for hospitals (upper plot), two measures of hospital inputs, patient selection, and patient outcomes (lower plot). We present alternate estimates for each of these outcomes using seven different robustness checks and compare them to the baseline estimate from the preferred model. To simplify presentation, we focus on average effects across the gaming period.

Our baseline approach uses Coarsened Exact Matching (CEM) to reweight the comparator set of hospitals. An alternative but analogous approach is to 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, therefore, 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 similar estimates to the baseline method.

Next, to assess sensitivity to alternative matching strategies, we replicate our estimates

[21] We tag 60 Tenet hospitals as gamers and the average Tenet hospital received 7.9 million in all-payer revenue per year (Table 4 reports the result for all for-profits, which is similar). Therefore, Tenet's total estimated windfall is \$2.9 billion and the \$1.1 billion distributed to executives and shareholders represents about 40% of this amount. However, this is likely an underestimate of the reward for these groups. As a for-profit corporation, Tenet's incremental profits would be subject to state and federal taxes, which collectively were about 40% during this period. Taking this into account, executives and shareholders received more than 50% of the windfall after tax.

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.5 shows that the estimates are quite similar to baseline even after these modifications, though under PSM, effects on all-payer revenue and operating costs are attenuated.

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.

Finally, we consider three modifications to our strategy for identifying gamers. First, we modify the threshold of growth in charges and simulated outlier payments above which we tag a hospital as a likely gamer. In the baseline model, this threshold was the 90^{th} percentile. In robustness, we lower it to the 85^{th} percentile, which yields essentially identical results. Second, we modify the algorithm to use realized outlier payments rather than simulated outlier payments. This approach also does not change our findings. Third, we use only charge growth to identify gamers rather than additionally using growth in the ratio of outlier payments to DRG payments. In this approach, gamers are those in the top decile of charge growth, and non-gamers are those under the 85^{th} percentile of charge growth. The results are similar using this method, though the scale of revenue is, as expected, smaller than in the baseline approach.

7 Discussion and Conclusion

In this paper, we use a design flaw in Medicare's outlier payments program to study how hospitals allocate revenue obtained by exploiting loopholes or gaming. CMS was first warned of the potential for outlier payments gaming 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 together 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 hospital owner type. For-profit hospitals drive the observed transfer of funds off balance sheets. For-profits also reduce spending on hospital and staff FTE, contributing to a decline in operating costs. In contrast, nonprofit hospitals mainly allocate excess revenue to increasing operating costs, particularly non-salary costs on general services and inpatient care. Nonprofit hospitals also produce a modest improvement in mortality rates. However, they deliver a lower mortality improvement for the incremental revenue than could have been obtained by reallocating patients to higher-spending hospitals. Consistent with the argument that greater spending on patient care decreases mortality, there are no quality improvements among for-profit hospitals since little of the excess revenue is invested in the hospital. Overall, these results suggest hospitals engineered a windfall with significant fiscal costs, while the benefits vary by ownership type.

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, Carlton and David, 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. An additional reason for this different behavior may be the source of funds. Since managers may perceive revenue from this loophole as less legitimate and less permanent, they may spend it differently than other income. 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 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 may influence hospital spending.

The loophole in the outlier payments program also serves as a warning of the 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 (Arnold and Whaley, 2020). 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 deploy windfalls engineered by exploiting payment loopholes. However, the issue of intermediaries exploiting loopholes 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 and K-12 education delivered by charter schools. 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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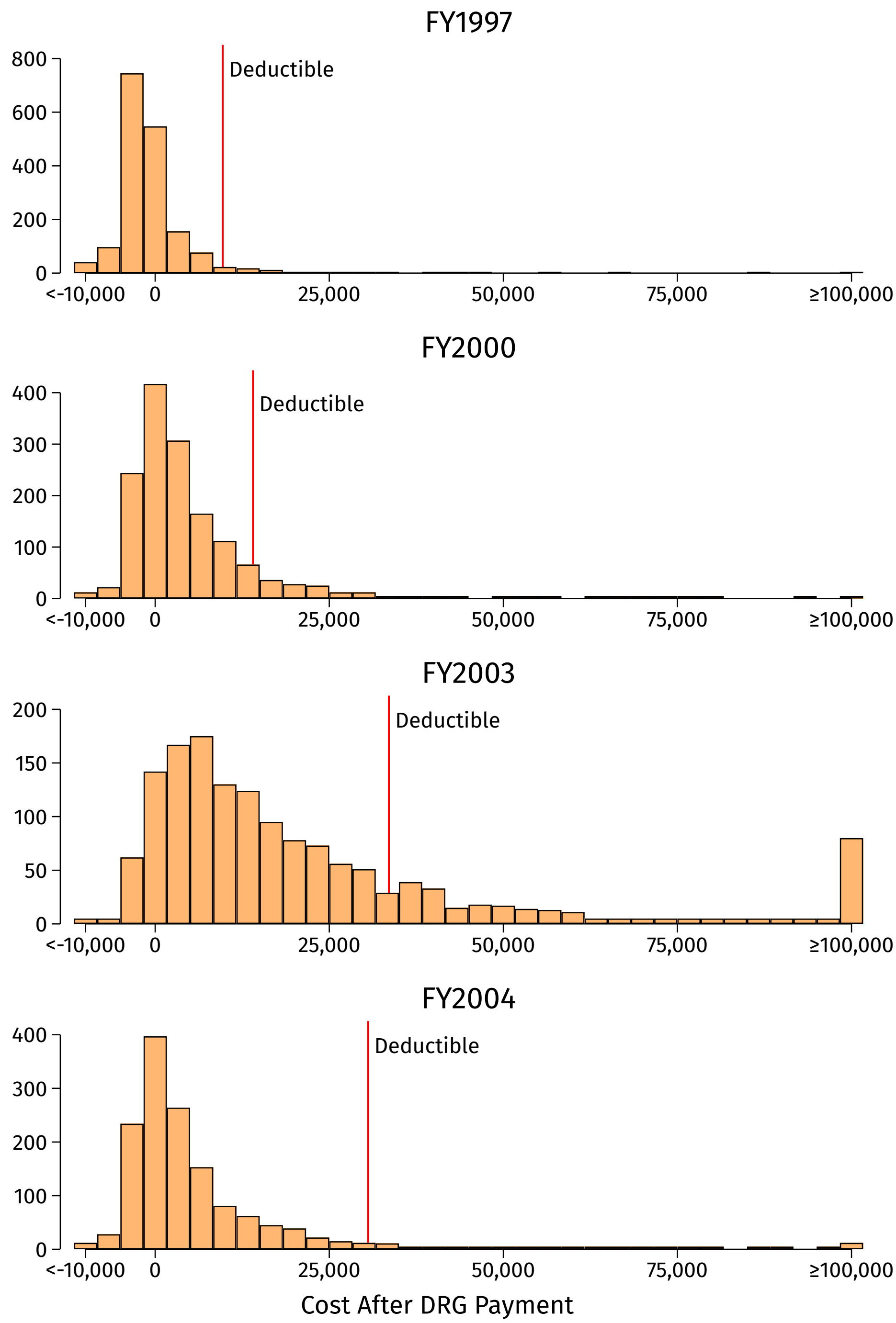

Figure 1: Evolution of excess "cost" distributions at an extreme gamer hospital

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.

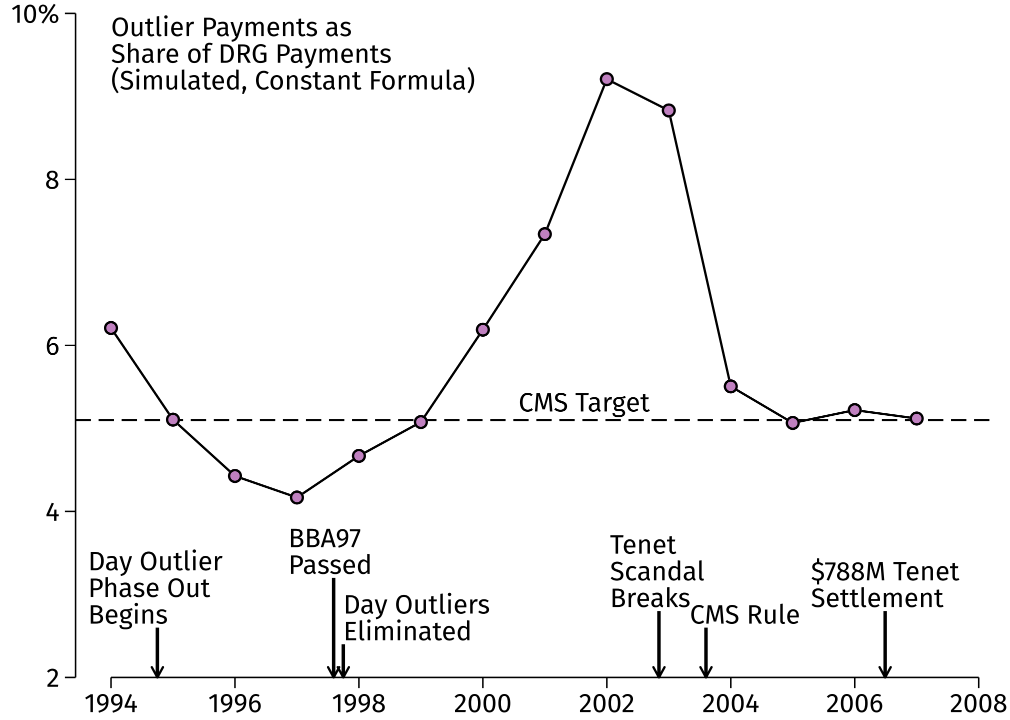

Figure 2: Trend in Medicare outlier payments

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.6 shows the same time series using actual payment data.

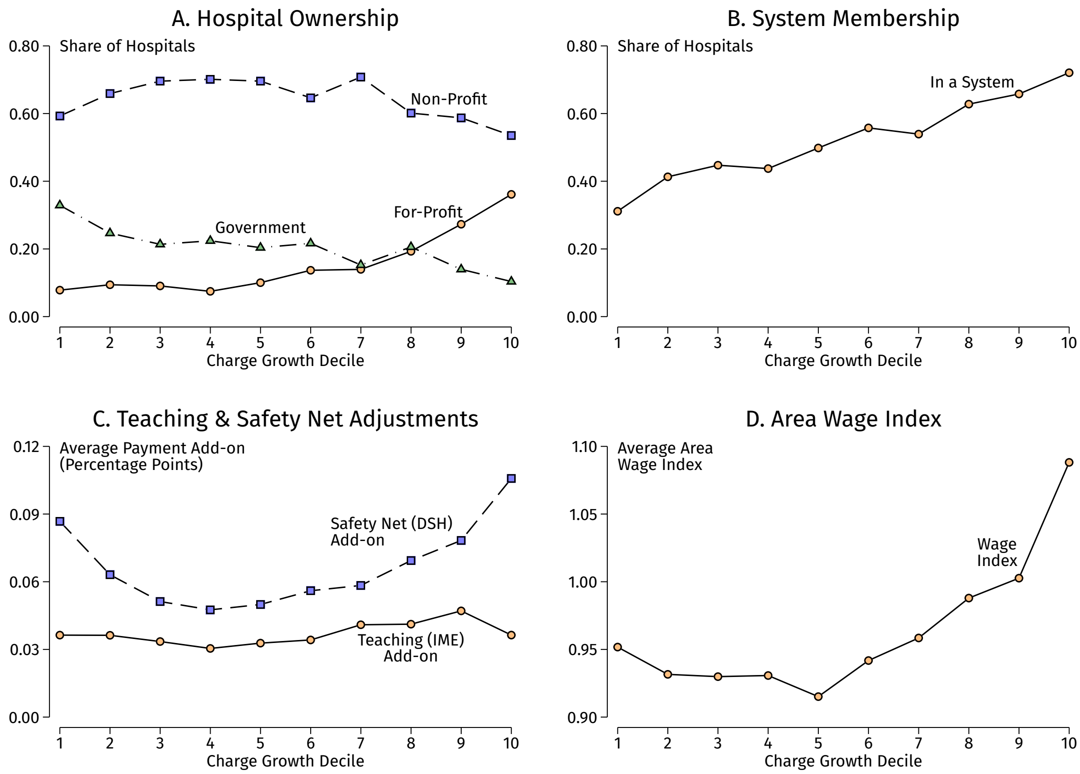

Figure 3: Characteristics of Hospitals by Charge Growth Decile

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, 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.

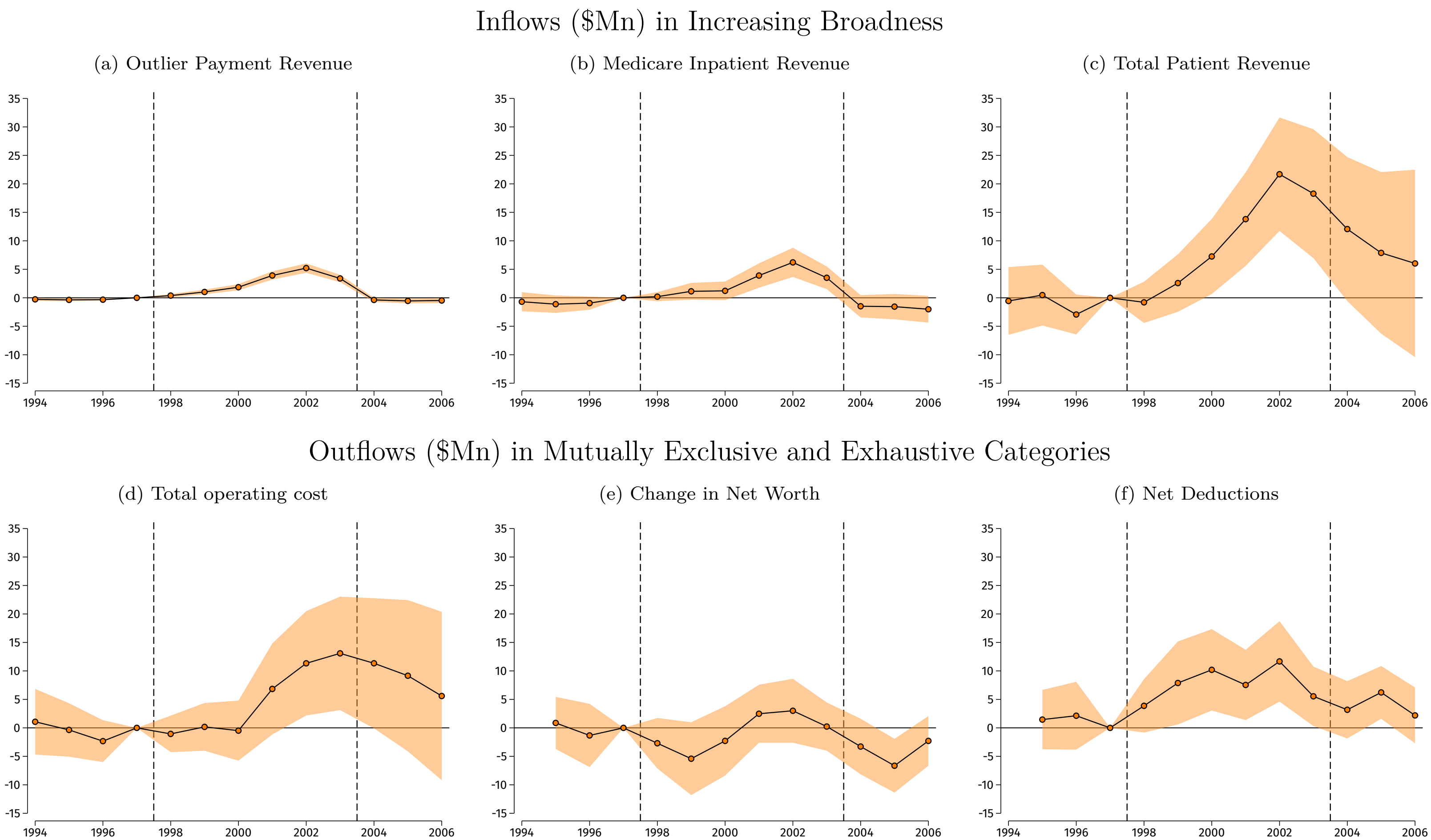

Figure 4: Flow of funds

Notes: The figure presents event study plots obtained by estimating the dynamic effects model in Equation 3 on 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.

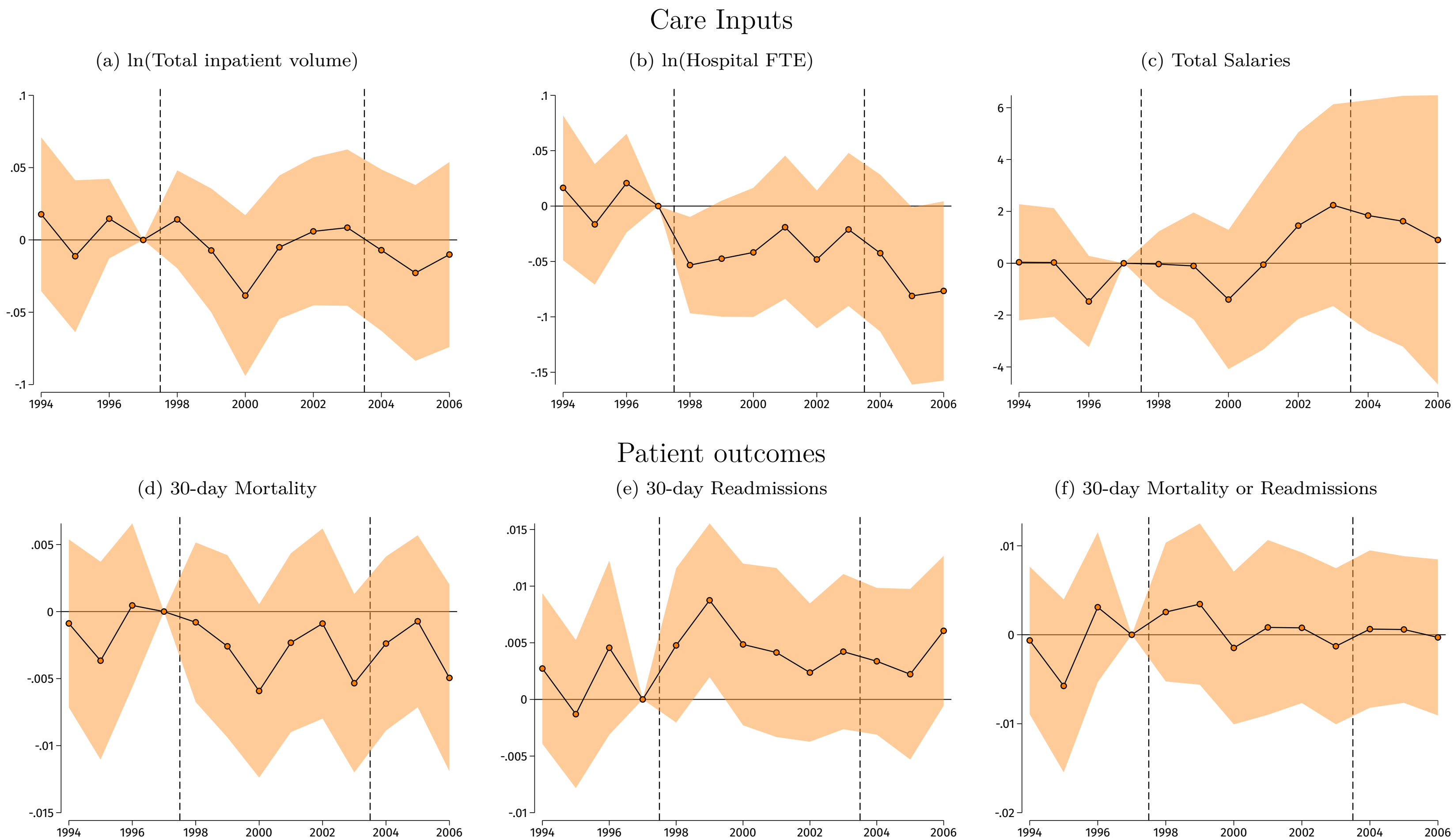

Figure 5: Inputs and Patient Outcomes

Notes: The figure presents event study plots obtained by estimating the dynamic effects model in Equation 3 on our main analysis sample. The outcomes here are measures of care inputs (total number of inpatients, full-time equivalent employment, and total salaries) and measures of health outcomes for the cohort of patients admitted with non-deferrable conditions (30-day mortality and readmission rates). Event studies for inpatient volume and full-time equivalent employment are estimated with Poisson models. Data on inputs is sourced from the Medicare cost reports, while health outcomes are observed for 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.

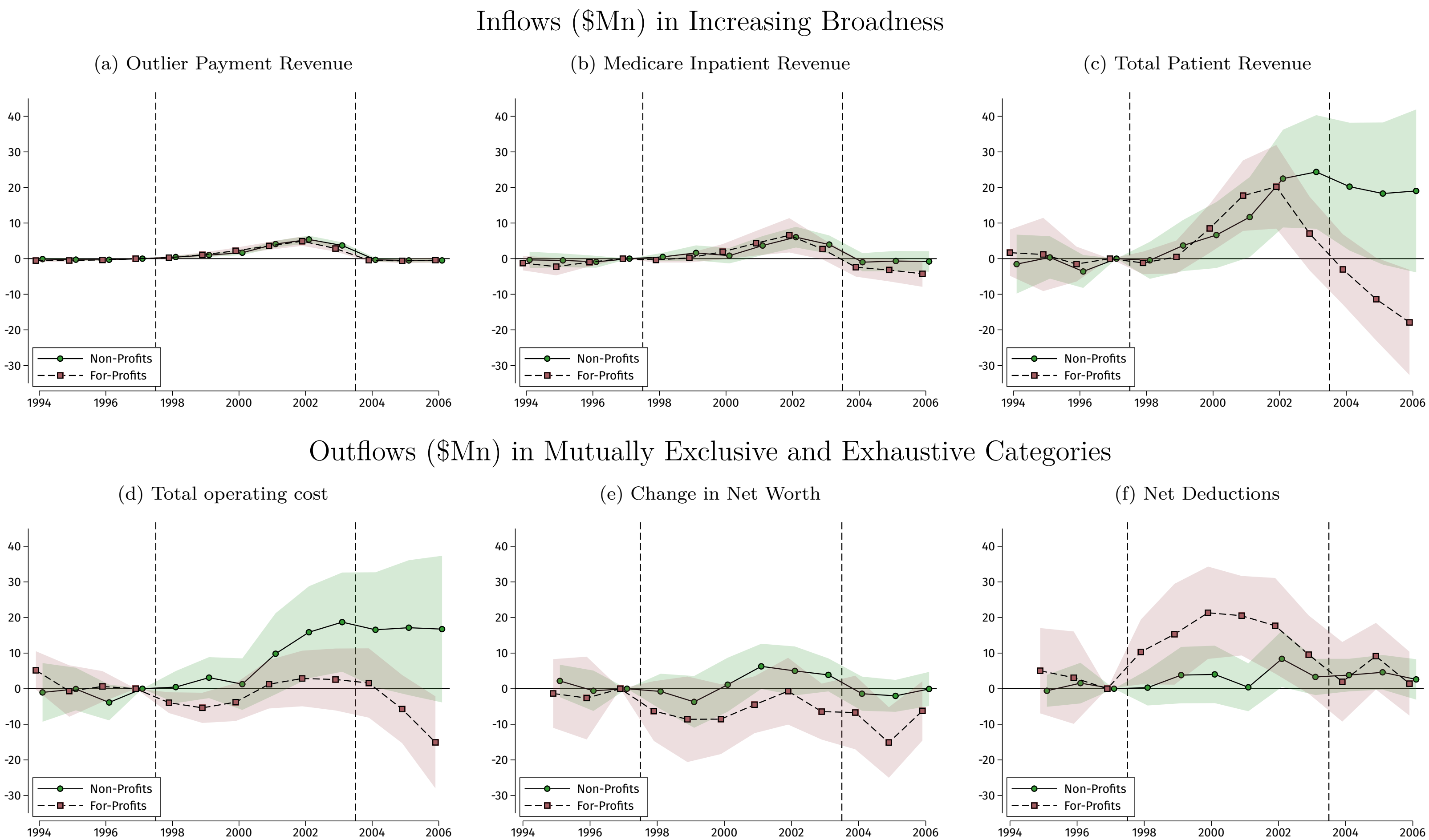

Figure 6: Flow of funds for nonprofits and for-profits

Notes: 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.

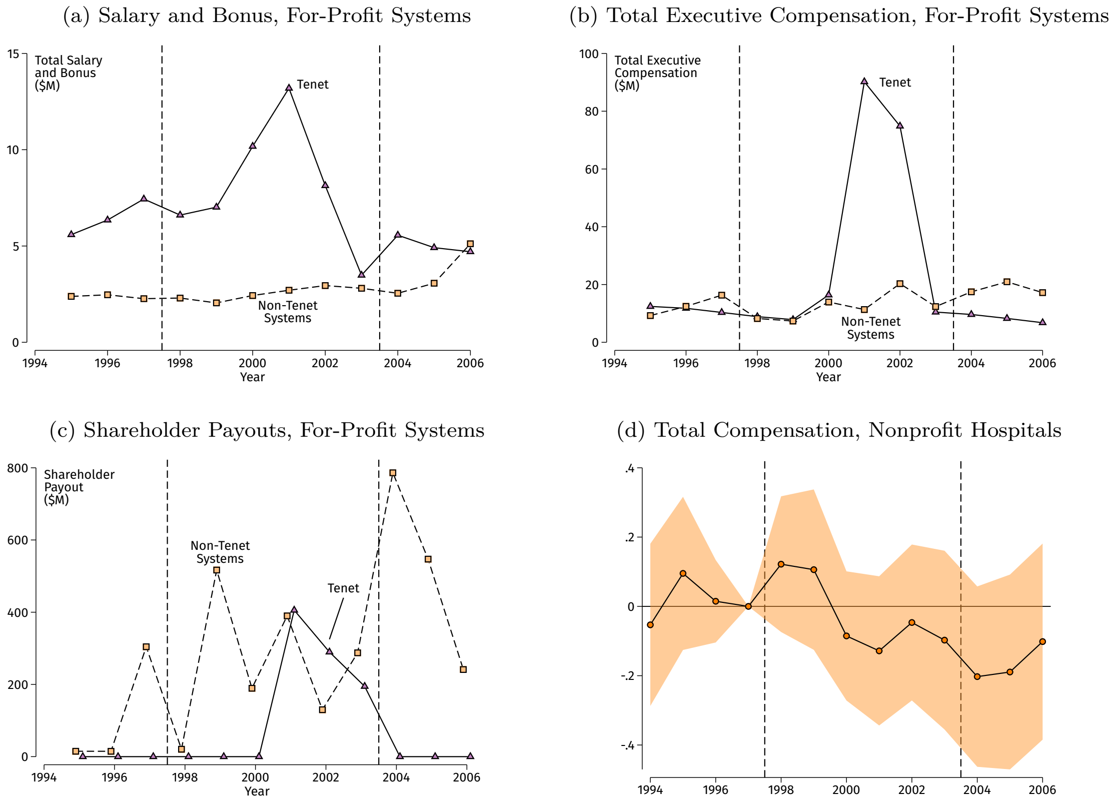

Figure 7: Compensation of Executives and Shareholders

<u>Notes:</u> Figure (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. Figure (b) is an extension of Figure (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. Figure (c) presents the total shareholder payouts representing the sum of dividends and the purchase of common and preferred stock. Figure (d) presents event study plots obtained by estimating the dynamic effects model in Equation 3 for the compensation of key individuals measured in 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.

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		
Non-Profit	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.

Table 2: Flow of Funds

	(1) DV Mean	(2) 1998–2000	(3) 2001–2003	(4) 1998–2003	(5) Observations
ln(Medicare Charges/Patient)	20,430.4	0.254***	0.671***	0.463***	19,706
		(0.0198)	(0.0241)	(0.0185)	
Panel A. Income in Increasing Broadness					
Medicare Outlier Payments	1.715	1.331***	4.419***	2.875***	19,699
		(0.235)	(0.347)	(0.257)	
Medicare Inpatient Payments	32.94	1.537+	5.232***	3.384***	19,699
		(0.855)	(1.249)	(0.993)	
ln(Medicare Payments/Patient)	9,150.2	0.0732***	0.197***	0.135***	19,706
		(0.0114)	(0.0185)	(0.0133)	
All-Payer Revenue	111.0	3.776	18.66***	11.22**	19,515
		(3.021)	(5.528)	(4.089)	
Panel B. Outflows in Mutually Exclusive Categories					
Operating Costs	111.9	-0.0489	10.82*	5.387	19,580
		(2.755)	(5.056)	(3.745)	
Total Salaries	46.85	-0.158	1.565	0.703	19,699
		(1.302)	(1.998)	(1.584)	
ΔNet Worth	5.199	-3.317+	2.058	-0.630	17,949
		(1.768)	(1.450)	(1.383)	
ΔTotal Assets	4.156	0.979	4.329*	2.654	18,040
		(1.979)	(2.130)	(1.736)	
ΔFixed Assets	0.707	-0.173	0.410	0.118	17,943
		(0.884)	(0.891)	(0.769)	
ΔLiabilities (subtracted)	-0.662	3.489*	1.989	2.739*	18,009
		(1.694)	(1.534)	(1.265)	
Net Deductions	1.703	6.112**	7.048**	6.580***	17,949
		(2.187)	(2.258)	(1.960)	

Notes: The table presents the coefficients estimated using Equation 2. Each row presents coefficients from a separate regression on a different dependent variable, typically estimated on a slightly different sample. Column 1 presents the sample mean value of the dependent variable for gamers during 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 for 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. Effects on Medicare charges per patient and payments per patient are estimated using Poisson regression; these coefficients have a log-point interpretation. All-payer revenue includes both inpatient and outpatient components. The change in net worth is equal to the change in assets minus the change in liabilities. Net deductions refers to the funds transferred off the hospital's balance sheet, typically to its corporate parent. Standard errors are in parentheses and are clustered by hospital. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Care Inputs, Patient Risk, and Outcomes

	(1) DV Mean	(2) 1998–2000	(3) 2001–2003	(4) 1998–2003	(5) Observations
Panel A. Care Inputs					
ln(Total Inpatient Volume)	10,812.4	-0.0160	-0.00192	-0.00895	19,519
		(0.0209)	(0.0256)	(0.0218)	
ln(Hospital FTE)	1,076.8	-0.0526*	-0.0345	-0.0436^{+}	19,505
		(0.0243)	(0.0312)	(0.0262)	
Panel B. Patient Risk (Non-Deferrable Conditions)					
Mortality	0.134	-0.000917	-0.00157	-0.00125	19,064
		(0.00109)	(0.00139)	(0.00113)	
Readmission	0.135	0.000274	0.000941**	0.000607*	19,064
		(0.000259)	(0.000345)	(0.000274)	
Mortality or Readmission	0.258	-0.000666	-0.000662	-0.000664	19,064
		(0.00111)	(0.00143)	(0.00115)	
Panel C. Patient Outcomes (Non-Deferrable Conditions)					
Mortality	0.139	-0.00208	-0.00183	-0.00196	19,064
		(0.00193)	(0.00219)	(0.00182)	
Readmission	0.134	0.00463*	0.00208	0.00335^{+}	19,064
		(0.00198)	(0.00213)	(0.00183)	
Mortality or Readmission	0.264	0.00232	0.000926	0.00162	19,064
		(0.00249)	(0.00281)	(0.00237)	

Notes: The table presents the coefficients estimated using Equation 2. Each row presents coefficients from a separate regression on a different dependent variable, typically estimated on a slightly different sample. Column 1 presents the sample mean value of the dependent variable for gamers 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 for 1998–2003. Column 5 presents the number of observations used for each regression. The health outcomes are estimated using the two-step approach described in Section 6.2.2. All health outcomes are computed for patients admitted with non-deferrable conditions, following the algorithm used in Card, Dobkin and Maestas (2009). Mortality and readmissions are measured at 30 days following discharge from the index admission. We generate predicted risk values using one-year history of co-morbidities associated with the patient and their principal diagnosis category, but not co-morbidities recorded on the index stay itself. The analyses in Panels B and C have slightly smaller sample sizes because they are restricted to hospital-years with at least 5 non-deferrable patients. Standard errors are in parentheses and are clustered by hospital. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Results for Nonprofits and For-Profits

	(1)	(2)	(3)	(4)	(5)	(6)
	Non-Profits			For-Profits		
	1998–2000	2001–2003	1998–2003	1998–2000	2001–2003	1998–2003
Panel A. Income in Increasing Broadness						
Medicare Outlier Payments	1.225***	4.580***	2.903***	1.536***	4.128***	2.832***
	(0.303)	(0.431)	(0.310)	(0.363)	(0.581)	(0.453)
Medicare Inpatient Payments	1.409	4.987**	3.198*	1.725+	5.642**	3.684**
	(1.192)	(1.554)	(1.299)	(0.940)	(2.011)	(1.405)
All-Payer Revenue	4.482	20.70**	12.59*	2.289	14.64*	8.466+
	(4.164)	(7.663)	(5.662)	(3.507)	(6.236)	(4.648)
Panel B. Outflows in Mutually Exclusive Categories						
Operating Costs	2.864	16.04*	9.453+	-5.640*	0.954	-2.343
	(3.881)	(7.166)	(5.288)	(2.577)	(4.199)	(3.225)
Total Salaries	0.776	3.369	2.073	-2.053*	-2.011	-2.032+
	(1.934)	(2.921)	(2.332)	(0.881)	(1.405)	(1.080)
Compensation of Key Personnel	0.0320	-0.104	-0.0360			
	(0.0999)	(0.112)	(0.0997)			
ΔNet Worth	-1.665	4.509*	1.422	-6.483*	-2.551	-4.517+
	(2.036)	(1.834)	(1.569)	(3.221)	(2.173)	(2.534)
Net Deductions	2.392	3.718	3.055+	12.94**	13.21**	13.07**
	(2.252)	(2.399)	(1.821)	(4.375)	(4.440)	(4.216)
Panel C. Care Inputs						
ln(Total Inpatient Volume)	-0.0285	-0.0204	-0.0245	0.0262	0.0561	0.0412
	(0.0241)	(0.0300)	(0.0252)	(0.0381)	(0.0428)	(0.0393)
ln(Hospital FTE)	-0.0321	-0.0123	-0.0222	-0.119**	-0.103*	-0.111**
	(0.0288)	(0.0367)	(0.0309)	(0.0388)	(0.0498)	(0.0425)
Panel D. Patient Risk (Non-Deferrable Conditions)						
Mortality	0.00258*	0.00330*	0.00294**	-0.00710***	-0.0101***	-0.00862***
	(0.00118)	(0.00143)	(0.00112)	(0.00172)	(0.00202)	(0.00174)
Readmission	0.000664*	0.00140***	0.00103**	-0.000460	0.0000764	-0.000192
	(0.000310)	(0.000408)	(0.000326)	(0.000427)	(0.000577)	(0.000456)
Panel E. Patient Outcomes (Non-Deferrable Conditions)						
Mortality	-0.00492*	-0.00339	-0.00415*	0.00320	0.00109	0.00215
	(0.00200)	(0.00252)	(0.00197)	(0.00367)	(0.00380)	(0.00333)
Readmission	0.00656**	0.00480+	0.00568*	0.00112	-0.00276	-0.000820
	(0.00243)	(0.00269)	(0.00232)	(0.00296)	(0.00301)	(0.00251)

Notes: The table presents key outcomes from Tables 2 and 3 separately for nonprofit and for-profit gamers. Each row presents coefficients from a separate regression on a different dependent variable, typically estimated on a slightly different sample. Columns 1–3 consider effects for nonprofit hospitals while columns 4–6 consider for-profit hospitals. See notes to tables 2 and 3 for more details on the outcome measures. Standard errors are in parentheses and are clustered by hospital. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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

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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 1988*a*, 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, 1988*b*, 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, 1988*b*, 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 (n.d.)'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, 2006*a*,*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 5.1 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. $BASE$ and θ came from the PC PRICER COBOL code available from CMS. $WAGE$ 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 put 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 $CCR_{h,t}^{OP}$ is the hospital's operating cost-to-charge ratio and $CCR_{h,t}^{CAP}$ 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:

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

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:

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

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:

$$OUTLIER_i^{FC} = 0.8 \times \max\left(BILLCOST_i - THRESH_{h,t}^{FC} - DRGPAY_i, 0\right). \quad \text{(B.9)}$$

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:

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

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.

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:

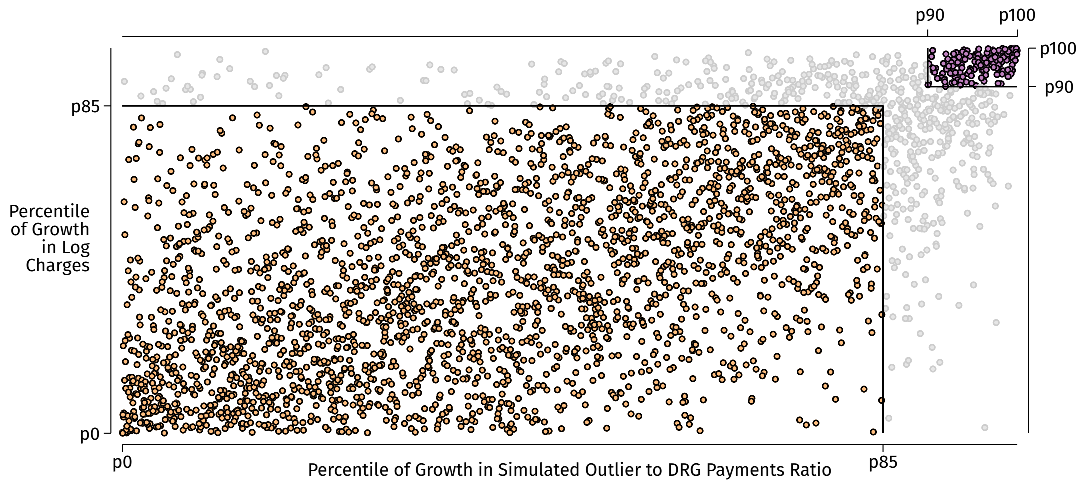
$$\Delta NetWorth_t = NetIncome_t - NetDeductions_t.$$

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)

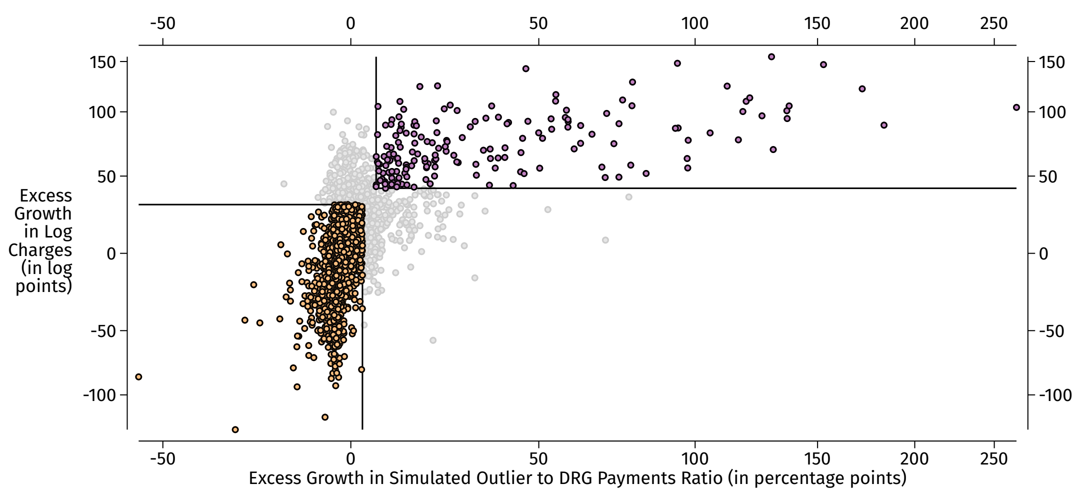


Figure D.1: Designating hospitals as "gamers"

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.

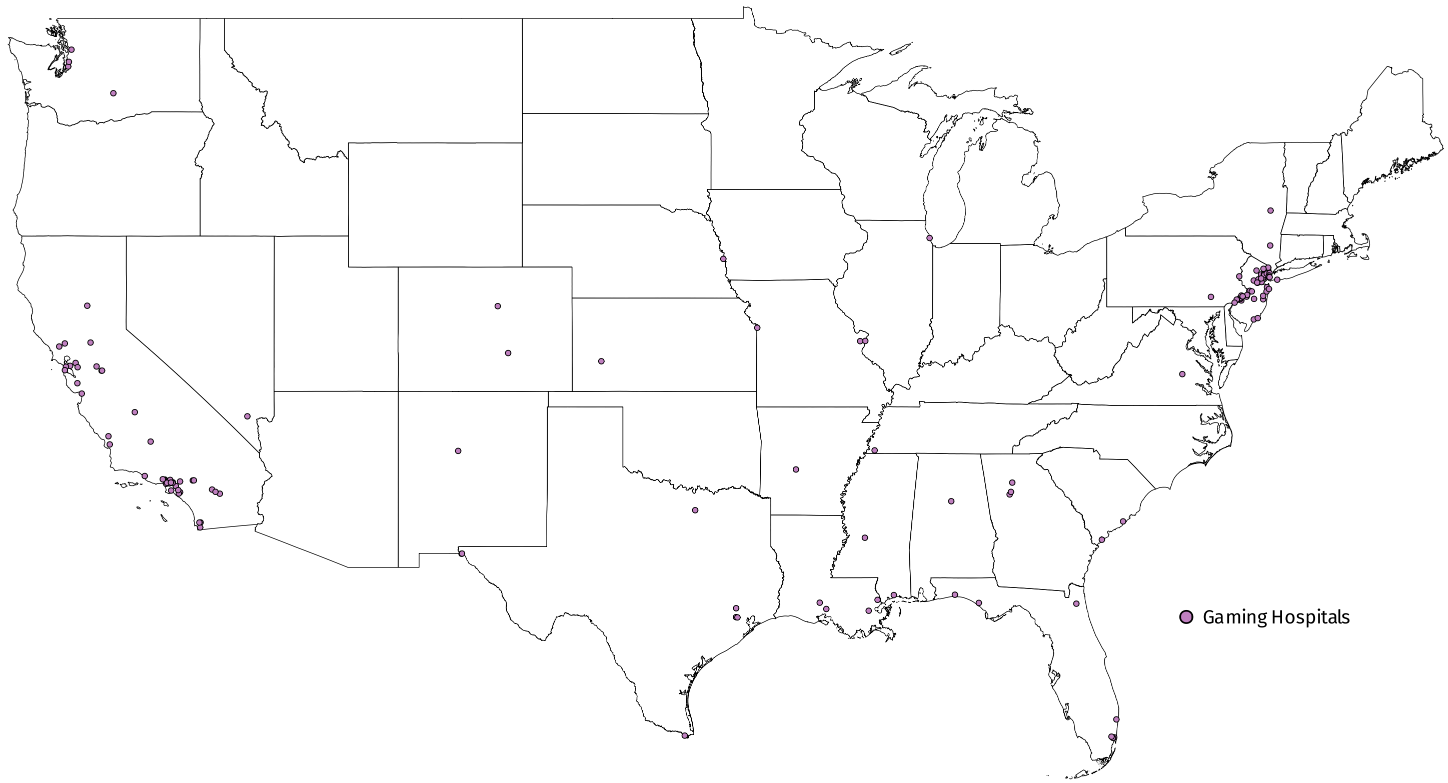


Figure D.2: Map of hospitals flagged as "gamers"

Notes: This figure displays the geographic distribution of the 145 hospitals flagged as gamers of outlier payments and meeting analysis criteria.

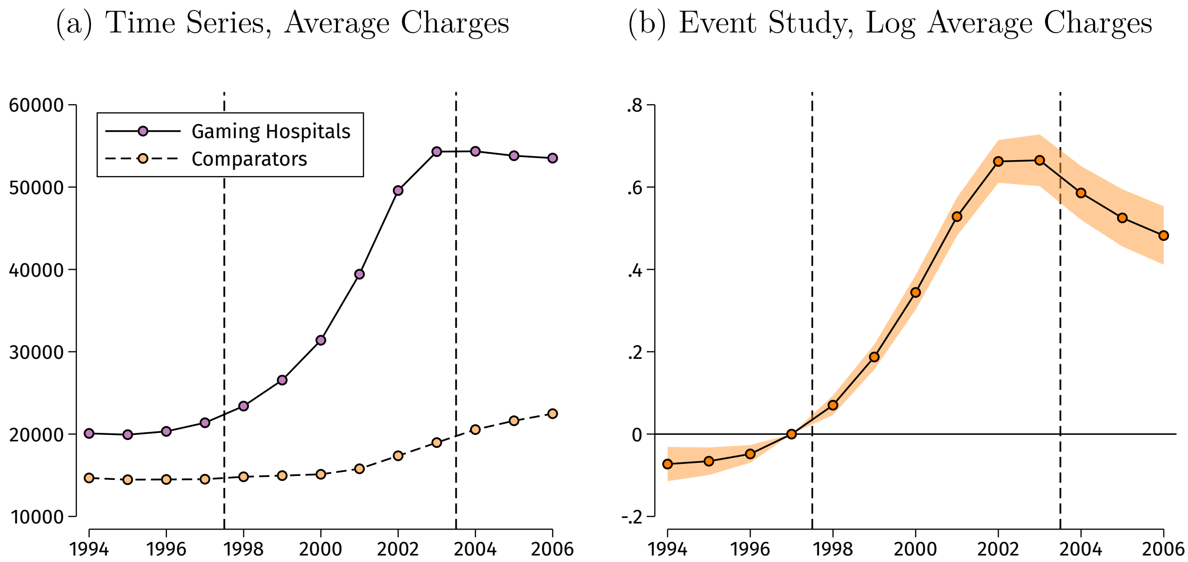


Figure D.3: Time Series and Event Study Plots of Hospital Charges

Notes: This figure visualizes the evolution of average charges for Medicare patients 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.

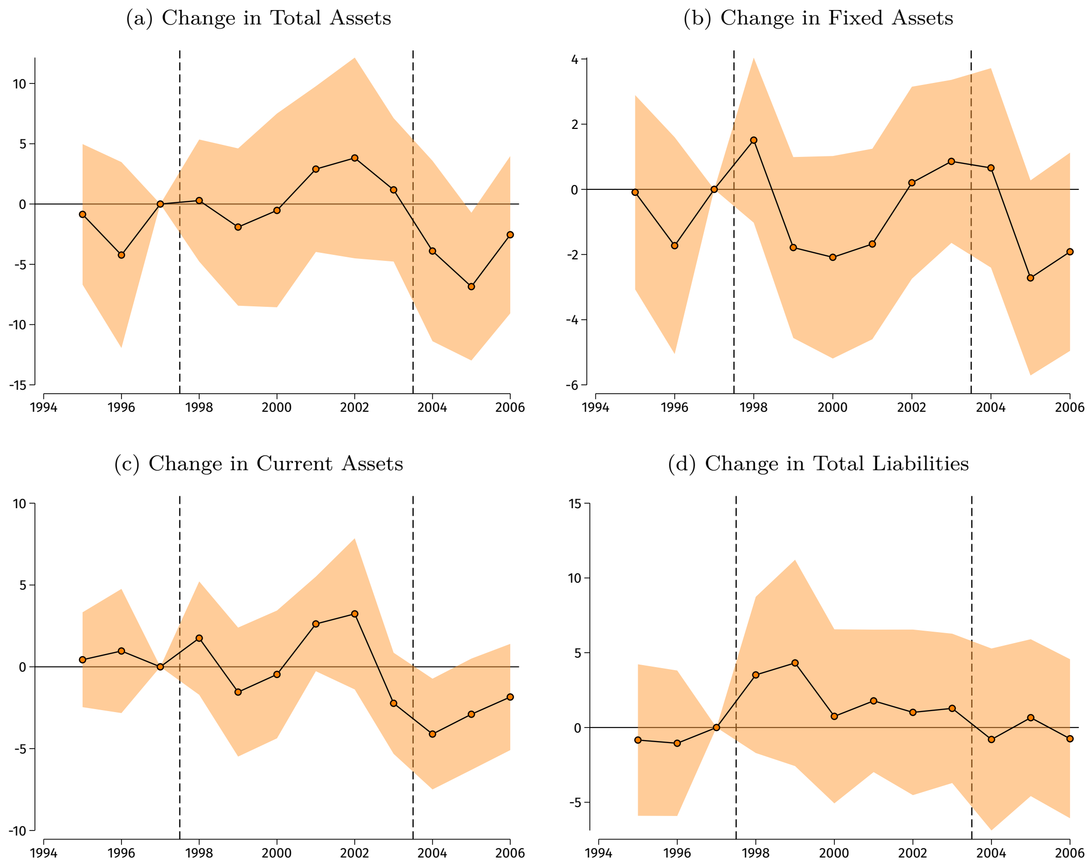


Figure D.4: Changes in Assets and Liabilities

Notes: The figure presents event study plots obtained by estimating the dynamic effects model in Equation 3 on our main analysis sample. The outcomes here are changes in assets or liabilities, as reported in Medicare cost reports for the corresponding years. All coefficients are estimated relative to 1997 as the reference year. The shaded area represents 95% confidence intervals. Standard errors are clustered by hospital.

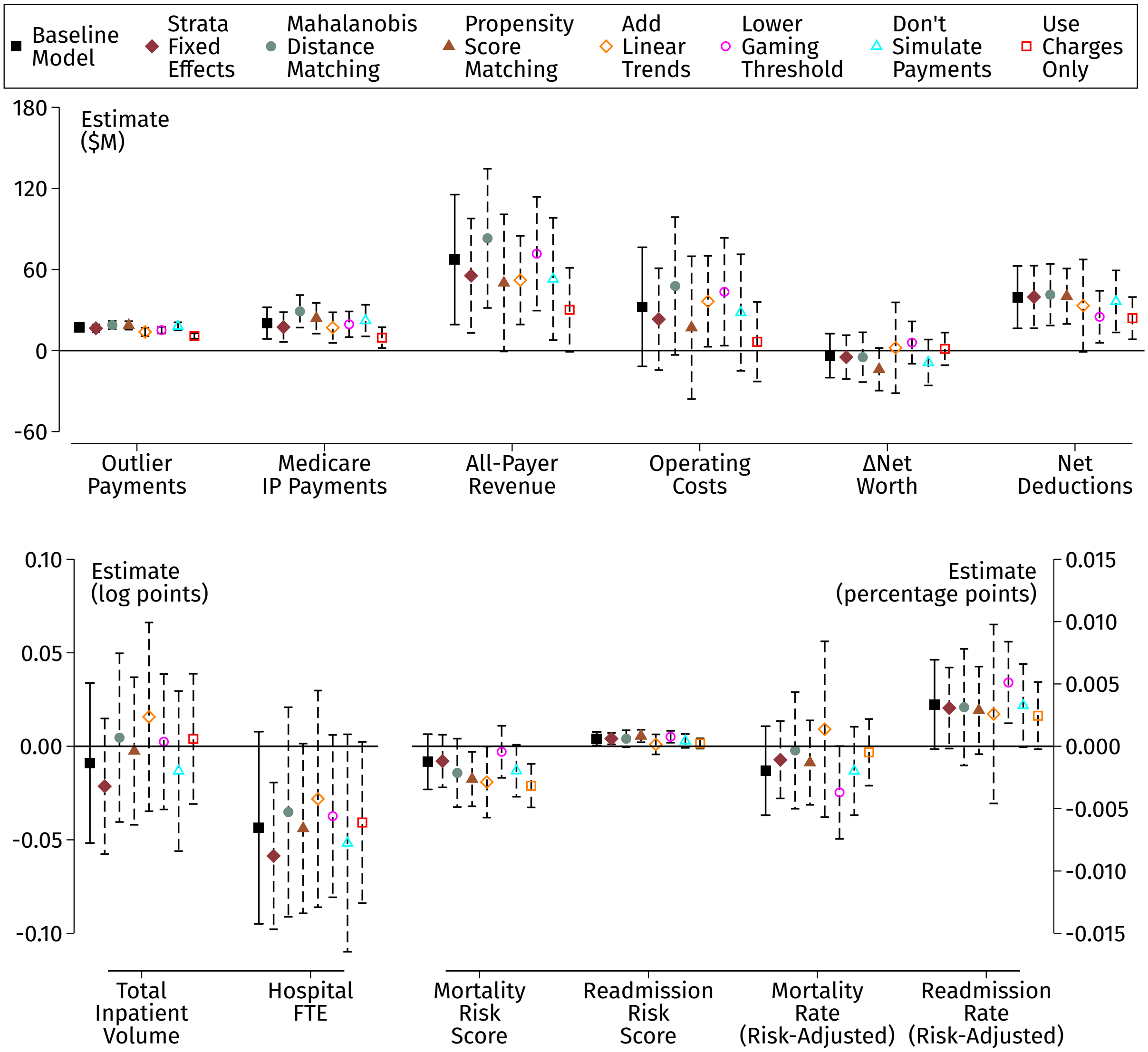


Figure D.5: Robustness checks

Notes: The figure presents estimates obtained from a number of robustness checks for the key measures of revenue and use of funds that were also presented in Table 2 (upper plot) and key measures of inputs, selection, and patient outcomes presented in Table 3 (lower plot). The dollar-valued estimates in the upper plot simply reproduce the main coefficients from Table 2 column 4 multiplied by 6, to reflect the total flow over 1998–2003. The log point and percentage point estimates in the lower plot reproduce the coefficients from Table 3 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.

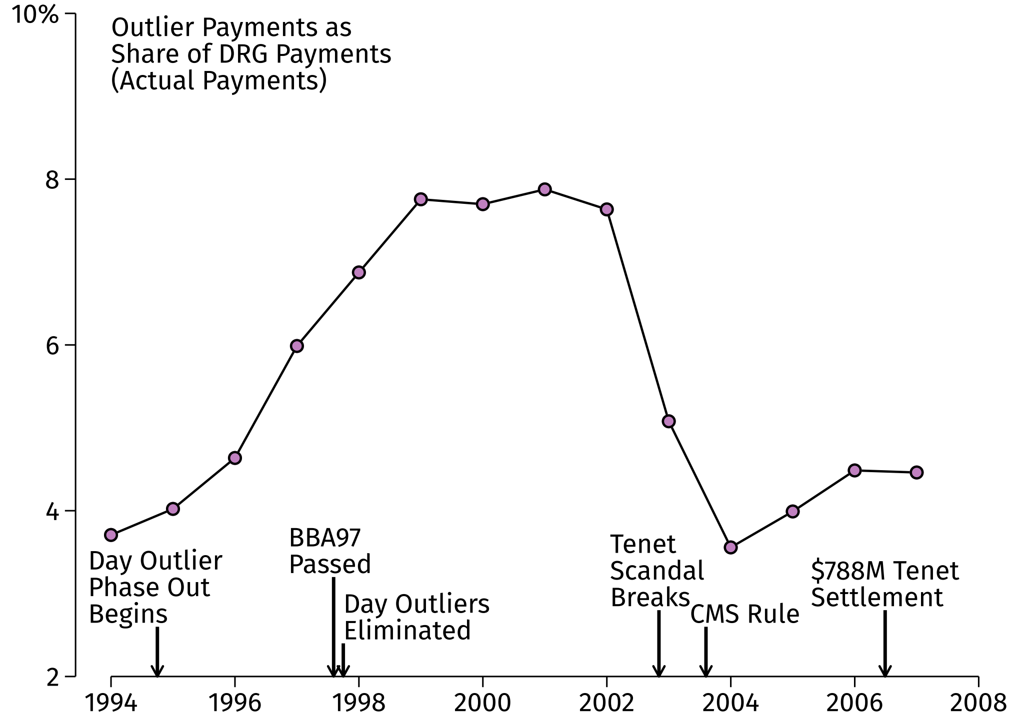


Figure D.6: Trend in Medicare outlier payments, actual payments

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 view. 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: Targeting Regression

	(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: Non-Profit)				
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)
Adjusted R^2	0.012	0.012	0.107	0.089
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 5.1. 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. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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	89.47	86.54	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. 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-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
D. 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
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. See Table 1 for additional notes.

Table D.4: Effects on Cost Components for Nonprofits

	(1) DV Mean	(2) 1998–2000	(3) 2001–2003	(4) 1998–2003	(5) Observations
Operating Costs	132.8	2.864	16.04*	9.453+	15,699
		(3.881)	(7.166)	(5.288)	
Direct Costs	127.5	3.219	13.77*	8.494+	15,813
		(3.726)	(6.843)	(5.079)	
Direct Salaries	57.50	0.724	3.384	2.054	15,813
		(1.960)	(3.002)	(2.395)	
Other Direct	70.03	2.567	10.41*	6.487*	15,813
		(2.220)	(4.531)	(3.242)	
General Service	42.57	-0.307	4.612+	2.153	15,813
		(1.281)	(2.589)	(1.840)	
Hospital Inpatient	2.561	-0.00292	1.182**	0.590+	15,813
		(0.220)	(0.458)	(0.321)	
Ancillary Service	15.65	0.486	1.357	0.921	15,813
		(0.627)	(1.241)	(0.900)	
Other	9.039	1.107	1.534	1.321	15,813
		(0.921)	(1.144)	(1.012)	

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 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 4 panel B columns 1–3. Direct costs are a slightly narrower measure of expenditures and are divided into direct salaries and other direct costs (the measurement of direct salaries differs slightly from the total salaries reported in Table 4). Other direct costs are divided into general service costs, hospital inpatient routine service costs, ancillary service costs, and other costs. 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: Additional Results on Flow of Funds

	(1) DV Mean	(2) 1998–2003	(3) 2004–2006	(4) Observations
ln(Medicare Charges/Patient)	20,430.4	0.463***	0.577***	19,706
		(0.0185)	(0.0322)	
Panel A. Income in Increasing Broadness				
Medicare Outlier Payments	1.715	2.875***	-0.224	19,699
		(0.257)	(0.177)	
Medicare Inpatient Payments	32.94	3.384***	-0.996	19,699
		(0.993)	(1.209)	
ln(Medicare Payments/Patient)	9,150.2	0.135***	0.00417	19,706
		(0.0133)	(0.0161)	
All-Payer Revenue	111.0	11.22**	9.412	19,515
		(4.089)	(7.821)	
Panel B. Outflows in Mutually Exclusive Categories				
Operating Costs	111.9	5.387	9.100	19,580
		(3.745)	(7.098)	
Total Salaries	46.85	0.703	1.806	19,699
		(1.584)	(2.712)	
ΔNet Worth	5.199	-0.630	-3.923*	17,949
		(1.383)	(1.636)	
ΔTotal Assets	4.156	2.654	-2.739	18,040
		(1.736)	(2.224)	
ΔFixed Assets	0.707	0.118	-0.720	17,943
		(0.769)	(1.030)	
ΔLiabilities (subtracted)	-0.662	2.739*	0.335	18,009
		(1.265)	(1.637)	
Net Deductions	1.703	6.580***	2.666	17,949
		(1.960)	(1.761)	

Notes: The table presents the coefficients estimated using Equation 2. Each row presents coefficients from a separate regression on a different dependent variable, typically estimated on a slightly different sample. Column 1 presents the sample mean value of the dependent variable for gamers in 1994–1997. Column 2 presents the coefficients pertaining to the 1998–2003 period when hospitals used turbocharging. Column 3 presents the coefficients pertaining to 2004–06 after turbocharging ended. Column 5 presents the number of observations used for each regression. All dollar values are expressed in millions of real year 2000 dollars. Effects on Medicare payments per patient are estimated using Poisson regression and these coefficients have a log-point interpretation. All-payer revenue includes both inpatient and outpatient components. The change in net worth is equal to the change in assets minus the change in liabilities. Net deductions refers to the funds transferred off the hospital's balance sheet, typically to its corporate parent. 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: Additional Results on Care Inputs and Quality

	(1) DV Mean	(2) 1998–2003	(3) 2004–2006	(4) Observations
Panel A. Care Inputs				
ln(Total Inpatient Volume)	10,812.4	-0.00895	-0.0185	19,519
		(0.0218)	(0.0297)	
ln(Hospital FTE)	1,076.8	-0.0436^{+}	-0.0719^{+}	19,505
		(0.0262)	(0.0391)	
Panel B. Patient Risk (Non-Deferrable Conditions)				
Mortality	0.134	-0.00125	0.000200	19,064
		(0.00113)	(0.00161)	
Readmission	0.135	0.000607*	0.00134**	19,064
		(0.000274)	(0.000476)	
Mortality or Readmission	0.258	-0.000664	0.00142	19,064
		(0.00115)	(0.00170)	
Panel C. Patient Outcomes (Non-Deferrable Conditions)				
Mortality	0.139	-0.00196	-0.00166	19,064
		(0.00182)	(0.00230)	
Readmission	0.134	0.00335^{+}	0.00238	19,064
		(0.00183)	(0.00211)	
Mortality or Readmission	0.264	0.00162	0.00113	19,064
		(0.00237)	(0.00287)	

Notes: The table presents the coefficients estimated using Equation 2. Each row presents coefficients from a separate regression on a different dependent variable, typically estimated on a slightly different sample. Column 1 presents the sample mean value of the dependent variable for gamers in 1994–1997. Column 2 presents the coefficients pertaining to the 1998–2003 period when hospitals used turbocharging. Column 3 presents the coefficients pertaining to 2004–06 after turbocharging ended. Column 4 presents the number of observations used for each regression. Standard errors are in parentheses and are clustered by hospital. See notes to Table 2 for more details on the outcomes. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$