Competition and Fraud in Health Care*

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Governments often rely on private firms to provide public goods and services. Competition among these firms theoretically reduces costs and increases quality but has an ambiguous effect on fraud: competition can both dissipate the rents that attract fraudulent firms to the market while at the same time reducing margins to the point where legitimate firms can no loner operate profitably and only fraudulent firms 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.

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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 government faces the challenge of verifying the quality and integrity of large swaths of suppliers. Such challenges have created opportunities for unscrupulous firms to defraud the government by overbilling or failing to provide contracted goods and services, a particularly acute problem 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. Increased competition could eliminate the incentives to commit fraud by reducing prices and markups (MedPac, 2018) but could also potentially exacerbate it. Competitive pressure may advantage fraudulent firms that, due to their lower quality, have costs below those of legitimate suppliers, 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 the market for durable medical equipment (DME). DME has been plagued by high levels of fraud for decades, with rates of improper payments estimated at over 20% (Centers for Medicare & Medicaid Services, 2023). Moreover, the DME market is especially diffuse, comprising tens of thousands of suppliers selling thousands of products ranging from power mobility devices to bedpans to oxygen tanks. Beginning in 2011, the Centers for Medicare and Medicaid Services (CMS) switched from a system of regulated prices to one in which firms compete through procurement auctions to sell DME to beneficiaries. Past research (Ji, 2023; Ding et al., 2025) has shown this switch led to a large reduction in Medicare spending, driven almost entirely by declines in the prices paid for DME. Left unexplored is the impact the lower prices from these auctions had on the incidence of fraud, the market structure of suppliers, and the quality of products supplied to beneficiaries.

We find that fraudulent firms benefited from Medicare's switch to procurement auctions and the increased competition they introduced. Following the lower prices from procurement auctions, the firms we identify as fraudulent increased their market share at the expense of legitimate firms. Although fraudulent firms are larger and larger firms gained more market share, firm-size effects do not fully explain the ascendance of fraudulent firms, as they gained market share even conditional on their size. We further show that fraudulent firms participated in the auctions at a much higher rate, although bidding behavior within the auctions was similar for fraudulent and legitimate firms. In addition, we find evidence of only small changes in quality, both in terms of the physical quality of DME and patients' match-quality for medical necessity. Taken together, our results show that increased competition benefited fraudulent firms by reducing margins to the point where legitimate firms no longer remained viable in the market for DME.

For our empirical analysis, we begin by identifying fraudulent DME firms. We hand collected data on hundreds of DME suppliers ever subject to anti-fraud enforcement, either through civil whistleblower anti-fraud litigation, criminal lawsuits, or administrative exclusion from the Medicare program. We use this set of sanctioned firms to infer a set of "suspicious" firms that did not face enforcement but appear to be fraudulent by identifying firms with connections to those formally charged, including shared ownership, same address, or high levels of common referrals by physicians potentially complicit in DME overprescribing. We show our measures of suspiciousness are robust to different detection mechanisms and validate that the firms we identify as suspicious engage in high levels of dubious behavior before the advent of competitive bidding.

We then use the staggered rollout of competitive bidding across geographic regions and DME product categories to identify the causal effects of increased competition on fraud. In particular, we focus on the effects of the program on the market structure of fraudulent and legitimate firms as well as the overall level of fraud. Consistent with past research (Ji, 2023; Ding et al., 2025), we find competitive bidding led to a 40% reduction in firm revenue, driven largely by a decrease in the price of DME products. Building on these studies, we find this reduction came almost exclusively from legitimate firms, with the revenue of fraudulent firms remaining largely unchanged and resulting in a 10 percentage point increase in the market share of fraudulent firms.

We test several potential mechanisms that could explain why fraudulent firms gain market share under competitive bidding. For one, fraudulent firms tend to be larger than legitimate firms, which could leave 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 revenues, this cannot fully explain our results. Even conditional on firm size, fraudulent firms increase their market share.

A second potential mechanism could be fraudulent firms' behavior within the procurement auctions. Prior 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 empirically investigate the possibility that fraudulent firms may be more willing to bid in bad faith. 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 a very low bid. At the same time, fraudulent firms are more likely to participate in the auctions: 11% of bids come from fraudulent firms despite these firms comprising just 2% of the market for DME. Our results are therefore consistent with fraudulent firms having lower costs that make them more likely to participate in the auctions rather than manipulating the bidding process.

As a third and final potential mechanism, we consider whether competitive bidding led to a change in the quality of the goods and services 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 goods and services for a number of reasons: compressed profit margins may force some firms to cut costs in ways that reduce quality or make it so that only low-cost, low-quality firms 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 was unchanged by competitive bidding and fraudulent firms appear to redirect their business toward patients with fewer comborbidities (i.e., less likely to have a medical necessity) as well as slightlu older patients (i.e., who may be more susceptible to fraud). 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.

Finally, to quantify the level of fraud in the market before and after competitive bidding, we estimate a model of demand for DME where fraudulent firms inflate their sales by supplying DME to illegitimate patients. Estimating the model for the hospital bed market in Charlotte, NC, we find that 89% of fraudulent firms' patients are inappropriate and should not have received DME. In line with our reduced-form results, the structural model suggests competitive bidding favored fraudulent firms over legitimate ones, with the amount of fraud increasing 17% after competitive bidding. Although increased competition may reduce the potential gains from committing fraud, we find in this setting that lower prices drive out legitimate firms that bear the full costs of supplying high-quality DME.

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 how increased competition affects quality in health care markets. Past work has shown competition can have mixed effects on quality. Cooper et al. (2011) and Gaynor et al. (2013), for instance, show that greater competition among hospitals in England improved health care quality, whereas Duggan et al. (2000) find that increased competition may exacerbate quality concerns. Our focus on competitive bidding highlights a new mechanism by which competition might influence market outcomes by providing an advantage to fraudulent firms, particularly in settings where quality is difficult to monitor and enforce.

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 inpatient 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 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 to commit fraud.

More narrowly, our research contributes to a growing literature that evaluates the impact of competitive bidding on DME. Prior work has documented the competitive bidding program's effects on prices and quantities, with Ji (2023) and Ding et al. (2025) both showing significant reductions. In addition, Newman et al. (2017) note that the resulting prices were similar to those negotiated by private insurers, while Ji and Rogers (2024) argue these price cuts led to less innovation. These past studies have largely overlooked 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 focused on the incentives of firms that contract with the government. In the seminal framework of Hart et al. (1997), the government faces a tradeoff between reducing costs and providing high-quality goods and services, where the contracting of public services leads to inefficiently large cuts to quality due to incomplete contracts. In health care, where quality is often difficult to monitor, cost-focused mechanisms like competitive bidding may favor firms with lower costs, even if they achieve these efficiencies through undesirable means such as fraud. 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 supplies 10 million beneficiaries each year with equipment such as wheelchairs, medical beds, and CPAP machines. The program costs $7-10 billion per year and is covered under Part B. DME must be prescribed by a physician through an order, prescription, or certificate of medical necessity, after which a Medicare-approved supplier can take assignment and supply the product. Beneficiaries typically pay 20% of the Medicare-approved amount, with Medicare supplying the other 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). 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).

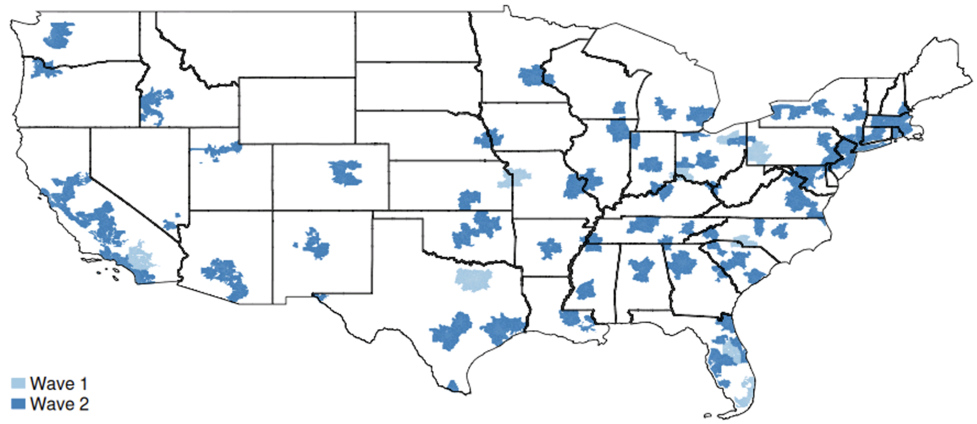
Fraud has long been a problem among DME suppliers. In 2023, HHS estimated a total of $100 billion in improper payments for Medicare and Medicaid, implying that over 40% of the government's improper payments originate from health care (GAO, 2024).[1] DME fraud primarily involves providing Medicare beneficiaries with DME they do not need and never requested, a form of fraud called "medical necessity fraud" (Leder-Luis and Malani, WIP). In many cases, a health care provider receives a kickback from the supplier in exchange for DME prescriptions that 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. Suppliers also employ a form of upcoding by billing 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, such as Lincare Holdings Inc., which agreed to pay $29 million to resolve improper billing for 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 collaborate to detect and prosecute fraud, with initiatives like the Medicare Fraud Strike Force targeting high-risk regions and providers. In 2019, the government announced the results of "Operation Brace Yourself," a months-long investigation into DME fraud that led to significant criminal convictions, including lengthy prison sentences for those involved (DOJ, 2024).

The Medicare DME Competitive Bidding program was established by the Medicare Modernization Act in 2003 to bring down excessively high prices but also to explicitly combat waste and fraud (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

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

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.

years. The auction price is set to the median of the winning bids, meaning half of the winning bidders receive a price below what they bid. Because the auctions do not prevent bidders from later withdrawing their supply commitment, Cramton et al. (2015) shows that submitting a low bid before deciding whether to accept the price determined by the auction is a non-dominated strategy. Despite the nonstandard auction format, others (Ji, 2023; Ding et al., 2025, e.g.) have shown Medicare's switch to competitive bidding led to substantially lower prices for DME.

The first round of bidding was conducted for nine product categories in nine areas starting in 2009, and the resulting prices went into effect on January 1, 2011. The program was expanded across further product categories and geographies over time, with prices going into effect July 2013, January 2017, and January 2021.[2] Figure 1 shows the geographic rollout of competitive bidding over the first two waves.

Product groups subject to competitive bidding were typically those where Medicare anticipated the greatest potential 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).

[2]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.

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 (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.

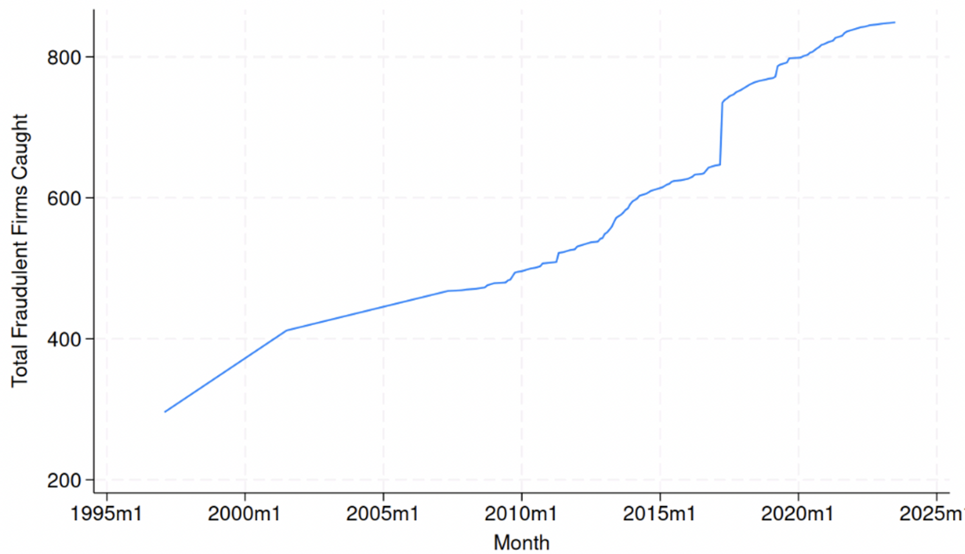
For DME suppliers, we use the full set of NPIs that have supplied DME in the claims data. This results in a total of 150,764 NPIs that submitted claims to supply DME. We use the National Plan & Provider Enumeration System (NPPES) to obtain firm-level information, including a supplier's name, mailing address, business address, and authorized owner. To ensure comprehensive coverage, we incorporate both historical and recent NPPES data.

We use two distinct sources of data to identify fraudulent firms in the DME industry. First, we create a novel dataset based on press releases from the DOJ that mention violations of the FCA related to DME. For each press release, we extract the date of the press release and the name of the firm involved. Using the firm's name, we manually search for and identify any NPIs associated with the firm. We analyze a total of 389 press releases, which we link 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 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. To ensure comprehensive coverage, we use historical versions of the LEIE from the Wayback Machine. 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. Thus, 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." We use the timing of when the firms were charged to create Figure 2, which plots the number of fraudulent firms sanctioned over time. We find that firms have steadily continued committing — and getting caught — for fraud.

Data on the timing of competitive bidding come from the online competitive bidding program for DME archives. It includes the timing for each HCPCS and ZIP code combination, spanning multiple waves, including the 2011, 2013, and 2017 rollouts. For product-geographies that underwent multiple waves of competitive bidding, the data capture the timing for both rollouts. We conduct our analysis at the MSA level, as the rollout of competitive bidding was determined at the HCPCS and MSA level. To aggregate our data to the MSA level, we use a ZIP-code-to-MSA

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.

crosswalk from the Department of Labor.

The competitive bidding auction data were obtained through a FOIA request and include information from round one and round two of the competitive bidding auctions in 2011 and 2013, respectively. Each auction consists of a HCPCS, CBA, and bidtype, 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 NPIs are not included in the data, 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.

Each HCPCS code for DME is assigned to a broader product category. For example, HCPCS codes E0433 and E0434 represent two distinct portable liquid oxygen systems, both of which fall under the category "Oxygen Supplies and Equipment." To aggregate data at the product category level, we use a crosswalk that links HCPCS codes to their respective product categories. This crosswalk is derived from the competitive bidding program archives and thus includes only those product categories that were part of competitive bidding; not every product within a category participates in competitive bidding, even if other products in the same category do.

Finally, we consider various measures of quality. First, we look at the number of repairs using our claims data.[3] We also consider patient-match quality (i.e., the appropriateness of

[3]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

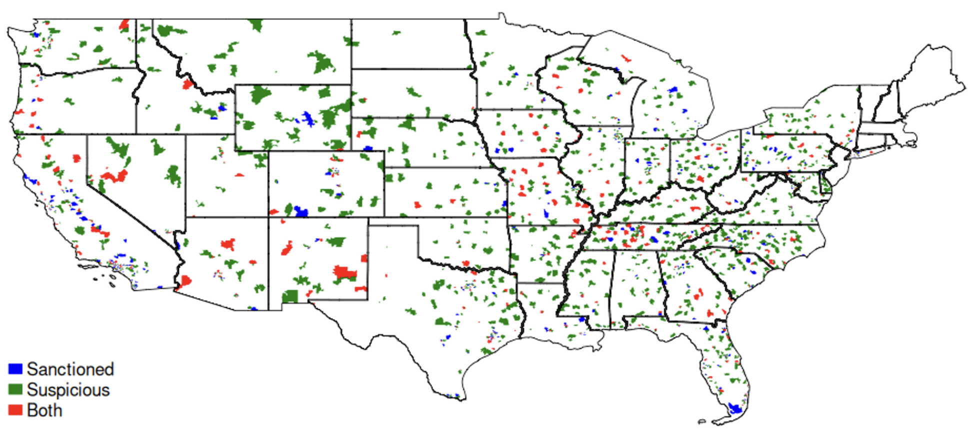
beneficiaries who receive DME) using a simple version of the Charlson Index using the Medicare Chronic Conditions file.

4 Measuring Suspicious Firms

To identify fraud in DME, we must account for both firms sanctioned for committing fraud as well as those that remained undetected. To identify suspicious firms, we start with the set of firms sanctioned for fraud and then search for other firms that have clear links to them. We consider a firm to be suspicious if it shares its name, owner, or address with a fraudulent firm. 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 sanction. We see wide geographic dispersion of these firms across the United States.

Figure 3: Location of Sanctioned and Suspicious Firms



Notes: ZIP codes where firms were sanctioned for fraud are 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 of the firms in our sample. Overall, we find that fraudulent firms are larger than legitimate firms by a number of measures. They have been active for longer, sell more types of products, and sell in more geographies.

Table 1: Average Firm Statistics by Firm Type

	Total	Legitimate	Sanctioned	Suspicious
Line Payment ($)	647,064.8	480,357.2	5,934,481	8,721,044
	(998,800.2)	(620,295.2)	(1.77e+07)	(5.98e+07)
Quarters Active	27.62	27.46	29.91	36.47
	(17.88)	(17.88)	(17.07)	(15.44)
HCPCS Sold	35.96	34.16	92.17	123.01
	(58.33)	(55.87)	(70.70)	(103.26)
MSAs Active	15.79	14.39	70.84	79.88
	(33.33)	(30.52)	(75.32)	(70.14)
Observations	150,764	147,428	846	2,490

Notes: The sample of firms here includes all firms that have submitted a DME claim to Medicare Part B. We calculate average line payment, average number of quarters active, average number of HCPCS products sold, and average MSAs active for each type of firm.

We also find significant variation in which product categories have a high share of fraudulent markets. Table 2 presents the total number of claims 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 of Fraud by Product Category Prior to Introduction of Competitive Bidding (2008-2010)

Category	**Total Payment**	**Fraudulent Payment**	**Share Fraud**
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%
Standard Wheelchairs	$999M	$218M	21.83%
Enteral Nutrition	$1.21B	$2.61B	21.55%
Hospital Beds	$566M	$125M	22.07%
Patient Lifts	$97.5M	$15.9M	16.35%
Walkers	$221M	$46M	20.83%
Commode Chairs	$103M	$727M	22.07%
Support Surfaces	$250M	$31.5M	12.60%
Off-the-shelf Back Braces	$4.12M	$231.9K	5.63%
NPWT Pumps	$414M	$81.4M	1.97%
Off-the-shelf Knee Braces	$4.24M	$145.2K	3.42%
TENS Devices	$132M	$2.07M	1.57%

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

5 Empirical Results

5.1 Empirical Strategy

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.[4]

For traditional TWFE results, we estimate

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

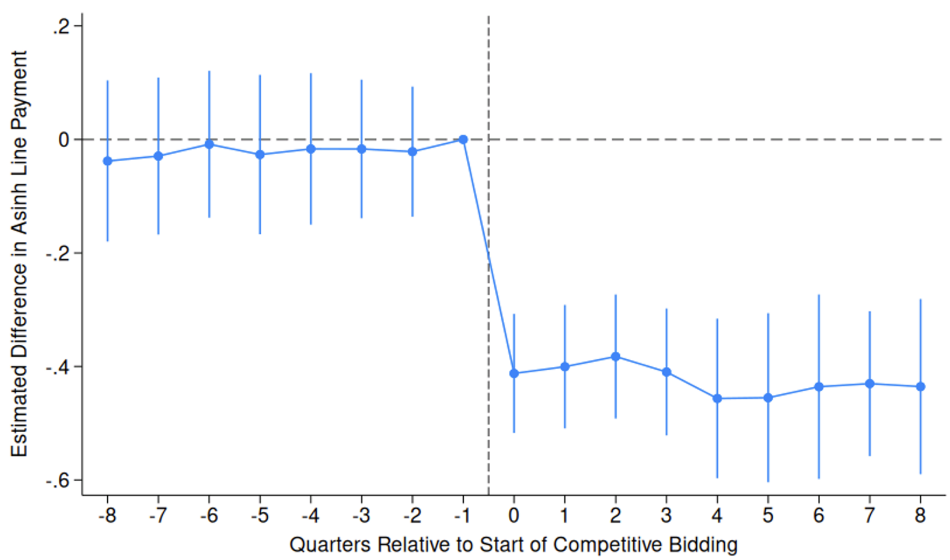
[4] We drop any HCPCS in the category of power mobility devices due to a change in regulations around the same time as the introduction of competitive bidding.

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.

5.2 Results

We first consider the effect of competitive bidding on total revenue. Firm revenues decrease by about $10,000, on average, 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 Equation (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%, amounting to a decrease of about $10,000 in Figure A1. We find that the effect of competitive bidding was large, immediate, and persistent.

Figure 4: Effect on Payments



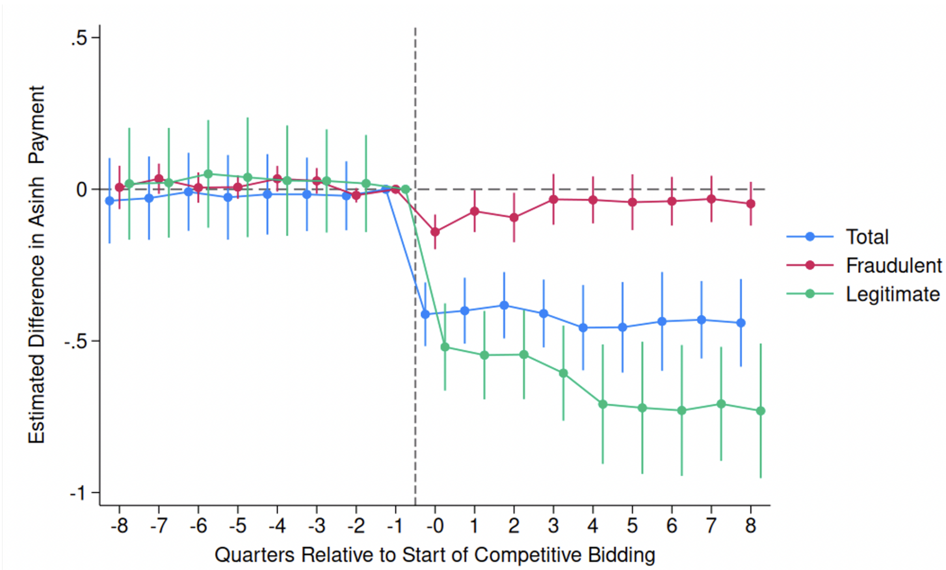
Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation (1). Dependent variable is total line payment transformed by taking the inverse hyperbolic sine. The data include payments from 2008 to 2019. An observation is an MSA-HCPCS-Quarter. Standard errors are clustered at the MSA-HCPCS level. 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 Figure A3. In terms of quantities, Figure A4 shows claims decrease by an average of 15%, or about 40 claims in Figure

A5.

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. Re-estimating our difference-in-differences results among firms of different types, we show in Figure 5 that the revenue of legitimate firms declines 50%, whereas fraudulent firms lose less than 10% of their revenue. In dollars, Figure A6 shows total revenue losses of \$8,000 for legitimate firms compared to \$2,000 for fraudulent ones.

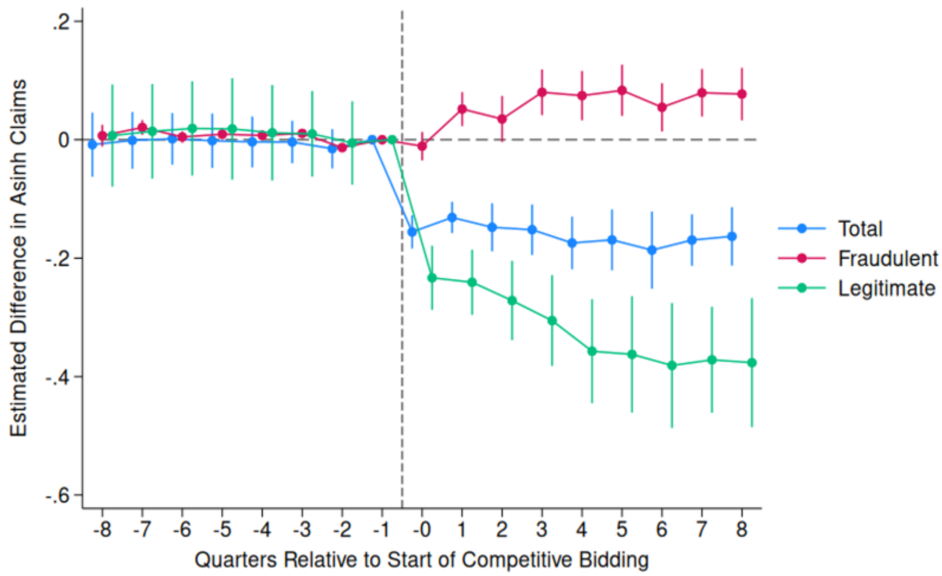
Figure 5: Effect on Payments by Firm Type



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 for 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

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

Figure 6: Effect on Claims by Firm Type

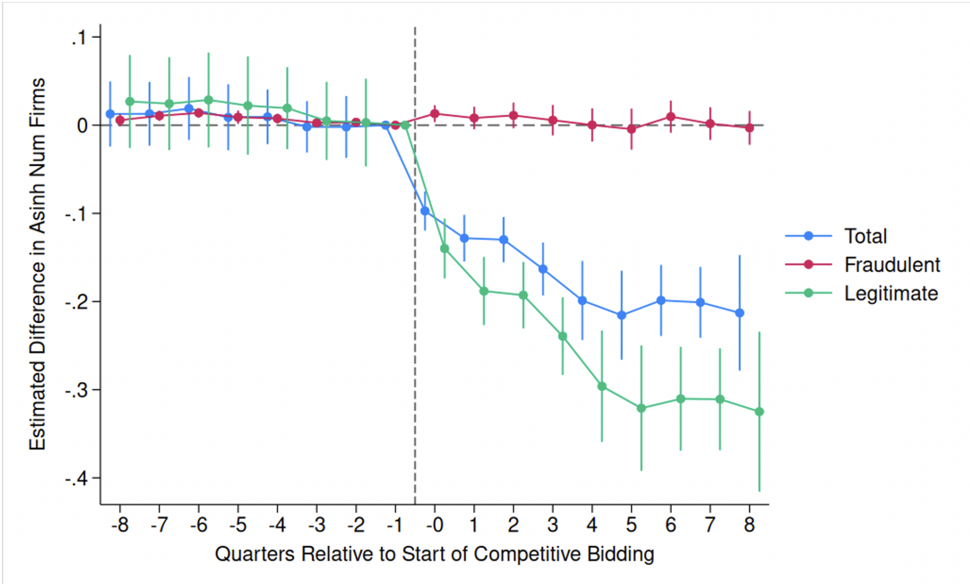


Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation (1). Dependent variable is asinh adjusted number of claims in a given market for all firms, legitimate firms and fraudulent firms, estimated separately. The data include payments from 2008 to 2019. An observation is a Firm Type-MSA-HCPCS-Quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represent the pointwise 95% confidence interval

We also 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 7, or approximately five firms per market in Figure A7. 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.

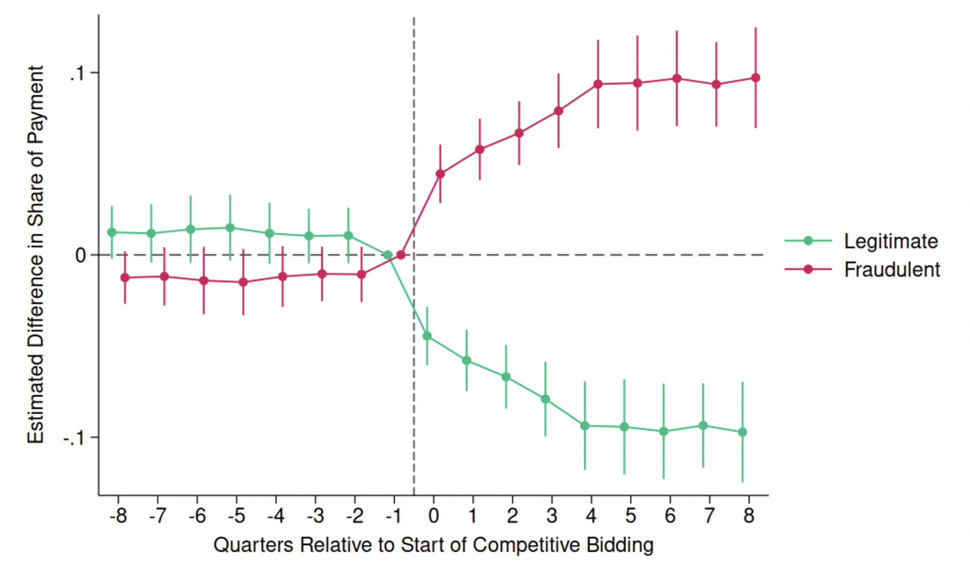
We also calculate the revenue share for legitimate and fraudulent firms within each MSA-HCPCS market for each quarter of our sample. We find fraudulent firms gain market share at the expense of legitimate firms. The estimates in Figure 8 show fraudulent firms gain nearly 10% of the revenue share, while Figure A8 shows the breakdown for sanctioned firms compared to those deemed fraudulent by our suspiciousness measures.

Figure 7: Effect on Number of Firms by Firm Type



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation (1). Dependent variable is total number of active firms transformed by taking the inverse hyperbolic sine for legitimate firms, fraudulent firms, and all firms, estimated separately. The data include firms 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 8: Effect on Market Share by Firm Type



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation (1). Dependent variable is share of line payment 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

Taken together, these results indicate that increased price competition led to a large decrease in legitimate firm activity within the DME market and a corresponding rise in fraudulent firms' market share.

6 Mechanisms

We consider three possible reasons 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 competitive bidding process. Third, we examine whether fraudulent firms have lower costs from providing lower-quality products or facilitating lower-quality matches with beneficiaries.

6.1 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 3. We define firms with lifetime revenue less than the 95th percentile, or $2,604,298, 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.

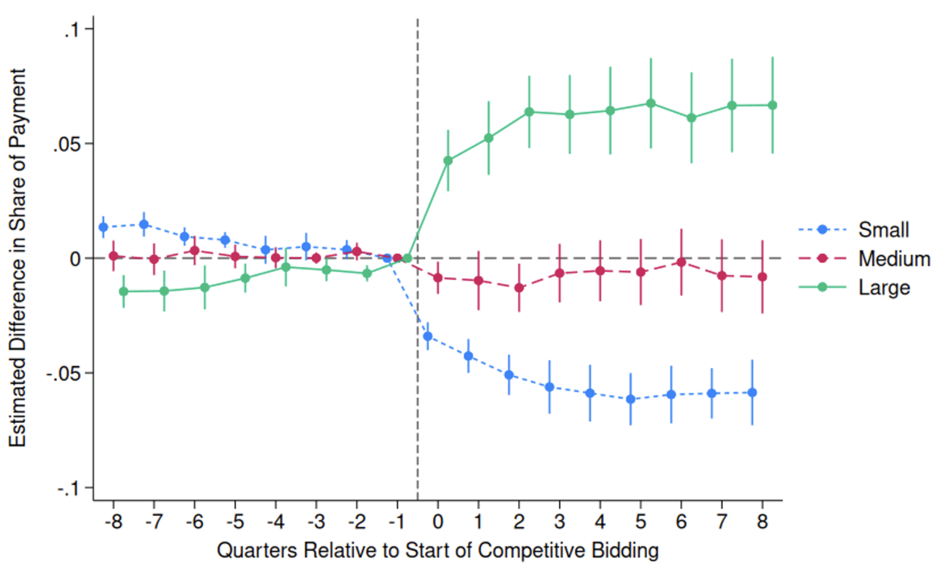
For each MSA-HCPCS market, we then calculate revenue shares by firm size and consider how these change following the introduction of competitive bidding. The results of the estimations using Equation (1) plotted in Figure 9 show that large firms gain approximately 6% market share, while small and medium firms lose approximately 5% and 1%, respectively.

Table 3: Summary Statistics of Total Line Payments

Description	**Value**
Total observations	150.764
Average payment	647,064.8
Standard Deviation	9988004
Smallest payment	0
1st percentile	0
5th percentile	71.46
10th percentile	439.05
25th percentile	4,592.16
50th percentile (Median)	88066.88
75th percentile	161,766.2
90th percentile	764,553.3
95th percentile	2,482,231
99th percentile	9.8M
Largest payment	2.53B
Categorization Counts	
Small Firms	143,225
Medium Firms	6,031
Large Firms	1,508

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.

Figure 9: Effect on Share of Line Payment by Firm Size



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation (1). Dependent variable is share of line payment in a given market for small, medium, and 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 4 summarizes the number of firms in each category.

Table 4: Counts of Legitimate and Fraudulent Firms by Size

Firm Size	**Firm Quality**	**Count**
Small	Legitimate	141,669
Small	Fraudulent	1,556
Total Small		143,225
Medium	Legitimate	4,545
Medium	Fraudulent	1,486
Total Medium		6,031
Large	Legitimate	976
Large	Fraudulent	532
Total Large		1,508

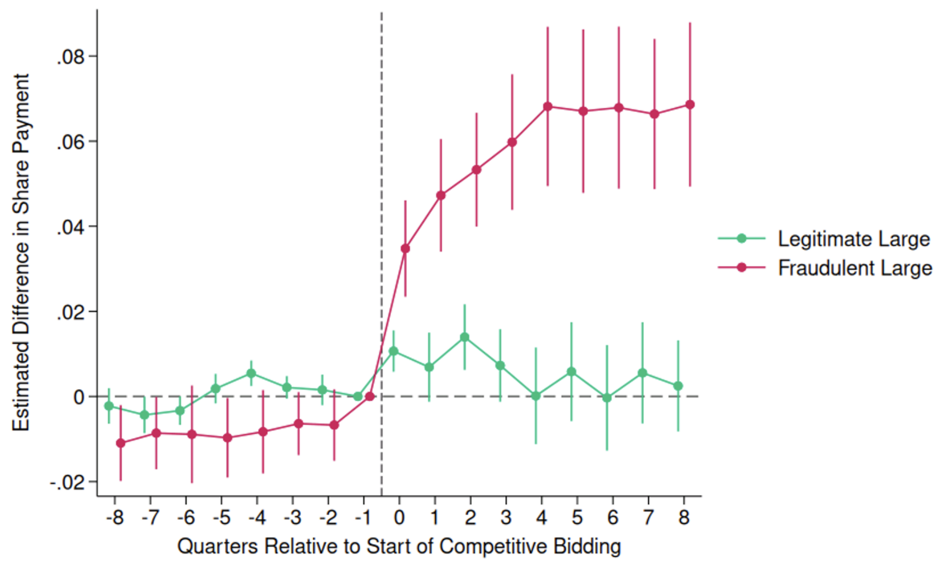
Notes: Sample here includes all firms that have submitted a DME claim to Medicare Part B from 2008 to 2019. Firms are considered fraudulent if they have been sanctioned for fraud or are suspicious by at least one of our suspiciousness measures. We group firms by size using percentile of lifetime revenue.

For each MSA-HCPCS market for each quarter, we then 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 10 shows that large fraudulent firms gain 7% market share compared to no change for large legitimate firms. Figure A9 shows this relative comparison of market share effects across fraudulent and legitimate firms also holds among medium- and small-size firms; fraudulent medium firms gain, legitimate small and medium firms lose, and fraudulent small firms experience no change in market share.

6.2 Bidding Behavior

We next examine whether fraudulent firms engage in undesirable behavior during the bidding process, such as lowballing or colluding on bids. As median price auctions 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 they participate in, where an auction is a

Figure 10: Effect on share of line payment for big firms



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation (1). Dependent variable is share of line payment in a given market 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.

bidcycle, product market (HCPCS[5]), geography (MSA[6]), and type of bid (rental or purchase). Over the two bidcycles, we have 20,219 unique auctions. Each firm submits a price at which they would supply the product in that geography, as well as an estimated capacity. CMS awards contracts to the firms with the lowest bids whose estimated total capacity meets current market demand.

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

[5]Here we also include the product category to define the auctions since a few HCPCS parts belong to both regular wheelchairs and power wheelchairs

[6]Also called a CBA or Competitive Bidding Area.

removing a second set of common words. 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.[7] 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.

Using this set of matches, we first measure whether fraudulent firms disproportionately participate in the auctions. We consider a bidder fraudulent if they match to at least one fraudulent NPI. Of the 3,061 matched bidders, we find 356 that match to at least one fraudulent NPI; at 11.6%, this rate is much higher than the 2.0% of firms found to be fraudulent in the claims data.

Fraudulent bidders also participate in more auctions than legitimate bidders do. On average, a bidder participates in 468 auctions, split into 1,019 auctions for fraudulent bidders and 395 for legitimate ones.

We find mixed evidence that fraudulent and legitimate firms bid differently within an auction. For each auction, we first normalize the bids. For the round one bid cycle, we use fee schedule prices from 2008, which acted as a cap on bids for each product to normalize the bids.[8] For the second bidcycle, we use fee schedule prices from 2012. We divide each bid by the relevant fee schedule price to normalize the bid. The maximum possible bid was the fee schedule price from the previous year, so the maximum normalized bid is one.[9]

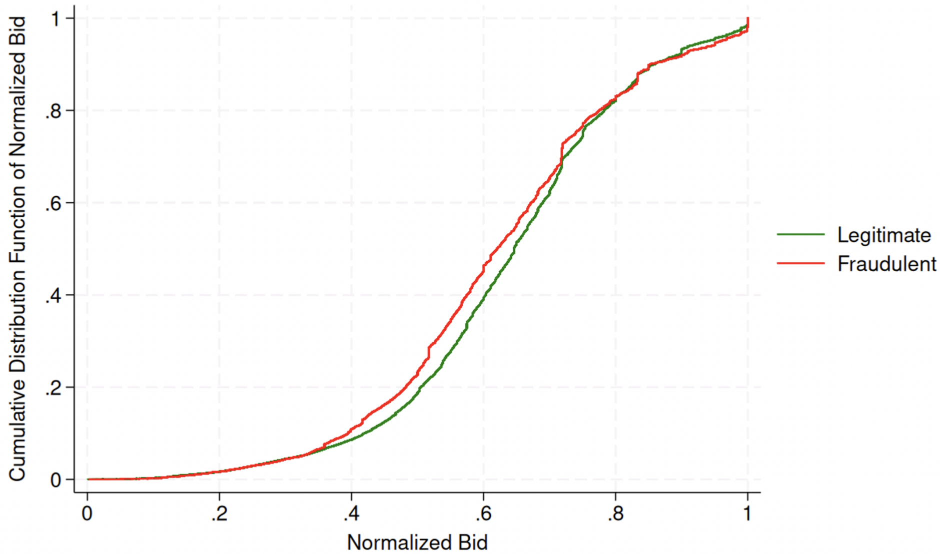
We plot the cumulative distribution function of the normalized bids in Figure 11 for fraudulent and legitimate firms. The distribution of submitted bids is nearly identical, although fraudulent firms submit slightly lower bids on average. In particular, we find no evidence that fraudulent firms were more likely to submit very low bids. That is, while fraudulent firms were much more likely to participate in the auctions, the bid similarly to legitimate firms while participating. As opposed to the unusual auction format disproportionately favoring fraudulent firms, our findings suggest instead that their willingness to participate in a market with greater price competition better explains their increase in market share.

[7]Please see Appendix D for more details.

[8]We ignore geographies here and use the maximum price of the product found in the fee schedule across states as the maximum possible bid.

[9]For a few products the fee schedule price is missing. In these cases we use the maximum bid submitted to normalize.

Figure 11: 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.

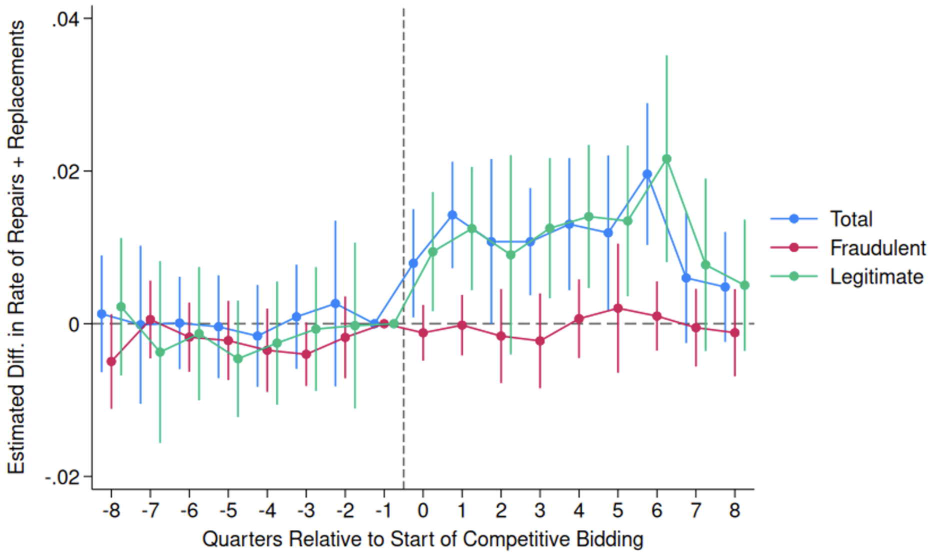
6.3 Quality

Finally, we consider differences in quality to better understand why fraudulent firms benefit from competitive bidding. We focus on two measures of quality: (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 1%, as shown in Figure 12. The increase stems mostly from legitimate firms, however, as the share of repair claims for fraudulent firms remains unchanged.

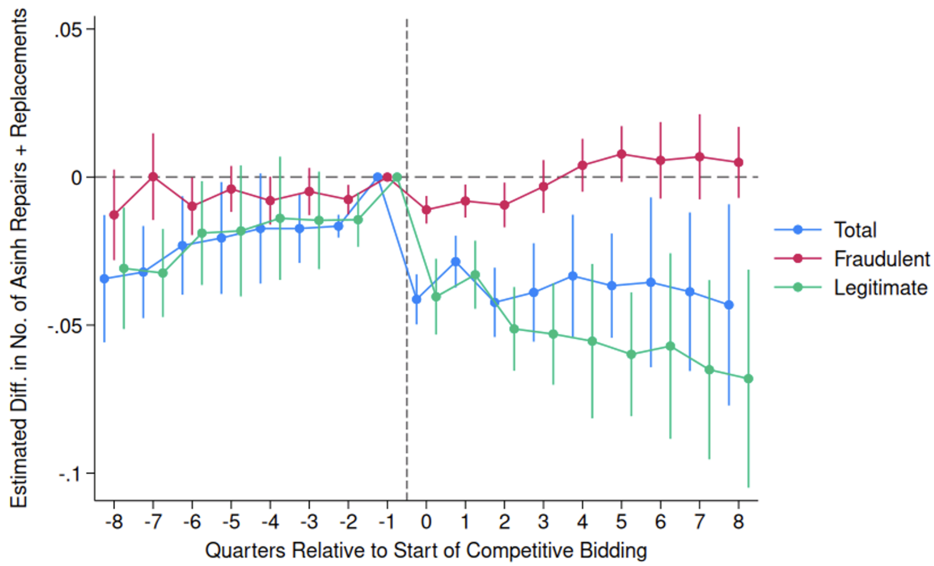
Figure 13 plots estimates for changes in asinh total repairs and replacements. We find that total replacements and repairs decrease by 5% and 6% for legitimate firms, respectively, and find no change in replacements and repairs for fraudulent firms. Taken together, these results suggest the quality of 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 12: Change in Repair Rate



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation (1). Dependent variable is the share of repairs and replacements by legitimate, fraudulent, and all firms, out of claims filled by each respective type. Each 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 represent the pointwise 95% confidence interval.

Figure 13: Change in Asinh Repairs and Replacements

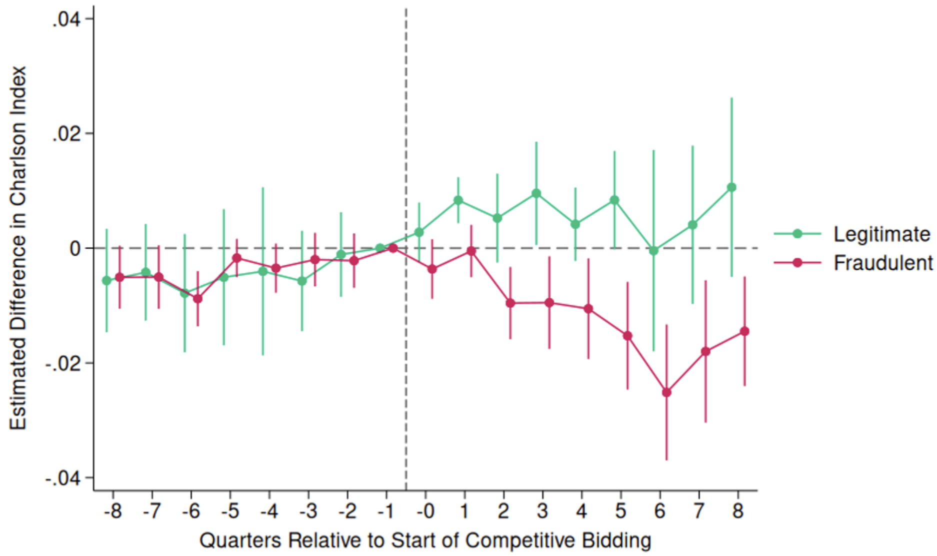


Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation (1). Dependent variable is the asinh transformed number of repairs and replacements by legitimate firms, fraudulent firms and all firms, estimated separately. The data include payments from 2008 to 2019. An observation is a Firm Type-MSA-HCPCS-Quarter. 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 calculate a version of the Charlson Comorbidity Index for each beneficiary receiving DME for each year using the Medicare Chronic Conditions file. We include all diagnoses that are traditionally included in the Charlson index, but we exclude those not found in the chronic conditions file as well as age. We merge the index into the claims data and calculate the average Charlson index value for a given HCPCS-MSA quarter observation, averaging across all submitted claims. We estimate regressions at the HCPCS-MSA-quarter level and weight by the number of claims.

We find some evidence that the average patient served by a fraudulent firm has a lower Charlson index following the start of competitive bidding compared to the average patient served by a legitimate firm. In the quarter before competitive bidding, the average Charlson index for claims served by a legitimate firm is 2.42, while the average Charlson for claims served by a fraudulent firm is 2.33. After competitive bidding, the gap widens further, with the average Charlson index for fraudulent claims declining by 0.02.

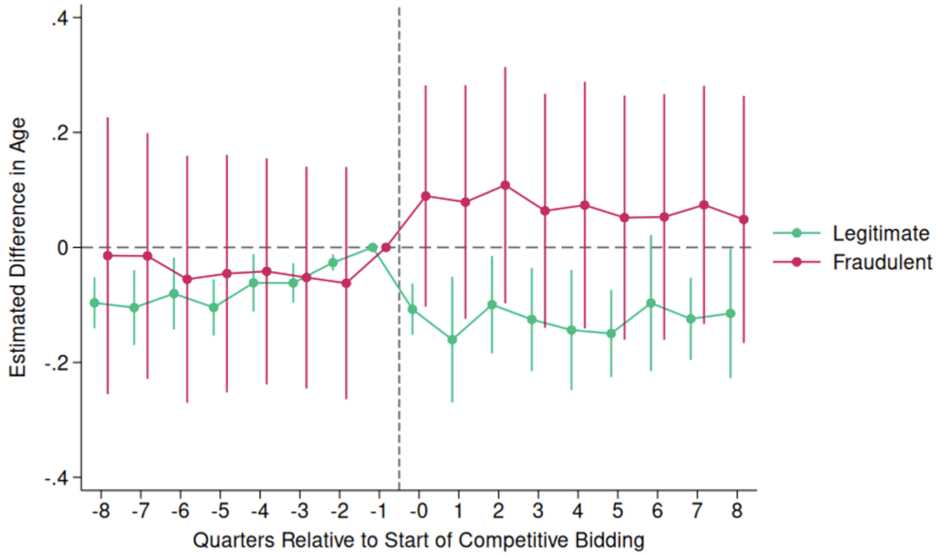
Figure 14: Change in Charlson Comorbidity Index by Firm Type



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation (1). Dependent variable is the average Charlson index across claims from legitimate firms, fraudulent firms and all firms, estimated separately. 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.

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 Charlson index value for a given 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 73.46 compared to an average age of 72.49 for fraudulent firms. After competitive bidding, fraudulent firms shift to serving older patients and legitimate to serving younger patients.

Figure 15: Change in Beneficiary Age Served by Firm Type



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation (1). Dependent variable is the average age of beneficiary across claims from legitimate firms, fraudulent firms and all firms, estimated separately. 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 represents the pointwise 95% confidence interval.

7 Model

In this section, we model the relationship between competition and fraud and estimate it empirically. In addition to highlighting the way that competition may select for fraudulent or non-fraudulent firms, or may affect the intensity of fraud committed by fraudulent firms, the model allows us to empirically estimate the share of inappropriate patients in each market.

Consider two types of patients, appropriate and inappropriate, depending on whether they meet Medicare's criteria for needing DME, and two types of firms, legitimate and fraudulent, where fraudulent firms are willing to induce inappropriate patients to use their services while legitimate firms are not. Each DME supplier s is endowed with a level of quality δ_s and marginal cost d_s and fraudulent firms choose in each period t a quantity of inappropriate patients q^I_{st} to induce at a cost $c(q^A_{st}, q^I_{st})$. This cost function is increasing and convex in the quantity of inappropriate patients and depends on the quantity of appropriate patients because, for example, the likelihood of being sanctioned may depend on the share of patients who are inappropriate rather than just the quantity. The cost of inducing no inappropriate patients is zero. Both fraudulent and legitimate firms choose whether to participate in the market. All firms face a common price p_t and may also serve q^A_{st} appropriate patients, where p_t is given exogenously and

q_{st}^A is determined by patient demand. Thus, the profit function of DME supplier s is given by

$$\Pi_{st} = (p_t - d_s)(q_{st}^A + q_{st}^I) - c(q_{st}^A, q_{st}^I),$$

so fraudulent firms choose q_{st}^{I*} such that

$$p_t - d_s = \frac{\partial c}{\partial q_{st}^I}(q_{st}^A, q_{st}^{I*}),$$

or the marginal revenue from inducing an additional inappropriate patient equals the marginal cost of doing so. Firms choose to participate in the market if their profits are non-negative when choosing q_{st}^{I*}.

The supply side model has several noteworthy implications for the relationship between competition and fraud. First, holding the number of appropriate patients constant, higher margins will lead fraudulent firms to induce more inappropriate patients. This is true for high margins that come from both low costs or high prices and captures the intuition that the large rents stemming from limited price competition induce more fraud. On the other hand, the effect of changing the margin is ambiguous if the cost of inducing an additional inappropriate patient depends on the quantity of appropriate patients.[10] The effect of competition on fraud therefore depends not only on how it affects price but also how it affects the reallocation of appropriate patients across firms. Finally, because firms face a non-negative profit constraint, changes to the level of competition that reduce price will select for lower-cost firms. If fraudulent firms are lower cost, increased competition will benefit them at the expense of legitimate firms.

On the demand side, appropriate patient i decides which DME supplier s in the market to use (if any) by choosing the option that maximizes

$$U_{is}^A = \delta_s + \varepsilon_{is},$$

where δ_s is the average quality of the DME from supplier s and ε_{is} is the taste shock to patient i for supplier s.

7.1 Estimation

We parameterize the model to take it to the data. First, we assume that ε_{is} is distributed type-1 extreme value with a correlation structure such that appropriate patients have separate nests on the outside option (which we normalize to zero) and all inside options with nesting parameter θ.

In line with the evidence presented in Section 6.3 that the composition of patients served by

[10]Note that $\frac{\partial q_{st}^{I^*}}{\partial (p_t - d_s)} = \left(\frac{\partial^2 c}{\partial q_{st}^I \partial q_{st}^I} + \frac{\partial^2 c}{\partial q_{st}^I \partial q_{st}^A} \frac{\partial q_{st}^A}{\partial (p_t - d_s)} \right)^{-1}$.

fraudulent firms after competitive bidding did not change, we assume that the share of fraudulent firms' business represented by inappropriate patients is unchanged in response to competitive bidding, and for simplicity we also assume that this share is constant across fraudulent firms (i.e., $\frac{q^I_{st}}{q^L_{st}+q^I_{st}} = \phi$ for all s and t.)[11]

Denoting the set of DME suppliers s in the market in period t that are legitimate as $\mathcal{G}_t$ and fraudulent as $\mathcal{B}_t$, the market share of supplier s in period t is given by

$$\sigma_{st} = \begin{cases} \frac{\exp\left(\frac{\delta_s}{\theta}\right)\left(\sum_{j\in\mathcal{G}_t\cup\mathcal{B}_t}\exp\left(\frac{\delta_j}{\theta}\right)\right)^{\theta-1}}{1+\left(\sum_{j\in\mathcal{G}_t\cup\mathcal{B}_t}\exp\left(\frac{\delta_j}{\theta}\right)\right)^{\theta}} & \text{if } s\in\mathcal{G}_t \\ \frac{\exp\left(\frac{\delta_s}{\theta}\right)\left(\sum_{j\in\mathcal{G}_t\cup\mathcal{B}_t}\exp\left(\frac{\delta_j}{\theta}\right)\right)^{\theta-1}}{(1-\phi)\left(1+\left(\sum_{j\in\mathcal{G}_t\cup\mathcal{B}_t}\exp\left(\frac{\delta_j}{\theta}\right)\right)^{\theta}\right)} & \text{if } s\in\mathcal{B}_t \\ 0 & \text{otherwise} \end{cases}.$$

Absent fraudulent firms, this demand system could be estimated with MLE using the market shares of each firm, with firms with higher quality δ_s commanding larger market shares. Because fraudulent firms' market shares are inflated by $\frac{1}{1-\phi}$, however, we cannot tell in the cross-section if fraudulent firms are large because they provide high-quality DME to appropriate patients (i.e., high δ_s) or commit lots of fraud (i.e., high ϕ). Nonetheless, we can use variation in patients' choice sets induced by the introduction of competitive bidding to separate these two explanations. In particular, we can use the differential substitution patterns of appropriate and inappropriate patients when their firm exits: appropriate patients will be reallocated to firms in accordance with their true quality δ_s while inappropriate patients will substitute to the outside option. Thus, we can separately identify ϕ and δ_s for all firms.

7.2 Results

We estimate this model for the market for hospital beds in the Charlotte-Gastonia-Concord, NC-SC competitive bidding area. We consider two periods t: the two years before and after competitive bidding was introduced in this market (2009–2010 and 2011–2012) and report estimates in Table 5. We find that 89% of fraudulent firms' patients are inappropriate, meaning that even though their quality is much lower than legitimate firms' on average, their market share is artificially large. We estimate that while the market share of fraudulent firms went from 39% to 54% following competitive bidding, the share of inappropriate patients in the market rose from

[11] This result can be generated by, for example, the cost function

$$c(q^A_{st}, q^I_{st}) = \begin{cases} 0 & \text{if } \frac{q^I_{st}}{q^L_{st}+q^I_{st}} \le \phi \\ C^2 q^I_{st} & \text{if } \frac{q^I_{st}}{q^L_{st}+q^I_{st}} > \phi \end{cases}$$

where C is some large constant.

35% to 48%. In fact, the *number* of inappropriate patients receiving DME rose 17%, while the number of appropriate patients fell by 33%. This means that for this market where the total number of patients served fell by 16%, more than 100% of this reduction came from legitimate patients, with the increase in fraud partially offsetting the reduction in appropriate patients served. In this proof-of-concept market, we see that not only did fraudulent firms increase their market share, the amount of fraud increased as well.

Table 5: Demand Parameter Estimates

Illegitimate Patient Share ϕ	0.888
Nesting Parameter θ	1.000
Fraudulent Firm Quality δ_s	
Mean	-9.55
Std. Dev.	1.18
Non-Fraudulent Firm Quality δ_s	
Mean	-7.25
Std. Dev.	0.64

Notes: Estimated using market shares in terms of number of unique patients given DME in the "Hospital Beds" product category in the Charlotte-Gastonia-Concord, NC-SC competitive bidding area in 2009–2010 and 2011–2012. Standard errors given in parentheses.

8 Conclusion

We find that greater price competition leads to more fraud. Using novel data on fraudulent DME suppliers, we show that fraudulent firms increase their market share by 10% after Medicare introduced competitive bidding. Larger fraudulent firms benefit the most, as these firms use 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 choose to participate in auctions and compete on price but do not appear to bid differently than legitimate firms. Increased competition did not lead to meaningful within-firm changes in the quality of the equipment 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.

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 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 first group NPIs using owner names. We use first and last name to create initial firm groups; if there are name groups that have conflicting middle names that may indicate multiple people with the same first and last name, we then include middle initial or middle name to differentiate those groups further.

Case 1: We match owners by name, initially using just first and last name. If there is just one person with that first and last name, we consider all NPIs owned as a single firm. i.e. All firms owned by Thomas Smith are considered an entity. If one NPI owned by Thomas Smith is a sanctioned fraudulent firm, the other NPIs are labeled suspicious.

Case 2: If there exists Thomas Smith and Thomas A. Smith, we ignore the middle initial.

Case 3: If there exists Thomas Smith, Thomas Adam Smith, and Thomas A. Smith, we ignore the middle initial.

Case 4: If there exists Thomas Smith, Thomas A. Smith, and Thomas B. Smith, we include the middle initial. We also consider Thomas Smith as a separate firm since we cannot know whether Thomas Smith should be grouped with Thomas A. Smith or Thomas B. Smith.

Then, within each group of NPIs that we consider likely 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.

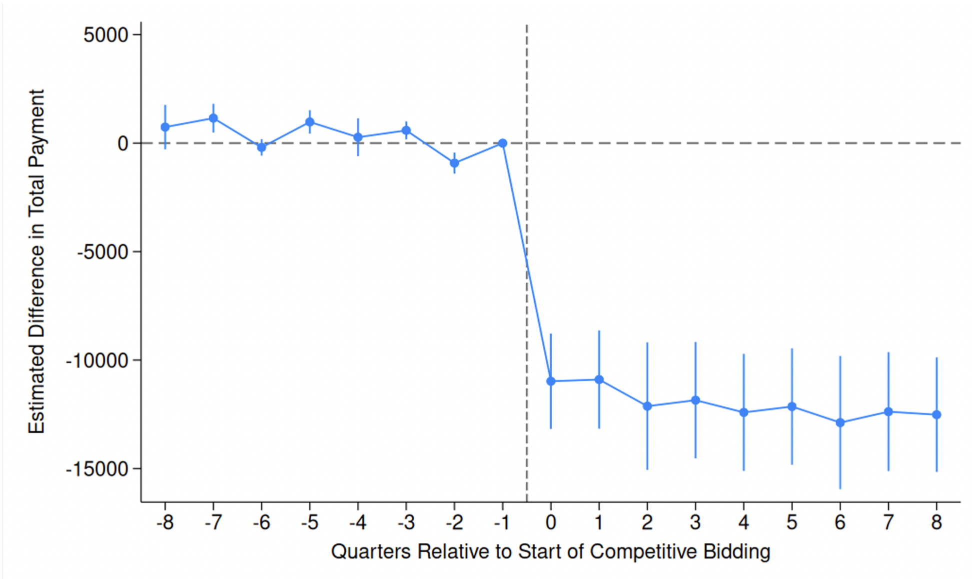
We construct a multidimensional grid by iterating over these measures at various percentile thresholds, defined using the dataset of tagged firms — those identified as fraudulent or suspicious by the initial three methods. For each supplier-referrer pair, we determine whether their connection constitutes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

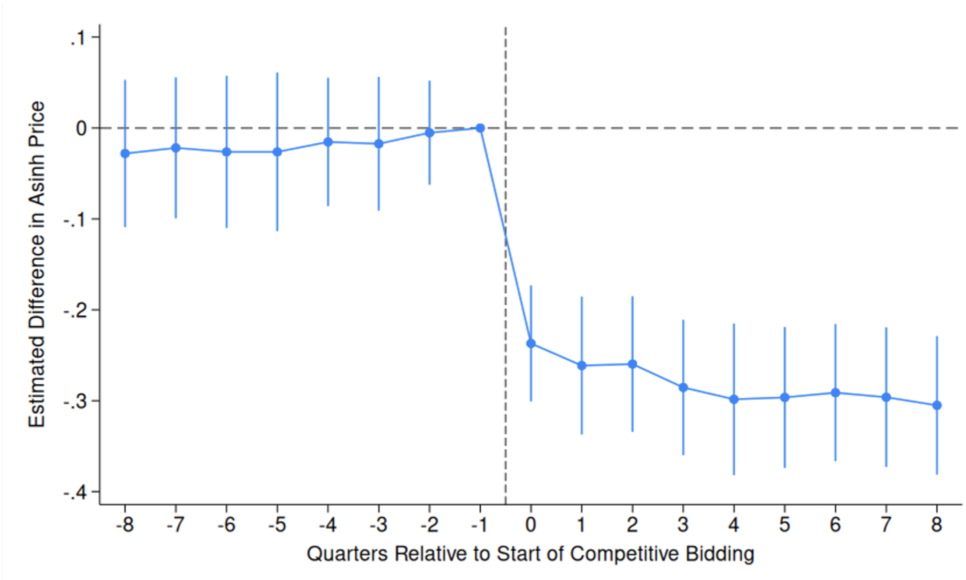
B Appendix Results Figures

Figure A1: Effect on line payment



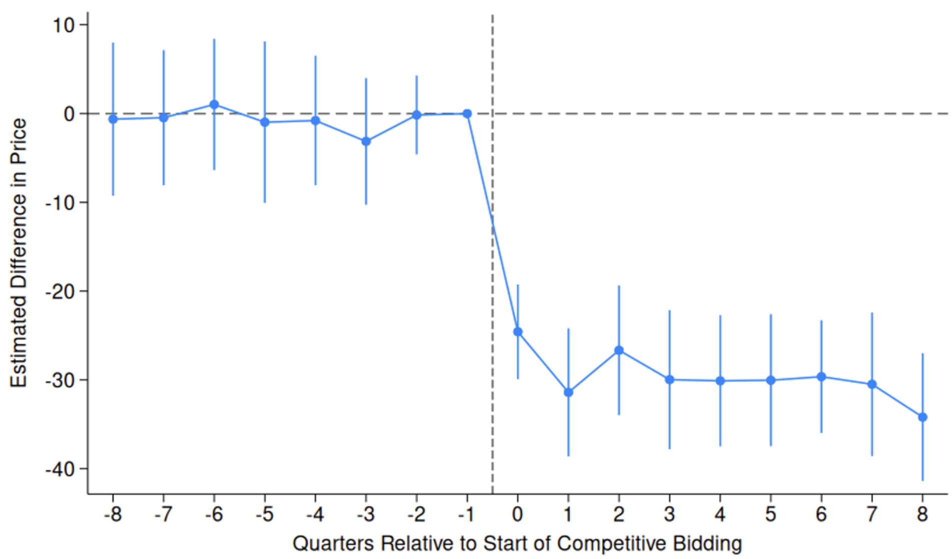
Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Dependent variable is total line payment in a given market. The data include payments from 2008 to 2019. An observation is a Firm Type-MSA-HCPCS-Quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represents the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

Figure A2: Effect on asinh prices



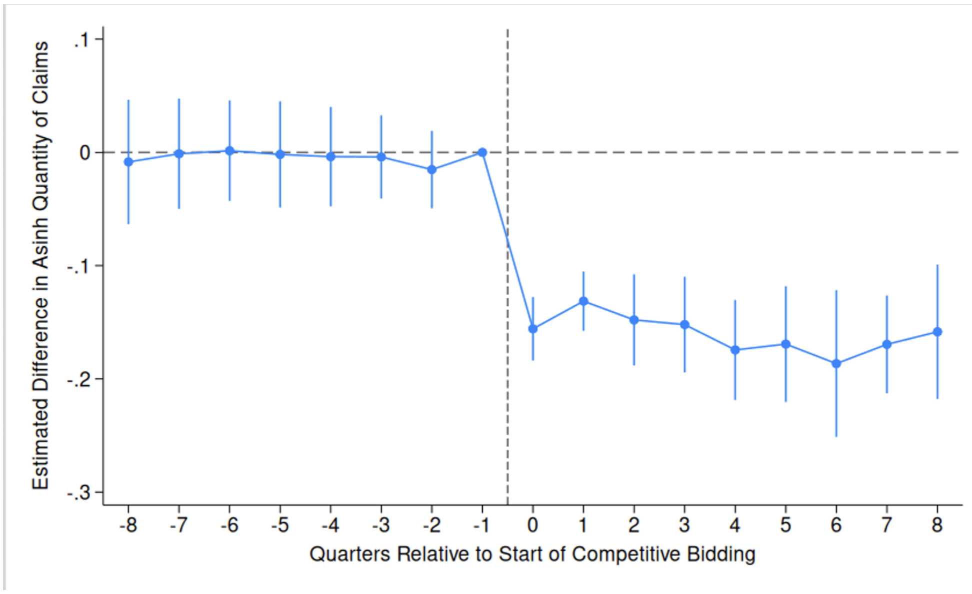
Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Dependent variable is asinh transformed price in a given market. The data include payments from 2008 to 2019. An observation is a Firm Type-MSA-HCPCS-Quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represents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

Figure A3: Effect on prices



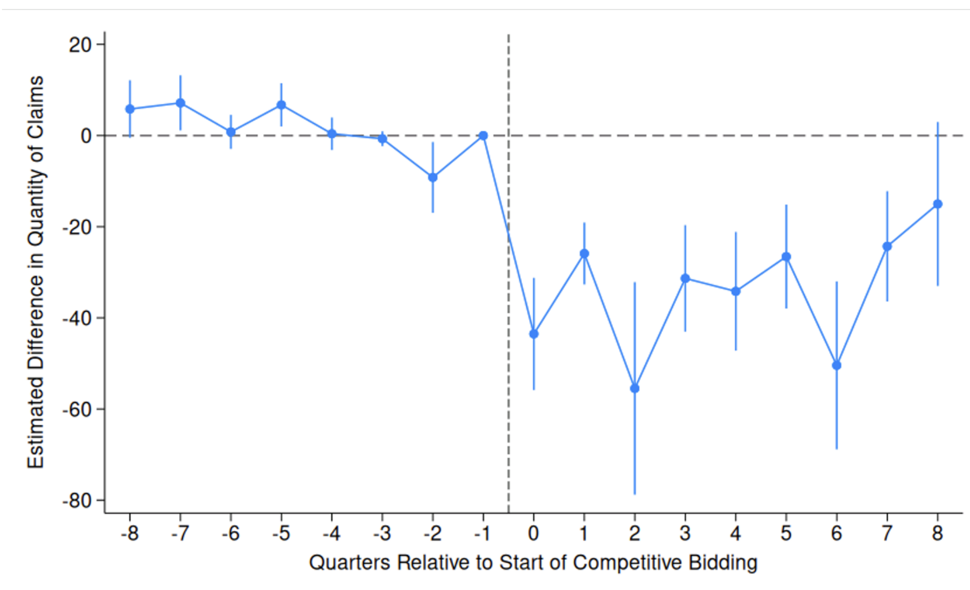
Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Dependent variable is price in a given market. The data include payments from 2008 to 2019. An observation is a Firm Type-MSA-HCPCS-Quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represents the pointwise 95%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

Figure A4: Effect on asinh quantity of claims



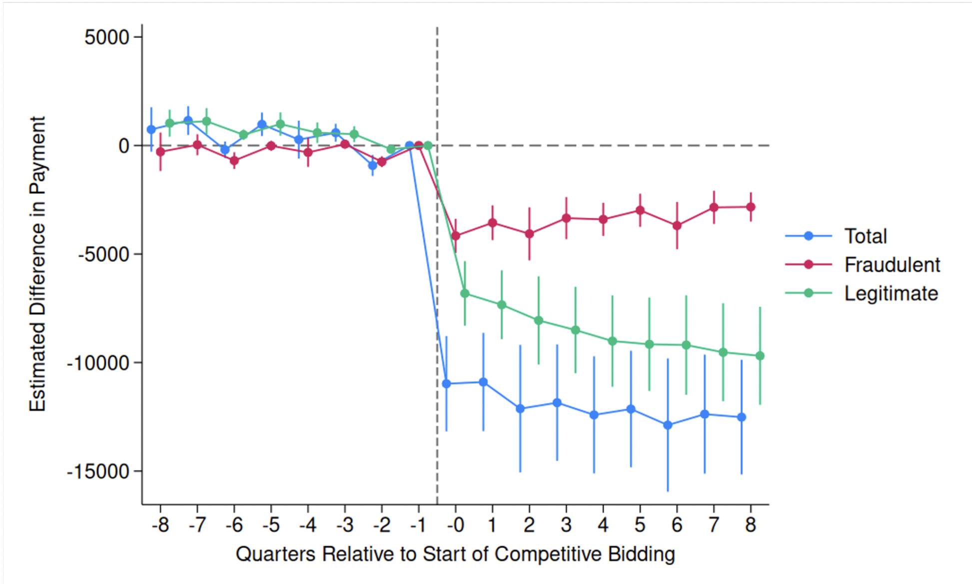
Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Dependent variable is asinh transformed number of claims in a given market. The data include payments from 2008 to 2019. An observation is a Firm Type-MSA-HCPCS-Quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars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

Figure A5: Effect on quantity of claims



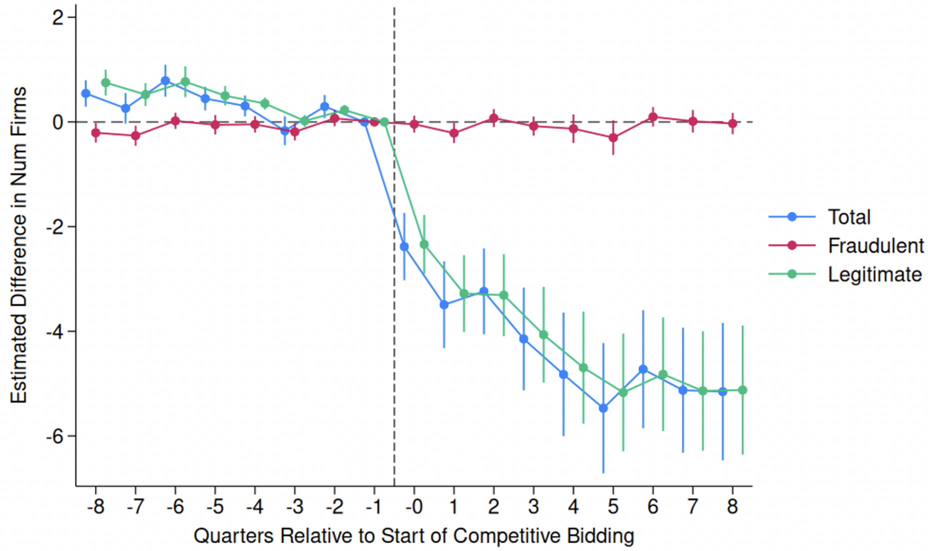
Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Dependent variable is total number of claims in a given market. The data include payments from 2008 to 2019. An observation is a Firm Type-MSA-HCPCS-Quarter. Standard errors are clustered at the MSA-HCPCS level. Error bars represents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

Figure A6: Effect on line payment by firm type



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Dependent variable is total line payment in a given market paid to all firms, 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 represents the pointwise 95% confidence interval.

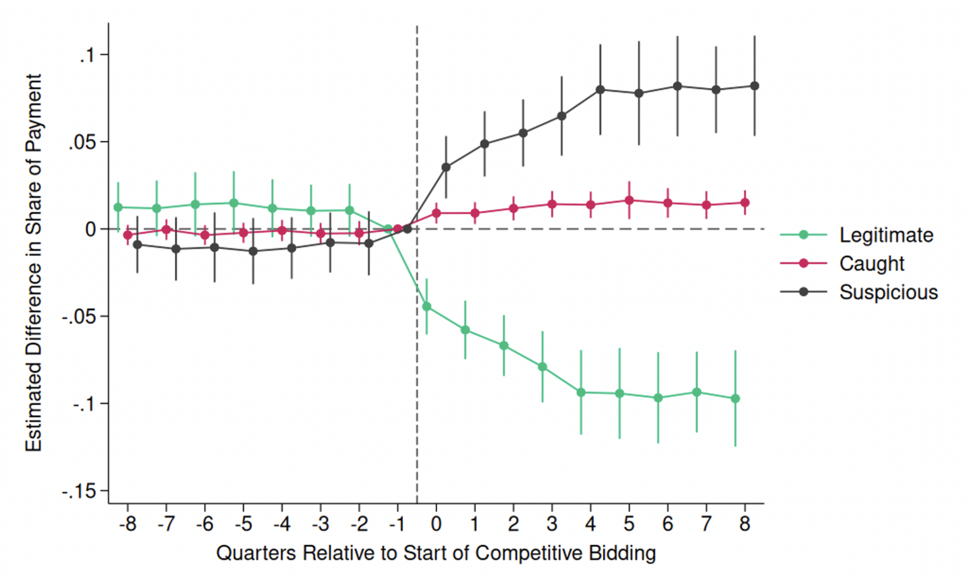
Figure A7: Effect on number of firms by firm type



Notes: Estimates of β_e for $e \in [-8, 8]/\{-1\}$ from equation 1. Dependent variable is number of firms in a given market. 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.

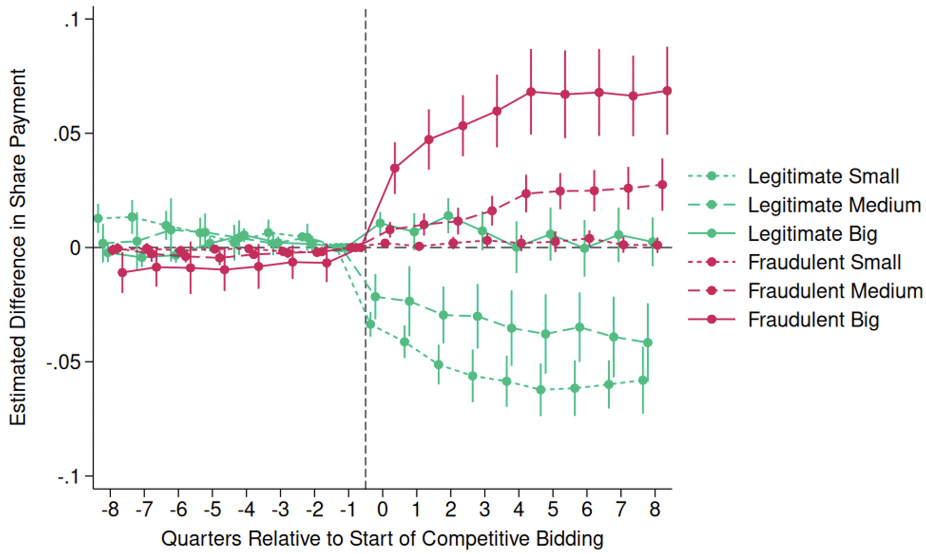
C Detailed Breakdown of Market Share

Figure A8: Effect on share of line payment 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.

Figure A9: 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.

D Details on Matching Bidder Names to NPIs

We first 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 A2: First set of excluded words for name matching

INCORPORATED	PLLC	LLC
INC	CORPORATION	CORP
CO	LIMITED	LTD

Table A3: Second set of excluded words for name matching

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

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