Competition and Fraud in Health Care*

Renuka Diwan[†], Paul Eliason[‡], Riley League[§], Jetson Leder-Luis[¶],
Ryan C. McDevitt[‖], James W. Roberts[**]

July 2025

Governments rely on private firms to provide public goods and services. Competition among these firms theoretically reduces costs for the government but 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 Medicare's procurement of durable medical equipment (DME), where the staggered rollout of competitive bidding allows us to identify the relationship between competition and fraud. Fraudulent firms increased their market share after competitive bidding, with the gains coming from legitimate firms exiting the market rather than fraudulent firms manipulating their bids or committing more fraud.

*We thank Jon Gruber, Yunan Ji, Jim Poterba, Andrei Shleifer, and the participants of the ASHEcon Conference, the Penn Health Policy Research Seminar, and University of Wisconsin Institute for Research on Poverty Seminar for their comments. This project was funded by Arnold Ventures under grant 22-08498, and Riley League thanks the National Institute on Aging, grant number T32-AG000186, for its support.

[†]Boston University

[‡]David Eccles School of Business, University of Utah and NBER

[§]Gies College of Business, University of Illinois Urbana-Champaign and NBER

[¶]Boston University and NBER

[‖]Duke University and NBER

[**]Department of Economics, Duke University and NBER

1 Introduction

Governments contract with hundreds of thousands of private firms to deliver public goods and services. Competition among these firms theoretically reduces costs for the government, but the difficulty of verifying the quality and integrity of suppliers creates opportunities for unscrupulous firms to defraud the government by overcharging for the contracted goods and services or failing to provide them altogether. This problem is particularly acute in health care, where the US government pays trillions of dollars each year to private suppliers, a sizable fraction of which may be fraudulent (Centers for Medicare & Medicaid Services, 2024).

The relationship between competition and fraud is not obvious. Although increased competition could eliminate the incentive to commit fraud by reducing prices and profits, it could instead exacerbate it if the low quality of fraudulent firms allows them to crowd out legitimate suppliers with higher costs. This is a pressing concern in health care, where quality has a direct influence on patients' outcomes but can be difficult to monitor effectively.

We examine the relationship between competition and fraud in Medicare's procurement of durable medical equipment (DME), a market with more than $15 billion in government spending each year and a rate of improper payments estimated at over 20% (Centers for Medicare & Medicaid Services, 2023). Historically, Medicare obtained DME for its beneficiaries by allowing suppliers across the country to sell equipment at a fixed, regulated rate, which in some cases resulted in profit margins exceeding 1000% and attracted a large number of fraudulent sellers. In response to the outsize levels of spending and fraud, Medicare began piloting a series of procurement auctions in 2011 that forced suppliers to compete with one another to sell DME to beneficiaries within a particular product category and region. Past research has shown the switch to competitive bidding achieved Medicare's primary aim of reducing spending, mostly through a decline in the prices paid for DME (Ji, 2023; Ding et al., 2025). Left unexplored is the effect of competitive bidding on the incidence of fraud, the market structure of suppliers, and the quality of products received by beneficiaries.

We find that fraudulent firms disproportionately benefited from Medicare's switch to procurement auctions. After competitive bidding reduced prices for DME, the firms we identify as fraudulent increased their market share at the expense of legitimate firms. We further show that fraudulent firms participated in the auctions at a much higher rate, bidding behavior within the auctions was similar for fraudulent and legitimate firms, and quality — both in terms of the physical attributes of DME and patients' match-quality for medical necessity — remained largely unchanged. Taken together, our results show that increased competition benefited fraudulent firms by reducing prices to the point where legitimate firms no longer remained profitable, leading them to exit the market and relinquish their sales to fraudulent competitors.

For our empirical analysis, we begin by identifying fraudulent and suspicious DME suppliers.

We hand collected data on hundreds of firms ever subject to anti-fraud enforcement, either through civil whistleblower litigation, criminal lawsuits, or administrative exclusion from the Medicare program. We 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 connections to those formally charged, including common ownership, a shared address, or an inordinate number of referrals from complicit physicians.

We then use the staggered rollout of competitive bidding across geographic regions and DME categories to identify the causal effects of increased competition on fraud. Consistent with past research, we find competitive bidding led to a 40% reduction in firm revenue, driven largely by a decrease in the prices of DME (Ji, 2023; Ding et al., 2025). Building on these studies, we find the reduction came almost exclusively from legitimate suppliers, as their exit from the market resulted in a 10 percentage point increase in the market share of fraudulent firms despite fraudulent firms' revenue remaining largely unchanged.

Several potential mechanisms could explain why fraudulent firms 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 from economies of scale. We find that, although larger firms do experience a smaller reduction in revenues, this cannot fully explain our results. Even conditional on firm size, fraudulent firms increase their market share.

Second, fraudulent firms' behavior could differ within the procurement auctions themselves. Past work has shown these 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 meaningful differences in bidding behavior conditional on participating in the auctions. Although bids from fraudulent firms were slightly lower on average, bid distributions are nearly identical across fraudulent and legitimate firms, with no notable difference in the probability of submitting very low bids. At the same time, fraudulent firms are more likely to participate in the auctions: 9.5% of bids come from fraudulent firms despite these firms making up just 1.5% of the market. Our results are therefore consistent with fraudulent firms having lower costs that make them more likely to participate in the auctions rather than gaining market share by manipulating their bids.

Finally, competitive bidding may have led to a change in the quality of equipment provided by suppliers. In this setting, quality encompasses both the physical properties of the DME itself as well as the match-quality between the patient and product, as the government intends only to provide DME to beneficiaries who have a medical need for it (Office of the Inspector General, 2011; Whoriskey and Keating, 2014). Heightened price competition could lead to lower-quality DME for a number of reasons, such as compressed profit margins forcing firms to cut costs in ways that reduce quality or making it so that only low-cost, low-quality firms earn profits large enough to remain in operation. Despite this possibility, we find evidence of only small changes in firm-level quality: the repair rate for DME supplied by fraudulent firms did not change after competitive bidding and fraudulent firms appear to only slightly redirect their business towards older patients (i.e., who may be more susceptible to fraud) and patients with fewer comborbidities (i.e., patients who are less likely to have a medical need for DME). Given the small magnitude of these quality changes, we can rule out the possibility that competition causes fraudulent firms to "go straight" and stop committing fraud.

Our work complements existing studies in health and public economics that have largely examined questions of competition and fraud in isolation. Most directly, our results contribute to broader debates about the effect of competition on 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 also 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), studies across various empirical 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. We extend this literature by demonstrating that competition can spur illegal activity even without relying on demand-side preferences. In particular, we find evidence that asymmetric information allows suppliers contracting with the government to inflate their revenues by misreporting what they provide.

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), Sanghavi et al. (2021), and Shekhar et al. (2023), have documented the extent of such overbilling. A more recent literature has discussed anti-fraud policy, with research on the effects of civil litigation by whistleblowers (Howard and McCarthy, 2021; Leder-Luis, 2023) and comparing regulation to litigation (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.

In addition, our research contributes to work on procurement auctions, including a growing literature that evaluates the impact of competitive bidding on DME. Past studies have shown the competitive bidding program's effects 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 et al. (1997), the government faces a tradeoff between reducing costs and providing high-quality goods and services, where incomplete contracts lead to inefficiently large cuts to quality. In health care, where quality is often difficult to monitor, mechanisms like competitive bidding may favor firms with lower costs, even if they achieve these efficiencies through fraud or substandard equipment. By empirically demonstrating that fraudulent firms thrive under competitive bidding, our study provides a novel application of these theories, reinforcing the importance of understanding the nuanced incentives faced by government contractors.

2 Background

Medicare's DME program spends nearly $16 billion per 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 patient, 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 remaining 80%.

Prior to competitive bidding, Medicare paid for DME on a fee-schedule basis using rates based on supplier charges adjusted over time for inflation. This approach often resulted in products with prices far above costs, with Medicare's payment rates sometimes three to four times higher than what suppliers paid to purchase from manufacturers or wholesalers (CMS, 2013). A 2006 OIG report, for example, found that Medicare was paying $7,215 to rent oxygen concentrators for 36 months that cost an average of $587 to purchase (OIG, 2006), while another report found that Medicare paid $17,165 for negative pressure wound therapy pumps that cost suppliers $3,604 (OIG, 2007). A 2018 MedPAC report concluded that these high payment rates increased expenditures and likely encouraged inappropriate utilization (MedPac, 2018).

Improper payments and outright fraud have long been a problem among government health programs. In 2023, HHS estimated a total of $100 billion in improper payments for Medicare and Medicaid, implying that over 40% of the government's improper payments originate from health care (GAO, 2024).[1] Contributing to the billions 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

[1]Medicare improper payments are payments that do not meet CMS requirements, including overpayments, underpayments, or payments where insufficient information was provided CMS (2024b).

provided (Leder-Luis and Malani, 2025).

In many cases, a health care provider receives a kickback from the supplier in exchange for writing DME prescriptions, which the supplier can then use to bill the insurer. Typically, recruiters find beneficiaries either by advertising free products and requesting beneficiaries' Medicare numbers at an event, sales pitch, or phone call. In one case, beneficiaries testified they were promised vitamins, diabetic shoes, and other items for providing their beneficiary numbers (USA v. Shubaralyan, 2008; DOJ, 2009). In another, a beneficiary attempting to purchase a hospital bed was told that to get one she had to accept a power wheelchair she did not need (USA v. Ijewere et al., 2009; DOJ, 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 oxygen, oxygen equipment, and CPAP machines. More recently, telehealth has been used to recruit illegitimate patients or conduct sham screenings to provide patients with prescriptions for DME (CMS, 2023).

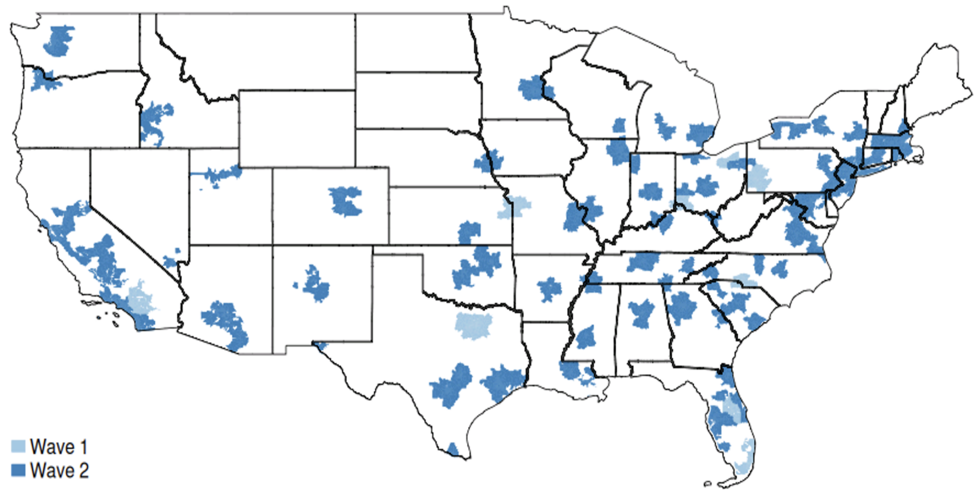
DME suppliers regularly face legal action for health care fraud. The False Claims Act (FCA) allows whistleblowers to sue fraudulent health care providers under civil law for up to triple damages and receive a share of the recoveries, as in the recent suit against Lincare Holdings, which agreed to pay $29 million for the improper billing of oxygen equipment (DOJ, 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 (DOJ, 2024).

In an effort to reduce DME spending and fraud, Medicare established the DME Competitive Bidding program as part of the Medicare Modernization Act in 2003 (CMS, 2024a). 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 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.[2] Winners of the auction can then sell 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.[3] Despite the nonstandard auction format, previous

[2]The number of winning bids is chosen so that the amount of DME expected to be supplied does not exceed the reported capacities of the winning bidders.

[3]Appendix E provides more details on the auction format.

Figure 1: Geographic Rollout of Competitive Bidding Auction Program.



Notes: Data on competitive bidding rollout timings from the competitive bidding archives. Data is plotted for ZIP codes and only includes the first two waves. Gray ZIP codes are those that did not experience competitive bidding. White areas are those that do not have ZIP codes.

studies have shown Medicare's switch to competitive bidding led to substantially lower prices and spending for DME (Ji, 2023; Ding et al., 2025).

Medicare piloted the first round of bidding for nine product categories in nine areas starting in 2009, and the resulting prices went into effect on January 1, 2011. The program was later expanded across additional product categories and geographies, with prices going into effect July 2013, January 2017, and January 2021.[4] 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 had significant reductions: the average Medicare-allowed monthly payment amount fell 33% for stationary oxygen equipment, for example, and 37% for semi-electric hospital beds (CMS, 2013).

3 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 accessory and is denoted using the product's Healthcare Common Procedure Coding System

[4]Additional rounds or recompetes also occurred. The full set of dates is: 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 in 2015, effective January 1, 2017; and Round 2021 began 2019, with prices effective January 1, 2021.

(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.

For DME suppliers, we use the full set of NPIs that supplied DME in the claims data, resulting in a total of 154,042. 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 use two distinct sources of data to identify fraudulent firms. First, we create a novel dataset based on press releases from the 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 the firm. In total, we analyzed 389 press releases, which we linked to 981 unique NPIs, of which 743 appear in our DME claims data. We also use the List of Excluded Individuals and Entities (LEIE) dataset, 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 provides a total of 7,674 excluded NPIs, of which 109 appear in the DME claims data. Three firms appear in both the press releases and the LEIE.

With 743 firms named in the press releases, 109 excluded firms, and 3 found in both, we have 849 unique fraudulent NPIs. We classify these firms as "sanctioned." Figure 2 plots the number of fraudulent firms sanctioned over time. We find that firms have steadily continued committing — and getting caught — for fraud.

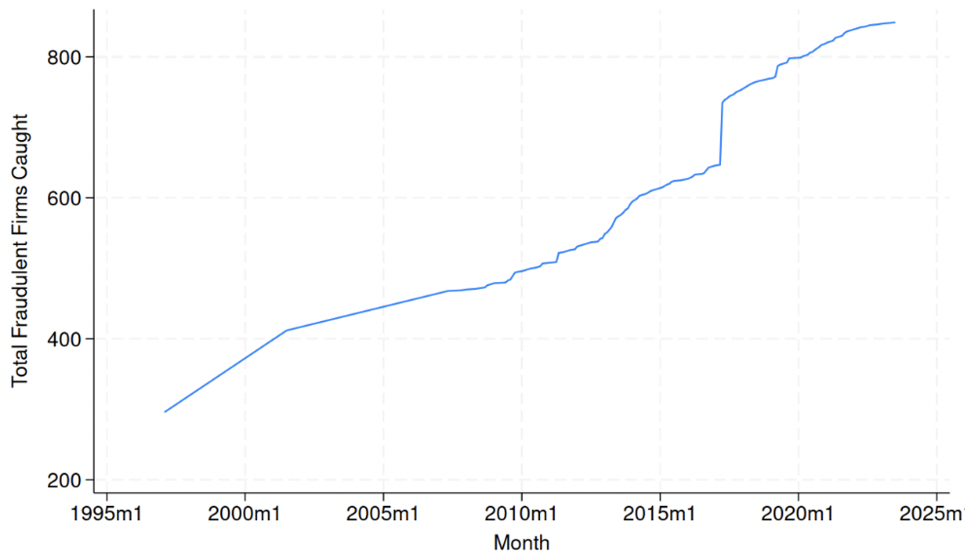
We obtained the competitive bidding data through a FOIA request and include information from rounds one and two of the auctions in 2011 and 2013, respectively. Each auction consists of a HCPCS, CBA, and bidtype, which is either a rental or purchase. The dataset includes firm names, the prices submitted 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.

For our measures of quality, we first look at the number of repairs using our claims data.[5] We also consider patient-match quality (i.e., the appropriateness of beneficiaries who receive DME) using a simplified version of the Charlson Index from the Medicare Chronic Conditions file.

To identify fraud among DME suppliers, we must account for both firms sanctioned for committing fraud as well as those that remained undetected. To identify the full set of fraudulent firms, we start with the set of firms sanctioned for fraud and then search for other firms that

[5] We consider a DME repair claim as any claim with a HCPCS modifier code of "RA", "RB," or "RP." The RP modifier was superseded by RA and RB in 2009

Figure 2: Sanctioned Firms Over Time

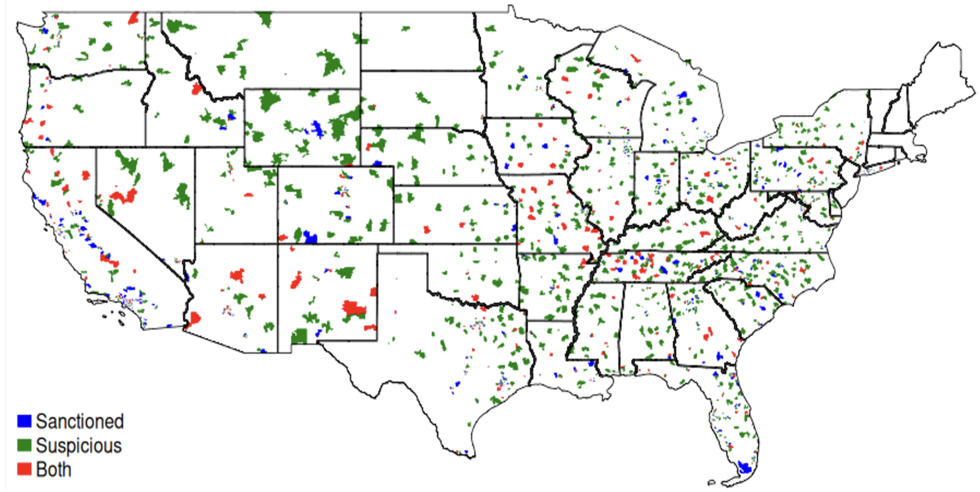


Notes: The sample includes firms sanctioned for engaging in fraud by the DOJ and named in a press release or excluded from the LEIE. Dates used are the date of the press release or date of exclusion listed.

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 high share of their DME referrals from physicians who also refer extensively to sanctioned firms. Appendix A provides the full details of our suspiciousness measures.

For the majority of our analysis, we combine "sanctioned" and "suspicious" firms into one category we call "fraudulent" firms. We label firms not flagged as fraudulent as "legitimate." Figure 3 shows a map of the ZIP codes of suspicious firms as well as those subject to sanctions.

Figure 3: Location of Sanctioned and Suspicious Firms



Notes: ZIP codes where firms were sanctioned for fraud in blue. Additional suspicious firms are located in ZIP codes marked in green. Both sanctioned and suspicious firms are located in ZIP codes shaded in red.

Table 1 presents summary statistics for the firms in our sample. Overall, we find that fraudulent firms are larger than legitimate firms by a number of measures. They have also been active for longer, sell more types of products, and sell in more geographies.

Table 1: Summary Statistics by Firm Type

	Total	Legitimate	Sanctioned	Suspicious
Line Payment ($)	683K	548k	6.4M	7.4M
	(10.7M)	(9.9M)	(1.92M)	(3.21M)
Quarters Active	26.9	26.8	29.6	35.0
	(17.8)	(17.8)	(17.2)	(16.1)
HCPCS Sold	37.4	35.8	94.8	116.9
	(59.5)	(57.7)	(70.9)	(94.4)
MSAs Active	16.6	15.3	74.7	79.2
	(35.3)	(32.7)	(80.5)	(73.7)
Observations	154,042	150,869	849	2,324

Notes: Sample includes all firms submitting a DME claim to Medicare Part B. We calculate mean line payment, number of quarters active, number of HCPCS products sold, and MSAs active for each firm-type.

We also find significant variation in fraudulence by product category. Table 2 presents the total and share of spending from fraudulent firms in each product category in the period before competitive bidding. Prior to competitive bidding, the most fraudulent categories were oxygen & oxygen equipment, CPAP machines, power mobility devices, and nebulizers.

Table 2: Share from Fraudulent Firms by Product Category Prior to Competitive Bidding (2008-2010)

	Payments		
Category	Total	Fraudulent	Share
Oxygen & Oxygen Equip.	\$5.37B	\$2.55B	47.58%
CPAP	\$1.76B	\$787M	44.71%
Power Mobility Devices	\$2.02B	\$814M	40.37%
Nebulizers	\$167M	\$66.7M	39.86%
Hospital Beds	\$566M	\$125M	22.07%
Commode Chairs	\$103M	\$22.7M	22.07%
Standard Wheelchairs	\$999M	\$218M	21.83%
Enteral Nutrition	\$1.21B	\$261M	21.55%
Walkers	\$221M	\$46M	20.83%
Patient Lifts	\$97.5M	\$15.9M	16.35%
Support Surfaces	\$250M	\$31.5M	12.60%
Off-the-shelf Back Braces	\$4.12M	\$231.9K	5.63%
Off-the-shelf Knee Braces	\$4.25M	\$145.2K	3.42%
NPWT Pumps	\$414M	\$8.14M	1.97%
TENS Devices	\$132M	\$2.07M	1.57%

Notes: For all DME claims from 2008-2010, we sum both the total payments and payments received by fraudulent firms and then calculate the share of payments to fraudulent firms by product category.

4 Empirical Results

We use the staggered rollout of competitive bidding across MSAs and different DME products to identify the causal effect of competition on fraud. We perform all analyses at the MSA-HCPCS level by quarter, which is the level of treatment.[6] For traditional TWFE results, we estimate

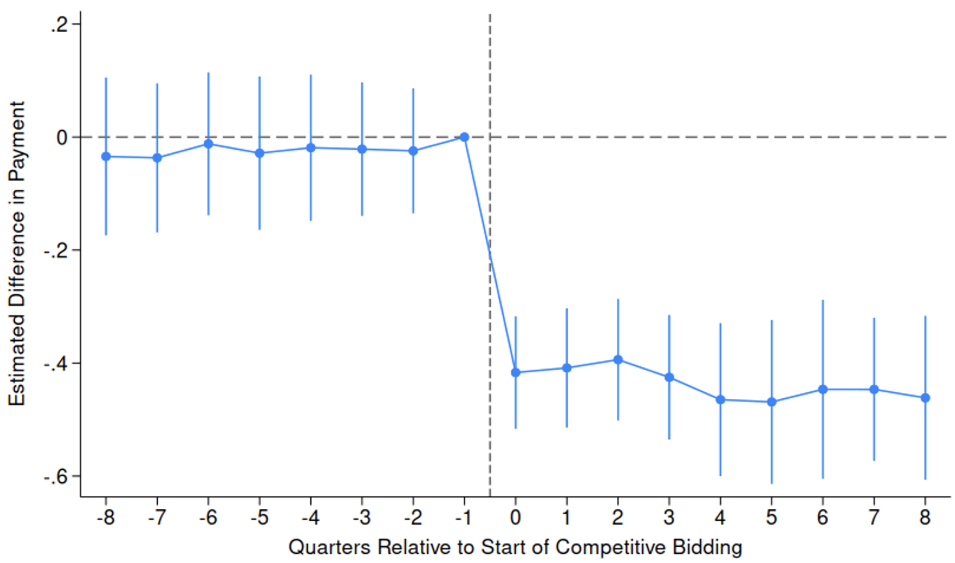
$$Y_{mht} = \sum_{e=-K, e\neq -1}^{K} \beta_e T_{mht}(e) + \alpha_{mt} + \alpha_{ht} + \alpha_{mh} + \varepsilon_{mht} \tag{1}$$

[6] We drop any HCPCS in the category of power mobility devices due to a change in regulations around the same time as the introduction of competitive bidding.

for MSA m and HCPCS product h in quarter t; Y_{mht} is our outcome of interest, such as total payments in an MSA-HCPCS-quarter; and $T_{mht}(e)$ is an indicator for being e quarters from the treatment date (i.e., introduction of competitive bidding). We set $K = 8$, estimating coefficients for eight quarters on either side of competitive bidding.

We first consider the effect of competitive bidding on total revenue. As shown in Figure A1, firm revenues decrease by an average of approximately \$10,000 after the start of competitive bidding for a geography and product (MSA-HCPCS). Figure 4 shows the dynamic difference-in-differences results, or estimates of β_e for $e \in [-8, 8]/\{-1\}$ in (1), with inverse hyperbolic sine (asinh) transformed total payments as the dependent variable. Following the introduction of competitive bidding, we estimate an average decrease in revenue of almost 40%. The effect of competitive bidding was large, immediate, and persistent.

Figure 4: Effect on Payments



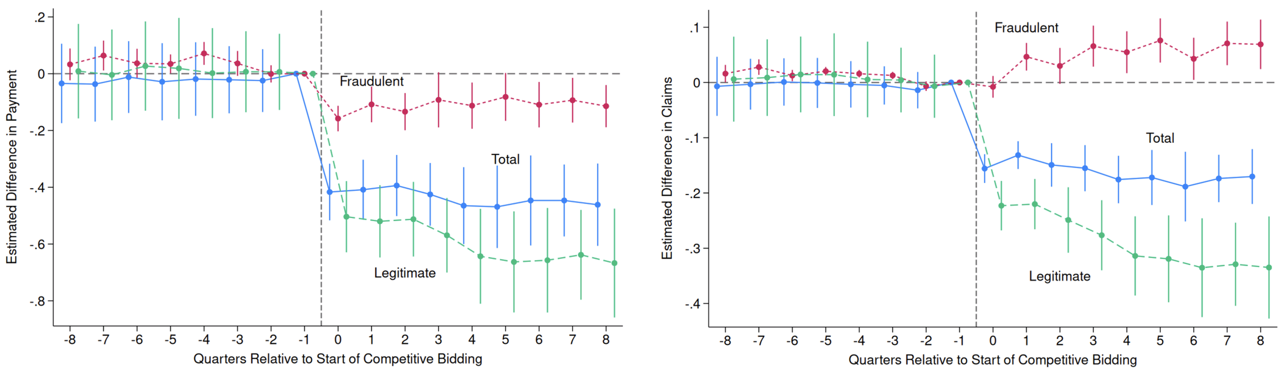
Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation (1). Dependent variable is total line payment transformed by taking the inverse hyperbolic sine. The data include payments from 2008 to 2019. An observation is an MSA-HCPCS-quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represent the pointwise 95% confidence interval

We then replicate the findings of previous papers that show the decrease in revenue stems from a decrease in both prices and quantities. As shown in Figure A2, the price of a product exposed to competitive bidding decreases 30%, for an average of \$30. In terms of quantities, Figure A3 shows claims decrease by an average of 15%, or about 40 claims.

Although competitive bidding clearly reduced Medicare spending, the decline masks heterogeneity among the types of firms affected by the new procurement process. We find that price competition disproportionately affects legitimate firms. From a difference-in-differences specification that separates firms of different types, we show in Figure 5a that the revenue of legitimate firms declines more than 50%, whereas fraudulent firms lose about 10%. In dollar terms, Figure A4 shows total revenue losses of \$8,000 for legitimate firms compared to \$3,000 for fraudulent ones.

Figure 5: Effects on Payment and Claims by Firm Type

(a) Payments (b) Claims



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from (1). 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. The data include claims from 2008 to 2019. An observation is a firm-type-MSA-HCPCS-quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represent the pointwise 95% confidence interval

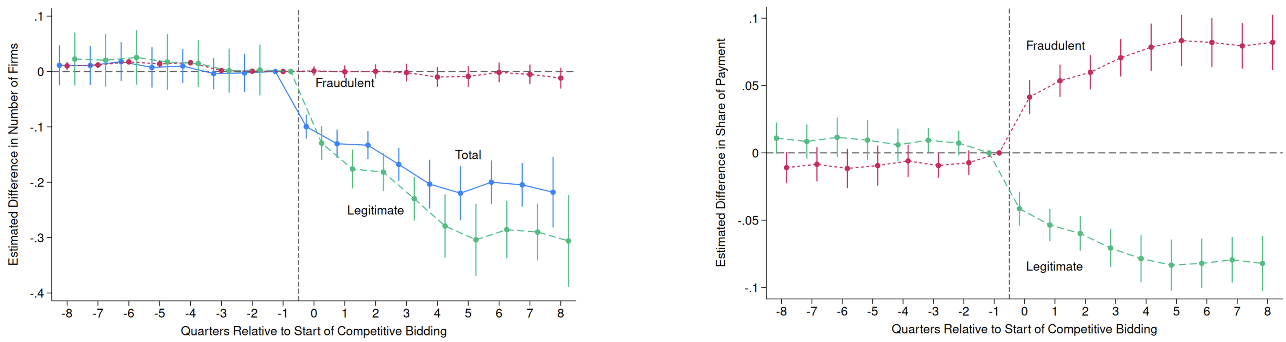
The change in revenue for legitimate relative to fraudulent firms can be explained by their respective number of claims. Although both types of firms are exposed to the same decline in prices, the total number of claims paid to fraudulent firms increases 5–10%, whereas legitimate firms' falls 30–40%.

We also find that the composition of active firms in each product market changes after competitive bidding. Defining active firms as those with a positive line payment in an MSA-HCPCS in a given quarter, the total number declines by an average of 20%, as shown in Figure 6a, or approximately five firms per market in Figure A5. The decline in the number of firms is almost entirely concentrated among legitimate firms, which decrease 30% compared to virtually no decrease among active fraudulent firms.

Figure 6: Effects on Number of Firms and Market Share by Firm Type

(a) Number of Firms

(b) Share of Payments



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from (1). Dependent variable in panel (a) is the number of firms transformed by taking the inverse hyperbolic sine for legitimate type, fraudulent type, and all types estimated separately. Panel (b) plots estimates for the share of line payments in a given market for legitimate firms and fraudulent firms estimated separately. The data include payments from 2008 to 2019. An observation is a firm-type-MSA-HCPCS-quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represent the pointwise 95% confidence interval

We also calculate the revenue share for legitimate and fraudulent firms within each MSA-HCPCS market for each quarter of our sample. We find fraudulent firms gain market share at the expense of legitimate firms. The estimates in Figure 6b show fraudulent firms gain nearly 10% of the revenue share, while Figure A6 shows the breakdown for sanctioned firms compared to those deemed fraudulent by our suspiciousness measures.

Taken together, our results show that increased price competition led to a large decrease in the participation of legitimate firms supplying DME and a corresponding rise in the market share of fraudulent firms.

5 Mechanisms

We consider three possible reasons for why price competition disproportionately benefited fraudulent firms. First, it is possible that fraudulent firms are larger and therefore better able to navigate the introduction of price competition. Second, we consider whether fraudulent firms engage in anticompetitive behavior during the procurement auctions. Third, we examine whether fraudulent firms have lower costs from providing lower-quality products or facilitating lower-quality matches with beneficiaries.

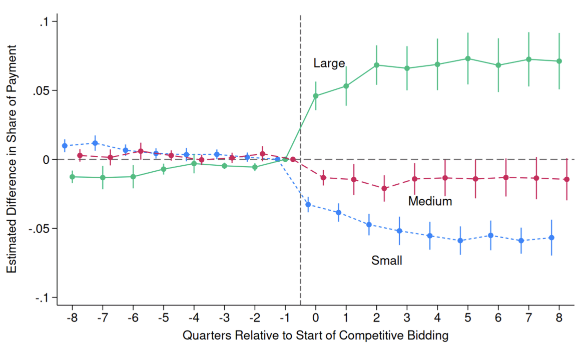
5.1 Firm Size

Fraudulent firms tend to be larger, and larger firms may be better equipped to bear the administrative burdens of procurement auctions. Such economies of scale may therefore give fraudulent firms an advantage in light of heightened competition. To explore this possibility, we first label firms as small, medium, or large according to their lifetime revenue, summarized in Table A2. We define firms with lifetime revenue less than the 95th percentile, or \$2.6M, as small; firms with lifetime revenue between \$2.6 million and \$10.3 million, corresponding to the 95th to 99th percentiles, as medium; and firms with lifetime revenue greater than \$10.3 million, or above the 99th percentile, as large. Based on these classifications, we have 146,340 small, 6,161 medium, and 1,541 large firms.

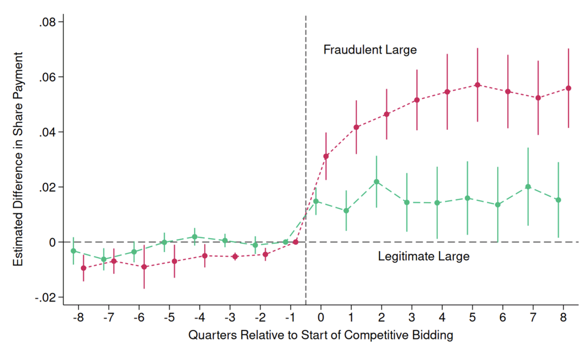
For each MSA-HCPCS, we then calculate revenue shares by firm size and consider how these change following the introduction of competitive bidding. The results of the estimations using (1) plotted in Figure 7a show that large firms gain approximately 6% market share, while small and medium firms lose approximately 5% and 1%, 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 Big 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, estimated separately. Panel (b) plots estimates for share of payments for legitimate large firms and fraudulent large firms, estimated separately. The data include payments from 2008 to 2019. An observation is a firm-type-MSA-HCPCS-quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represent the pointwise 95% confidence interval.

We then use our measure of fraudulence to separate firms into six categories, crossing legitimate and fraudulent with small, medium, and large. Table A3 summarizes the number of firms in each category. For each MSA-HCPCS market for each quarter, we also calculate total line payments and revenue shares by each firm-type and estimate how the composition of the market changes after the start of competitive bidding, taking into account firm size and fraud status. We find that the gains in revenue share for large firms are concentrated among fraudulent firms: Figure 7b shows that large fraudulent firms gain 6% market share compared to 2% for large legitimate firms. Figure A7 shows the equivalent comparison of market share effects across fraudulent and legitimate firms also holds among small and medium suppliers: fraudulent medium firms gain, legitimate small and medium firms lose, and fraudulent small firms remain flat.

5.2 Bidding Behavior

We next examine whether fraudulent firms engage in undesirable behavior during the bidding process, such as lowballing or colluding on bids. As a median price auction without commitment, submitting a very low bid before deciding whether to accept the price determined by the auction is a non-dominated strategy (Cramton et al., 2015). Each firm that participates in the bidding process has the option to choose which auctions it participates in, with separate auctions for each DME product in each geographic area for each bidding cycle.[7] We have bidding data for rounds one (prices effective January 2011) and two (prices effective July 2013). Over the two bid cycles, we have 20,219 unique auctions. For each auction, a firm submits a bid price at which they would supply the relevant product in the relevant geography, as well as an estimated capacity the firm could supply. CMS awards contracts to the firms with the lowest bids whose estimated total capacity meets current market demand, subject to a few caveats discussed in Appendix E along with further details on the auction format.

Matching the firm names reported in the bid data to our NPI-level information on firms' fraudulence, we first measure whether fraudulent firms disproportionately participate in the auctions.[8] We find that fraudulent firms comprise 290 of the 3,061 bidders, or 9.47%. This rate is much higher than the 1.5% of firms found to be fraudulent in the claims data. Furthermore, fraudulent bidders participate in more auctions than legitimate bidders do. On average, a bidder participates in 468 auctions, with fraudulent bidders participating in an average of 1,113 and legitimate bidders participating in an average of 401.

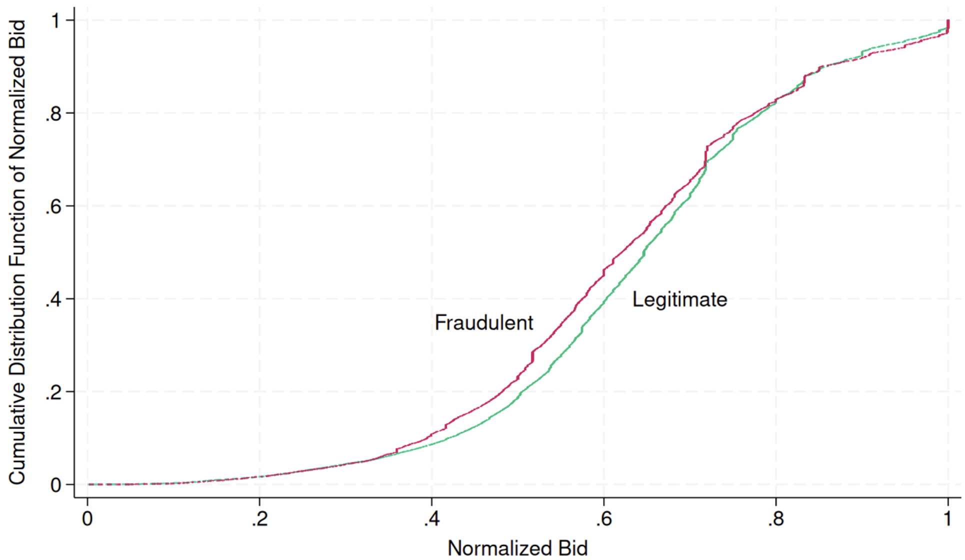
In contrast to the vastly different levels of participation, we find little evidence that fraudulent and legitimate firms bid differently within an auction. Normalizing bids as a share of the pre-

[7] When analyzing the bidding data, we treat the collection of bids submitted for each procedure code as a separate auction. In practice, participants submitted a single bid outlining their price and estimated capacity for each procedure code within a product category, with winners for each product category being 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. Also note the geographic areas are called competitive bidding areas (CBAs) and correspond very closely to metropolitan statistical areas (MSAs).

[8] Appendix F provides more details on this matching process.

auction fee schedule amount, we present the distributions of bids in Figure 8.[9] The bids submitted by fraudulent firms are slightly lower, on average, than those submitted by legitimate firms, but the distributions have a very similar shape overall. In particular, we find no evidence that fraudulent firms were more likely to submit very low bids. Despite the unusual auction format potentially leading to bad-faith bids, fraudulent firms were not more likely to engage in this behavior, perhaps indicating CMS's attempts to authenticate bids proved effective.

Figure 8: Cumulative Distribution Function of Normalized Bids



Notes: We plot 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.

5.3 Quality

Finally, we consider differences in quality using two measures: (i) the quality of the product and (ii) the quality of the patient-match (i.e., the appropriateness of the patient receiving the equipment). Fraudulent firms may have lower costs due to providing lower-quality products on either of these dimensions, which may therefore allow them to gain market share in the face of heightened price competition.

We first measure the quality of the equipment delivered using claims marked as repairs or replacements. We find that following the introduction of competitive bidding, the share of repairs or replacements among claims increases 2%, as shown in Figure 9a. The increase stems

[9]This allows for comparability across auctions for products that cost drastically different amounts. 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.

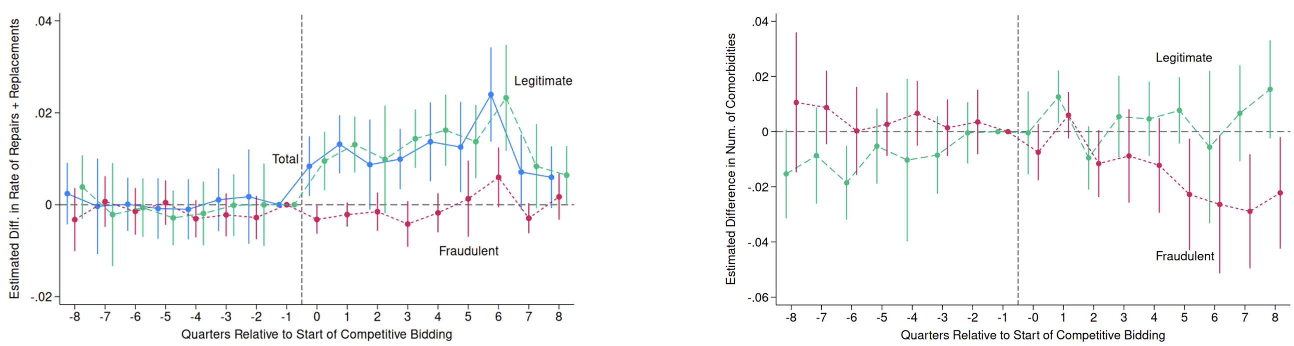
mostly from legitimate firms, however, as the share of repair claims for fraudulent firms remains unchanged.

Figure A9 plots estimates for changes in asinh total repairs and replacements. We find that total replacements and repairs decrease by 5% and 6% for legitimate firms, respectively, and find no change in replacements and repairs for fraudulent firms. Taken together, these results suggest the quality of DME did not change substantially following competitive bidding: fraudulent firms did not change their behavior at all, while legitimate firms had a somewhat smaller reduction in the number of repairs they performed than in the amount of new DME they provided.

Figure 9: Effects on Quality

(a) Repair Rate

(b) Number of Comorbidities



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from (1). Dependent variable in panel (a) is the share of repairs and replacements by legitimate, fraudulent, and all firms, out of claims filled by each respective type. Panel (b) plots estimates for average number of comorbidities across claims from legitimate firms, fraudulent firms, and all firms, estimated separately. The data include payments from 2008 to 2019. An observation is a firm-type-MSA-HCPCS-quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represent the pointwise 95% confidence interval.

As a second measure of quality, we consider the appropriateness of DME recipients, as firms typically commit fraud by selling equipment to patients without a medical need for it. To do so, we sum the number of comorbidities for each beneficiary receiving DME for each year using the 27 chronic conditions variables in Medicare Chronic Conditions file. We merge the comorbidity index into the claims data and calculate the average number of comorbidities for a given firm-type-HCPCS-MSA-quarter observation, averaging across all submitted claims. We estimate regressions at the HCPCS-MSA-quarter level and weight by the total number of submitted claims.

We find some evidence that the average patient served by a fraudulent firm has fewer comorbidities following the start of competitive bidding compared to the average patient served by a legitimate firm. In the quarter before competitive bidding, the average number of comorbidities for claims served by a legitimate firm is 6.63, while the average number of comorbidities for claims served by a fraudulent firm is 6.37. After competitive bidding, the gap widens further, with the average number of comorbidities across fraudulent claims in a given HCPCS-MSA declining by 0.03.

Finally, we estimate the change in patient age following the start of competitive bidding. For each claim, we take the age of the beneficiary served in that year and calculate the average age for a given firm-type-HCPCS-MSA-quarter, averaging across all submitted claims. We estimate the regressions at the HCPCS-MSA-quarter level and weight by the number of claims. In the pre-period, legitimate firms serve patients with an average age of 73.44 compared to an average age of 72.37 for fraudulent firms. After competitive bidding, there is limited evidence that both sets of firms switch to serving slightly younger patients.

6 Conclusion

We find that greater price competition leads to more Medicare fraud. Using novel data on fraudulent DME suppliers, we show that fraudulent firms increased their market share by 10% after Medicare introduced competitive bidding. Larger fraudulent firms benefited the most, as these firms used their scale to drive out legitimate suppliers who cannot match the artificially low costs of supplying low-quality products to ineligible beneficiaries. We also find that fraudulent firms disproportionately chose to participate in auctions and compete on price but do not appear to bid differently than legitimate firms or alter the quality of the equipment they provided. Rather than reducing fraud by dissipating rents, our results suggest increased competition can exacerbate fraud by making profit margins too low for legitimate firms to remain in the market.

References

Leder-Luis and Malani (2025). The economics of health care fraud.

Bennett, V. M., L. Pierce, J. A. Snyder, and M. W. Toffel (2013). Customer-driven misconduct: How competition corrupts business practices. *Management Science 59*(8), 1725–1742.

Centers for Medicare & Medicaid Services (2023). 2023 medicare fee-for-service supplemental improper payment data. Accessed: 2025-01-09.

Centers for Medicare & Medicaid Services (2024). Fiscal year 2024 improper payments fact sheet.

CMS (2013). Medicare's DMEPOS Competitive Bidding Program.

CMS (2023). Exploring fraud, waste, and abuse within telehealth. Accessed: 2025-02-05.

CMS (2024a). Details for: Change to the Competitive Bidding Program for Certain Durable Medical Equipment, Prosthetics, Orthotics, and Supplies.

CMS (2024b). Fiscal Year 2024 Improper Payments Fact Sheet.

Colla, C., J. Bynum, A. Austin, and J. Skinner (2016). Hospital competition, quality, and expenditures in the us medicare population. Technical report, National Bureau of Economic Research.

Cooper, Z., S. Gibbons, S. Jones, and A. McGuire (2011). Does hospital competition save lives? evidence from the english nhs patient choice reforms. *The Economic Journal 121*(554), F228–F260.

Cramton, P., S. Ellermeyer, and B. Katzman (2015). Designed to fail: The medicare auction for durable medical equipment. *Economic Inquiry 53*(1), 469–485.

Currie, J., A. Li, and M. Schnell (2023). The effects of competition on physician prescribing. Technical report, National Bureau of Economic Research.

Dafny, L. S. (2005). How do Hospitals Respond to Price Changes? *American Economic Review 95*(5), 1525–1547.

Dewatripont, M. and J. Tirole (2019). Incentives and ethics: How markets and organizations shape our moral behavior. Technical report, Working Paper.

Ding, H., M. Duggan, and A. Starc (2025). Getting the price right? the impact of competitive bidding in the medicare program. *Review of Economics and Statistics 107*(1), 204–220.

DOJ (2009, February). Owners of Los Angeles-area Medical Equipment Company Sentenced to Prison for Medicare Fraud. Office of Public Affairs. Accessed: 2025-02-05.

DOJ (2010, November). Jury Convicts Oakland, California, Patient Recruiter for Participating in Wheelchair Scam to Defraud Medicare. Office of Public Affairs. Accessed: 2025-02-05.

DOJ (2023, August). Lincare holdings agrees to pay $2.9 million to resolve claims of overbilling medicare for oxygen. U.S. Attorney's Office, Eastern District of Washington. Accessed: 2025-02-05.

DOJ (2024). Mt. Pleasant Man Sentenced to Nine Years in Federal Prison for Role in One of the Largest Medicare Fraud Schemes in History.

Eliason, P., R. League, J. Leder-Luis, R. McDevitt, and J. Roberts (2025). Ambulance taxis: The impact of regulation and litigation on health care fraud. *Journal of Political Economy 0*(ja), null.

Fang, H. and Q. Gong (2017). Detecting Potential Overbilling in Medicare Reimbursement via Hours Worked. *American Economic Review 107*(2), 562–591.

GAO (2024). Medicare and Medicaid: Additional Actions Needed to Enhance Program Integrity and Save Billions.

Gaynor, M., R. Moreno-Serra, and C. Propper (2013). Death by market power: reform, competition, and patient outcomes in the national health service. *American Economic Journal: Economic Policy 5*(4), 134–166.

Hart, O., A. Shleifer, and R. W. Vishny (1997). The proper scope of government: theory and an application to prisons. *The Quarterly Journal of Economics 112*(4), 1127–1161.

Howard, D. H. and I. McCarthy (2021). Deterrence effects of antifraud and abuse enforcement in health care. *Journal of Health Economics 75*, 102405.

Janssen, A. and X. Zhang (2023). Retail pharmacies and drug diversion during the opioid epidemic. *American economic review 113*(1), 1–33.

Ji, Y. (2023). Can competitive bidding work in health care? evidence from medicare durable medical equipment. Technical report, Working Paper.

Ji, Y. and P. Rogers (2024). The long-run impacts of regulated price cuts: Evidence from medicare. Technical report, National Bureau of Economic Research.

Kessler, D. P. and M. B. McClellan (2000, 05). Is hospital competition socially wasteful?*. *The Quarterly Journal of Economics 115*(2), 577–615.

Leder-Luis, J. (2023). Can whistleblowers root out public expenditure fraud? evidence from medicare. *Review of Economics and Statistics*.

McDevitt, R. C. (2011). Names and reputations: An empirical analysis. *American Economic Journal: Microeconomics 3*(3), 193–209.

McDevitt, R. C. (2014). 'a' business by any other name: Firm name choice as a signal of firm quality. *Journal of Political Economy 122*(4), 909–944.

MedPac (2018). Issues in Medicare's medical device payment policies. .

Newman, D., E. Barrette, and K. McGraves-Lloyd (2017). Medicare competitive bidding program realized price savings for durable medical equipment purchases. *Health Affairs 36*(8), 1367–1375.

Office of the Inspector General, U. D. o. H. . H. S. (2011). Most power wheelchairs in the medicare program did not meet medical necessity guidelines.

OIG (2006). Medicare Home Oxygen Equipment: Cost and Servicing.

OIG (2007). Comparison of Prices for Negative Pressure Wound Therapy Pumps.

Sanghavi, P., A. B. Jena, J. P. Newhouse, and A. M. Zaslavsky (2021). Identifying outlier patterns of inconsistent ambulance billing in Medicare. *Health Services Research 56*(2), 188–192. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1475-6773.13622.

Shekhar, S., J. Leder-Luis, and L. Akoglu (2023, February). Unsupervised machine learning for explainable health care fraud detection. Working Paper 30946, National Bureau of Economic Research.

Shleifer, A. (2004). Does competition destroy ethical behavior? *American economic review 94*(2), 414–418.

Silverman, E. and J. Skinner (2004). Medicare Upcoding and Hospital Ownership. *Journal of Health Economics 23*(2), 369–389.

USA v. Ijewere et al. (2009). United States District Court for the Central District of California. No. 2:09-cr-01173-DSF, filed 4 November 2009.

USA v. Shubaralyan (2008). United States District Court for the Central District of California. No. 2:08-cr-00532-SVW, filed 14 November 2008.

Whoriskey, P. and D. Keating (2014, August). A medicare scam that just kept rolling. Accessed: 2025-01-09.

Appendix: For Online Publication

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

Appendix A provides more detail on the method used to find suspicious firms.

Appendix B contains additional results on line payment regressions using raw dollars and number of firms, and replications of results on price and quantity found in previous literature.

Appendix C contains additional regressions on changes in market share

Appendix D contains additional details on firm size classification and regressions.

Appendix E provides more details on the auction format.

Appendix F contains additional information on the matching process to match firm bidder names to the NPPES

A Detailed Information on Finding Suspicious Firms

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

A.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) that do not contribute to identifying the firm. Next, we eliminate frequent terms such as "INC," "LTD," and "CO." Appendix Table A1 shows the words we eliminate. This step standardizes the names for better matching.

INCORPORATED	PLLC	LLC
INC	CORPORATION	CORP
CO	LIMITED	LTD

Table A1: List of excluded words for name matching

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).

The formula for the Jaccard index is given by:

$$J(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

where:

- A and B are the sample sets.
- $|A \cap B|$ is the number of elements common to both sets.
- $|A \cup B|$ is the total number of elements in both sets, counted only once.

For each pair of NPIs that we match, we identify pairs where one NPI is tagged as fraudulent and the other is not. If the name of an NPI matches the name of another NPI already identified as fraudulent, the untagged NPI is then flagged as a suspicious firm.

A.2 Firm Owner

Our second method uses firms' authorized owner names from the NPPES to find suspicious firms. We group NPIs using first, middle and last name of authorized owner to create firm groups. Then, within each group of NPIs that we consider to be owned by the same person, we label firms suspicious if there exists a sanctioned NPI among them.

A.3 Firm Address

Our third method for identifying suspicious firms uses the mailing and business addresses from the NPPES. First, we 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 a fraudulent NPI, we label all the firms that share either the business address or the mailing address as suspicious.

A.4 Firm Referrer Links

Our fourth method uses the previously identified fraudulent firms alongside our three other suspiciousness measures to uncover additional suspicious entities. Each prescription for DME includes a health provider listed as the referrer on the claim. We analyze this referral network to pinpoint suspicious firms, noting that fraudulent or otherwise suspicious firms may be larger than average. 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 line 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 supplier's business attributable to the referrer.
4. The percentage of the referrer's total DME line payments that go to the supplier.

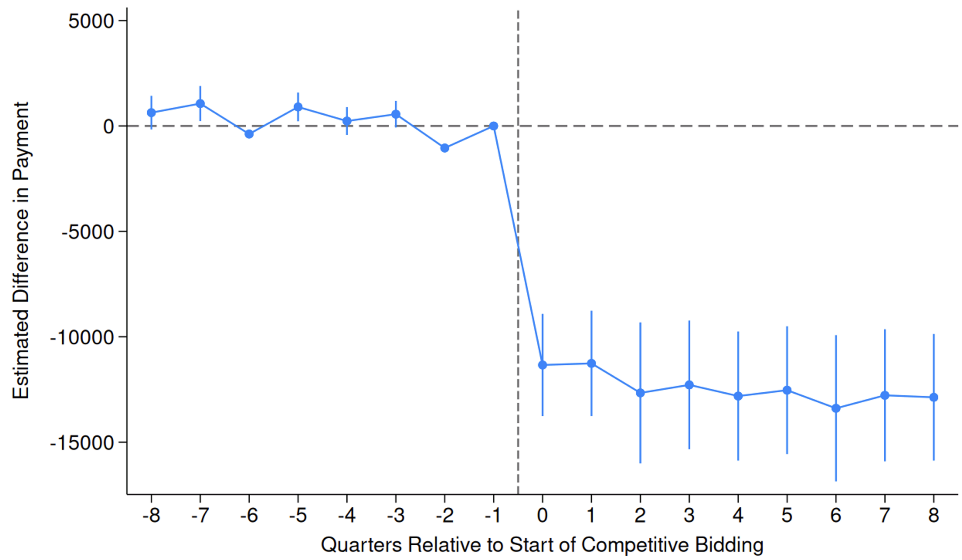
We construct a multidimensional grid by iterating over these measures at various percentile thresholds, defined using the dataset of tagged firms — those identified as fraudulent or suspicious by the initial three methods. For each supplier-referrer pair, we determine whether their connection constitutes a real link based on the thresholds.

Upon establishing significant relationships through these defined links, we measure each supplier's connectivity within the network, specifically looking at connections to both fraudulent and legitimate firms. We then calculate homophily, a measure that gauges the tendency of similar entities to cluster together, focusing particularly on its manifestation among fraudulent firms. We test each combination of thresholds to find the one that maximizes homophily among fraudulent firms, indicating the most effective parameters for distinguishing between fraudulent and legitimate referral patterns.

Using the optimal thresholds, we define relationships between suppliers and referrers. Any referrer linked to a fraudulent firm under these conditions is tagged as suspicious. We identify all suppliers connected to these suspicious referrers, according to the established thresholds, that are not already marked as fraudulent and label them as suspicious.

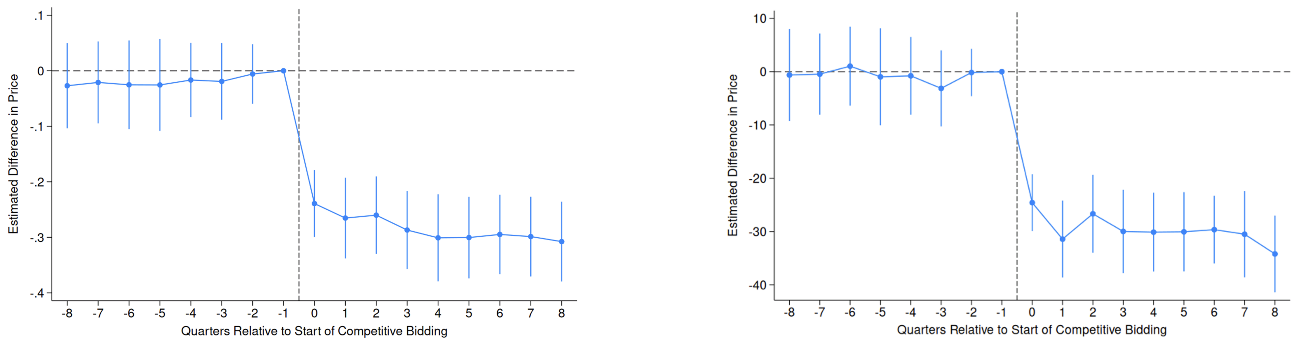
B Appendix Results Figures

Figure A1: Effect on raw payment



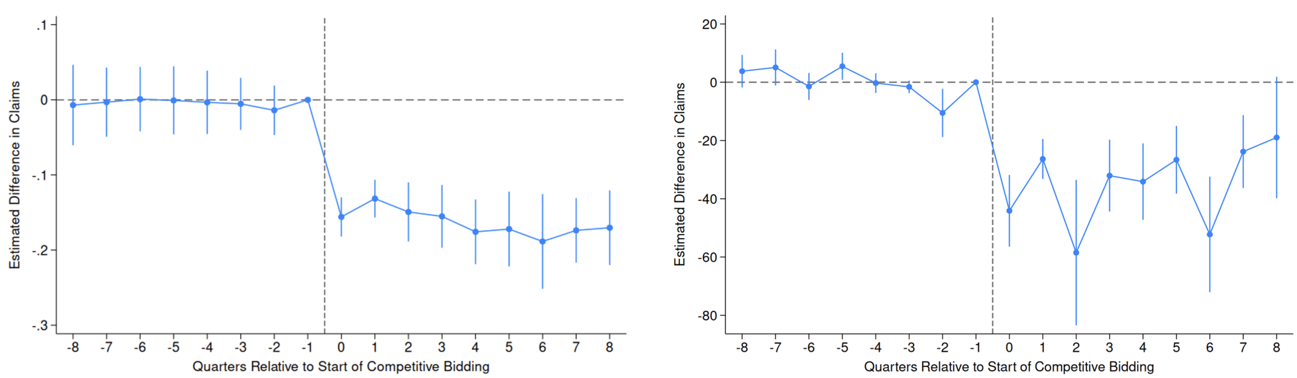
Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Dependent variable is total payment in a given market. The data include payments from 2008 to 2019. An observation is a MSA-HCPCS-quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represents the pointwise 95% confidence interval.

Figure A2: Price



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Panel (a) dependent variable is asinh price in a given market. Panel (b) dependent variable is price in a given market. The data include payments from 2008 to 2019. An observation is a MSA-HCPCS-quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represent the pointwise 95% confidence interval.

Figure A3: Claims



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Panel (a) has estimates for asinh number of claims in a given market. Panel (b) has estimates for total number of claims. The data include payments from 2008 to 2019. An observation is a MSA-HCPCS-quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represent the pointwise 95% confidence interval.

Figure A4: Effect on Payment

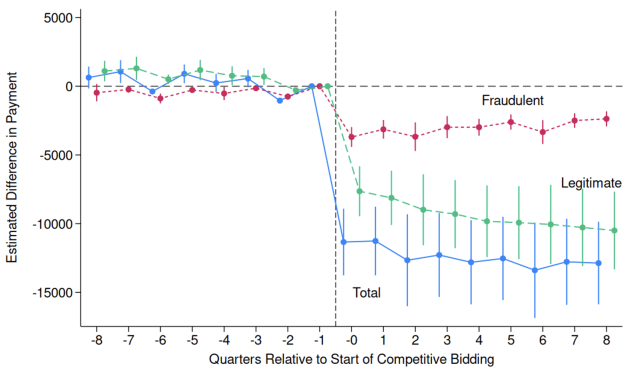
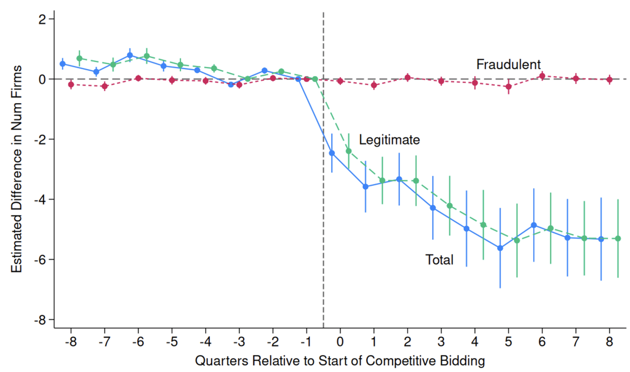


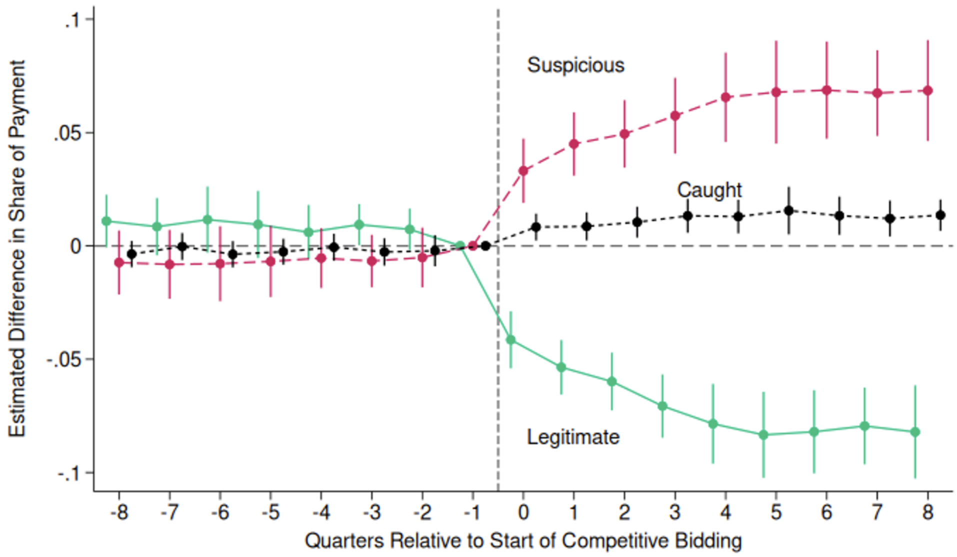
Figure A5: Effect on Number of Firms



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Dependent variable in panel (a) is raw payments by firm type. Panel (b) dependent variable is the number of firms by firm type. The data include payments from 2008 to 2019. An observation is a firm-type-MSA-HCPCS-quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represent the pointwise 95% confidence interval.

C Detailed Breakdown of Market Share

Figure A6: Effect on Share of Line Payments by Firm Type



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Dependent variable is share of line payment for legitimate firms, sanctioned fraudulent firms and suspicious firms, estimated separately. The data include payments from 2008 to 2019. An observation is a firm-type-MSA-HCPCS-quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represents the pointwise 95% confidence interval.

D Firm Size

Table A2: Summary Statistics of Total Line Payments

Description	Value
Total observations	154,042
Average payment	683k
Standard Deviation	10.7M
Smallest payment	0
1st percentile	0
5th percentile	98.2
10th percentile	725.8
25th percentile	6757.9
50th percentile (Median)	45555.4
75th percentile	176,617.5
90th percentile	824,654.3
95th percentile	2.6M
99th percentile	10.3M
Largest payment	2.73B
Categorization Counts	
Small Firms	146,340
Medium Firms	6,161
Large Firms	1,541

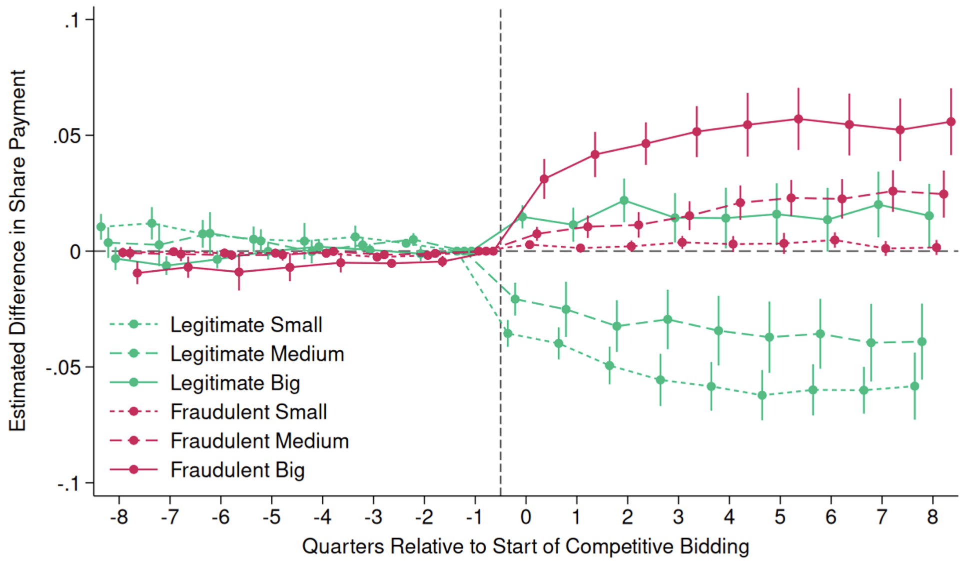
Notes: Sample includes all firms that have submitted a DME claim to Medicare Part B from the years 2008-2019. This table shows summary statistics of payments made to all firms through Medicare Part B DME.

Table A3: Counts of Legitimate and Fraudulent Firms by Size

Firm Size	**Firm Quality**	**Count**
Small	Legitimate	145,046
Small	Fraudulent	1,294
Total Small		146,340
Medium	Legitimate	4,779
Medium	Fraudulent	1,382
Total Medium		6,161
Large	Legitimate	1,044
Large	Fraudulent	497
Total Large		1,541

Notes: Sample here includes all firms that have submitted a DME claim to Medicare Part B from 2008 to 2019. Firms are considered fraudulent if they have been sanctioned for fraud or are suspicious by at least one of our suspiciousness measures. We group firms by size using percentile of lifetime revenue.

Figure A7: Effect on share of line payment firms by size and goodness



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Dependent variable is share of line payment for legitimate and fraudulent firms by size – small, medium and large. Each of the six dependent variables was estimated separately. The data include payments from 2008 to 2019. An observation is a firm-type-MSA-HCPCS-quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represents the pointwise 95% confidence interval.

E Auction Format Details

This appendix provides additional details on the auction format. It is based on `https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/DMEPOSCompetitiveBid/downloads/DMEPOSRegSumm.pdf`, 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 group of 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 product (HCPCS-by-modifier-code) level.

Each bidding supplier submits a bidding worksheet, an example of which is shown in Figure A8, 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 or provide proof of necessary capacity expansions.[10]

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

[10] See `https://www.dmecompetitivebid.com/Palmetto/Cbic.Nsf/files/R1RC_Fact_Sheet_Bona_Fide_Bid.pdf/$File/R1RC_Fact_Sheet_Bona_Fide_Bid.pdf` and `https://www.govinfo.gov/content/pkg/FR-2014-11-06/pdf/2014-26182.pdf`.

reach CMS's target capacity.[11] 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.

Figure A8: 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).

[11] 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.

F Details on Matching Bidder Names to NPIs

We encountered various challenges while working with these data. First, the bidding data we received from our FOIA request contain bidder names associated with masked NPIs. Many of these bidder names are associated with multiple NPIs, so it is difficult to determine 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 and commas. After applying this initial cleaning, we have 3,511 unique bidders.

We match cleaned bidder names to cleaned versions of firm names in the NPPES. We only consider NPIs that have supplied DME in our claims data. We first remove an initial set of words and match an initial set of bidders to firms in our claims. We then run a second iteration after removing a second set of common words.

To choose words to remove, we run a frequency analysis on the bidder names from the bidding data and the firm names from the NPPES restricted to DME supplier. We choose the words that are frequently used while omitting specific words like "WALMART" that appear frequently due to a large number of NPIs.

Table A4: First set of excluded words for name matching

INCORPORATED	PLLC	LLC
INC	CORPORATION	CORP
CO	LIMITED	LTD

Table A5: Second set of excluded words for name matching

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

We keep matches with a similarity score greater than 0.95. Finally, for any bidders that remain unmatched, we run a fuzzy match on the bidder name and owner name contained in the NPPES. From the matching process, we successfully match 3,061 of the 3,511 bidders to at least one NPI that supplied DME in the claims data, leaving 450 bidders that cannot be matched to the claims data.

In total, the 3,061 matched bidder names match to 12,100 NPIs. On average, each bidder matches to 3.95 NPIs, with significant variation. Some large bidders, such as Walmart, match to 1,300 NPIs, while nearly half of the bidders match to only one unique NPI. At the higher percentiles, the numbers increase slightly, with the 95th percentile matching to eight NPIs and the 99th percentile matching to 31, indicating that a small fraction of bidders are associated with many NPIs.

G Quality

Figure A9: Repairs and Replacements

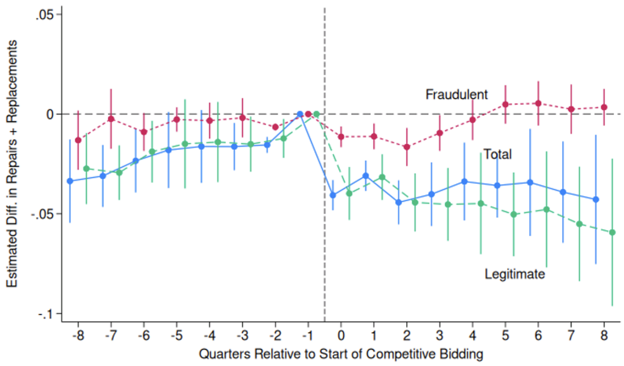
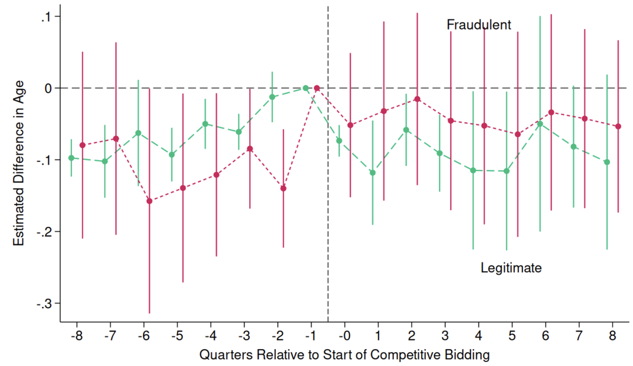


Figure A10: Beneficiary Age Served by Firm Type



Notes: Panel (a) presents estimates of β_e from equation (1) for the asinh transformed number of repairs and replacements, estimated separately by legitimate firms, fraudulent firms, and all firms. Panel (b) shows the average age of beneficiaries served, also broken down by firm type. Data spans from 2008 to 2019 with observations at firm-type-MSA-HCPCS-quarter level. Standard errors are clustered at the MSA-HCPCS level. Error bars represent pointwise 95% confidence intervals.

H Comorbidity Index

Table A6: 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

I Suspicious Firms Restricted pre-Competitive Bidding

Figure A11: Payment

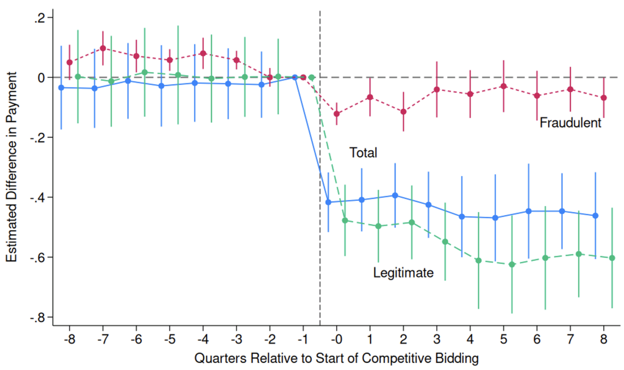
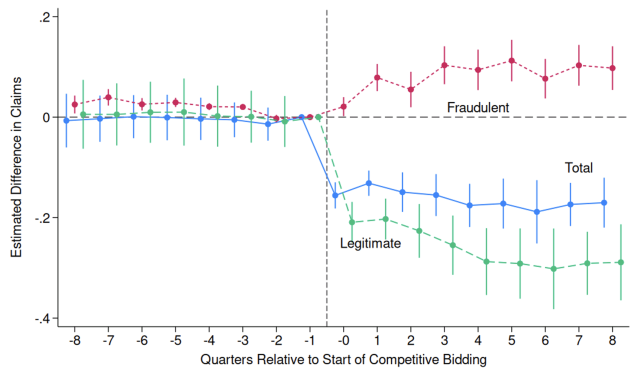


Figure A12: Claims



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation (1). Firms are fraudulent 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. The data include claims from 2008 to 2019. An observation is a firm-type-MSA-HCPCS-quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represent the pointwise 95% confidence interval

Figure A13: Number of Firms

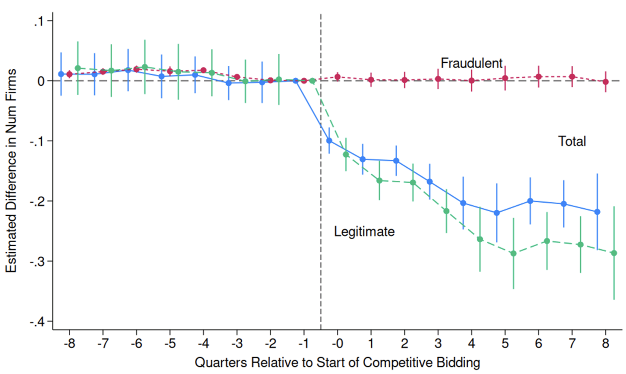
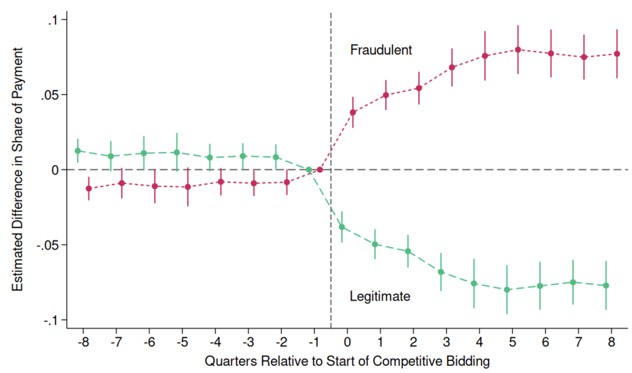


Figure A14: Share Payment



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