Competition and Fraud in Health Care*

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Governments rely on private firms to provide public goods and services. Although competition among these firms reduces prices and the costs of procurement, it has an ambiguous effect on fraud: competition can both dissipate the rents that attracted fraudulent firms to the market while at the same time reducing margins to the point where legitimate firms no longer remain viable. We study this tradeoff in the government's procurement of durable medical equipment. Following Medicare's switch from regulated prices to competitive bidding, we find that fraudulent firms' cost advantage allowed them to gain market share as legitimate firms exited the market.

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1 Introduction

Governments contract with hundreds of thousands of private firms to deliver public goods and services. Although competition among these firms reduces the costs of procurement, the difficulty of verifying the integrity of many hard-to-monitor suppliers allows unscrupulous firms to defraud the government, either by overcharging for the contracted goods and services or failing to provide them altogether. This problem is particularly acute in health care, where government programs such as Medicare and Medicaid pay more than a trillion dollars each year to suppliers, a large fraction of whom may be fraudulent (Centers for Medicare & Medicaid Services, 2024).

The relationship between competition and fraud is not obvious. Competition could dampen the incentives to commit fraud by making it less lucrative to engage in illicit behavior, through lower prices and profits, but could instead exacerbate fraud if the lower costs and quality of fraudulent sellers allow them to crowd out legitimate ones that cannot operate profitably when faced with diminished margins. Which effect dominates is, ultimately, an empirical question.

We study the relationship between competition and fraud in Medicare's procurement of durable medical equipment (DME), where each year Medicare spends nearly $10 billion across thousands of suppliers, with the rate of improper payments estimated at over 20% (Centers for Medicare & Medicaid Services, 2023a). Such high levels of inappropriate spending may have historically stemmed from Medicare's decision to pay suppliers a fixed, regulated price for each piece of equipment, which often resulted in exceptionally high profit margins that proved enticing to fraudulent sellers. In response to the outsize levels of spending and fraud, Medicare began piloting a series of procurement auctions in 2011, forcing suppliers to compete with one another for the right to sell DME to beneficiaries within a particular product category and region (U.S. Government Accountability Office, 2009, 2010). Although past research has shown the switch to competitive bidding achieved Medicare's primary aim of reducing prices and spending (Ji, 2023; Ding et al., 2025), no previous work has evaluated whether the auctions ultimately succeeded in reducing fraud within the DME program as well.

We begin by identifying fraudulent and suspicious DME suppliers. We collected data on the hundreds of firms ever subject to anti-fraud enforcement, either through civil whistleblower litigation, criminal lawsuits, or administrative exclusion from the Medicare program. We further use this set of sanctioned firms to identify a set of "suspicious" firms that did not face enforcement yet appear to be fraudulent from their ties to those formally charged, such as by having the same owner, a shared address, or an inordinate number of referrals from complicit prescribers.

We then use the staggered rollout of competitive bidding across geographic regions and DME categories to identify the causal effect of competition on fraud. Consistent with past research, we find competitive bidding led to a 40% reduction in suppliers' revenue (Ji, 2023; Ding et al., 2025). Building on these studies, we show the reduction came almost exclusively from the exit of legitimate suppliers, with fraudulent firms increasing their market share by 8.1 percentage points after competitive bidding while submitting roughly the same number of claims as before.

The increase in fraudulent suppliers' market share could stem from a change in their business practices — a treatment effect that increases the overall level of fraud — or from the selection effect of competitive bidding disproportionately favoring firms with lower costs. That is, heightened price competition could lead all firms to engage in more fraudulent activity in an attempt to reduce their costs and remain viable, but it could also selectively push out legitimate suppliers that cannot break even selling high-quality equipment at low prices. Despite the first possibility, we find evidence of only small within-firm changes in quality that might reflect an uptick in fraudulent behavior: both the repair and replacement rate for DME as well as the share of DME supplied to beneficiaries who likely have a legitimate medical need for equipment remained largely unchanged after competitive bidding. In short, the selection effect predominates.

Having ruled out a meaningful increase in the level of fraud among suppliers, we next consider several possible mechanisms through which fraudulent firms may have gained market share under competitive bidding. First, fraudulent firms tend to be larger than legitimate firms, potentially leaving them better positioned to bear the administrative costs associated with procurement auctions or better able to compete on price due to the lower average costs that come from economies of scale. We find that, although larger firms do experience a smaller reduction in revenue after competitive bidding, this alone cannot explain our results. Even conditional on firm size, fraudulent firms gain market share.

Second, fraudulent firms could behave differently within the procurement auctions themselves. Past work has shown Medicare's DME auctions were poorly designed, such that submitting a very low, bad-faith bid was a non-dominated strategy (Cramton et al., 2015). Using the universe of bids submitted from 2011 to 2013, we find no evidence that fraudulent firms were more likely to engage in such behavior. Although fraudulent firms do submit slightly lower bids on average, the distribution of bids from fraudulent and legitimate firms are nearly identical, with no notable difference in the probability of submitting very low bids. At the same time, fraudulent firms are much more likely to participate in the auctions: 15.6% of bids come from fraudulent firms despite these firms making up just 1.9% of the market.

Taken together, our results suggest that price competition increased the market share of fraudulent firms because it selectively favored low-cost suppliers. Fraudulent firms both participated in Medicare's procurement auctions at a higher rate and subsequently submitted slightly lower bids, a reflection of their cost advantage over legitimate suppliers. Rather than bear the full costs of providing high-quality DME to eligible beneficiaries, fraudulent firms can inflate bills through upcoding, provide equipment to ineligible patients, and bill Medicare for goods that ultimately never get delivered, all of which allow fraudulent firms to outcompete legitimate firms on price.

Building on these insights, we conclude our paper with a stylized model of the DME market that formalizes the theoretical effect of price competition on fraud and allows us to quantify the extent to which fraudulent firms would gain market share at various counterfactual prices. From the model, we find that lower prices lead to more fraudulent firms and that the selection effect grows stronger as the price of DME decreases.

Our work complements past studies that have largely examined questions of competition and fraud in isolation. Most directly, our results contribute to broader debates about the relationship between competition and quality in health care. Cooper et al. (2011) and Gaynor et al. (2013), for instance, show that greater competition among hospitals in England improved health care quality, whereas Colla et al. (2016) find mixed results considering a broader class of conditions. Beyond quality, heightened competition can lead to more waste, as in Kessler and McClellan (2000), where it spurred hospitals to provide more unnecessary services.

Competition can also bring about unethical behavior. Building on a series of theoretical papers (Shleifer, 2004; Dewatripont and Tirole, 2019), empirical studies across various settings have found, for example, that both pharmacies and physicians sell more opioids when faced with more competition (Janssen and Zhang, 2023; Currie et al., 2023). Beyond health care, Bennett et al. (2013) show that increased competition among vehicle emissions testers is associated with more lenient inspections. Our work extends this literature by showing that increases in fraud may stem from the selective entry of fraudulent firms rather than through direct changes in firms' unscrupulous behavior.

Our findings also add to the literature on fraud and overbilling in Medicare. The seminal works of Silverman and Skinner (2004) and Dafny (2005) lay out the incentives for hospitals to upcode care to receive larger reimbursements, while other studies, such as Fang and Gong (2017), Geruso and Layton (2020), and Shekhar et al. (2023), have documented the extent of this overbilling. A more recent body of work has evaluated the policies used to combat such fraud, such as civil litigation by whistleblowers (Howard and McCarthy, 2021; Leder-Luis, 2023) and regulations like prior authorization (Eliason et al., 2025). We build on this research by examining the role of competition and rents in providing incentives for firms to commit fraud as well as their underlying determinants.

In addition, our research contributes to a growing literature evaluating the impact of competitive bidding on Medicare's DME program. Past studies have shown the effect of competitive bidding on prices and quantities, with Ji (2023) and Ding et al. (2025) both finding significant reductions. Newman et al. (2017) further note that the resulting prices were similar to those negotiated by private insurers, while Ji and Rogers (2024) argue the price cuts hindered innovation. These past studies did not focus on the connection between market structure and firm behavior, however, particularly as it relates to fraud.

Finally, our work relates to an older literature in political economy on the incentives of firms that contract with the government. In the framework of Hart, Shleifer, and Vishny (1997), the government faces a tradeoff when outsourcing to private firms, which reduces costs but can lead to inefficiently large cuts to quality due to incomplete contracts. In health care, where quality is often difficult to monitor, mechanisms like competitive bidding may indiscriminately favor firms that have lower costs — even if those lower costs stem from unscrupulous behavior. By empirically demonstrating that fraudulent firms thrive under competitive bidding, our study provides a novel application of these theories.

The remainder of this paper proceeds as follows. Section 2 discusses the history of fraud in Medicare's DME program and the staggered rollout of competitive bidding. Section 3 describes our data and our identification of fraudulent firms. Section 4 outlines our empirical strategy and presents our main results. Section 5 explores the underlying mechanisms that could explain why fraudulent firms gained market share under competitive bidding. Section 6 estimates a stylized model of the DME market that quantifies how competition shapes fraudulent activity and evaluates counterfactual pricing policies. Section 7 concludes. The appendix provides additional robustness checks, analyses, and details of our data.

2 Background

Medicare's DME program spends nearly \$10 billion each year to supply 10 million beneficiaries with equipment such as wheelchairs, medical beds, and CPAP machines. To sell DME through Medicare, a physician must first prescribe it to the beneficiary, after which a Medicare-approved supplier can take assignment and supply the product. Covered under Part B, beneficiaries typically pay 20% of the Medicare-approved amount, with Medicare covering the remainder.

Before competitive bidding, Medicare paid for DME using a fee schedule based on supplier charges adjusted over time for inflation.[1] This approach often resulted in products with exceptionally large profit margins, with Medicare's payment rates sometimes three to four times higher than what suppliers paid to purchase the equipment from manufacturers or wholesalers (Centers for Medicare & Medicaid Services, 2013). A 2006 report by the Office of the Inspector General for Health and Human Services, for example, found that Medicare was paying \$7,215 to rent oxygen concentrators for 36 months that cost an average of \$587 to purchase (U.S. Department of Health and Human Services, Office of Inspector General, 2006), while another found that Medicare paid \$17,165 for negative pressure wound therapy pumps that cost suppliers \$3,604 (U.S. Department of Health and Human Services, Office of Inspector General, 2007). Over a decade later, a 2018 MedPAC report concluded that these high payment rates increased expenditures and likely encouraged inappropriate utilization (Medicare Payment Advisory Commission, 2018).

[1] Historically, the fee schedule was largely based on inflation-adjusted supplier charges during the 1980s and undiscounted list prices (Medicare Payment Advisory Commission, 2018).

Improper payments and outright fraud have long been a problem among government health programs. In 2024, the Department of Health and Human Services estimated a total of $88 billion in improper payments for Medicare and Medicaid, implying that over 50% of the government's improper payments originate from health care (U.S. Government Accountability Office, 2025).[2] Contributing to the billions of dollars in inappropriate payments, DME fraud primarily involves providing Medicare beneficiaries with equipment they do not need and never requested, a form of fraud called "medical necessity fraud," as well as billing for equipment never provided (Leder-Luis and Malani, 2025).

In many cases of DME fraud, a health care provider receives a kickback from the supplier in exchange for writing DME prescriptions, which the supplier can then use to bill Medicare. Recruiters often find beneficiaries by advertising free products and requesting their Medicare numbers over the phone or at an event or sales pitch, with telehealth being used more recently to recruit illegitimate patients or conduct sham screenings to provide patients with prescriptions for DME (Centers for Medicare & Medicaid Services, 2023b). In one case, beneficiaries testified they were promised vitamins, diabetic shoes, and other items for providing their beneficiary numbers (USA v. Shubaralyan, 2008; U.S. Department of Justice, 2009). In another, a beneficiary attempting to purchase a hospital bed was told that to get one she had to accept an unneeded power wheelchair as well (USA v. Ijewere et al., 2009; U.S. Department of Justice, 2010). Medicare numbers are also allegedly sold to other nearby DME suppliers for the purposes of false billing, and suppliers routinely bill for costly products with additional accessories or features the patient does not require. Some of the most billed-for fraudulent products include CPAP machines and oxygen and related equipment.

DME suppliers regularly face legal action for health care fraud. The False Claims Act (FCA) allows whistleblowers to sue fraudulent health care providers under civil law for up to triple damages and receive a share of the recoveries, as in the suit against Lincare Holdings, which agreed to pay $29 million for the improper billing of oxygen equipment (U.S. Department of Justice, 2023). The US can also pursue criminal enforcement, which may result in both fines and prison sentences. The Department of Justice (DOJ), Health and Human Services Office of Inspector General (HHS-OIG), and other federal agencies often collaborate to investigate and prosecute fraud, with initiatives like the Medicare Fraud Strike Force targeting high-risk regions and providers. As one prominent example of this approach, a months-long investigation of DME fraud dubbed "Operation Brace Yourself" resulted in significant criminal convictions and lengthy prison sentences (U.S. Department of Justice, 2024b).

In an attempt to bring down the outsize levels of DME spending and fraud, Medicare established the DME Competitive Bidding program as part of the Medicare Modernization Act

[2] Improper payments are Medicare payments that do not meet CMS requirements, including overpayments, underpayments, or payments where insufficient information was provided (Centers for Medicare & Medicaid Services, 2024). Not all improper payments constitute fraud.

in 2003 (Centers for Medicare & Medicaid Services, 2009). Under the program, DME suppliers submit bids to compete for Medicare contracts to supply specific products in designated competitive bidding areas for a period of about three years, with the auction price set at the median of the winning bids, meaning half of the winning bidders receive a price below what they bid.[3] Winners of the auction can then sell DME at the median price and face no quantity limits on the amount of DME they can supply. Because this auction format does not prevent bidders from later withdrawing their supply commitment, Cramton et al. (2015) show that submitting a very low bid before deciding whether to accept the price determined by the auction is a non-dominated strategy, although CMS attempted to authenticate bids to screen out those believed to be made in bad faith.[4] Despite the nonstandard auction format, previous studies have shown Medicare's switch to competitive bidding succeeded at reducing prices and spending for DME (Ji, 2023; Ding et al., 2025).

Medicare piloted the first round of bidding for nine product categories in nine metropolitan statistical areas (MSAs) starting in 2009, with the resulting prices going into effect in January 2011, and later expanded the program to cover additional product categories and geographies, with those prices going into effect July 2013, January 2017, and January 2021.[5] After a temporary gap period beginning in 2024, CMS has scheduled a new competitive bidding round, with supplier registration and bidding planned to occur in 2026 and contract prices expected to take effect in 2028 (Centers for Medicare & Medicaid Services, 2025). Figure 1 shows the geographic rollout of competitive bidding over the first two waves, where Medicare targeted product groups they anticipated had the greatest potential for cost savings. Following round one, prices for many products fell substantially: the average Medicare-allowed monthly payment amount dropped 33% for stationary oxygen equipment, for example, and 37% for semi-electric hospital beds (Centers for Medicare & Medicaid Services, 2013).

3 Data

3.1 Medicare Utilization and Bidding Data

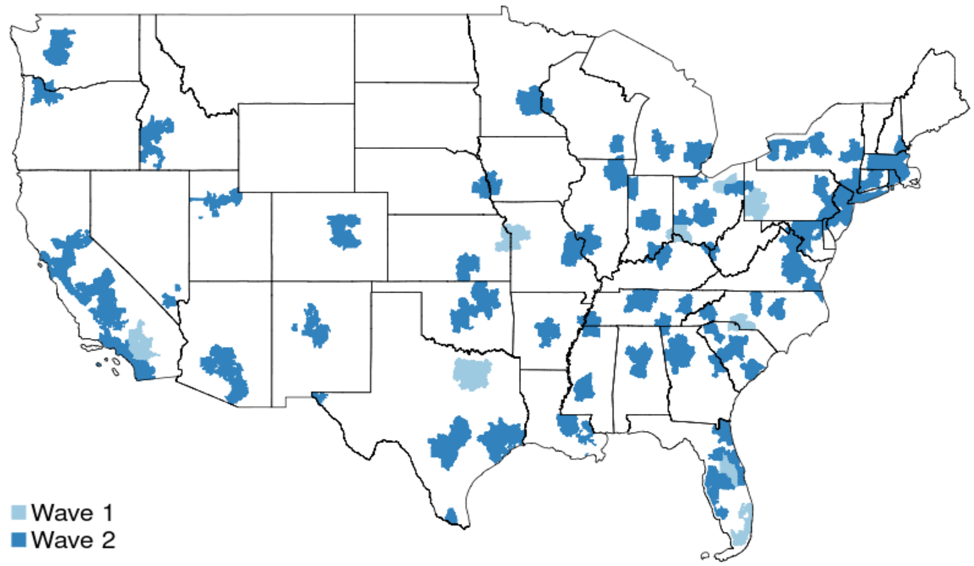
We use claims data for the universe of patients who received DME through Medicare between 2008 and 2019. Each observation represents a unique product or service within a claim and is linked to a specific beneficiary. For DME, this is typically an individual product or item

[3]The number of winning bids is chosen so that the reported capacities of the winning bidders is sufficient to meet the amount of DME expected to be demanded by beneficiaries.

[4]Appendix A provides more details on the auction format.

[5]Additional rounds or recompetes occurred as follows: Test rollout in 2007 with prices effective July 1, 2008; Round 1 Rebid in 2009, prices effective January 1, 2011; Round 2 and National Mail-Order in 2011, effective July 1, 2013; Round 2 Recompete in 2014, effective January 1, 2016; Round 2017, with bidding conducted in 2015, effective January 1, 2017; and Round 2021, which began in 2019, with prices effective January 1, 2021.

Figure 1: Geographic Rollout of Competitive Bidding Auction Program.



Notes: This map shows the rollout of DME competitive bidding. Data on competitive bidding rollout timing come from the competitive bidding archives. Data are plotted for ZIP codes and only include the first two waves of bidding. The third wave of competitive bidding took place in the same areas as the first wave, but with additional products covered. Map data are drawn from official U.S. Census TIGER/Line shapefiles and include water boundaries between states.

accessory and is denoted using the product's Healthcare Common Procedure Coding System (HCPCS) code. Each observation includes the claim date, supplier's National Provider Identifier (NPI), HCPCS code, and line payment amount. We use beneficiary ZIP codes from the master beneficiary summary files to determine the geographic location of the claim. To aggregate our data to the MSA level, we use a ZIP-code-to-MSA crosswalk from the Department of Labor. Each HCPCS code maps to a broader product category (e.g., codes E0433 and E0434 correspond to distinct portable liquid oxygen systems within the "Oxygen Supplies and Equipment" category), and we aggregate data to the product-category level by creating a crosswalk from the competitive bidding program archives, which includes only categories participating in competitive bidding.

For DME suppliers, we use the full set of NPIs that supplied DME in the claims data, resulting in a total of 154,046 suppliers. We then use the National Plan & Provider Enumeration System (NPPES) to obtain firm-level information related to these NPIs, including a supplier's name, mailing address, business address, and authorized owner.

We also obtained data on the firms participating in the Competitive Bidding Program used in Ji (2023) from the author, which were originally obtained through a Freedom of Information Act (FOIA) request. These data include information from rounds one and two of the auctions, with prices implemented in 2011 and 2013, respectively. Each auction consists of a product (HCPCS), geographic area (competitive bidding area, or CBA), and bid type (either rental or purchase). The dataset includes firm names, the prices submitted by bidders for products in each geography, and the estimated capacity of each firm. Because the data do not include NPIs, we connect bidders to possible NPIs using fuzzy string matching on firm names. We match each firm name in the bidder data to firms that provide DME in the claims data using firm names obtained from the NPPES. Throughout the paper, we use the terms "supplier," "firm," and "NPI" interchangeably to refer to an NPI-level DME supplier, except in the bidding section, where "firm" refers to a bidding entity identified by firm name.

Data on the timing of competitive bidding come from the online competitive bidding program for DME archives. They include the timing for each HCPCS and ZIP code combination, spanning multiple waves, including the 2011, 2013, and 2017 rollouts. For product-geographies with multiple waves of competitive bidding, we use the timing of the first rollout. We conduct our analysis at the MSA level, as the rollout of competitive bidding was determined at the HCPCS and MSA level.

Finally, we construct outcome variables using Medicare claims data, including payments and number of claims at the firm level. When examining product quality, we use the rate of repair claims (i.e., any claim with a HCPCS modifier code of RA, RB, or RP, with the RP modifier superseded by RA and RB in 2009). To examine whether a patient is likely to be an appropriate match for DME, we use two measures of their health condition. First, we construct a comorbidity index from the Medicare Chronic Conditions file that counts the number of comorbid conditions for each beneficiary.[6] Second, we examine the share of first-time DME product category receipts associated with a hospitalization in the same or previous month, as these patients are more likely to have a legitimate medical need for DME.

3.2 Identifying Fraudulent DME Suppliers

We combine several data sources to identify fraudulent DME suppliers. First, we create a novel dataset using press releases from the Department of Justice (DOJ) that mention health care fraud related to DME. For each press release, we extract the date of the press release and the name of the firm involved, and then use the firm's name to manually search for and identify any NPIs associated with it. In total, we analyzed 389 press releases, which we linked to 980 unique NPIs, of which 743 appear in our DME claims data. We also use the List of Excluded Individuals and Entities (LEIE) maintained by the Office of the Inspector General (OIG), which contains records of health care providers excluded from participation in federally funded health care programs for a variety of reasons, including a conviction for Medicare or Medicaid fraud. From this we extract the date they were excluded and the NPIs of excluded providers. The LEIE

[6]More details on the construction of this index are available in Appendix B.

provides a total of 7,674 excluded NPIs, of which 109 supply DME.[7]

In total, we have 849 unique NPIs ever subject to enforcement. We classify these firms as "sanctioned," with Figure A2 in Appendix C plotting the cumulative number of firms sanctioned over time. We find that firms have continued facing enforcement for DME fraud, with no noticeable trend break associated with the rollout of competitive bidding.

Beyond these sanctioned firms, we also identify firms that appear likely to have committed fraud yet remain undetected. To do so, we start with the set of sanctioned firms and then identify other entities that have clear links to them. Following the approach of previous studies, we consider a firm to be "suspicious" if it shares its name, owner, or address with a sanctioned firm (McDevitt, 2011, 2014). We also label as suspicious any firm that receives a large proportion of its DME referrals from physicians who also refer extensively to sanctioned firms. Appendix D provides the full details of our suspiciousness measures.

For the majority of our analysis, we combine "sanctioned" and "suspicious" firms into a single group of "fraudulent" firms. We label firms not flagged as fraudulent as "legitimate." Figure A3 in Appendix shows a map of the ZIP codes of suspicious firms as well as those subject to sanctions, showing wide dispersion of fraudulent activity across the country.

3.3 Summary Statistics of DME Suppliers

Table 1 presents summary statistics for the firms in our sample, comparing legitimate firms to both sanctioned and suspicious firms. Overall, we find that fraudulent firms are much larger than legitimate firms in terms of revenue and geographic spread, have been active for longer, and supply a more diverse set of products, as measured by unique HCPCS codes. Such differences may reflect an advantage fraudulent firms have in being able to grow through fraudulent activity, but could also stem from differences in other characteristics, such as specializing in DME.[8]

[7]Three firms appear in both the press releases and the LEIE. Most firms that appear in press releases were subject to civil enforcement, which does not result in exclusion.

[8]In Appendix E, we restrict the sample to firms whose primary classification is DME. This restriction increases the prevalence of fraudulent firms but yields very similar results to those in the main text.

Table 1: Summary Statistics by Firm Type

	Total	Legitimate	Sanctioned	Suspicious
Payment ($M)	$0.7	$0.6	$6.4	$7.6
	(10.7)	(9.7)	(19.2)	(36.9)
Quarters Active	26.9	26.8	29.6	34.1
	(17.8)	(17.8)	(17.2)	(16.6)
HCPCS Sold	37.4	36.1	94.8	110.0
	(59.5)	(58.1)	(70.9)	(89.3)
MSAs Active	16.5	15.4	74.4	76.1
	(35.3)	(33.0)	(80.4)	(73.9)
N	154,046	151,144	849	2,053

Notes: Sample includes all firms submitting a DME claim to Medicare Part B from 2008 through 2019. An observation is a firm. Payment is the total payments to the firm by Medicare during our sample period, quarters active is the number of calendar quarters in which the supplier submitted at least one paid claim to Medicare, HCPCS sold is the number of distinct products supplied by the supplier, and MSAs active is the number of distinct metropolitan statistical areas in which the supplier supplied at least one piece of DME. The table reports the mean value across firms, with the standard deviation reported in parentheses.

We also find substantial variation in the presence of fraudulent firms across different DME categories. Table 2 presents summary statistics for total Medicare spending, payments to fraudulent firms, and share of Medicare payments going to fraudulent firms before the start of competitive bidding for each product category included in the competitive bidding program. Throughout this period, fraudulent firms had the largest market share in oxygen & oxygen equipment, power mobility devices, CPAP machines, and nebulizers. Because our measures of fraud are at the firm rather than claim level, the percentages presented in Table 2 are the market shares of firms we classify as fraudulent even though some of their claims may have been legitimate.

Table 2: Share of Spending by Fraudulent Firms by Product Category Prior to Competitive Bidding

	Medicare Payments ($M)		
Category	Total	Fraudulent	Fraudulent Share
Oxygen and Oxygen Equipment	$5,685.3	$2,255.6	39.7%
Standard Power Mobility Devices	$2,321.7	$866.8	37.3%
CPAP Devices and RADs	$1,873.6	$627.1	33.5%
Nebulizers	$180.2	$55.2	30.6%
Enteral Nutrition	$1,310.3	$233.2	17.8%
Standard Manual Wheelchairs	$878.7	$139.9	15.9%
Hospital Beds	$618.0	$92.7	15.0%
Commode Chairs	$112.8	$15.7	13.9%
Walkers	$242.9	$31.9	13.1%
Patient Lifts and Seat Lifts	$103.1	$11.2	10.9%
Support Surfaces (Groups 1 and 2)	$275.3	$19.2	7.0%
TENS Devices	$139.5	$5.8	4.2%
Off-The-Shelf Back Braces	$4.4	$0.2	4.0%
Negative Pressure Wound Therapy Pumps	$444.3	$11.5	2.6%
Off-The-Shelf Knee Braces	$4.7	$0.1	2.1%

Notes: Dollar amounts are reported in millions and rounded to one decimal place. Fraudulent share is reported as a percentage and rounded to one decimal place. Fraudulent share is calculated as the ratio of payments to fraudulent firms to total payments. Product categories follow competitive bidding groupings. Non-invasive ventilators were included in competitive bidding beginning in 2021; the relevant HCPCS code was not introduced until after 2011, so spending is zero in the pre-period. We identify fraudulent firms rather than fraudulent claims; not every claim submitted by a fraudulent firm is illegitimate, and some claims by legitimate firms may be fraudulent.

4 Results

We use the staggered rollout of competitive bidding across markets and DME categories to identify the causal effect of competition on fraud. Our unit of observation is an MSA $\times$ HCPCS $\times$ quarter. Treatment is assigned at the MSA $\times$ HCPCS level and varies over time.[9] For traditional

[9] We drop any HCPCS in the category of power mobility devices due to a contemporaneous change in regulations for power mobility devices in areas overlapping with the rollout of competitive bidding. The regulations included the introduction of a prior authorization requirement and a requirement that power mobility devices be rented rather than purchased.

TWFE results, we estimate

$$(1) \qquad Y_{mht} = \sum_{e \in [-K,K]/\{-1\}} \beta_e T_{mht}(e) + \alpha_{mt} + \alpha_{ht} + \alpha_{mh} + \varepsilon_{mht}$$

for MSA m and HCPCS product h in quarter t; Y_{mht} is our outcome of interest, such as total payments in an MSA $\times$ HCPCS $\times$ quarter; $T_{mht}(e)$ is an indicator for being e quarters from the treatment date, which is the start of competitive bidding in that market for that product; and α_{mt}, α_{ht}, and α_{mh} are MSA-quarter, product-quarter, and MSA-product fixed effects, respectively. We set $K = 8$, estimating coefficients for eight quarters on either side of competitive bidding, with $\beta_e(e)$ capturing the causal effect of competitive bidding after e quarters, under the assumption that any differential changes in MSA-product markets subject to competitive bidding are attributable to the introduction of competitive bidding.

Aggregating the periods immediately before and after competitive bidding, we also estimate a static regression that allows us to report a single parameter, β, for the effect of competitive bidding over the K quarters after implementation:

$$(2) \qquad Y_{mht} = \gamma \sum_{e \in (-\infty,-K) \cup (K,\infty)} T_{mht}(e) + \beta \sum_{e \in [0,K]} T_{mht}(e) + \alpha_{mt} + \alpha_{ht} + \alpha_{mh} + \varepsilon_{mht}.$$

Because competitive bidding is introduced at different times across MSAs and product categories, we also estimate the event study separately for each competitive bidding wave in Appendix F, restricting comparisons between units treated in each cohort to never-treated units, thereby avoiding the "forbidden comparison" that may otherwise introduce bias (Borusyak et al., 2024).

4.1 Effect of Competitive Bidding

We first consider the effect of competitive bidding on total Medicare spending. Converting DME payments using the inverse hyperbolic sine (asinh) transformation in Figure 2, the dynamic difference-in-differences estimates show a large, immediate, and persistent reduction in total DME spending for the targeted categories at the onset of competitive bidding. The estimates of the static specification in Table 3 similarly show a 35% decrease in Medicare spending, echoing Ji (2023) and Ding et al. (2025). As in these studies, we find the reduction came from drops in both prices and quantities, at 23% and 15%, respectively.[10]

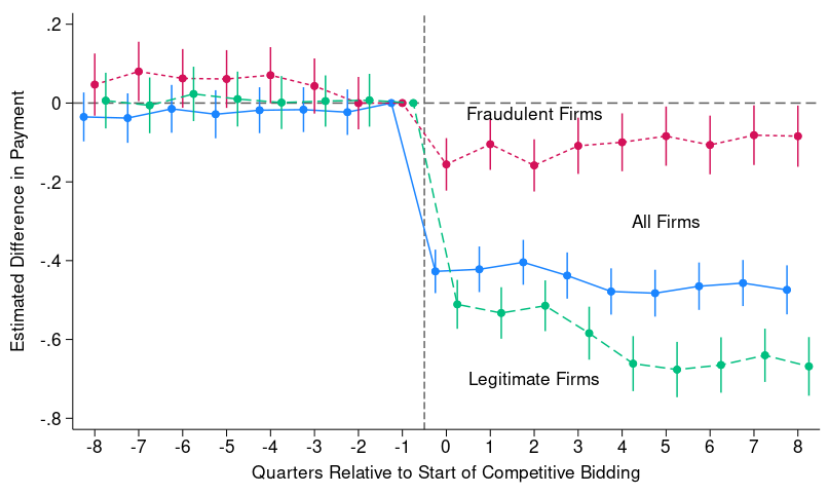
[10] In Appendix G, we report estimates measuring the outcomes in levels.

Table 3: Effect of Competitive Bidding

	Payments	Claims	Firms	Price
Competitive Bidding	-0.4280***	-0.1648***	-0.1874***	-0.2672***
	(0.0107)	(0.0045)	(0.0036)	(0.0037)
N	30,879,965	30,879,965	30,879,965	10,370,722
Implied Effect	-34.8%	-15.2%	-17.1%	-23.4%
Pre-Period Dep Var Mean	27,953	344.5	18.5	121.3
HCPCS–MSA FE	Yes	Yes	Yes	Yes
HCPCS–Quarter FE	Yes	Yes	Yes	Yes
MSA–Quarter FE	Yes	Yes	Yes	Yes

Notes: Each column reports the estimate of β from the static specification in (2), which aggregates event-time indicators over the eight quarters following competitive bidding ($e \in [0, 8]$). Outcomes are measured at the MSA $\times$ HCPCS $\times$ quarter level and are transformed using the inverse hyperbolic sine. We define price as average payment per claim, rather than using list prices. The dependent variable mean reports the pre-period mean of each outcome in levels. Implied percentage effects are computed as $100 \times [\sinh(\text{asinh}(\bar{y}) + \beta) - \bar{y}]/\bar{y}$, where β is the estimated coefficient on competitive bidding and $\bar{y}$ is the pre-period mean of the outcome in levels. All regressions include HCPCS–MSA, HCPCS–quarter, and MSA–quarter fixed effects. Standard errors are clustered at the MSA–quarter level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

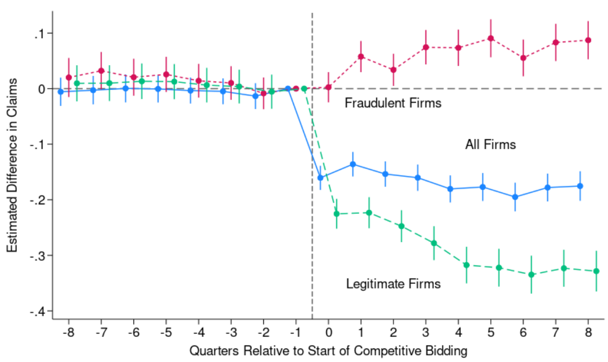
Figure 2: Effect on Payments



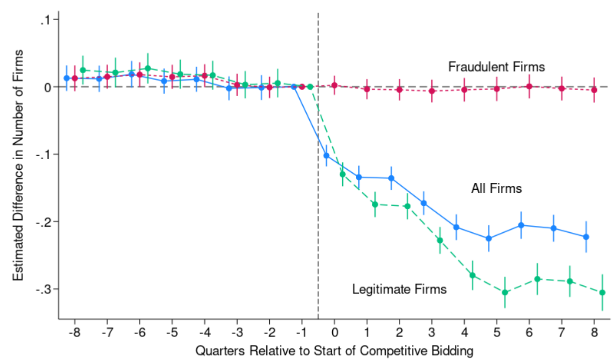
Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from (1). The dependent variable is payments for DME, transformed by inverse hyperbolic sine. Estimates are shown separately for legitimate firms, fraudulent firms, and all firms. The data include claims from 2008–2019, with observations at the MSA $\times$ HCPCS $\times$ quarter level. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

Figure 3: Effect on Claims and Firm Entry

(a) Claims



(b) Number of Firms



Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from (1). Panel (a) plots total claims and Panel (b) plots the number of firms; outcomes are transformed using the inverse hyperbolic sine. Estimates are shown separately for legitimate firms, fraudulent firms, and all firms. The data include claims from 2008–2019, with observations at the MSA $\times$ HCPCS $\times$ quarter level. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

As the dashed lines in Figure 2 show, fraudulent and legitimate firms fared differently under competitive bidding. Quantifying these differences in Table 4, payments to legitimate firms fell by 46% compared to a 14% reduction for fraudulent firms.[11] Figure 3a shows the divergence primarily stems from the number of claims submitted after competitive bidding: claims paid to fraudulent firms increased by 5%, whereas those to legitimate firms fell by 26%.[12]

The differential effect of competitive bidding on fraudulent and legitimate firms led to structural changes in the market for DME. As shown in Figure 3b, the total number of active firms declined by 18.7%, with the decline almost entirely concentrated among legitimate firms, at 25.7%, compared to virtually no change in the number of fraudulent firms. The corresponding reallocation of DME payments from legitimate to fraudulent firms appears in Figure 4, where the market share of fraudulent firms rises by 8.1 percentage points. Among the group of firms we classify as fraudulent, Appendix Figure A5 shows that although both sanctioned and suspicious firms experienced gains, suspicious firms increased by more. Taken together, our results show that heightened price competition led to a large decrease in the number of legitimate firms supplying DME and a corresponding rise in the market share of fraudulent firms.

[11] In Appendix H, we replicate these and all other results excluding fraudulent firms that were not present before the first round of competitive bidding, demonstrating that our results are not driven solely by fraudulent new entrants.

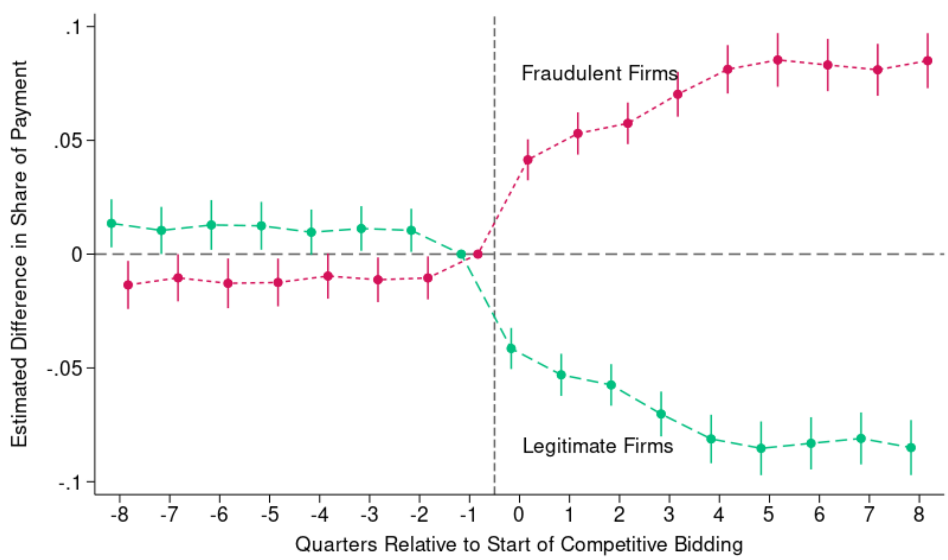
[12] Differential price changes were much smaller. As shown in Table A2 and Figure A4 in Appendix C, fraudulent firms were exposed to a price reduction of 29.0% compared to a 23.0% reduction for legitimate firms, owing to differences in geography and product mix.

Table 4: Effect of Competitive Bidding on Fraudulent and Legitimate Firms

	Fraudulent			Legitimate			Share
	Payments	Claims	Firms	Payments	Claims	Firms	Fraudulent
Competitive Bidding	-0.1547***	0.0479***	-0.0128***	-0.6124***	-0.2957***	-0.2568***	0.0810***
	(0.0132)	(0.0059)	(0.0032)	(0.0125)	(0.0059)	(0.0043)	(0.0020)
N	30,879,965	30,879,965	30,879,965	30,879,965	30,879,965	30,879,965	10,370,722
Implied Effect	-14.3%	4.9%	-1.3%	-45.8%	-25.6%	-22.7%	
Pre-Period Dep Var Mean	8,553.8	106.6	4.6	19,399	238.0	14.0	
HCPCS–MSA FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
HCPCS–Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSA–Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports the estimate of β from the static specification in (2), which aggregates event-time indicators over the eight quarters following competitive bidding ($e \in [0, 8]$). Outcomes are measured at the MSA × HCPCS × quarter level and, except for the fraudulent share, are transformed using the inverse hyperbolic sine. The dependent variable mean reports the pre-period mean of each outcome in levels. Implied percentage effects are computed as $100 \times [\sinh(\text{asinh}(\bar{y}) + \beta) - \bar{y}]/\bar{y}$, where β is the estimated coefficient on competitive bidding and $\bar{y}$ is the pre-period mean of the outcome in levels. All regressions include HCPCS–MSA, HCPCS–quarter, and MSA–quarter fixed effects. Standard errors are clustered at the MSA–quarter level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure 4: Effect on Market Share of Payments by Firm Type



Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from (1). The dependent variable is the share of total line payments accounted for by legitimate or by fraudulent firms. The data include payments from 2008–2019, with observations at the MSA × HCPCS × quarter level. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

4.2 Quality

Firms may have responded to competitive bidding by increasing their within-firm levels of fraud. Past work in this area has largely focused on the quality of procurement, with Hart et al. (1997) noting, for example, that when the government contracts with a private firm based on price, but that contract is incomplete with respect to quality, quality inevitably deteriorates. Similarly, Shleifer (2004) argues that heightened competition can induce firms to engage in unethical behavior. Applying these theories to the context of DME, the increase in fraudulent firms' market share could reflect an increase in the level of fraud if suppliers responded to lower prices by cutting costs in ways that make them more fraudulent or if they seek to offset their diminished revenue by providing more equipment to beneficiaries who lack a medical need for it.

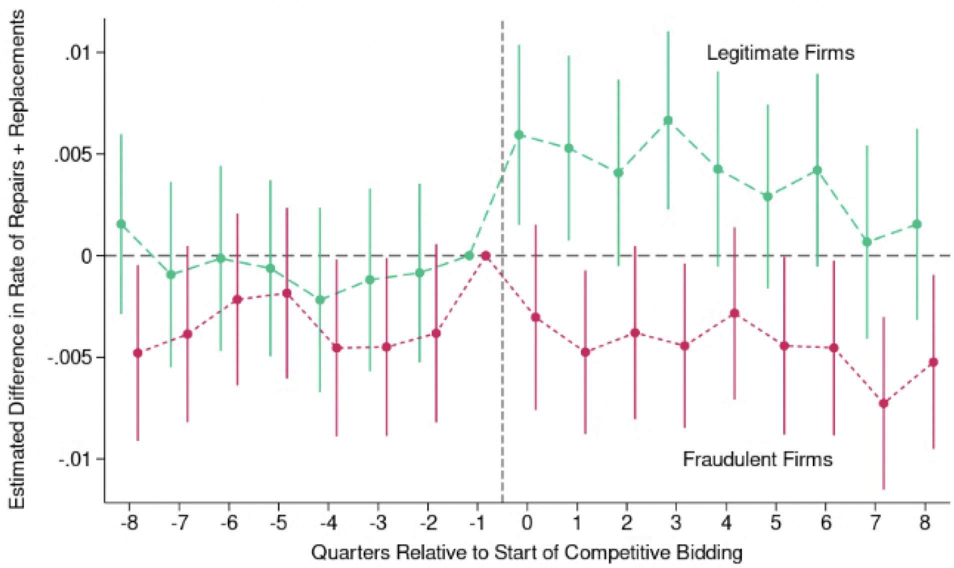
By contrast, increased competition could instead motivate firms to improve their quality and reduce the amount of fraud in the market. For example, fraudulent firms may respond to the exit of legitimate suppliers by capturing their legitimate business, thereby "going straight" and supplying legitimate DME to beneficiaries who actually need it. At the same time, the lower prices from competitive bidding may discourage firms from committing fraud in the first place if the potential profits from doing so no longer outweigh the risks of getting caught. In the event this effect dominates, the total amount of DME fraud could remain constant — or even decrease — despite fraudulent firms gaining market share.

We assess two dimensions of quality in the provision of DME to determine whether competitive bidding increased the overall level of fraud: the quality of the physical equipment itself and the quality of the patient-equipment match (i.e., whether an appropriate patient received the equipment). Both dimensions reflect important aspects of DME fraud. Providing substandard equipment and billing Medicare for it violates the False Claims Act, as does supplying DME to patients without a corresponding medical need.

To measure the physical quality of DME, we use claims-level data for repairs and replacements as a proxy, as in Ji and Rogers (2024). An increase in the frequency with which equipment needs to be repaired or replaced may reflect a decrease in its quality. In our setting, an increase in the rate of repairs could also indicate fraud if the DME falls below Medicare's quality standards.

Figure 5 shows at most a small change in repairs and replacements after the start of competitive bidding. Before competitive bidding, repairs and replacements accounted for 0.6% of claims overall, with nearly identical rates among legitimate and fraudulent firms, at 0.60% and 0.56%, respectively. After competitive bidding, the repair and replacement rate increased slightly for legitimate firms, although the effect is noisy and difficult to interpret given the large reduction in total claims for these firms (i.e, the slight increase may be confounded by lags associated with normal wear and tear and the contemporaneous reduction in non-repair claims).[13] By contrast, repair rates for fraudulent firms remained flat or declined slightly, with no evidence of an increase after competitive bidding.[14] In short, the data on replacement and repair rates do not suggest the physical quality of DME changed substantially as a result of heightened competition.

Figure 5: Effect on Product Quality



Notes: This figure plots estimates of quality changes from competitive bidding. The coefficients of interest are estimates of β_e for $e \in [-8, 8]/\{-1\}$ from (1). The dependent variable is the share of repairs and replacements by legitimate and fraudulent firms, out of claims filled by each respective type. The data include claims from 2008 to 2019. An observation is a MSA $\times$ HCPCS $\times$ quarter. Standard errors are clustered at the MSA-quarter level. Error bars represent the pointwise 95% confidence interval.

As a second measures of quality, we consider whether firms provide DME to beneficiaries appropriately, as a common form of DME fraud is supplying equipment to individuals who lack a medical need for it. We measure patient "match quality" in two ways: (i) by examining changes in the average number of comorbidities among Medicare beneficiaries receiving DME and (ii) by estimating changes in the share of first-time DME claims preceded by a recent hospitalization. Because hospitalization claims are difficult to falsify and DME often plays an important role in helping patients transition to home-based care after a hospitalization, post-hospitalization claims likely reflect a legitimate need for DME.

Figure 6 presents our results on patient-match quality. In panel (a), we do not find evidence of meaningful changes in the number of comorbidities among patients receiving DME after com-

[13]Appendix Figure A7 shows that the total claims for repairs and replacements submitted by legitimate firms fell after competitive bidding, further supporting our interpretation. There was no meaningful change in the number of repair and replacement claims submitted by fraudulent firms.

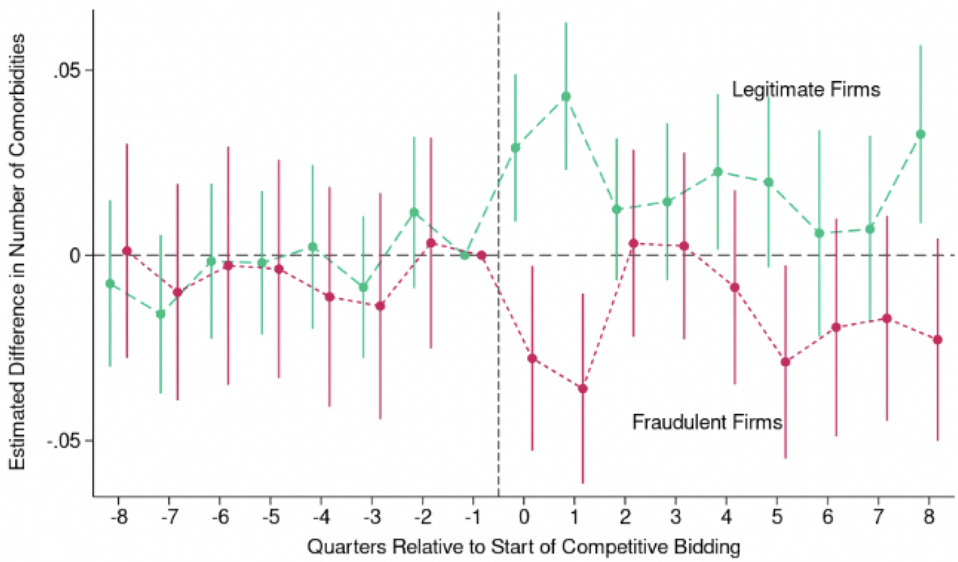
[14]Appendix I presents the static version of all results for which only the dynamic version is presented in the main text.

petitive bidding, for both fraudulent and legitimate firms. In the quarter before competitive bidding, the average patient served by a fraudulent firm had virtually the same number of comorbidities as those served by a legitimate firm, at 6.15 and 6.52, respectively. After competitive bidding, the average number of comorbidities of patients served by fraudulent firms declined by a negligible 0.01 comorbidities. As a related measure, Appendix Figure A8 shows no meaningful change in the average age of beneficiaries receiving DME from either type of firm.

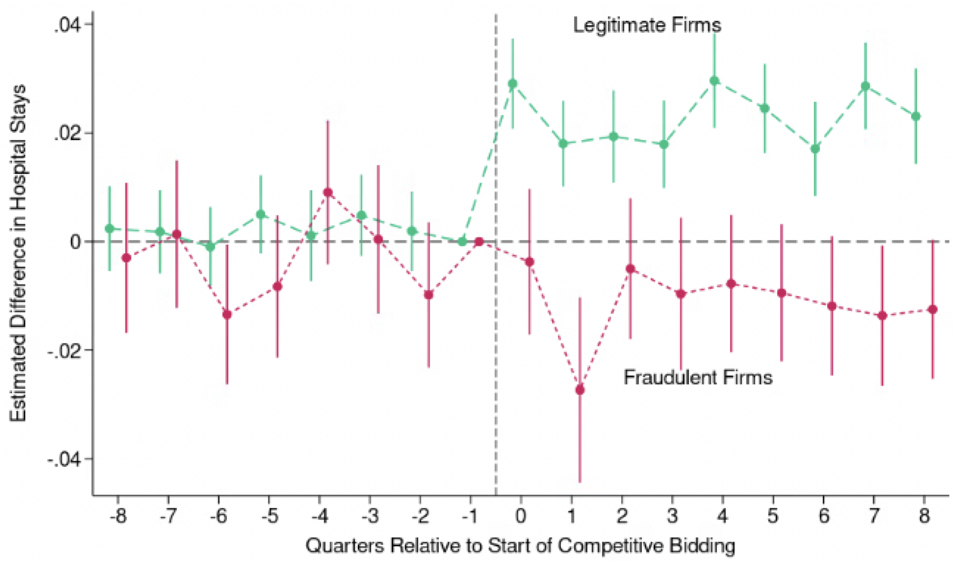
In panel (b), we similarly find no meaningful changes in the share of patients receiving DME after a recent hospitalization. Here, we limit our sample to patients receiving DME in a given product category for the first time to focus on patients for whom the DME is most likely to reflect medical necessity. We find the share of patients receiving DME from legitimate firms who had a recent hospitalization increased by approximately two percentage points after competitive bidding, whereas this share declined by about one percentage point for patients supplied by fraudulent firms. As with the results for comorbidities, we find no evidence of fraudulent firms "going straight" in response to competitive bidding, nor of legitimate firms engaging in more fraudulent behavior themselves.

Figure 6: Effects on Patient Match Quality

(a) Number of Comorbidities



(b) Beneficiaries with Recent Hospitalizations



Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from (1). Panel (a) reports event-study estimates of the average number of comorbidities across claims. Panel (b) reports event-study estimates where the dependent variable is an indicator for whether a claim was preceded by a recent hospitalization. Regressions are estimated at the claim level, weighting each observation by the number of claims it represents. The unit of observation is a beneficiary × product category × firm type × quarter. The sample covers 2008–2019. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

5 Mechanisms

Given our finding above that competitive bidding did not result in within-firm increases in fraud, we consider three possible mechanisms through which competitive bidding may have disproportionately benefited fraudulent firms through a selection effect. First, fraudulent firms tend to be larger, and larger firms' economies of scale could allow them to better navigate the costs and complexities associated with competitive bidding. Second, fraudulent firms may be more willing to engage in undesirable behavior during the procurement auctions themselves, which could then increase their probability of winning the right to supply DME within a particular region. Finally, heightened price competition may selectively benefit fraudulent firms because, unlike legitimate suppliers, they do not bear the full costs of providing high-quality DME to eligible beneficiaries or have cost advantages along other dimensions.

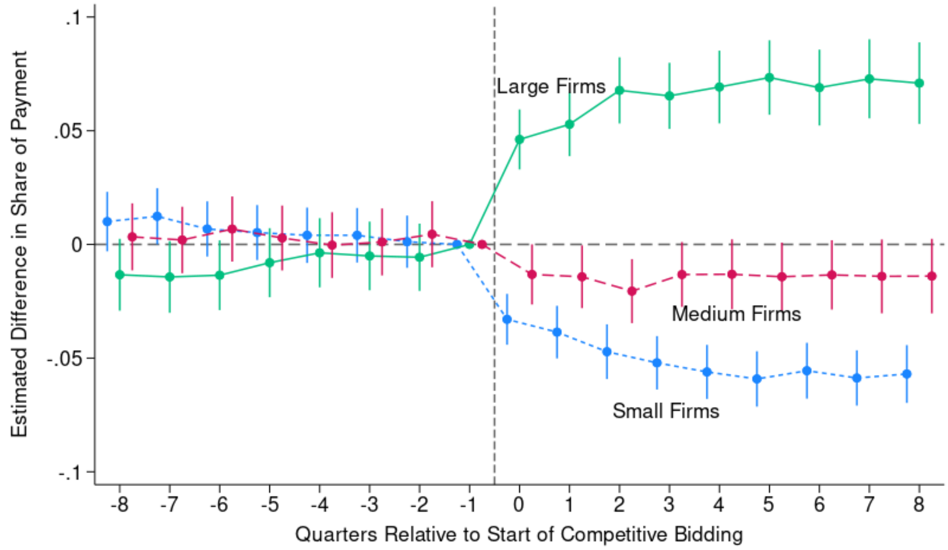
5.1 Scale

As previously shown in Table 1, fraudulent firms tend to be larger than legitimate ones, and one potential mechanism driving our results could be that larger firms are better equipped to bear the administrative burdens and hassle costs of procurement auctions. To explore this possibility, we first classify firms as small, medium, or large according to their lifetime revenue. We define firms with lifetime revenue less than the 95th percentile of \$2.6 million as small; those with lifetime revenue between the 95th and 99th percentiles as medium; and those with lifetime revenue above the 99th percentile of \$10.3 million as large. Based on these classifications, we have 146,343 small, 6,162 medium, and 1,541 large firms. For each MSA-HCPCS market, we then calculate revenue shares by firm size and evaluate how these change following the introduction of competitive bidding.

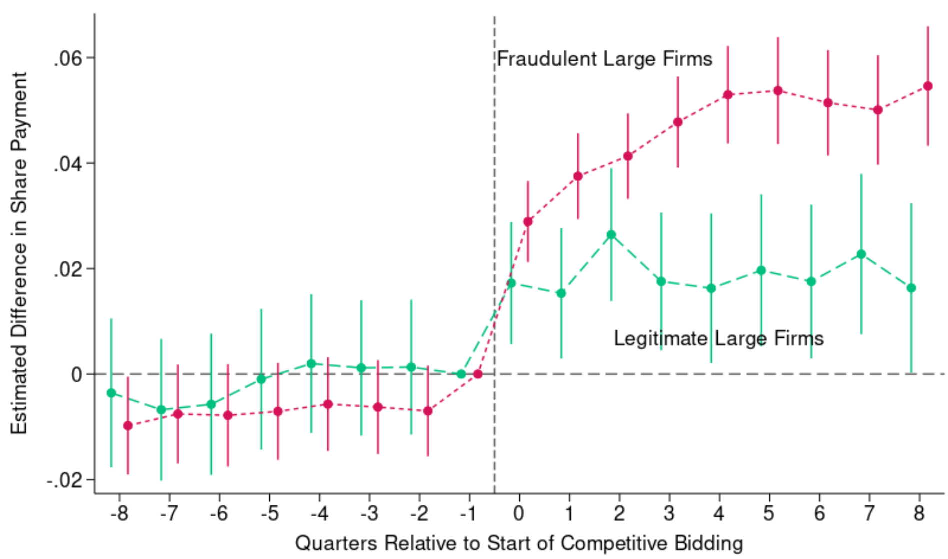
As shown in Figure 7, large firms disproportionately benefited from competitive bidding; they gained 7% market share in Figure 7a, whereas small and medium firms lost 6% and 2%, respectively.

Figure 7: Effects on Share of Payment by Firm Size and for Large Firms

(a) Share of Payment by Firm Size



(b) Share of Payment For Large Firms



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from (1). Panel (a) shows estimates for the share of payments for small, medium, and large firms. Panel (b) plots estimates for share of payments for legitimate large firms and fraudulent large firms. The data include payments from 2008 to 2019. An observation is a MSA $\times$ HCPCS $\times$ quarter. Standard errors are clustered at the MSA-quarter level. Error bars represent the pointwise 95% confidence interval.

We further consider the interaction between firm size and fraud by assessing the change in market share of fraudulent and legitimate firms conditional on firm size. We find the increase in market share for large firms is concentrated among large fraudulent firms.[15] As shown in Figure 7b, large fraudulent firms gained 5% market share compared to only 2% for large legitimate firms. Figure A6 shows similar patterns among small- and medium-sized firms: fraudulent firms gain market share relative to legitimate ones.[16]

From the preceding results, firm size alone cannot explain our findings. Across the entire distribution of firm sizes, fraudulent firms benefited from the introduction of price competition — and among large firms in particular, fraudulent firms gained the most.

5.2 Bids

Although the results above suggest competition disproportionately benefited fraudulent firms, Medicare's peculiar auction format may confound that interpretation. As a median price auction without commitment, submitting a very low bid before deciding whether to accept the price determined by the procurement auction is a non-dominated strategy (Cramton et al., 2015), and fraudulent firms may be more willing to submit very low, bad-faith bids.

To consider this possibility, we examine the bids submitted during the first two rounds of competitive bidding, with prices going into effect January 2011 and July 2013, respectively. The two bid cycles collectively contain 23,219 unique auctions, for which firms choose whether to submit a bid and, if so, the price at which they would supply each product in the relevant category for that area and an estimated capacity they could supply.[17] CMS awards contracts to the firms with the lowest bids whose estimated total capacity in aggregate meets current market demand, subject to a few additional stipulations. Appendix A provides further details on the auction format. Because the bid data released through FOIA requests do not include firm NPIs, we identify firms by matching firm names reported in the bid data to the NPI-level information we use to classify fraudulent and legitimate firms. Appendix J provides details on this matching process.

We first consider whether fraudulent firms disproportionately participated in the DME auc-

[15] Appendix Table A3 shows how firms in our sample break down into these types.

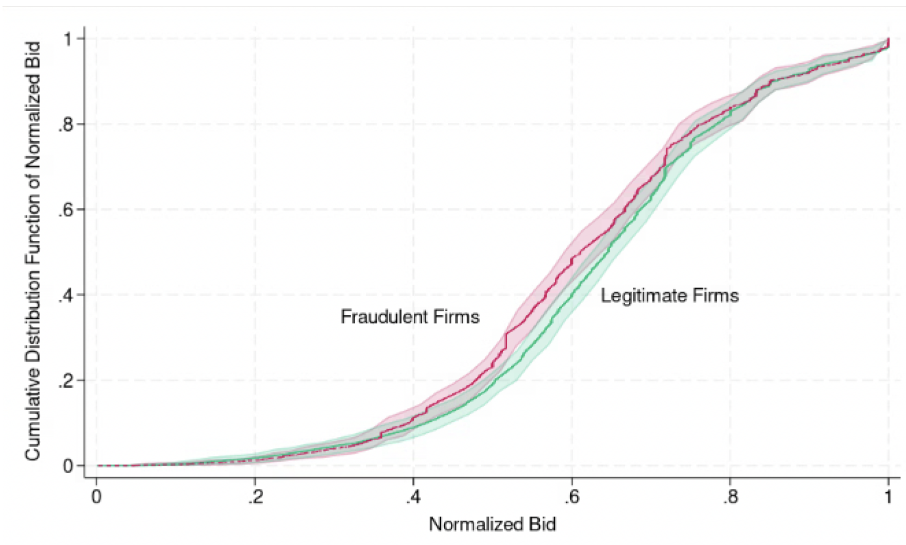
[16] Note that as shown in Appendix Table A3, large fraudulent firms are slightly smaller on average than large legitimate ones, meaning that our results cannot be driven by fraudulent firms being larger even conditional on whether they are small, medium, or large. More generally, our results are robust to different definitions of small, medium, and large firms.

[17] There are separate auctions for each DME product category in each geographic area for each bidding cycle, and each firm can make auction participation decisions independently. Participants submit a single bid outlining their price and estimated capacity for each procedure code within a product category, with winners for each product category determined based on the composite bids. Because the relative importance of each component of the composite bids is not available, we consider the distribution of bids at the component rather than composite bid level. Thus, when we refer to "auctions" in our empirical analysis, we are referring to a component auction, rather than composite auction. Also note the geographic areas are called competitive bidding areas (CBAs) and correspond very closely to metropolitan statistical areas (MSAs).

tions. We find that fraudulent firms comprise 199 of the 3,085 bidders, or 6.5%, a rate notably higher than the 1.9% of firms found to be fraudulent in the claims data.[18] Furthermore, fraudulent bidders participate in more auctions than legitimate bidders do. On average, a bidder participates in 466 auctions, with fraudulent bidders participating in an average of 1,129 compared to 421 for legitimate bidders. We find that 15.6% of bids come from fraudulent firms.

Conditional on participating in the auctions, we find only small differences in the behavior of fraudulent and legitimate firms. Figure 8 presents the distribution of bids normalized as a share of the pre-auction fee schedule amount.[19] Fraudulent firms submit slightly lower bids, on average, but the distributions have a similar shape overall and their 95% confidence intervals overlap throughout the entire distribution.[20] In particular, we find no evidence that fraudulent firms were more likely to submit very low bids.

Figure 8: Cumulative Distribution Function of Normalized Bids



Notes: This figure plots the CDFs of normalized bids across all auctions for legitimate and fraudulent firms. Bids are normalized by product for bid cycle 1 using fee schedule prices from 2008 and for bid cycle 2 using prices from 2012. Shaded regions show 95 percent confidence intervals from 200 bootstrapped samples.

[18]We consider a fraudulent bidder to be one that we match to at least one fraudulent firm, or NPI, as defined in the claims data. For this reason, one may worry that this definition of a fraudulent bidder artificially inflates the apparent participation of fraudulent firms in the auctions. We match 11,411 unique NPIs into the bidding data, 2,003 of which are for fraudulent firms, so if we measure participation at the NPI level instead of at the bidder level, we find that fraudulent firms are 17.6% of the firms participating in the auction vs only 1.9% of the firms in the claims data. This further strengthens our conclusion that fraudulent firms are much more likely to participate in the auctions than legitimate firms.

[19]This normalization allows us to compare products that have different magnitudes for costs. Furthermore, the maximum bid price that could be submitted was the fee schedule amount, meaning the highest allowable normalized bid has a value of 1.

[20]A Kolmogorov–Smirnov test of the equality of these distributions with bootstrapped standard errors clustered at the bidder level yields a p-value of 0.017.

Table 5 provides further evidence that fraudulent firms were not more likely to submit very low, potentially bad-faith bids. Regressing the normalized or log price on an indicator variable for whether the bid is linked to a fraudulent firm along with controls for the number of potential entrants in addition to product and MSA fixed effects, we find that fraudulent firms' bids are slightly lower on average, but the difference is not statistically distinguishable from zero. Consistent with this pattern, columns (3) and (4) show that fraudulent firms were not more likely to submit bids below either five or ten percent of the maximum bid.

Table 5: Relationship Between Fraudulent Status and Bidding Behavior

	Bid Price		Low-Ball Bid Indicators	
	(1) Bid Price (Log)	(2) Normalized Bid Price	(3) Bid Price $< 10\%$ of Max.	(4) Bid Price $< 5\%$ of Max.
Fraudulent Firm	-0.0334	-0.0209	-0.000513	-0.000334*
	(0.0316)	(0.0178)	(0.00138)	(0.000162)
Bid Capacity and Entrant Controls	Yes	Yes	Yes	Yes
Product FE	Yes	Yes	Yes	Yes
MSA FE	Yes	Yes	Yes	Yes
N	1,361,965	1,361,965	1,361,965	1,361,965

Notes: Each column reports coefficients from regressions of bidding behavior on an indicator for whether the bidder is identified as fraudulent. Columns (1) and (2) examine bid levels using log and normalized bid prices, respectively. Columns (3) and (4) examine whether a bid falls below 10% or 5% of the maximum allowable bid. All specifications control for the number of potential entrants, product fixed effects, and MSA fixed effects. Potential entrants are defined as the number of unique bidders participating in auctions for the same product in any market. Standard errors are clustered by bidder and given in parentheses.

5.3 Costs

The distribution of bids above highlights the key mechanism underpinning our results: price competition selects for low-cost firms, and fraudulent firms behave in ways consistent with having lower costs. Although bids do not necessarily reflect a firm's true costs in this setting given the poorly designed auction format, they nevertheless reveal that fraudulent firms are more willing to operate at the lower prices associated with competitive bidding, leading to their large gains in market share.

Fraudulent firms benefit from price competition because fraud is a low-cost way of supplying DME. Reflecting this cost advantage, fraudulent firms had greater economies of scale at baseline, as shown in Table 1, and they engage in low-cost schemes such as selling used equipment as though it were new (U.S. Department of Justice, 2024a), dropping off equipment that beneficiaries did not need or ask for (Elkind, 2024), and billing for patients under stolen identities (U.S.

Department of Justice, 2025). When compared to legitimate suppliers that must incur selling and marketing costs to attract eligible beneficiaries, deal with administrative burdens to validate medical necessity, and then supply costly high-quality equipment, fraudulent firms can operate at a substantial cost advantage and therefore thrive in a more competitive, low-margin environment.

6 Model

To better understand the relationship between competition and fraud, we present a stylized model of the market for DME. Our model serves two purposes. First, it formalizes the ambiguous theoretical effect of price competition on fraud, both along the intensive and extensive margins. Second, it allows us to quantify the extent to which fraudulent firms would gain market share at counterfactual prices.

Consider two types of firms, fraudulent and legitimate, with fraudulent firms distinguished by their willingness to engage in some degree of fraud. Indexing firms by i and time by t, firms receive a fixed price p_t for supplying DME that can be either fraudulent, with quantity denoted q_{it}^f, or legitimate, q_{it}^l. Firms have a variable cost function $c_{it}(q_{it}^f, q_{it}^l)$ and fixed costs F_{it}. Note that costs can vary arbitrarily across firms, and in particular they can differ by firm type. The profit function for firm i at time t is thus

$$\Pi_{it}(q_{it}^f, q_{it}^l; p_t) = (q_{it}^f + q_{it}^l)p_t - c_{it}(q_{it}^f, q_{it}^l) - F_{it}.$$

Assuming convex variable costs, legitimate firms will choose quantity q_{it}^l to set marginal cost equal to p_t, while fraudulent firms will choose q_{it}^f and q_{it}^l such that the marginal cost of both activities is equal to p_t. Firms of each type may choose to set either type of DME equal to zero if it is more profitable to exit a market.

When faced with a lower price p_t, the amount of fraudulent and legitimate activity can rise or fall through two distinct channels. Along the intensive margin, if costs are convex, firms of either type will respond to a lower price by reducing the fraudulent or legitimate quantities they choose to supply, but fraudulent firms may choose to commit more fraud if, for example, the marginal cost of fraud falls as profits fall (i.e., legitimate behavior is a normal good). In that case, price reductions can have a treatment effect of reducing or increasing the amount of fraud, either as fraudulent firms move down an upward-sloping supply curve or have lower perceived marginal costs of fraud.

Along the extensive margin, a lower price p_t will lead to (weakly) less market participation as profits fall. A lower price will therefore cause the lowest-profit (or, equivalently, highest-average cost) firms to exit, which may be either fraudulent or legitimate suppliers. As discussed above, fraudulent firms may have cost advantages for a number of reasons, including the ability to achieve economies of scale through fraud, lower customer acquisition costs through selling the product illegitimately, and lower product costs from lower-quality offerings, among others. On the other hand, fraudulent firms may have higher costs, particularly due to the implicit costs of sanction not faced by legitimate firms. As with the treatment effect, the selection effect of a price change is theoretically ambiguous.

To apply this model to our empirical setting, we consider firms' decisions on how much DME to supply in the periods immediately before and after the first round of competitive bidding. We treat the relevant quantity as the number of unique beneficiaries supplied with DME from the relevant product category. In the data, we find no change along the intensive margin for either type of firm and no change in the participation of fraudulent firms. That is, the selection effect of low prices favoring low-cost fraudulent firms and driving out high-cost legitimate firms fully explains our results. Thus, in estimating our model, we assume fraudulent firms do not alter quantity supplied in response to price changes and all changes in the quantity supplied by legitimate firms come along the extensive margin.

Parameterizing the model to estimate this selection effect, we assume legitimate firms have normally distributed average costs $AC_{ijmt} = \frac{c_{ijmt}(0, q^n_{ijmt})}{q^n_{ijmt}} \sim \mathcal{N}(\mu_{jmt}, \sigma_{jmt})$, where μ_{jmt} is the mean average cost of potential entrants for product j in market m at time t and σ_{jmt} is the standard deviation of average costs.[21] Firms choose to participate in the market if and only if $AC_{ijmt} \leq p_{jmt}$. We assume $\mu_{jmt} = \gamma_m + \gamma_j$ and $\sigma_{jmt} = \sigma_j$. That is, we assume average costs vary by product and market but not over time, and the variation in costs depends only on the product.

We estimate the model using OLS, noting that the share of legitimate potential entrants active in a given market s_{jmt} is given by

$$s_{jmt} = \Pr(AC_{ijmt} \leq p_{jmt}) = \Phi\left(\frac{p_{jmt} - \mu_{jmt}}{\sigma_j}\right),$$

which can be inverted such that its parameters can be obtained by estimating the following regression equation:

$$p_{jmt} = \sigma_j \, \Phi^{-1}(s_{jmt}) + \gamma_m + \gamma_j + \varepsilon_{mj},$$

where p_{jmt} and $\Phi^{-1}(s_{jmt})$ are observed data, and σ_j, γ_m, and γ_j are vectors of fixed effects.

We define potential entrants in various ways to assess the robustness of our results: firms supplying the product in question in the relevant market in any time period, firms supplying any type of DME in the relevant geographic market, firms that supply the relevant product in any market, and, finally, all DME firms. We consider two periods t, 2010 and 2011, the year before

[21] Note that we have added j and m subscripts to the cost function and its arguments. Implicitly, this means that we are assuming that legitimate firms make their participation decisions in each market independently of their participation decision in other markets.

and the year after the start of competitive bidding.

Estimates of the model appear in Table 6. We find substantial variation in both the mean and standard deviation of costs across markets, with the standard deviation of both parameters exceeding half the mean for all market definitions and exceeding 85% for the smallest market definition.

Table 6: Model Estimates

	(1)	(2)	(3)	(4)
Potential Entrant Definition	Market-Product	Market	Product	All
Across-Market Mean of Mean Average Cost μ	392.0	1550.02	1739.6	2810.7
	(20.3)	(98.8)	(171.5)	(308.2)
Across-Market Standard Deviation of Mean Average Cost μ_{pmt}	401.1	2023.6	970.7	1772.59
	(29.6)	(164.3)	(97.1)	(229.3)
Across-Market Mean of Standard Deviation of Average Cost σ_{pmt}	415.9	715.2	845.05	1109.8
	(36.07)	(87.33)	(131.3)	(163.8)
Across-Market Standard Deviation of Standard Deviation of Average Cost σ_{pmt}	436.06	899.5	245.1	434.5
	(46.4)	(100.0)	(69.5)	(102.8)

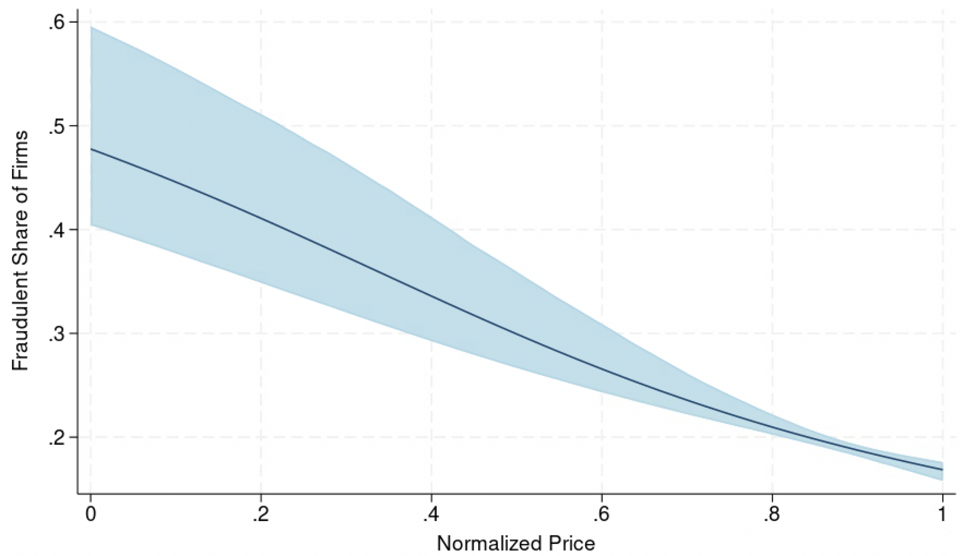
Notes: Estimated using market shares in terms of number of unique patients given DME in the each product category in each MSA in 2010 and 2011. Standard errors from 2000 bootstrap iterations are given in parentheses. Each column represents a different definition of potential entrants: Column (1) uses firms ever selling the product-market pair. Column (2) considers any firm active in the geographic market. Column (3) uses any firm that supplies the product. Column (4) uses all DME firms as potential entrants.

From these parameter estimates, we simulate the share of fraudulent firms in the market for various counterfactual prices. Treating all firms that we observe supplying the product as potential entrants, Figure 9a shows the share of fraudulent firms along the continuum of counterfactual prices, normalized by the pre-competitive bidding price.[22] Consistent with the results presented in Section 4, lower prices lead to a larger market share for fraudulent firms. We also find that the selection effect grows slightly stronger as prices decrease, as shown in Figure 9b, which reports the estimated marginal effect of a price reduction on the share of fraudulent firms for each market, both at the pre-competitive bidding price and at the average normalized post-competitive bidding price. Three insights stand out. First, in all markets, reducing the price selects for more fraudulent firms. Second, the strength of this selection effect varies widely. Third, at lower prices, the extent to which a marginal reduction in price selects for fraudulent firms is both much larger on average and more heterogeneous across markets.

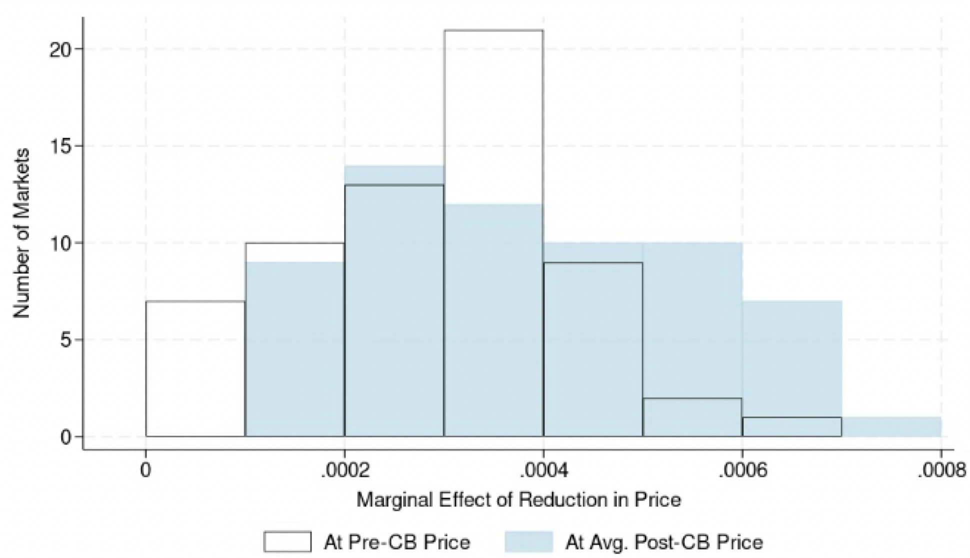
[22]The figure shows the mean share across markets, while Figure A9 shows the counterfactual fraudulent share for each market.

Figure 9: Counterfactual Fraudulent Firm Shares

(a) Mean Fraudulent Share



(b) Marginal Effect of Price Reduction on Fraudulent Share



Notes: Panel (a) gives the share of firms in market that are fraudulent for counterfactual prices normalized to the pre-competitive bidding price. The blue shaded area gives the 95% confidence interval from 2000 bootstrap iterations. Panel (b) gives a histogram of the estimated marginal effect of a price reduction on the share of fraudulent firms for each product category-MSA. The clear bars with black outlines give the estimated marginal effects at the pre-competitive bidding price in each market. The light blue bars give the estimated marginal effects at the average normalized post-competitive bidding price.

7 Conclusion

Although competition in government procurement can reduce prices and dissipate rents, the adverse selection of low-cost fraudulent firms has the potential to crowd out legitimate suppliers that bear the full costs of providing high-quality products and services. To our knowledge, our study is the first to show this relationship empirically.

Using Medicare claims data and a novel dataset of fraudulent DME suppliers, we study how the heightened price competition following Medicare's staggered adoption of procurement auctions affected both spending and fraud. We find that greater price competition allows fraudulent firms to increase their market share by 8.1 percentage points, with the gains not coming from greater economies of scale or gaming the auction process. Instead, fraudulent firms thrive under the lower prices of competitive bidding by using their cost advantage to drive out legitimate suppliers that cannot match the artificially low costs of supplying low-quality products to ineligible beneficiaries. Although fraudulent firms capture more of the market, we find no evidence of within-firm changes in the amount of fraudulent DME they provide.

Our findings have important implications for policymakers. The DME Competitive Bidding Program was specifically designed to reduce fraud, waste, and abuse (U.S. Department of Health and Human Services, Office of Inspector General, 2017), under the assumption that fraud had proliferated in large part due to the excessive rents available to unscrupulous suppliers from administratively set prices. Although theoretically possible, our stylized model makes clear that competition need not reduce fraud. In the market for DME, increased price competition benefited fraudulent firms with lower costs, and our empirical results therefore provide key insights for combating fraud through market-based mechanisms.

That price competition may favor fraudulent firms holds lessons for procurement policies more broadly. Fraudulent firms in this market are able to engage in cost-reducing behavior that skirts regulations, echoing the framework of Hart et al. (1997). Although the potential to capture large profits through high prices may entice fraudulent firms to enter a particular market, reducing those prices may not have the converse effect of deterring them, as was the case for DME. As such, any policies that aim to reduce prices should be paired with verifiable standards for quality, such as increased audits and validation of patients' medical necessity. Without these safeguards, reducing prices can inadvertently exacerbate the existing failures of the procurement process.

Assessing the overall impact of competitive bidding requires nuance. Although overall spending declined, mostly through a reduction in low-value care (Ding et al., 2025), firms with a track record of fraudulent behavior gained market share without any evidence suggesting they committed less fraud in the process. Given their more dominant position in the market, such firms may now have the opportunity to defraud the government even further, particularly if regulators view the remaining suppliers as essential to providing beneficiaries with life-sustaining equipment. At the same time, regulators may find it more efficient to oversee fewer suppliers, even if those suppliers have more fraudulent tendencies, a dynamic effect in need of future research.

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Appendix: For Online Publication

The following appendices provide additional robustness checks, analyses, and details on our data.

Appendix A provides more details on the auction format.

Appendix B contains additional information on the comorbidities included in the construction of the comorbidity index.

Appendix C contains additional tables and figures directly referenced in the main text.

Appendix D provides more detail on the method used to classify suspicious firms.

Appendix E presents our main results limiting the sample of firms to those with a taxonomy code indicating the firm is primarily a DME firm.

Appendix F presents our event study results separately by when competitive bidding was implemented in that market.

Appendix G demonstrates the robustness of our results to alternative dependent variable transformations, presenting our main results with the dependent variable measured in levels, logs, and a binary indicator for being non-zero.

Appendix H presents robustness results using a restricted sample of fraudulent firms, retaining only those present in our data prior to the introduction of competitive bidding in 2011.

Appendix I contains the corresponding static regression coefficient estimates for outcomes for which the only results in the main text are dynamic.

Appendix J contains additional information on the process to match firms in the auctions with firm NPIs in the NPPES.

A Auction Format Details

This appendix provides additional details on the auction format, drawing on a CMS DMEPOS regulatory summary,[23] the *Federal Register* (2006 Vol. 71 No. 83), and Appendix A of Ji (2023).

Each auction is for the ability to supply Medicare beneficiaries with DME in a product category in a competitive bidding area for the period covered by the auction. Competitive bidding areas correspond to metropolitan statistical areas (MSAs), and suppliers do not need to be physically located in the competitive bidding area to participate in the auction for that area. The time period covered by each auction is three years.

A product category is a set of related DME products that CMS groups together for a single composite auction. There is a single composite auction for each product category to determine the winning bidders, but the price set by the auction is determined at the individual product (HCPCS-by-modifier-code) level.

Each supplier participating in the auction submits a bidding worksheet, an example of which is shown in Figure A1, in which the bidder records its bid price for each product in the product category. The bidding worksheet also provides necessary information to bidders, such as the weights used compute the composite bid and the maximum bid price for each product, which is the previous, administratively-set price. Suppliers also use the bidding worksheet to report the volume of each product they are able to supply.

CMS requires the bids to be "bona fide" and may investigate bids to ensure this requirement is met. For example, CMS may require suppliers to submit invoices to validate their bid price is above their costs or provide proof of necessary capacity expansions if their reported capacity exceeds their existing quantity supplied.[24] Interestingly, there does not appear to be any consideration of the possibility of bidders submitting capacities well below what they would be able to

[23]Found at `https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/DMEPOSCompetitiveBid/downloads/DMEPOSRegSumm.pdf`.

[24]See the documents "Requirement to Submit a Bona Fide Bid", "Review of Supplier Capacity and Expansion Plans", and "Required Financial Documentation" available on the competitive bidding program website `https://www.dmecompetitivebid.com/cbic/cbicr2021.nsf/DocsCat/Home` and the federal register comment and response document available at `https://www.govinfo.gov/content/pkg/FR-2014-11-06/pdf/2014-26182.pdf`.

supply, with CMS appearing most concerned with infeasible low-price or high-capacity bids.

Once the bids are submitted, CMS calculates the composite bid for the product category for each bidding supplier. The composite bids are ranked from lowest to highest price, with the lowest-price bidders being offered contracts until the reported capacities of the winning bidders reach CMS's target capacity.[25] The winning price for each product is the median bid price submitted by the winning suppliers.

After the auction concludes, the winning suppliers are the only ones able to bill Medicare for DME in the product category. They are paid the price set by the auction, and there are no restrictions on the quantity of DME they actually supply.

[25] CMS caps each supplier's capacity at 20% of the target capacity and requires that small suppliers (those with annual revenue below $3.5 million) constitute at least 30% of the target capacity.

Figure A1: Bid Preparation Sheet Example

Product Category: Standard Power Wheelchairs, Scooters, and Related Accessories				Bidder Data (Enter your bid amount and estimated capacity information in DBidS - Form B)		
HCPCS Code	**HCPCS Code Description**	**Definition of a Bidding Unit**	**Weight** (The relative market importance of the item in the product category based on utilization)	**Your Estimated Capacity** (Number of units you can furnish in CBA for one [1] year)	**Bid Limit** (Fee Schedule: Bid amounts must be at or below this amount)	**Your Bid Amount** (To provide **one** [1] unit as described in **Definition of a Bidding Unit**)
E2361	Power Wheelchair Accessory, 22nf Sealed Lead Acid Battery, Each, (E.G. Gel Cell, Absorbed Glassmat)	purchase of one (1) new item	0.0669417495		$126.22	
E2363	Power Wheelchair Accessory, Group 24 Sealed Lead Acid Battery, Each (E.G. Gel Cell, Absorbed Glassmat)	purchase of one (1) new item	0.0623440908		$168.33	
E0990	Wheelchair Accessory, Elevating Leg Rest, Complete Assembly, Each	purchase of one (1) new item	0.0433494421		$99.71	
E2601	General Use Wheelchair Seat Cushion, Width Less Than 22 Inches, Any Depth	purchase of one (1) new item	0.0373781194		$55.35	
E2386	Power Wheelchair Accessory, Foam Filled Drive Wheel Tire, Any Size, Replacement Only, Each	purchase of one (1) new item	0.0199483729		$136.21	
E0978	Wheelchair Accessory, Positioning Belt/Safety Belt/Pelvic Strap, Each	purchase of one (1) new item	0.0156467577		$37.52	
E2392	Power Wheelchair Accessory, Solid (Rubber/Plastic) Caster Tire With Integrated Wheel, Any Size, Replacement Only, Each	purchase of one (1) new item	0.0151320843		$48.76	
E0951	Heel Loop/Holder, Any Type, With Or Without Ankle Strap, Each	purchase of one (1) new item	0.0146838657		$16.06	
E2366	Power Wheelchair Accessory, Battery Charger, Single Mode, For Use With Only One Battery Type, Sealed Or Non-Sealed, Each	purchase of one (1) new item	0.0132263065		$202.79	
E2370	Power Wheelchair Component, Motor And Gear Box Combination, Replacement Only	purchase of one (1) new item	0.0126106061		$726.57	
E2611	General Use Wheelchair Back Cushion, Width Less Than 22 Inches, Any Height, Including Any Type Mounting Hardware	purchase of one (1) new item	0.0112474519		$282.68	
K0019	Arm Pad, Each	purchase of one (1) new item	0.0105810534		$15.24	

Notes: Excerpt from a bid preparation worksheet provided to suppliers, downloadable from `https://www.dmecompetitivebid.com`. This figure also comes from Ji (2023).

B Comorbidity Index

To construct the comorbidity index, we rely on the 27 CCW Chronic Condition indicators provided in the Medicare Beneficiary Summary File (MBSF). Using the mid-year flags, we sum the number of chronic conditions for each beneficiary in each calendar year. The CCW chronic condition indicators are not mutually exclusive—for example, beneficiaries may be flagged for both Alzheimer's Disease and Alzheimer's/Related Disorders. Following common practice in studies using CCW data, we construct the comorbidity index by summing all 27 indicators without collapsing overlapping conditions. Table A1 contains the full list of conditions included.

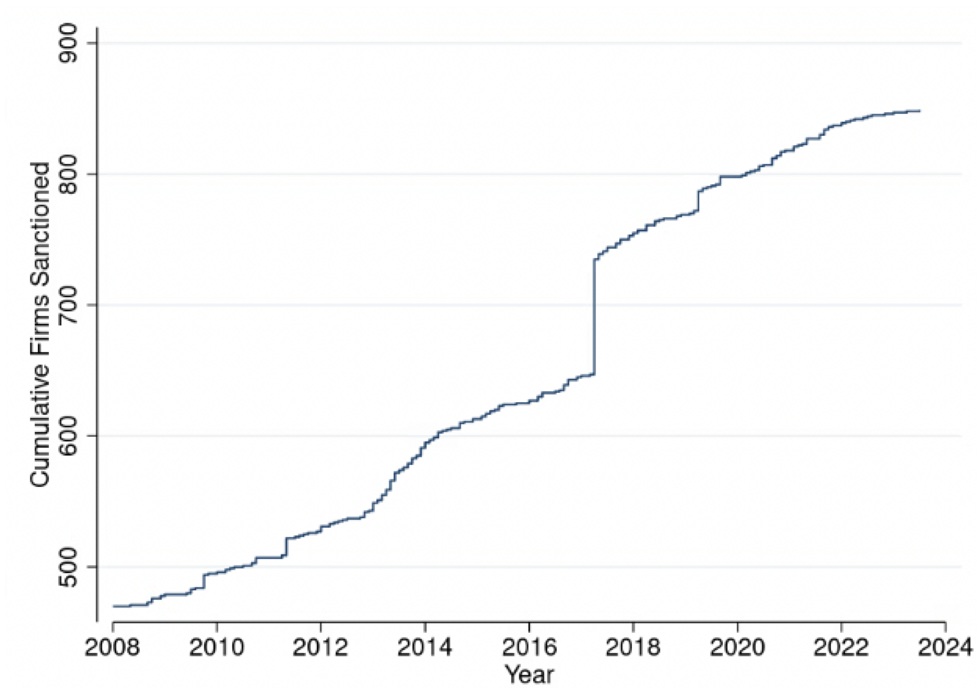
Once we construct the index for a beneficiary-year we merge this index to all claims for the beneficiary in that year, and estimate claim-level regressions weighted by all claims.

Table A1: List of Conditions Included in Comorbidity Index

Acute Myocardial Inf.	Alzheimer's Disease	Alzheimer's/Related Disorders
Atrial Fibrillation	Cataract	Chronic Kidney Dis.
COPD	Heart Failure	Diabetes
Glaucoma	Hip/Pelvic Fracture	Ischemic Heart Dis.
Depression	Osteoporosis	Rheumatoid Arthritis/OA
Stroke/TIA	Breast Cancer	Colorectal Cancer
Prostate Cancer	Lung Cancer	Endometrial Cancer
Anemia	Asthma	Hyperlipidemia
Benign Prostatic Hyperplasia	Hypertension	Hypothyroidism

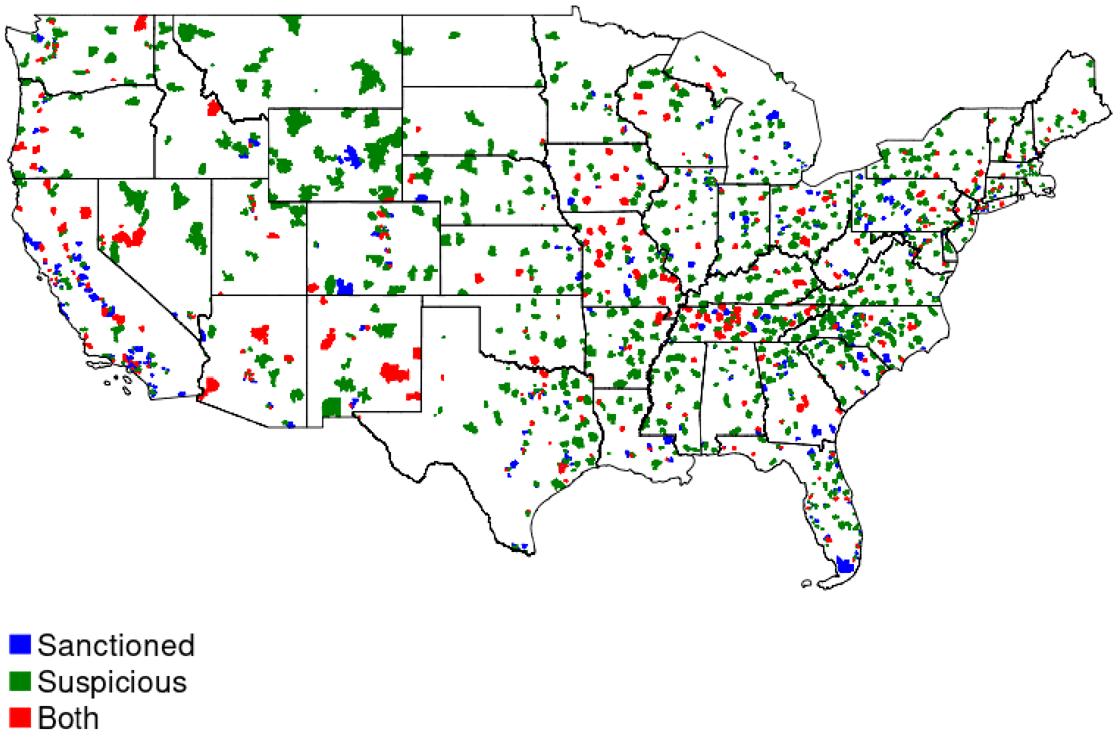
C Additional Tables and Figures Referenced in the Main Text

Figure A2: Sanctioned Firms Over Time



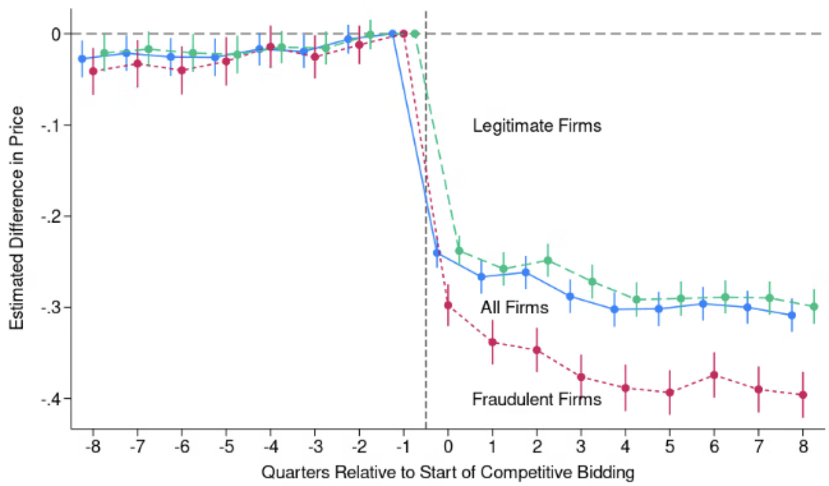
Notes: This figure shows the number of firms subject to DME-related health care fraud enforcement over time. The sample includes firms sanctioned for engaging in fraud by the DOJ and named in a press release or appearing in the LEIE. Dates used are the date of the press release or date of exclusion. The spike in 2017 corresponds to Medicare "strike force" actions targeting multiple DME providers.

Figure A3: Location of Sanctioned and Suspicious Firms



Notes: This map plots the location of sanctioned and suspicious DME firms. Blue ZIP codes mark where firms were sanctioned for fraud. Green ZIP codes mark firms we classify as suspicious. Red ZIP codes contain both sanctioned and suspicious firms.

Figure A4: Effect on Prices



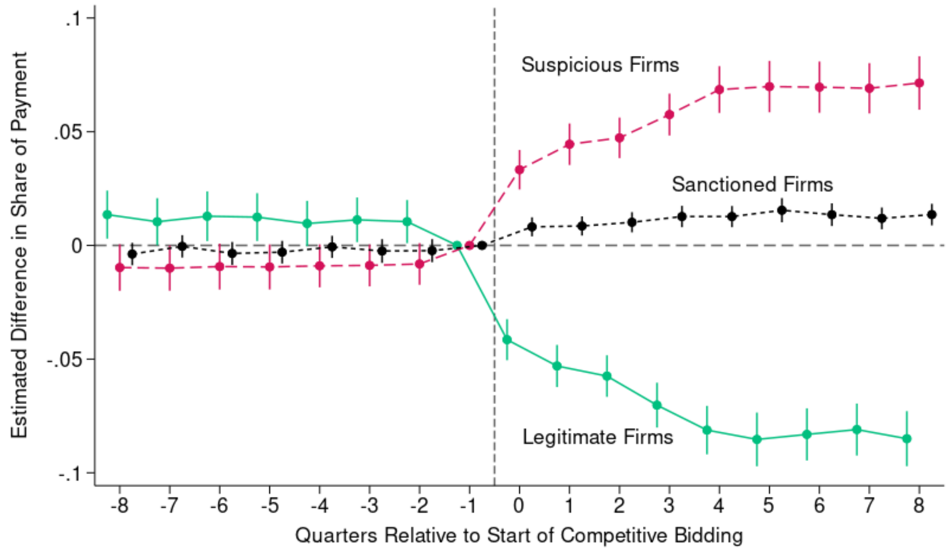
Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from equation (1). The dependent variable is of price transformed by inverse hyperbolic sine. We define price as average payment per claim, rather than using list prices. Estimates are shown separately for legitimate firms, fraudulent firms, and all firms. The data include claims from 2008–2019, with observations at the MSA $\times$ HCPCS $\times$ quarter level. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

Table A2: Effect of Competitive Bidding on Prices (Asinh), by Firm Type

	Fraudulent Firms	Legitimate Firms
Competitive bidding	-0.342***	-0.261***
	(0.005)	(0.004)
Dep. var mean (price)	112.48	121.64
Implied effect (%)	-29.0%	-23.0%
Observations	3,000,103	10,027,890
HCPCS–MSA FE	Yes	Yes
HCPCS–Quarter FE	Yes	Yes
MSA–Quarter FE	Yes	Yes

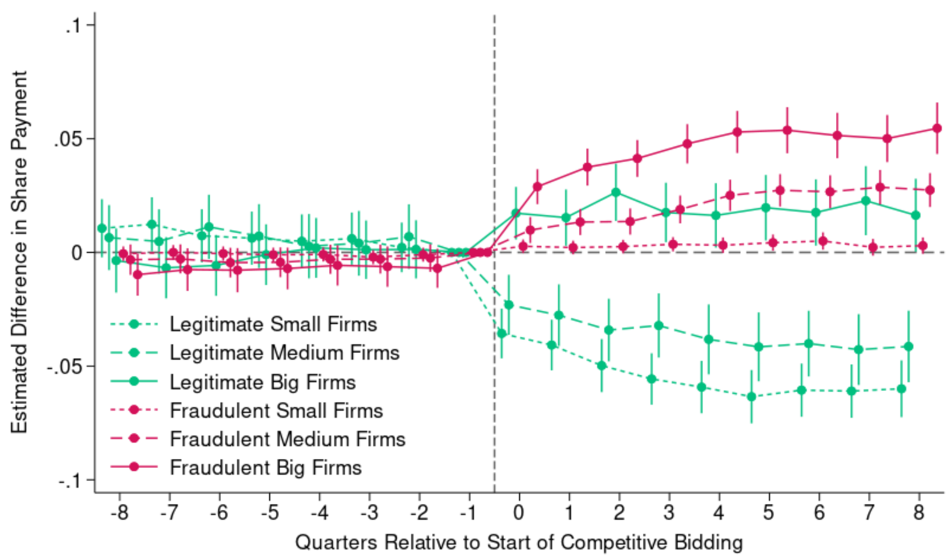
Notes: Each column reports the estimate of β from the static specification in equation (2), which aggregates event time indicators over the eight quarters following competitive bidding ($e \in [0, 8]$). Outcomes are measured at the MSA $\times$ HCPCS $\times$ quarter level. Price is transformed using the inverse hyperbolic sine and is only defined for observations in which there was positive payment to at least one firm of the relevant type (fraudulent or legitimate). We define price as average payment per claim, rather than using list prices. Implied percentage effects are computed as $100 \times [\sinh(\text{asinh}(\bar{y}) + \beta) - \bar{y}]/\bar{y}$, where β is the estimated coefficient on competitive bidding and $\bar{y}$ is the pre-period mean of the outcome in levels. All regressions include HCPCS–MSA, HCPCS–quarter, and MSA–quarter fixed effects, with standard errors clustered at the MSA–quarter level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure A5: Effects on Market Share of Payments by Detailed Firm Status



Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from equation (1). The dependent variable is the share of total payments accounted for by legitimate, sanctioned, or suspicious firms. The data include payments from 2008–2019, with observations at the MSA $\times$ HCPCS $\times$ quarter level. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

Figure A6: Effect on Share of Payment by Size and Legitimacy



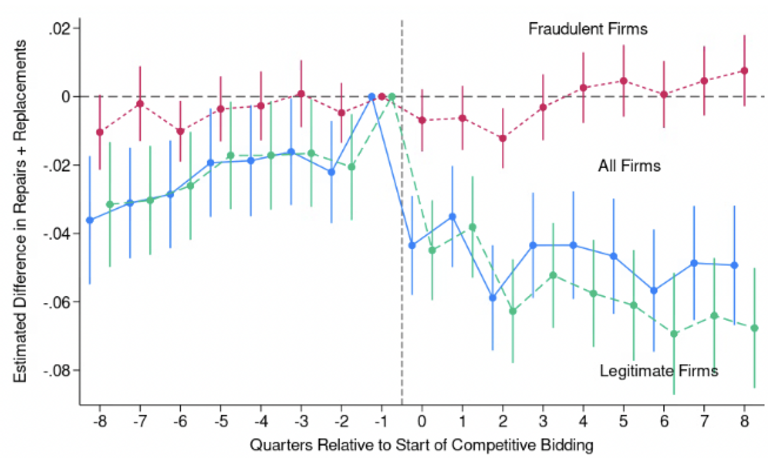
Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Dependent variable is share of payment for legitimate and fraudulent firms by size:small, medium and large. The data include payments from 2008 to 2019, with observations at the MSA $\times$ HCPCS $\times$ quarter level. Standard errors are clustered at the MSA-quarter level. Error bars represent the pointwise 95% confidence interval.

Table A3: Counts of Legitimate and Fraudulent Firms by Size

Firm Size	**Firm Quality**	**Count**	**Avg. Lifetime Payments ($M)**
Small	Legitimate	145,098	0.16
Small	Fraudulent	1,245	0.72
Total Small		146,343	**0.17**
Medium	Legitimate	4,956	0.49
Medium	Fraudulent	1,206	5.81
Total Medium		6,162	**5.09**
Large	Legitimate	1,090	33.3
Large	Fraudulent	451	29.2
Total Large		1,541	**32.1**

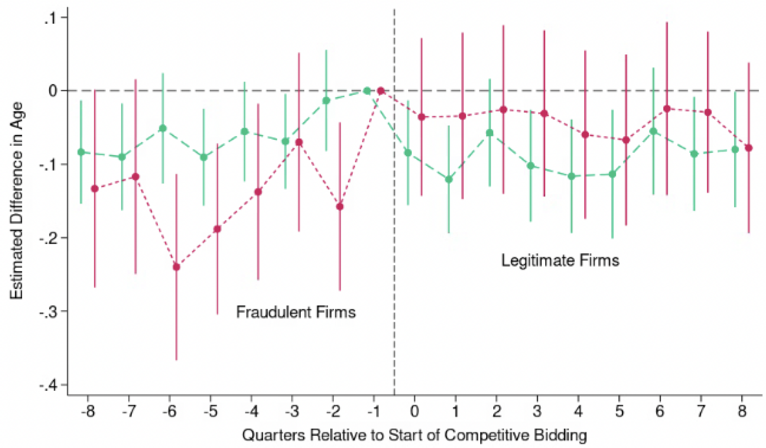
Notes: Sample includes all firms that submitted at least one DME claim to Medicare Part B from 2008 to 2019. Firms are classified as fraudulent if they were sanctioned for fraud or flagged as suspicious by at least one suspiciousness measure. Firm size is defined using percentiles of lifetime Medicare revenue: firms above the 99th percentile ($10.3 million) are classified as large, firms below the 95th percentile ($2.6 million) are classified as small, and the remaining firms are classified as medium. Average lifetime payments are calculated using total Medicare payments per firm over the sample period and reported in millions of dollars.

Figure A7: Repairs and Replacements



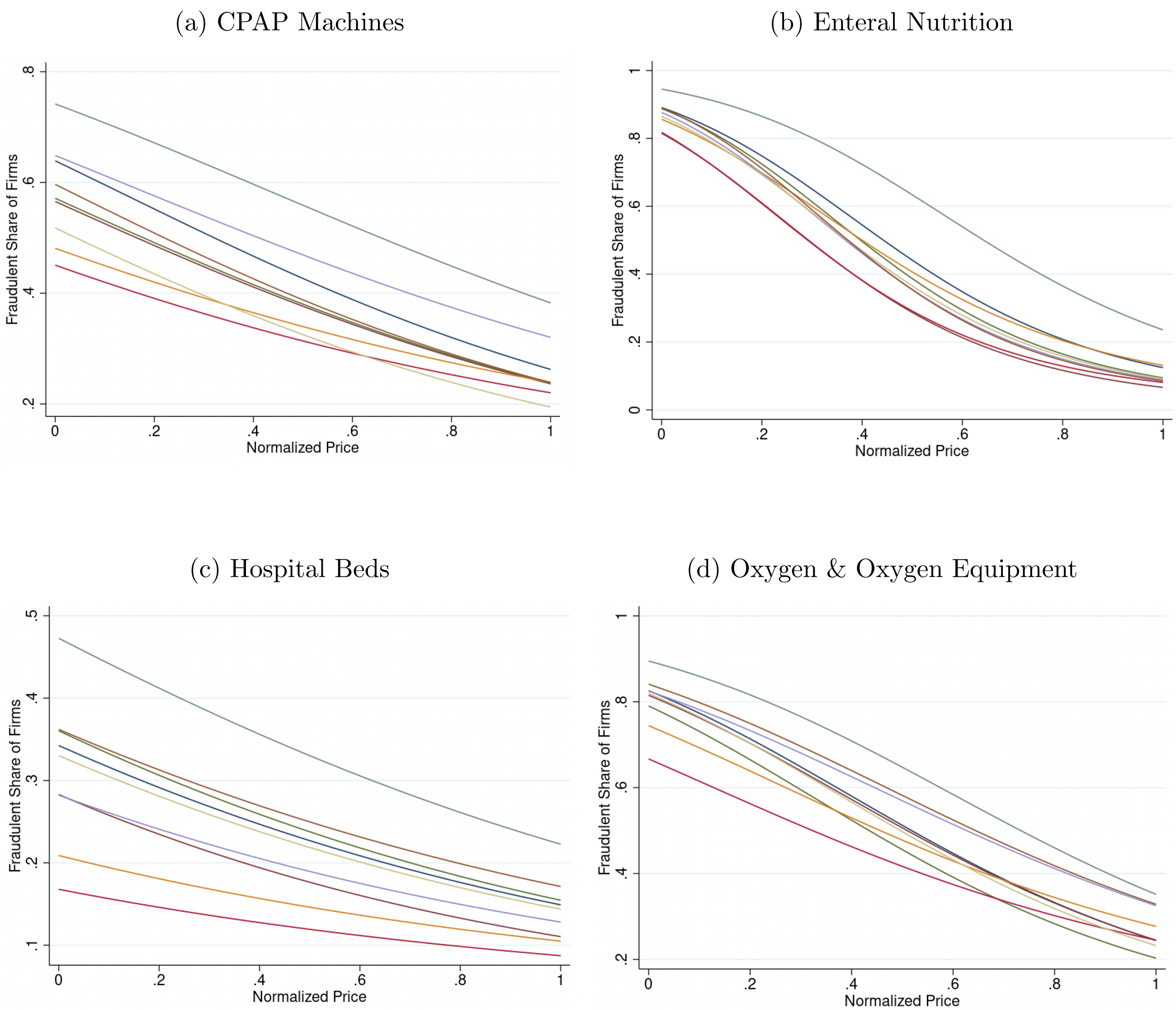
Notes: Estimates of β_e from equation 1 for the number of repairs and replacements (IHS-transformed), estimated separately for legitimate firms, fraudulent firms, and all firms. Data span 2008–2019 with observations at the MSA × HCPCS × quarter level. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

Figure A8: Beneficiary Age Served by Firm Type

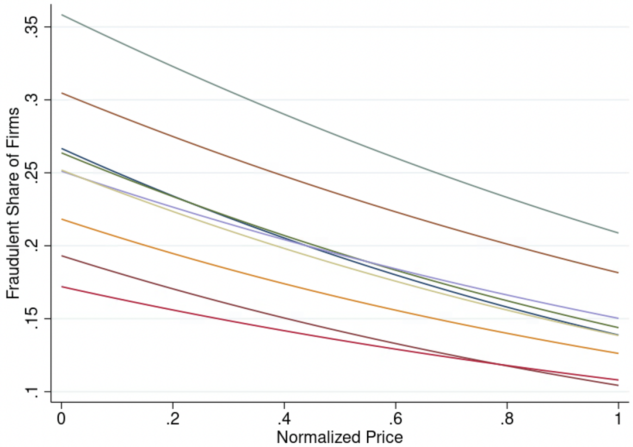


Notes: Estimates of β_e from equation (1). The dependent variable is the average age of beneficiaries served by legitimate and fraudulent firms. The data include observations from 2008–2019 at the MSA $\times$ HCPCS $\times$ quarter level. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

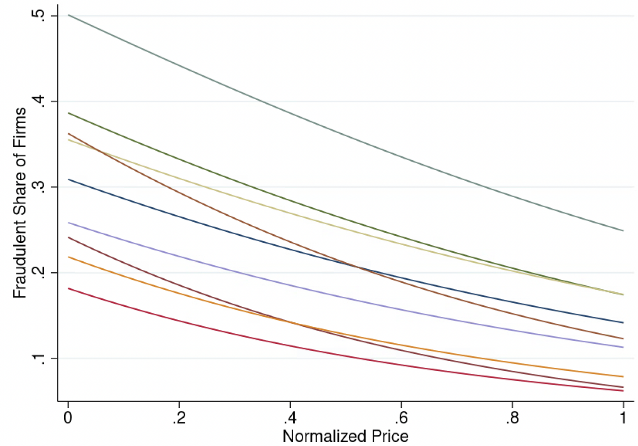
Figure A9: Model Counterfactuals by Product Category



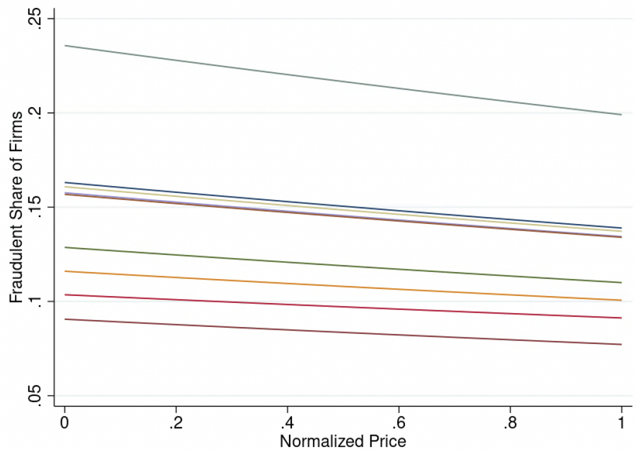
(e) Standard Manual Wheelchairs



(f) Support Surfaces



(g) Walkers



Notes: Each panel corresponds to a product category and reports the simulated share of fraudulent firms at counterfactual prices, normalized to the pre–competitive bidding price. Categories omitted from this figure (wave 2 or 3 categories) include commode chairs, nebulizers, NPWT pumps, non-invasive ventilators, back braces, knee braces, patient lifts, and TENS devices. Due to a change in regulation, we also exclude power mobility devices.

D Detailed Information on Finding Suspicious Firms

We use four different measures of suspiciousness, explained below, and label a firm flagged by at least one of our four measures as "suspicious."

D.1 Firm Name

Using the NPPES, we obtain a supplier's organization name. To clean the names, we first remove common punctuation marks (e.g., commas, periods, and hyphens) and spaces that do not contribute to identifying the firm. Next, we eliminate frequent terms such as "INC," "LTD," and "CO." Appendix Table A4 shows the words we eliminate. This step standardizes the names for better matching.

Table A4: List of Words Excluded From Name Matching

INCORPORATED	PLLC	LLC
INC	CORPORATION	CORP
CO	LIMITED	LTD

To group firms with the same or very similar names, we use STATA's matchit command. We use the default Jaccard method, which calculates the similarity between two names based on the intersection of their character sets relative to their union. The Jaccard index ranges from 0 (no similarity) to 1 (exact match), measuring how closely two names resemble one another. We set a similarity threshold (similscore > 0.95) to identify exact or nearly exact matches. A score greater than 0.95 indicates that the two names are sufficiently similar to be considered a match, allowing us to group firms that may have slight variations in their names (e.g., different spellings, abbreviations, or prefixes).

For each pair of NPIs, we focus on cases where one NPI is labeled as fraudulent due to being sanctioned and the other is not. If the name of the non-fraudulent NPI matches that of a known fraudulent NPI, we flag it as a suspicious firm. As shown in Table A5, 496 firms are identified as suspicious using this method, with 342 (69%) of these firms also being identified as suspicious using one of the other methods discussed in this appendix.

D.2 Firm Owner

Our second method uses firms' authorized owner names from the NPPES to identify suspicious firms. We first clean the owner names by removing punctuation and then group NPIs by exact matches on the first, middle, and last name of the authorized owner. Each group is treated as a set of NPIs owned by the same person. Within each group, if at least one NPI is sanctioned, we label all other NPIs in the group as suspicious. We flag 1,395 firms using this method, with 579 (42%) of these firms also flagged by other methods.

D.3 Firm Address

Our third method for identifying suspicious firms uses the mailing and business addresses from the NPPES. For each address, we include the street address, city or town name, state, and zip code. We then group firms that share the same business or mailing address. We allow a match if one firm's business address is listed as the mailing address for another firm and vice versa. For each sanctioned NPI, we label all firms that have an exact match with either the business address or the mailing address as suspicious. This method flags 855 firms as suspicious, with 578 (68%) of these firms also flagged by at least one other method.

D.4 Firm Referrer Links

Our fourth method uses the previously identified sanctioned firms and any firms labeled as suspicious by our three other measures to uncover additional suspicious entities. Each prescription for DME includes a provider listed as the referrer on the claim. We analyze this referral network to identify suspicious firms. To assess the legitimacy of the link between a supplier and a referrer, we evaluate four key measures for each supplier-referrer pair:

1. The total dollar amount of payments made to the supplier due to the referrer.

2. The total number of claims referred to the supplier by the referrer.

3. The percentage of the payments to the supplier attributable to the referrer.

4. The percentage of the total DME spending due to the referrer that goes to the supplier.

For a connection between a supplier and referrer to constitute a "real" link, we require all four of these measures to exceed a measure-specific threshold. We choose these thresholds to maximize the homophily of the resulting network of suppliers such that sanctioned firms are likely to cluster in similar parts of the network (Jackson, 2010). The thresholds that maximize the homophily of the network are as follows:

1. At least $80,973 of payments.

2. At least 982 claims.

3. At least 0.016% of the supplier's business coming from the referrer.

4. At least 17.6% of the referrer's referrals going to the supplier.

Using these thresholds, we first identify suspicious referrers as those who are linked to a sanctioned supplier. We then classify any other firms linked to these suspicious referrers as suspicious suppliers. Using this method, we flag 225 firms, 87 (39%) of which also flagged as suspicious by other methods.

Table A5: Distribution of Firms by Suspiciousness Measure Combinations

Suspiciousness Measure Combination	Number of Firms	Percentage
Name only	154	7.5%
Owner only	816	39.7%
Address only	277	13.5%
Referrals only	138	6.7%
Name and Owner	24	1.2%
Name and Address	75	3.7%
Name and Referrals	2	0.1%
Owner and Address	263	12.8%
Owner and Referrals	60	2.9%
Address and Referrals	3	0.1%
Name, Owner, and Address	219	10.7%
Name, Owner, and Referrals	4	0.2%
Name, Address, and Referrals	9	0.4%
Owner, Address, and Referrals	0	0.0%
Name, Owner, Address, and Referrals	9	0.4%

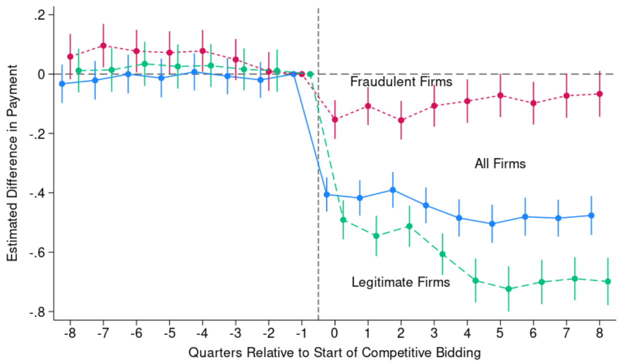
Notes: Each row reports the number and percentage of firms flagged as suspicious by a unique combination of suspiciousness measures. The sample includes all firms identified as suspicious by at least one measure.

E Firm Sample Restricted to Firms with DME Taxonomy Code

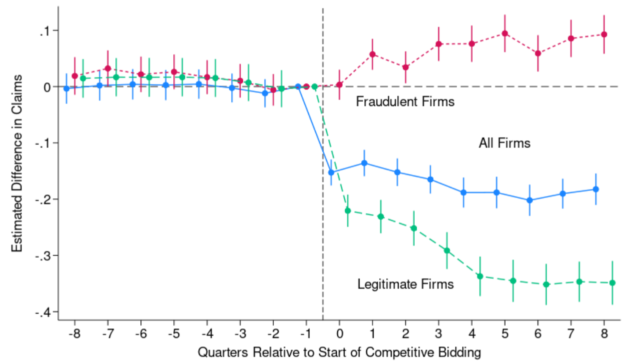
As a robustness exercise, we narrow the analytic sample from all firms that submitted at least one DME claim to those whose primary NPPES taxonomy code begins with 332B (Durable Medical Equipment). This restriction addresses concerns that very small, non-DME providers—such as optical providers or pharmacies that occasionally bill for DME—may introduce noise into our estimates of firm size and quality. Applying this filter reduces the sample from 154,046 to 67,324 firms. Notably, fraudulent firms are more prevalent in this DME-focused sample, increasing from 1.9% of firms in the main analysis to 4.0%. The composition of firms also shifts toward larger suppliers: the median firm's total DME payments nearly doubles, rising from $45k in the full sample to $98k under the taxonomy-restricted definition. These patterns are consistent with the idea that the smallest incidental billers are disproportionately non-DME entities and that excluding them sharpens comparisons across true DME suppliers. The results of this exercise are very similar to what we find in the baseline sample, with Figure A11 showing that competitive bidding led fraudulent firms to gain market share at the expense of legitimate ones even in this restricted sample.

Figure A11: Firms Restricted to DME Taxonomy Code

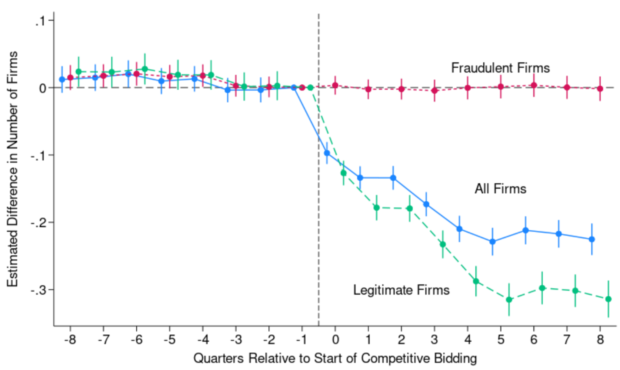
(a) Payment



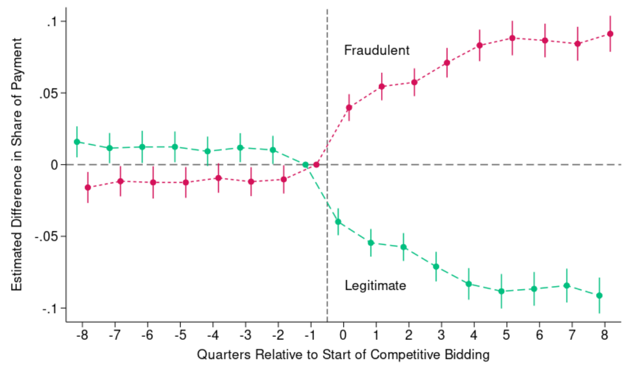
(b) Claims



(c) Number of Firms



(d) Share Payment



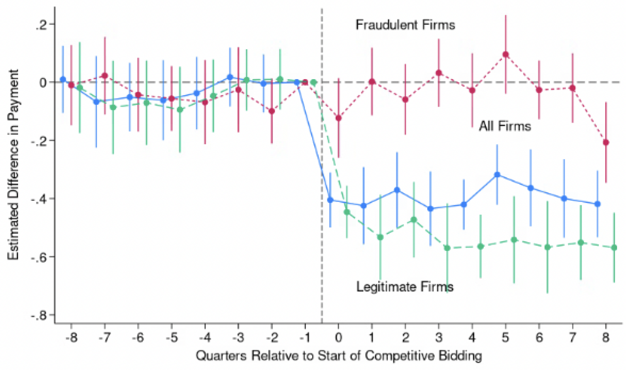
Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from equation (1). Firms are included only if their primary NPPES taxonomy code begins with "332B" designating them a primarily DME firm. Panel (a) shows estimates for total payment transformed by taking the inverse hyperbolic sine for legitimate firms, fraudulent firms, and all firms estimated separately. Panel (b) shows estimates for total claims transformed similarly. Panel (c) shows estimates for total number of firms transformed similarly. Panel (d) shows estimates for share of payment. The data include claims from 2008–2019. An observation is a MSA $\times$ HCPCS $\times$ quarter. Standard errors are clustered at the MSA-quarter level. Error bars represent pointwise 95% confidence intervals.

F Event Studies by Competitive Bidding Cohort

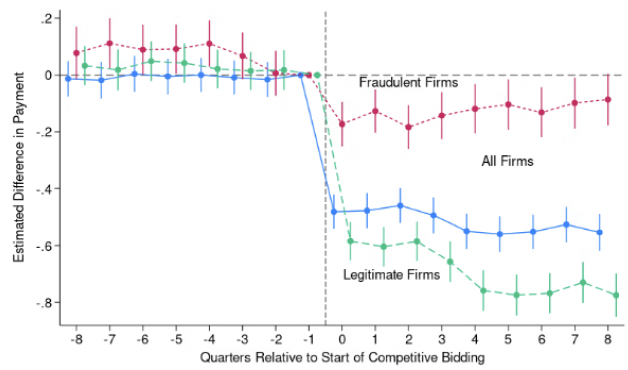
MSA-HCPCS markets are distributed across competitive bidding waves with some affected in multiple waves. HCPCS codes are grouped into product categories. Product categories in Round 1, with prices effective January 2011, include continuous respiratory equipment, enteral nutrition, hospital beds and related accessories, oxygen equipment, standard mobility equipment, support surfaces, and walkers. The July 2013 rollout represents the largest expansion of competitive bidding, with substantial numbers of newly affected markets across nearly all product categories, including continuous respiratory equipment, enteral nutrition, hospital beds, negative pressure wound therapy, oxygen equipment, support surfaces, and walkers. The January 2017 rollout introduced competitive bidding to a smaller set of newly affected product categories in the same set of MSAs as Round 1. In particular, commode chairs, nebulizers, patient lift–related products, and transcutaneous electrical nerve stimulation (TENS) devices were only affected in this final round and do not appear in earlier waves. Other product categories included in the 2017 rollout had already been subject to competitive bidding in prior rounds and are therefore classified according to the timing of their first exposure. Consistent with its broader geographic scope and category coverage, the 2013 rollout accounts for the largest share of MSA-HCPCS markets in the sample. We find very similar effects of waves 1 and 2 on payments, claims, number of firms, and fraudulent market share, as shown by Figures A12–A15. We find that wave 3 of competitive bidding did not lead to price cuts, as shown in Figure A16, and so did not lead to meaningful reallocation between fraudulent and legitimate firms. That the reallocation of the market from legitimate to fraudulent firms only occurred when the introduction of competitive bidding represented a real increase in competition supports our interpretation of competition as the causal mechanism affecting fraud.

Figure A12: Payment by Competitive Bidding Cohort

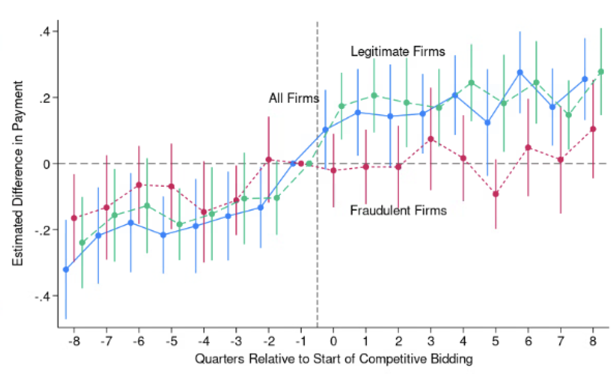
(a) Payment Wave 1



(b) Payment Wave 2



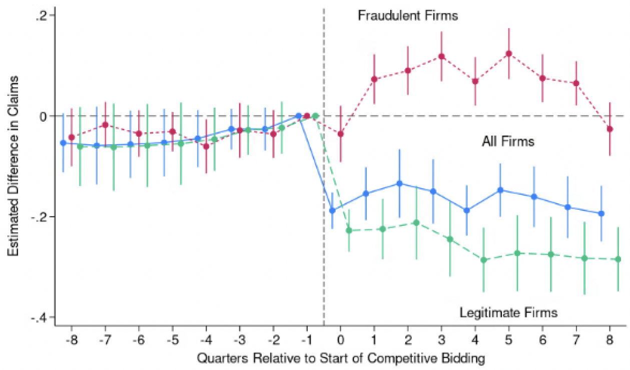
(c) Payment Wave 3



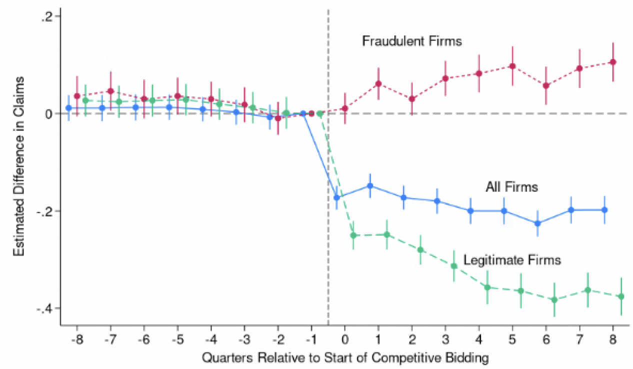
Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from equation (1). Panel (a) shows estimates for markets affected in the first wave of competitive bidding with prices in effect January 2011. Panel (b) shows estimates for markets affected in the second wave of competitive bidding with prices in effect July 2013. Panel (c) shows estimates for markets affected in the third wave of competitive bidding with prices in effect January 2017. The data include claims from 2008 to 2019. An observation is an MSA $\times$ HCPCS $\times$ quarter. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

Figure A13: Claims by Competitive Bidding Cohort

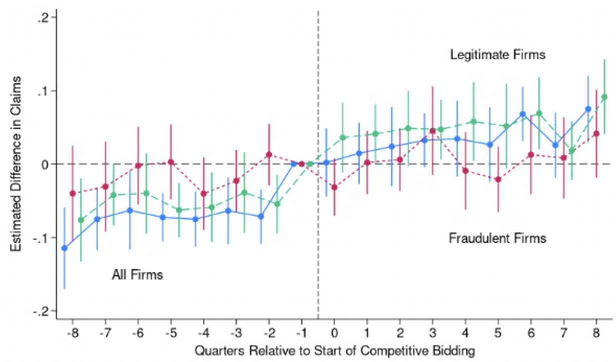
(a) Claims Wave 1



(b) Claims Wave 2



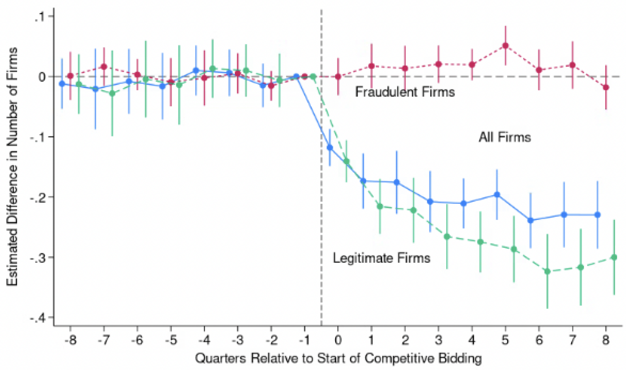
(c) Claims Wave 3



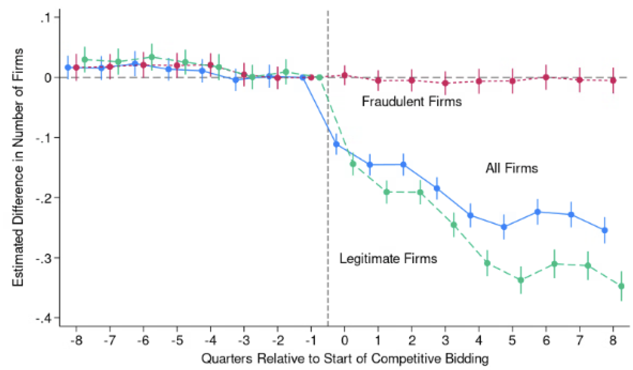
Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from equation (1). Panel (a) shows estimates for markets affected in the first wave of competitive bidding with prices in effect January 2011. Panel (b) shows estimates for markets affected in the second wave of competitive bidding with prices in effect July 2013. Panel (c) shows estimates for markets affected in the third wave of competitive bidding with prices in effect January 2017. The data include claims from 2008 to 2019. An observation is an MSA $\times$ HCPCS $\times$ quarter. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

Figure A14: Number of Firms by Competitive Bidding Cohort

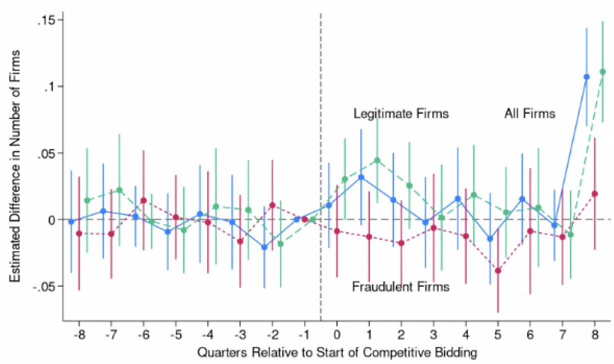
(a) Number of Firms Wave 1



(b) Number of Firms Wave 2



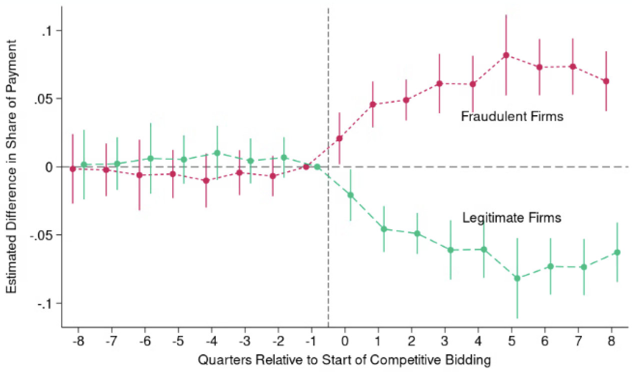
(c) Number of Firms Wave 3



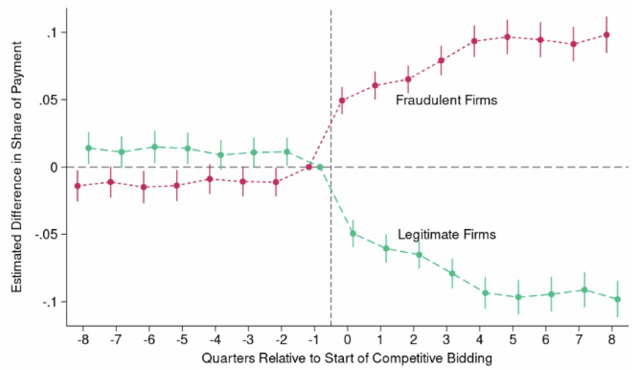
Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from equation (1). Panel (a) shows estimates for markets affected in the first wave of competitive bidding with prices in effect January 2011. Panel (b) shows estimates for markets affected in the second wave of competitive bidding with prices in effect July 2013. Panel (c) shows estimates for markets affected in the third wave of competitive bidding with prices in effect January 2017. The data include claims from 2008 to 2019. An observation is an MSA $\times$ HCPCS $\times$ quarter. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

Figure A15: Share Payment by Competitive Bidding Cohort

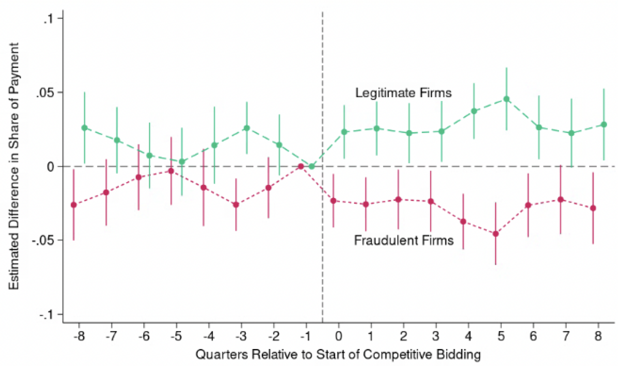
(a) Share of Payment Wave 1



(b) Share of Payment Wave 2



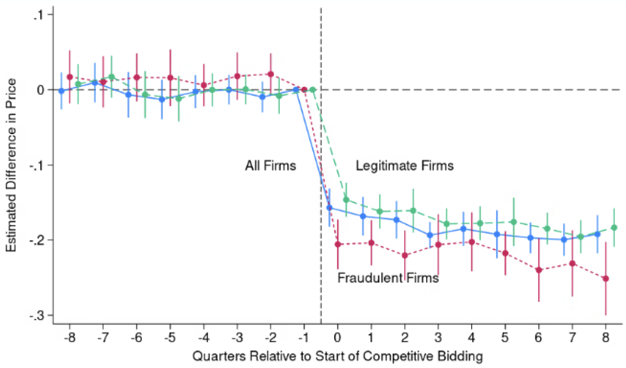
(c) Share of Payment Wave 3



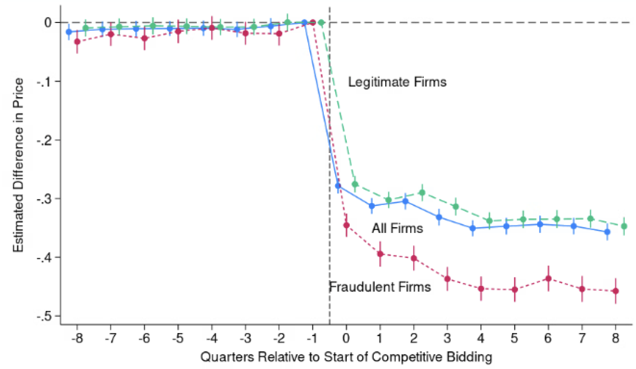
Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from equation (1). Panel (a) shows estimates for markets affected in the first wave of competitive bidding with prices in effect January 2011. Panel (b) shows estimates for markets affected in the second wave of competitive bidding with prices in effect July 2013. Panel (c) shows estimates for markets affected in the third wave of competitive bidding with prices in effect January 2017. The data include claims from 2008 to 2019. An observation is an MSA $\times$ HCPCS $\times$ quarter. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

Figure A16: Price by Competitive Bidding Cohort

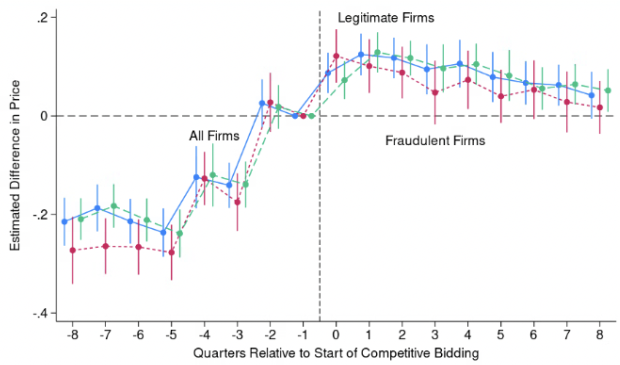
(a) Price Wave 1



(b) Price Wave 2



(c) Price Wave 3



Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from equation (1). Panel (a) shows estimates for markets affected in the first wave of competitive bidding with prices in effect January 2011. Panel (b) shows estimates for markets affected in the second wave of competitive bidding with prices in effect July 2013. Panel (c) shows estimates for markets affected in the third wave of competitive bidding with prices in effect January 2017. The data include claims from 2008 to 2019. An observation is an MSA $\times$ HCPCS $\times$ quarter. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

G Alternative Outcome Definitions

This appendix presents event-study estimates under alternative outcome transformations to assess the robustness of the main results to functional form and measurement choices. In the main text, we focus on inverse hyperbolic sine transformations, which allow us to retain zero-valued observations while approximating percentage changes. Here, we re-estimate equation (1) using outcomes in levels, log-transformed outcomes, and binary indicators that capture extensive-margin responses.

Figure A17 reports estimates using outcomes in levels with effects on raw payments in dollars shown in Figure A17a, effects on number of claims shown in Figure A17b, and effects on the number of firms shown in Figure A17c, estimated separately for legitimate firms, fraudulent firms, and all firms.

Figure A18 reports results using log-transformed outcomes. Figure A18 reports log-transformed outcomes, with effects on log payments shown in Figure A18a, effects on log claims shown in Figure A18b, and effects on the log number of firms shown in Figure A18c, estimated separately for legitimate firms, fraudulent firms, and all firms.

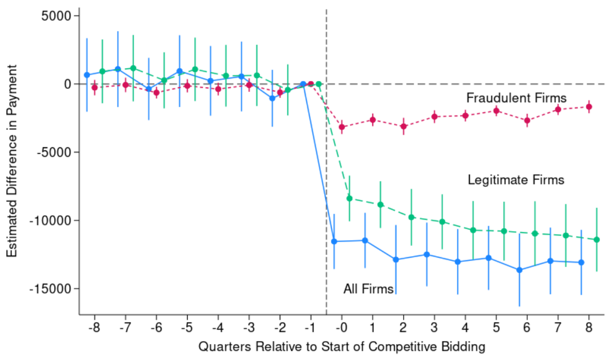
Finally, Figure A19 present results for binary outcomes that capture extensive-margin adjustments. Specifically, Figure A19a examines whether any positive payment occurs, Figure A19b examines whether any claim is paid, and Figure A19c examines whether at least one firm is active in a given MSA $\times$ HCPCS $\times$ quarter, estimated separately for legitimate firms, fraudulent firms, and all firms.

Across all alternative transformations, the qualitative patterns in the event-study estimates are consistent with the main findings, indicating that the results are not driven by the treatment of zero outcomes.

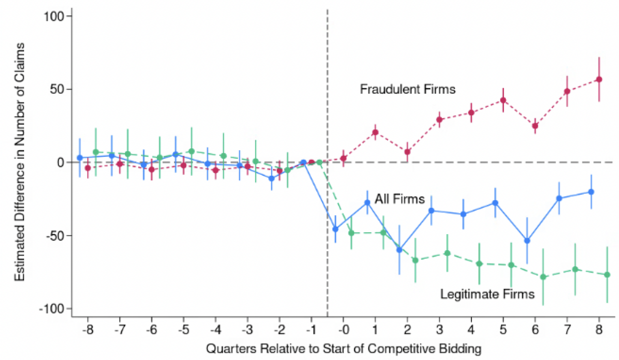
We note that while the estimated effect on overall outcomes typically lies between the estimated effect on fraudulent and legitimate firms when measuring the outcome in a transformation approximating percentage change, this is not the case when the outcome is measured in levels. This is because the total effect in levels is equal to the sum of the effect on fraudulent and legitimate firms.

Figure A17: Outcomes in Levels

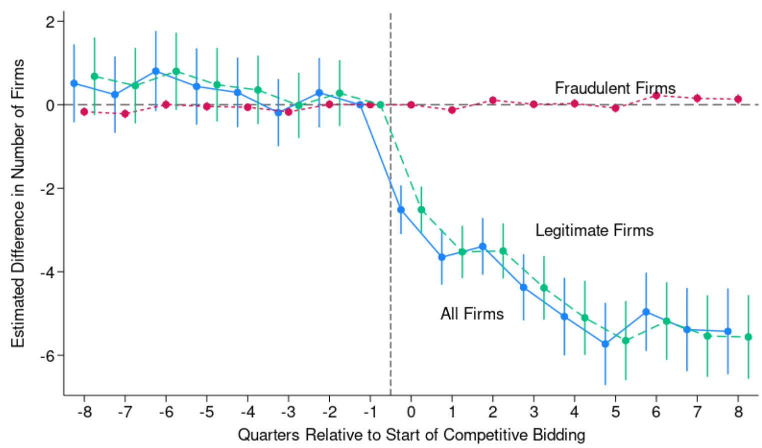
(a) Payments



(b) Claims



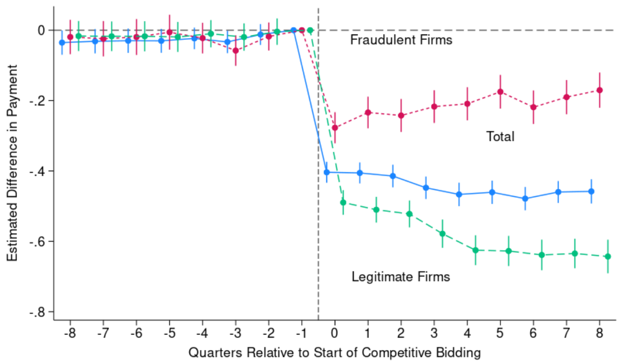
(c) Number of Firms



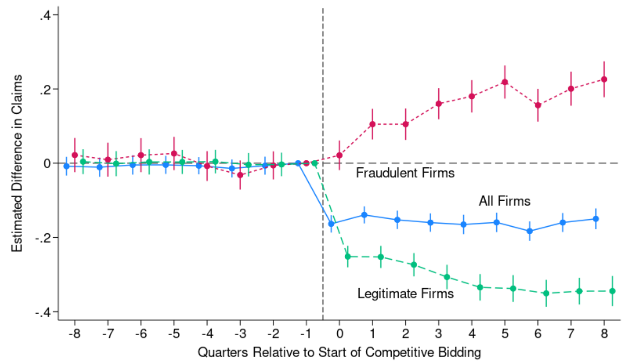
Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from equation (1). Panel (a) reports effects on raw payments by firm type, panel (b) reports effects on claims in levels by firm type, and panel (c) reports effects on the number of firms by firm type. The data include 2008–2019 at the MSA $\times$ HCPCS $\times$ quarter level. Standard errors are clustered at the MSA–quarter level. Error bars show pointwise 95% confidence intervals.

Figure A18: Log-Transformed Outcomes

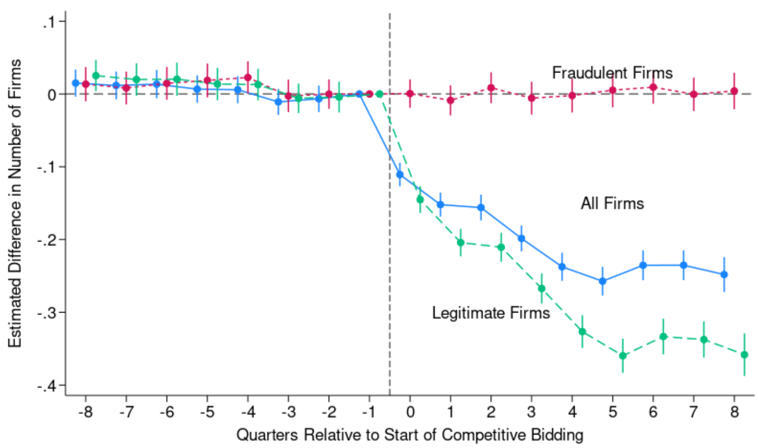
(a) Payments



(b) Claims



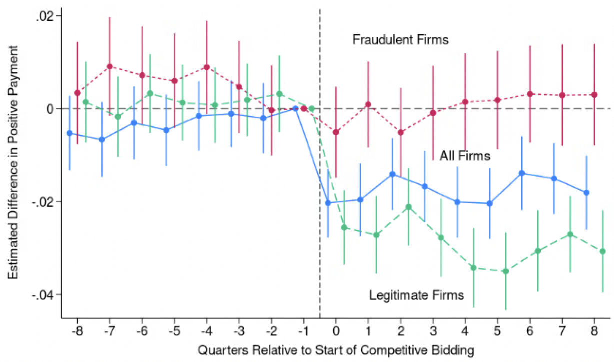
(c) Number of Firms



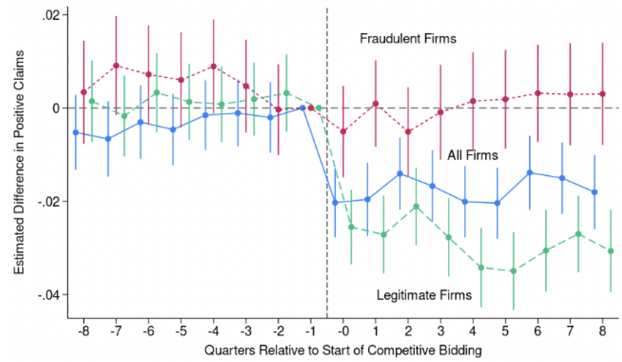
Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from equation (1). Panel (a) shows estimates for total payment transformed by log for legitimate firms, fraudulent firms, and all firms estimated separately. Panel (b) shows estimates for total claims transformed similarly. Panel (c) shows estimates for total number of firms. The data include claims from 2008 to 2019. An observation is an MSA $\times$ HCPCS $\times$ quarter. Standard errors are clustered at the MSA–quarter level. Error bars represent pointwise 95% confidence intervals.

Figure A19: Binary Outcomes

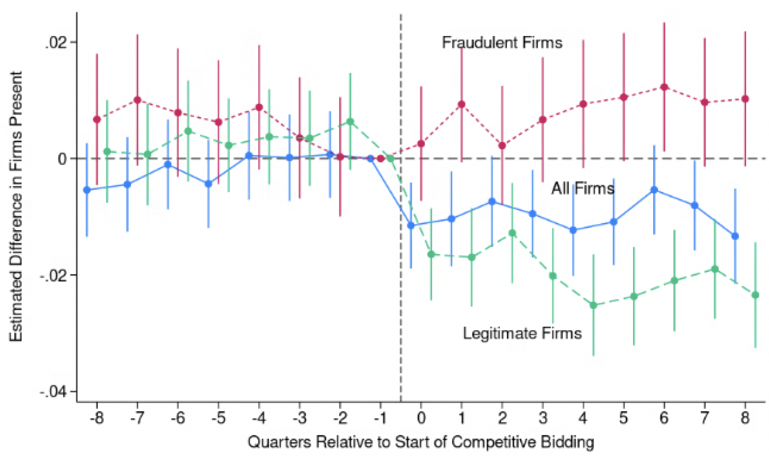
(a) Payments > 0



(b) Claims > 0



(c) Number of Firms > 0



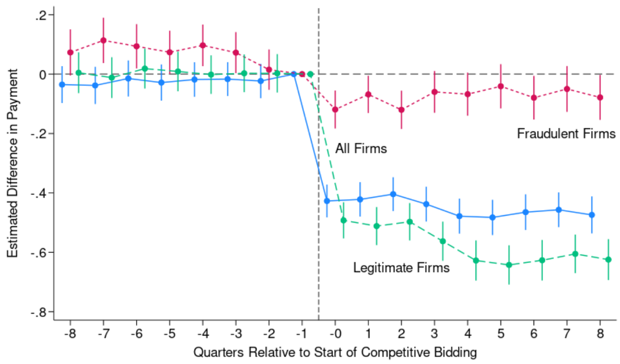
Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from equation (1). Panel (a) reports effects on whether a positive payment occurred by firm type, panel (b) reports effects on positive claim was paid by firm type, and panel (c) reports effects on whether at least one firm was active by firm type. The data include 2008–2019 at the MSA $\times$ HCPCS $\times$ quarter level. Standard errors are clustered at the MSA–quarter level. Error bars show pointwise 95% confidence intervals.

H Firms Limited to Those Present Before Competitive Bidding

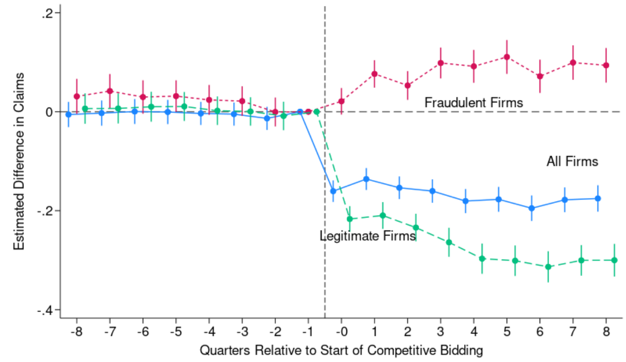
This appendix presents event-study estimates that restrict the sample of firms to those observed in the market prior to the introduction of competitive bidding in 2011. By fixing the set of firms based on pre-policy presence, this specification mitigates concerns that observed changes in outcomes are driven by endogenous entry, delayed detection, or compositional changes in firm classification following the introduction of competitive bidding. The full sample contains 154,046 firms, which falls to 117,992 when restricting attention to firms observed prior to the first wave of competitive bidding taking effect in 2011. Similarly, the number of suspicious firms declines from 2,053 in the full sample to 1,566 in the pre-2011 sample. Restricting the sample to firms present prior to 2011 yields similar patterns to those observed in the main results.

Figure A20: Firms Restricted pre-2011

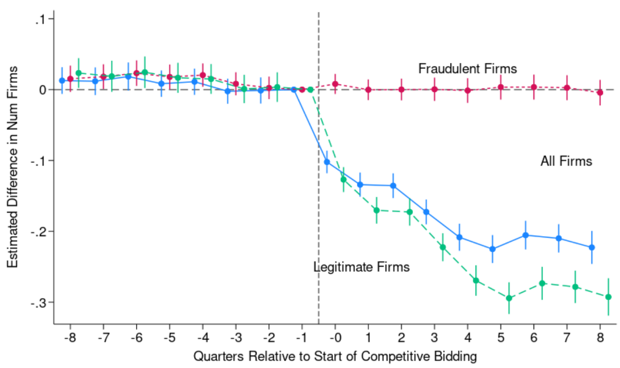
(a) Payment



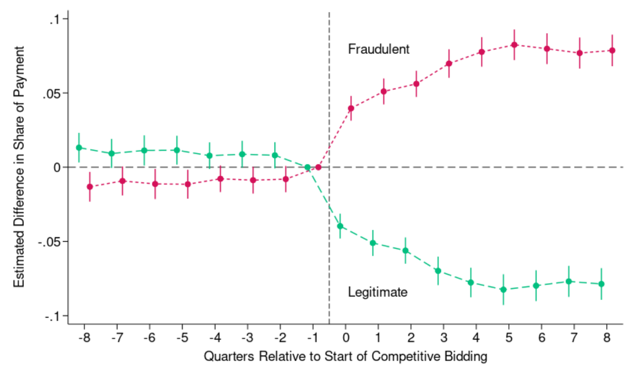
(b) Claims



(c) Number of Firms



(d) Share Payment



Notes: Estimates of β_e for $e \in [-8, 8] \setminus \{-1\}$ from equation (1). Firms are included only if present in sample prior to 2011. Panel (a) shows estimates for total payment transformed by taking the inverse hyperbolic sine for legitimate firms, fraudulent firms, and all firms estimated separately. Panel (b) shows estimates for total claims transformed similarly. Panel (c) shows estimates for total number of firms transformed similarly. Panel (d) shows estimates for share of payment. The data include claims from 2008–2019. An observation is a MSA × HCPCS × quarter. Standard errors are clustered at the MSA-quarter level. Error bars represent pointwise 95% confidence intervals.

I Additional Static Regression Results

In this appendix, we report coefficient estimates for the static regression corresponding to results in the main text that are only presented dynamically. Tables A6 and A7 report the estimates for how quality changes for fraudulent and legitimate firms, corresponding to Figures 5 and 6. Table A8 reports changes in market share by firm size, corresponding to Figure 7.

Table A6: Effect of Competitive Bidding on Fraudulent Firms

	Repair Rate	Comorbidities	Hospitalizations
Competitive	-0.00128*	-0.01220**	-0.00817***
Bidding	(0.00071)	(0.00523)	(0.00244)
Dependent var. mean	0.0483	6.15	0.4475
Observations	3,000,103	279,317,180	7,740,886
HCPCS–MSA FE	Yes	Yes	Yes
HCPCS–Quarter FE	Yes	Yes	Yes
MSA–Quarter FE	Yes	Yes	Yes

Notes: Each column reports the estimate of β from the static specification in equation (2), which aggregates event time indicators over the eight quarters following competitive bidding ($e \in [0, 8]$). The sample is limited to claims submitted by fraudulent firms. Outcomes are measured at the MSA $\times$ HCPCS $\times$quarter level. All regressions include HCPCS–MSA, HCPCS–quarter, and MSA–quarter fixed effects, with standard errors clustered at the MSA–quarter level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A7: Effect of Competitive Bidding on Legitimate Firms

	Repair Rate	Comorbidities	Hospitalizations
Competitive Bidding	0.00450*** (0.00078)	0.02415*** (0.00395)	0.02100*** (0.00149)
Dependent var. mean	0.0706	6.52	0.4437
Observations	10,027,890	905,443,961	26,454,511
HCPCS–MSA FE	Yes	Yes	Yes
HCPCS–Quarter FE	Yes	Yes	Yes
MSA–Quarter FE	Yes	Yes	Yes

Notes: Each column reports the estimate of β from the static specification in equation (2), which aggregates event time indicators over the eight quarters following competitive bidding ($e \in [0, 8]$). The sample is limited to claims submitted by legitimate firms. Outcomes are measured at the MSA $\times$ HCPCS $\times$quarter level; comorbidities and hospitalizations are claims-weighted. All regressions include HCPCS–MSA, HCPCS–quarter, and MSA–quarter fixed effects, with standard errors clustered at the MSA–quarter level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A8: Effect of Competitive Bidding on Payments, by Firm Size

	Small Firms	Medium Firms	Large Firms
Competitive Bidding	-0.05633*** (0.00214)	-0.01697*** (0.00264)	0.07330*** (0.00287)
Dependent var. mean	0.2019	0.3984	0.3997
Observations	10,370,722	10,370,722	10,370,722
HCPCS–MSA FE	Yes	Yes	Yes
HCPCS–Quarter FE	Yes	Yes	Yes
MSA–Quarter FE	Yes	Yes	Yes

Notes: Each column reports the estimate of β from the static specification in equation (2), which aggregates event time indicators over the eight quarters following competitive bidding ($e \in [0, 8]$). Outcomes are measured at the MSA $\times$ HCPCS $\times$quarter level. All regressions include HCPCS–MSA, HCPCS–quarter, and MSA–quarter fixed effects, with standard errors clustered at the MSA–quarter level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table A9: Effect of Competitive Bidding on Payments, by Firm Size and Firm Type

	Legitimate Firms			Fraudulent Firms		
	Small	Medium	Large	Small	Medium	Large
Competitive Bidding	-0.06028***	-0.04111***	0.02036***	0.00395***	0.02414***	0.05291***
	(0.00208)	(0.00259)	(0.00252)	(0.00058)	(0.00122)	(0.00175)
Dependent var. mean	0.3082	0.2777	0.2971	0.0064	0.0341	0.0765
Observations	10,370,722	10,370,722	10,370,722	10,370,722	10,370,722	10,370,722
HCPCS–MSA FE	Yes	Yes	Yes	Yes	Yes	Yes
HCPCS–Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
MSA–Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Each column reports the estimate of β from the static specification in equation (2), which aggregates event time indicators over the eight quarters following competitive bidding ($e \in [0, 8]$). Outcomes are measured at the MSA–HCPCS–quarter level. All regressions include HCPCS–MSA, HCPCS–quarter, and MSA–quarter fixed effects, with standard errors clustered at the MSA–quarter level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

J Details on Matching Bidder Names to NPIs

The bidding data do not report NPIs but rather only have a bidder names along with a list of masked NPIs, making identifying fraudulent bidders or otherwise matching bid data and claims data difficult. Because many bidder names correspond to multiple masked NPIs, it is difficult to identify which NPIs actually participated in the bidding process.

We run a fuzzy string match to connect bidders to their NPI counterparts in the claims data. We first clean bidder names by capitalizing all bidder names and removing periods, commas, and spaces. After applying this initial cleaning, we have 3,511 unique bidders. To match these cleaned bidder names to those reported in the NPPES for firms that we observe in the claims data, we clean the names in the NPPES by removing the set of words listed in Table A10 and match an initial set of bidders to firms in our claims. For those firms in the NPPES that remain unmatched, we run a second iteration after additionally removing a second set of common words listed in Table A11. For both of these sets of matched bidder names and firm names from the NPPES, we keep matches with a similarity score greater than 0.95. Finally, for any bidders that remain unmatched, we attempt to match the bidder name with the authorized owner name (rather than firm name) contained in the NPPES. From the matching process, we successfully match 3,085 of the 3,511 bidders to at least one NPI that supplied DME in the claims data, leaving 426 bidders that cannot be matched to the claims data.

In total, the 3,085 matched bidder names match to 12,193 NPIs from the NPPES. On average, each bidder matches to 3.95 NPIs, with significant variation. Some large bidders, such as Walmart, match to 1,300 NPIs, while more than half of the bidders match to only one unique NPI. Among bidders ranked by their number of NPI matches, the 95th-percentile bidder links to eight NPIs and the 99th-percentile bidder links to 31, indicating that a fraction of bidders link to many NPIs.

We treat bidders that match to at least one fraudulent NPI as fraudulent.

Table A10: First set of excluded words for name matching

INCORPORATED	PLLC	LLC
INC	CORPORATION	CORP
CO	LIMITED	LTD

Table A11: Second set of excluded words for name matching

DME	MEDICAL	SUPPLY
EQUIPMENT	COMPANY	SERVICES
GROUP	SPECIALISTS	SUPPLIES
HEALTH	ENTERPRISES	SERVICE