Can Competitive Bidding Work in Health Care? Evidence from Medicare Durable Medical Equipment

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Abstract

Prices are a significant driver of high health care spending in the US, but how to reduce prices remains an open question. I examine one widely-touted solution – setting prices via competitive bidding – in the context of a Medicare payment reform. The reform gradually replaced administratively-set prices with prices from competitive bidding for durable medical equipment (DME) in 100 metropolitan statistical areas. Using detailed claim-level data, I estimate that the competitive bidding program reduced the prices of covered items by 45%. However, the program also generated an 11% reduction in quantity, which several pieces of evidence suggest is associated with inefficient supply shortages. One likely cause of the shortage is the auction design, which allows winning bidders to renege on supply commitment. Leveraging novel bid data, I estimate an equilibrium model of optimal bidding and find that the program generated prices that were on average 7% below the market clearing price, which is consistent with the observed supply shortages. I use the results to show that counterfactual auction designs could reach the desired market quantity while saving 42% in government spending relative to administratively-set prices. The analysis highlights the importance of auction design in achieving desirable outcomes, and suggests that a well-designed competitive bidding program could potentially generate large savings in health care.

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1 Introduction

As health care spending reaches 18 percent of U.S. GDP—almost twice as much per capita as other developed countries—the financial sustainability of the health care system has become a pressing policy question (Anderson et al. 2005, Emanuel et al. 2012, Kesselheim, Avorn and Sarpatwari 2016, Papanicolas, Woskie and Jha 2018). Academics and policy makers are increasingly pointing to prices as a potential culprit of high health care spending, and are calling for solutions that improve pricing efficiency (Sinaiko and Rosenthal 2011, Emanuel et al. 2012, Cooper et al. 2018, Papanicolas, Woskie and Jha 2018, Verma 2018). One widely touted solution is the use of competitive bidding to set prices for health care services, allowing competition among providers to drive down the prices faced by public payers and patients (Emanuel et al. 2012, Song, Cutler and Chernew 2012).

The use of competitive bidding in health care has become increasingly common in recent years in both insurance plan contracting and service reimbursement. Many public insurers, including Medicare and Medicaid, have been using competitive bidding to set payments for their managed care programs (Layton, Ndikumana and Shepard 2018, Curto et al. 2021). Competitive bidding had been proposed for payments for clinical lab tests and for physician-administered drugs (Martin and Sharp 2018, MedPAC 2018). Similar programs also exist outside the US, for example, in the English National Health Service to procure community-based care and in the Chinese prescription drug procurement program (Frosini, Dixon and Robertson 2012, Cao, Yi and Yu 2021).

In this paper, I provide empirical evidence on the impact of the introduction of competitive bidding in health care. I focus on the Medicare durable medical equipment (DME) sector, which provides prescription medical devices for home use. Common examples of DME include glucose monitors, wheelchairs, and oxygen concentrators. One in every four Medicare beneficiaries uses DME, making it important to understand DME pricing and utilization as they affect the health and welfare of a substantial share of the US population.[1] Like the majority of products and services covered by public insurers, DME was traditionally paid based on administratively set prices. Starting in 2011, the Centers for Medicare and Medicaid Services (CMS) began to set DME prices based on competitive bidding in what eventually became 100 metropolitan statistical areas (MSAs), while con-

[1] Author's analysis of Medicare claims data.

tinuing to pay administratively-set prices in the remaining MSAs (MedPAC, 2018).

I start by estimating the impact of the DME competitive bidding program using detailed administrative data from the 100% Medicare enrollment and claims files from 2009-2015. The analysis employs a difference-in-differences strategy that compares prices and utilization in areas where competitive bidding replaced administrative pricing to those in areas where administrative pricing remained in place until the end of the study period. I find a 45% reduction in the price of the included items as well as a 11% reduction in utilization, measured by the share of beneficiaries using these items. This simultaneous reduction in price and quantity suggests a movement down the supply curve and the creation of a supply shortage.[2]

Furthermore, several pieces of evidence suggest that the allocation of the reduced quantity of DME across patients appears inconsistent with what one might expect under an efficient allocation. First, the marginal utilization eliminated under competitive bidding does not appear to generate lower surplus. For instance, I find comparable declines in utilization among patients who are new to DME (i.e. new equipment use and presumably higher surplus) and those who have received the same DME in the past (i.e. replacement or upgrade and presumably lower surplus). Similarly, I find that the marginal patient rationed out of DME under competitive bidding is not healthier, but is older, less likely to be white, and more likely to be on Medicaid (a measure of low resources). Furthermore, I show that patients discharged from an inpatient setting experience delays in DME use, which is consistent with temporal allocative inefficiencies arising from increased difficulty in obtaining the necessary DME when it is in short supply.

One plausible cause of this supply shortage is the auction design. In the CMS-designed auction, suppliers bid for the right to sell to Medicare beneficiaries at the auction-generated price, and CMS gives out contracts to the lowest bidders whose collective capacity – estimated based on quantities supplied in the past – satisfy the existing quantity in the market. Unlike most procurement auctions, the contracts are non-binding, effectively allowing suppliers to back out of contracts after the auction. Furthermore, CMS pays winning sup-

[2] In contrast, movement down the demand curve should result in higher, not lower, quantities. We also expect any demand response to be limited in scope since the majority of Medicare patients do not pay out-of-pocket for DME due to supplemental insurance that covers the copayment. For instance, in 2018, 83% of patients in Traditional Medicare had supplemental coverage (Koma, Cubanski and Neuman, 2021).

pliers the median of all winning bids, rather than the highest winning bid.[3]

In order to explore the mechanisms behind this quantity reduction, I specify an equilibrium model of optimal bidding and use it to estimate the underlying supplier costs in each market using the universe of supplier bids in the DME auction, which I obtained via a Freedom of Information Act request. The identification follows the spirit of Guerre, Perrigne and Vuong (2000) and exploits the mapping between the cost and the equilibrium bid provided by the bidder's optimization problem to invert the underlying cost from each observed bid. I find that the equilibrium prices generated under CMS's competitive bidding program are on average 7% below the competitive market price, leading to a supply shortage.

Given the apparent flaws of the observed DME auction design, it is useful to explore whether alternative designs could generate better outcomes. I compute equilibrium outcomes under two commonly used counterfactual auction designs—a uniform price auction where winning bidders are paid the lowest losing bid, and a pay-as-bid auction where winning bidders are paid their own bids. I find that these alternative auctions can lower prices by about 42% relative to the administrative fee schedule without generating a shortage. A back-of-the-envelope calculation suggests that 91% of the reduction in price after competitive bidding can be attributed to moving closer to the market clearing price while the remaining 9% resulted in negative profit-margins for some suppliers and consequently resulted in a supply shortage. The findings highlight the importance of auction design for achieving the desired outcome and the potential for a well-designed competitive bidding program to reduce health care prices.

This paper contributes to several related literatures. Most narrowly, this paper studies the DME market. Despite the fact that one in four Medicare beneficiaries use DME, academic research on DME is surprisingly scarce, but there have been several prior papers studying the introduction of the competitive bidding program in DME. Theoretical analysis predicted that the design of the DME auction would generate shortages (Merlob, Plott and Zhang 2012 and Cramton, Ellermeyer and Katzman 2015), consistent with time-series analysis documenting falling prices and quantities for specific, individual DME items (Cramton 2011, Cramton 2012, and Newman, Barrette and McGraves-Lloyd 2017). I expand on

[3] For example, if the 19 lowest bidders together have a capacity that meets the target quantity, CMS gives out 19 contracts but sets the price at the 10^{th} lowest bid.

this existing work in two ways. First, I analyze the universe of Medicare DME claims using a difference-in-differences framework to provide quasi-experimental evidence on the impact of the DME competitive bidding program on price and utilization. In concurrent and independent work, Ding, Duggan and Starc (forthcoming) finds similar reduced form results and explore the role of patient cost-sharing. I concentrate instead on the supply response by analyzing novel data on the universe of DME supplier bids using a structural model. My analysis provides the first empirical evidence on the DME auction design and sheds light on the allocation under counterfactual auction designs.

Somewhat more broadly, this paper complements the existing literature on the medical device market, which has examined the impact of entry regulation on consumer welfare as well as the impact of transparency and lobbying on hospitals' purchases of medical devices (Grennan and Swanson 2020, Grennan and Town 2020, Bergman, Grennan and Swanson 2021).

In addition, this paper contributes to the small but growing literature on competitive bidding in health care. Most of this literature has focused on the impact of regulatory changes to the competitive bidding system by which private insurers bid to provide private Medicare Advantage plans (Song, Landrum and Chernew 2012, Song, Landrum and Chernew 2013, Duggan, Starc and Vabson 2016, Cabral, Geruso and Mahoney 2018, Curto et al. 2021). Other papers have analyzed competitive bidding in the Chinese prescription drugs market and the European orthopaedic implants market (Cao, Yi and Yu 2021, Decarolis and Giorgiantonio 2015).

Furthermore, this paper relates to the empirical literature on procurement auctions, particularly papers that use quasi-experimental designs to study the impact of introducing competitive bidding in a market (e.g. Decarolis 2014 and Cicala 2017). This paper contributes to this literature by providing one of the first empirical analyses of the median-winning bid auction design utilized by Medicare.

Finally, this paper is related to the larger empirical literature on health care payment reform and its impacts on spending and utilization (e.g. Dafny 2005, Clemens and Gottlieb 2014, Alexander 2020, Gross et al. 2021, Gupta 2021, Einav et al. 2022). This paper contributes to this literature by providing one of the first empirical studies of a public insurer using auctions to allocate care, and by showing how auctions can be used to improve allocation and generate savings in the health care market.

The rest of the paper proceeds as follows: Section 2 provides an overview of the Medicare DME sector and its competitive bidding system and lays out a simple conceptual framework; Section 3 describes the data and summary statistics; Section 4 describes the empirical strategy and presents results on the impact of the observed competitive bidding program; Section 5 specifies a stylized model of suppliers bidding for contracts in the DME auction, presents results from the model and conducts counterfactual analysis; Section 6 concludes.

2 Setting

2.1 Durable Medical Equipment

Medicare defines DME as medical equipment that is prescribed by a physician, for home-use, and expected to last for at least three years.[4] DME, such as oxygen concentrators, wearable defibrillators, and wheelchairs, is essential to patients who receive care at home. Medicare covers a wide variety of DME products, ranging from items as small as glucose testing strips and diabetic shoe inserts to large equipment including hospital beds and patient lifts. Some types of DME are used independently (e.g. wheelchairs) while others require the relevant supplies (e.g. oxygen used with oxygen concentrators).

Medicare reimburses suppliers for DME used by beneficiaries based on the Healthcare Common Procedure Coding System (HCPCS), which is a standardized coding system for identifying health care products, supplies, and services. These codes are highly specific. For example, HCPCS code E1035 refers to "multi-positional patient transfer system, with integrated seat, operated by care-giver, patient weight capacity up to and including 300 lbs." In 2009, Medicare covered over 1,800 unique HCPCS codes in its DME fee schedule.[5] Related HCPCS codes are grouped into approximately 60 categories based on the Durable Medical Equipment Coding System Product Classification. For example, HCPCS code E1035 and seven other HCPCS codes fall into the "patient lift" category. Throughout this paper, I will use "items" to refer to unique HCPCS codes, and "product categories" or

[4] https://www.medicare.gov/coverage/durable-medical-equipment-coverage.html

[5] https://www.cms.gov/medicare/medicare-fee-for-service-payment/DMEPOSFeeSched/DMEPOS-Fee-Schedule.html

"types of product" to refer to product classifications.

DME is frequently prescribed to patients post-discharge from acute or post-acute care facilities, but certain types of DME are also often obtained following outpatient visits.[6] Not surprisingly, as I document in Section 3 below, Medicare beneficiaries who use DME are substantially less healthy and have higher health care use than non-users. To receive DME under Medicare benefits, a beneficiary needs to obtain a prescription from their physician, with which they can then obtain the relevant item from a Medicare-approved supplier. DME is covered under Medicare Part B benefits, and patients are responsible for a 20% coinsurance, which may be covered by supplemental insurance or Medicaid. The supplier is responsible for delivering the item to the patient in a timely manner.

Both retailers that specialize in DME and pharmacies that carry DME are considered "suppliers". Most DME suppliers are local or regional, and carry a selected set of products rather than the full spectrum of equipment. Appendix Table A1 reports summary statistics on Medicare DME suppliers. In 2009, the average supplier sold products from just 4.5 categories, out of the approximately 60 product categories reimbursed by Medicare. The average supplier served 168 patients from 4.6 MSAs, and received $114,069 in Medicare reimbursement.[7] In 2009, the average MSA has about 400 DME suppliers, although since most DME suppliers only carry a limited set of DME products, there are fewer suppliers for each given product category. For example, there were about 60 suppliers per MSA for oxygen equipment and about 75 for wheelchairs; among the 10 most used product categories, the average number of suppliers ranges from 29 for lenses to 193 for glucose monitors.[8]

Despite making up only 2% of total Medicare spending, DME is used by 26% of Medicare beneficiaries annually, more than the share of beneficiaries using acute care (17.7%) and post-acute care services (4.8%) combined.[9] Changes in DME policy could therefore have an impact on the health and well-being of a large share of beneficiaries.

[6]For example, continuous positive airway pressure (CPAP) devices are often prescribed to patients diagnosed with sleep apnea following an outpatient sleep study. See https://www.cms.gov/Regulations-and-Guidance/Guidance/Transmittals/Downloads/R96NCD.pdf

[7]Suppliers are defined as unique National Provider Identifiers (NPIs). Some suppliers could share ownership, which I cannot distinguish in the claims data.

[8]Excludes suppliers with fewer than 25 claims from a given MSA in 2009.

[9]Author's calculation based on the 2009 Medicare claims data.

2.2 Scope of Competitive Bidding in Medicare DME

Traditionally, DME has been paid based on administrative prices that largely followed the list prices and charges from the late 1980s (MedPAC 2018). Over time, this led to concerns of over-payment. In recent years, reports have shown that Medicare has been paying significantly more for DME than private insurers in the commercial market (MedPAC 2018). To address these concerns, Medicare began seeking alternative price-setting methods and tested out two small-scale competitive bidding pilot programs in Polk County, Florida, and San Antonio, Texas, between 1999 and 2002. Savings generated from the pilot programs prompted the adoption of competitive bidding at a larger scale. The Medicare Prescription Drug, Improvement, and Modernization Act (MMA) of 2003 authorized Medicare to implement competitive bidding programs for DME, starting with the largest MSAs and with the intention to expand to additional areas in later years (MedPAC 2018). On January 1, 2011, nine MSAs were assigned to competitive bidding (Round 1 MSAs).[10] On July 1, 2013, another 91 MSAs were also assigned to competitive bidding (Round 2 MSAs). Figure 1 shows a map of these MSAs in the continental U.S.. In these MSAs, Medicare selected items for competitive bidding that were deemed high cost and high volume, with the exception of Class III medical devices, the highest risk level of device classification by the Federal Drug Administration (FDA), which would not be subject to competitive bidding. 231 items in six product categories and 196 items in eight product categories were assigned to competitive bidding in Round 1 and Round 2 MSAs, respectively.[11] These items accounted for 54% of DME spending under administratively set prices in 2009. Prices for these chosen DME items would be determined based on supplier bids, whereas the prices for other DME continued to follow administratively-set fee schedules.

2.3 Rules of the DME Auction

Suppliers bid for the right to sell the included items to Medicare beneficiaries residing in competitive bidding MSAs. Winning suppliers are granted the right to sell for three years,

[10]Competitive bidding for these nine MSAs was initially slated to begin on 2008, but was postponed to 2011. Instead, Medicare imposed a 9.5% payment cut across all MSAs in 2008, regardless of whether they would be subject to competitive bidding.

[11]See Table 4 for examples of product categories and items in each category.

at a price set by Medicare based on the bids (CMS 2006).

Suppliers bid separately for each product category in each MSA (e.g. oxygen equipment and supplies in the Boston-Cambridge-Newton, MA-NH MSA), and the competition and contracting both occur at the product category-MSA level. The suppliers are required to bid for every item within a given product category, each of which is assigned a weight (the national volume of the given item relative to other items in the same category) that is known to the suppliers. Suppliers must bid at or below the administrative fee-schedule price. An example of the bidding form is shown in Appendix Figure A1.[12]

Medicare ranks suppliers based on each supplier's composite bid — the weighted sum of bids across all items in a product category, and offers contracts starting from the supplier with the lowest composite bid until there are enough suppliers to meet the target quantity, i.e. the number of units used by Medicare beneficiaries over a two-year baseline period, adjusting for time trends (CMS 2006). To determine how many contracts to give out, Medicare estimates each supplier's capacity based on its past supply and any proposed capacity expansions (if supported by appropriate financial documents).[13] For a more detailed description of the bidding process, see Appendix A.

Two features of this auction make it different from a standard procurement auction. First, the bids are non-binding in the sense that there are no mechanisms in place that prevents suppliers from reneging on their supply commitments upon winning the auction. Second, the price for a given item is set to the median of the winning bids, which means half of the winning suppliers are awarded a contract at a price below their own bid.[14]

Figure 2 illustrates the potential impact of the DME auction on price and quantity. Assuming that the administratively set price is above the market clearing price, which is con-

[12] In addition to the price bid, suppliers are also asked to enter an "estimated capacity", which should either be the number of units the supplier is currently providing in the MSA, unless the supplier has plans to expand, in which case it should also report any additional number of units it is able to furnish and provide financial evidence supporting the planned expansion. Medicare uses a supplier's past supply (and any proposed expansions, if applicable) to estimate their capacity and to determine how many contracts to award. See Appendix A for more details.

[13] https://www.cms.gov/medicare/provider-enrollment-and-certification/medicareprovidersupenroll/dmeposaccreditation.html

[14] Medicare explains its choice of using the median-winning bid as follows: "[The median-winning bid] satisfies the statutory requirement that single payment amounts are to be based on bids submitted and accepted... is representative of the winning bids... easily understood by suppliers and implemented by our contractors. It also results in what we consider to be a reasonable payment amount." The highest winning bid was not used to set the price because "this approach would have led to program payment amounts that were higher than necessary because some suppliers were willing to provide these items to beneficiaries at a lower cost." (CMS 2006)

sistent with the belief at the time as well as my findings (Newman, Barrette and McGraves-Lloyd 2017, MedPAC 2018), there should be excess supply in the market prior to competitive bidding.[15] Mechanically, since suppliers are required to bid no higher than the administratively set price, price would weakly decrease by design. Whether or not the auction also lowers quantity depends on whether the auction results in a price below the market clearing price. As Cramton, Ellermeyer and Katzman (2015) and Merlob, Plott and Zhang (2012) suggest, the auction design in which the price is set at the median of the wining bids would lead to prices below the market clearing price, thus moving the market from a situation of excess supply to one of excess demand (i.e. supply shortage). This is illustrated in Figure 2 and reflects what I find in my empirical work below.[16]

3 Data and Summary Statistics

3.1 Data

The main data for the analysis are the 100% Medicare enrollment and claims data from 2009 to 2015, which contain the universe of Medicare beneficiaries and their health care claims over this period. I observe the prices of different items in each market, the health care utilization of each Medicare beneficiary, and from which supplier each beneficiary purchases their DME. I also have data on patient characteristics, including age, race, sex, zip code of residence, Medicaid eligibility (a measure of low resources), and chronic conditions. I supplement these data with publicly available Medicare fee schedules and competitive

[15] Newman, Barrette and McGraves-Lloyd (2017) shows that for six respiratory and oxygen-related items, Medicare prices had been above commercial prices under administrative fee schedules, and were reduced to below commercial prices post-competitive bidding, suggesting that at least for these items, administrative prices were set above the market clearing price in the pre-period. Additionally, MedPAC (2018) shows that for nine of the ten highest spending products that were not subject to competitive bidding, Medicare reimbursement rates exceed that of the median private payer rate by 18% to 57%. This phenomenon likely applies to other DME products, all of which have traditionally been paid based on a fee schedule derived from the list prices in the 1980s and only adjusted annually based on the consumer price index (MedPAC, 2018).

[16] It is worth noting that although I model this as Medicare's procurement problem, in practice, transactions occur at the individual patient level and these patients may exhibit price elasticity due to cost-sharing (although in practice, the vast majority of Medicare patients have supplemental insurance that picks up the cost-sharing). As will become apparent in the results section, a reduction in both price and quantity is consistent with a movement down the supply curve rather than the demand curve, therefore changes in demand cannot affect the market quantity. However, holding fixed the overall quantity in the market, differential changes in demand across patient groups could affect the composition of patients receiving DME. I explore changes to patient composition after competitive bidding in Section 4.

bidding prices from the same period, which provide a denominator of all DME items covered by Medicare and their prices in each MSA.[17]

I obtained supplier bids for the DME auction from a Freedom of Information Act (FOIA) request. The data contain each suppliers' bids and their estimated capacity, which is the quantity each supplier is expected to sell based on their past quantities in the market. Medicare uses this estimate to determine the number of contracts to award but suppliers who are given a contract may end up supplying more or less than this estimate. I obtained additional data on the auctions from Medicare's competitive bidding website, including the number of winners in each auction.[18]

3.2 Sample Definition and Summary Statistics

The baseline sample includes all Medicare enrollees residing in an MSA between 2009 and 2015. I assign beneficiaries to MSAs based on their zip code of residence and county on file with Medicare. By Medicare's rule, a beneficiary's MSA is used to determine whether the prices for her DME purchases are determined by the prior administratively set fee schedule or the new competitive bidding process.[19,20] This feature of the program means that a beneficiary cannot be charged more or less when they travel outside their MSA of residence, although they may face a different set of suppliers depending on which suppliers are eligible to sell in each MSA.

Table 1 compares the characteristics and health care utilization of Medicare beneficiaries who do and do not use DME. Table 1(a) compares the demographics and health status of DME users and non-users. On average, compared to non-users, beneficiaries who use DME are 2.3 years older, 5.3 percentage points more likely to be female, and 10.6 percentage points more likely to be on Medicaid. DME users are also significantly sicker than non-users, as measured by the number of chronic conditions that they have. The average DME user has about five chronic conditions, more than double the average among non-users;

[17] Data available at https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/DMEPOSFeeSched/DMEPOS-Fee-Schedule.html and https://www.dmecompetitivebid.com/, accessed July 2018.

[18] https://www.dmecompetitivebid.com/

[19] https://www.cms.gov/Outreach-and-Education/Medicare-Learning-Network-MLN/MLNProducts/Downloads/DME_Travel_Bene_Factsheet_ICN904484.pdf

[20] Competitive bidding MSAs are determined by a set of zip codes, rather than based on the Census Bureau definition. See https://www.dmecompetitivebid.com/

80% of DME users have at least three chronic conditions, compared with 20% among non-users. Table 1(b) compares the health care utilization of DME-users and non-users. Notably, beneficiaries who use DME spend almost four times as much on health care services annually than non-users ($18,205 for DME users vs. $4,828 for non-users). Looking separately across different health care settings reveals that DME-users use health care services at a much higher rate – compared with non-users, those who use DME are three times as likely to have an inpatient admission (35.7% vs. 11.4%), four times as likely to use institutional post-acute care services, which include skilled nursing facilities, inpatient rehabilitation facilities, and long-term care hospitals (9.7% vs. 2.4%), and over six times as likely to use home health services (22.3% vs. 3.5%). Table 1(c) summarizes the utilization of DME among Medicare beneficiaries. Conditional on using any DME, the average beneficiary uses 1.7 distinct types of products (e.g. a wheelchair and an oxygen concentrator) or 4 distinct items, regardless of type (e.g. a wheelchair, an oxygen concentrator, liquid oxygen used with the concentrator, and a mask used with the oxygen concentrator.) The most common type of DME is a glucose monitor, used by 10.5% of all Medicare beneficiaries or 38% of those who use any DME. Other common items include oxygen supplies and equipment (4.3% of all beneficiaries), nebulizers and related drugs (3.8%), and wheelchairs (3.3%).

Among Medicare beneficiaries who live in MSAs, 9% live in the 9 MSAs that were assigned to competitive bidding in January 2011 ("Round 1"), 64% are live the 91 MSAs that were assigned in July 2013 ("Round 2"), and 27% live in the remaining 271 MSAs. Table 2 compares the 2009 characteristics of these three groups of MSAs. There are some pronounced differences between the MSAs that were assigned to competitive bidding and those that were not, but relatively little differences between the two sets of competitive bidding MSAs. Notably, MSAs assigned to competitive bidding have significantly higher populations (as population was the criterion for MSA selection). Competitive bidding MSAs also have a lower share of white residents and a slightly lower share of population on Medicare, but among enrollees, a similar share of Medicare-Medicaid dual-eligibles and similar numbers of chronic conditions as in non-competitive bidding MSAs. Total Medicare spending is very similar across the three groups of MSAs, and so are most subcategories of Medicare spending, with the exception that non-competitive bidding MSAs spend slightly more on hospital outpatient care, and on durable medical equipment. With the exception of wheelchairs, product categories assigned to competitive bidding are designed to be comprehensive, and include all relevant equipment of a given product type and any supplies used with the equipment.[21,22] Product categories were added and removed from the list of competitive bidding items over time and also differ across the two sets of MSAs. For the analysis, I restrict to items that were both subject to competitive bidding in all 100 competitive bidding MSAs, and were continuously paid under competitive bidding prices from the initial introduction of the program in an MSA until the end of the study period. These DME items fall into five product categories—oxygen equipment, continuous positive airway pressure (CPAP) devices, wheelchairs, walkers, and hospital beds—and make up 39% of overall DME utilization.[23]

I use the analogous sample definition in the analysis of supplier bids to focus on the five product categories consistently assigned to competitive bidding and on the first round of auctions conducted in each of the 100 MSAs.[24] In total, my sample includes 4,958 bidders representing 6,277 suppliers in 554 unique auctions.[25] As shown in Table 3, the median auction has 62.5 bidders; the median varies slightly across product categories, ranging from 53 for oxygen equipment to 75 for CPAP. The majority of bidders only bid in one MSA but often in multiple product categories within that MSA.

3.3 Variable Definitions

I perform all regression analyses at the MSA - half year level.[26] I define price as the Medicare reimbursement price for each DME item, including both the share paid by Medicare (80%), and patient cost-sharing (20%). The main utilization measure is the share of ben-

[21] For example, all walkers and walker accessories reimbursed by Medicare are subject to competitive bidding under the "walkers" category.

[22] In Round 1 MSAs, there are two categories of wheelchairs while in Round 2 MSAs, there was one category. For ease of analysis, I combine the two categories in Round 1 into one wheelchair category.

[23] Author's analysis of the Medicare claims data. Starting in 2014, walkers and wheelchairs were consolidated into one product category ("standard mobility equipment"), and oxygen concentrators and CPAP were consolidated into one product category ("respiratory equipment") while the same underlying items remain covered under competitive bidding.

[24] Following the auction design, a few large MSAs, such as New York City, were subdivided into competitive bidding areas.

[25] Suppliers (unique NPIs) in each market with the same ownership bid together in these auctions.

[26] Because Round 1 MSAs began competitive bidding in January and Round 2 MSAs began competitive bidding in July, using half years instead of full years allows me to more easily aggregate data across MSAs.

eficiaries in each MSA who use any DME item that is included in competitive bidding within each half year, which I obtain by dividing the number of beneficiaries with a medical claim for any included DME within each half year by the number of beneficiaries residing in each MSA. I also construct an alternative measure of utilization – standardized utilization per beneficiary, which is defined as the per beneficiary spending on the included DME after replacing the price paid for each item with the mean fee schedule price for that item in non-competitive bidding MSAs. By stripping away any price differences due to geography or competitive bidding, changes in this standardized utilization measure capture changes in the quantity of DME used. For ease of comparison across different sub-samples, I log transform all price and utilization outcomes in analyses throughout the paper.[27,28] Table 4 summarizes the price of competitive bidding DME in the first six months of the study period, prior to the auctions. The average price of a competitive bidding item is $157, with little variation across MSAs, but large variations across items (Table 3 row (1), columns (1) through (3)). Among all competitive bidding items, the cheapest is a wheelchair bearing, costing $0.6 per piece on average, and the most expensive is a heavy duty power operated vehicle, costing $2,138 per piece on average. Comparing across the five product categories, wheelchairs are the most expensive by average price. There is substantial heterogeneity in price within each category—for example, the lowest and highest priced items within the "hospital beds" category cost $3.6 and $699, respectively. This is largely because the categories contain both parts and full equipment, and in some cases, supplies.

[27]To avoid taking the log of zero, log share of beneficiaries is defined as log(share of beneficiaries + 0.0001) and log standardized utilization per beneficiary as log(standardized utilization per beneficiary + 0.0001). The only analysis in this paper where any of these measures contains zeros is in the first two columns of Table 7, where I restrict to the subset of beneficiaries with prior use. The share of MSA-years with zeros are 0.03% for wheelchairs and CPAP, 0.2% for oxygen, 0.9% for walkers, and 1.6% for hospital beds.

[28]These quantity measures are preferable to a simple count of "number of DME units used" because some items are designed to be used in large quantities (e.g. liquid oxygen, or disposable face mask) while others are designed to last a long time (e.g. an oxygen concentrator). Aggregating across different items therefore implicitly places a large weight on disposables and supplies over equipment.

4 Impact of DME Competitive Bidding

In this section, I estimate the impact of the competitive bidding program as introduced by Medicare on the price and quantity of DME, examine the heterogeneity in impact across product groups and patient types, and provide evidence that the reduction in quantity is consistent with the auction reducing prices below the market clearing level, and producing inefficient supply shortages.

4.1 Empirical Strategy

I estimate the effect of introducing competitive bidding by comparing the price and utilization of DME items in MSAs where competitive bidding was introduced during the study period to MSAs where administrative fee schedules remained in place.

Figure 3(a) shows the raw trends in log price for items subject to competitive bidding, separately for MSAs that were assigned to competitive bidding in January 2011, MSAs that were assigned to competitive bidding in July 2013, and MSAs that were paid by administrative fee schedule throughout this time period. Weighted averages are taken across items and MSAs, where the weights are each item's pre-period utilization, measured in 2009. Log price in 2009 is normalized to zero. Prior to competitive bidding, price trends in the three sets of MSAs closely followed each other. Log price decreased by 0.4 to 0.6, or 33% to 45% percent, when MSAs entered competitive bidding. A smaller, second reduction is seen following a round of bidding in 2014 for MSAs that initially entered bidding in 2011.[29] In Appendix Figure A2(a) I weight each item and MSA equally and find the same pattern.

As a check that the change in price was indeed due to competitive bidding rather than other changes at the MSA level, Appendix Figure A2(b) replicates Figure 3(a) for DME items that were paid under administratively set prices throughout the study period. For these items, the price trends remained flat over time for all three groups of MSAs.

Analogous to Figure 3(a), Figure 3(b) plots the raw trends of the main utilization measure—log share of beneficiaries using competitive bidding DME. The pattern of utilization in Figure 3(b) closely follows the pattern of price in Figure 3(a); the share of beneficiaries

[29] Competitive bidding prices remain in place for three years, and a new round of bidding is conducted at the end of each three year period.

who use competitive bidding DME declined sharply after competitive bidding was introduced.

To empirically quantify the impact of competitive bidding on price and utilization, I combine the two sets of MSAs that entered competitive bidding by creating a relative time measure— months since competitive bidding was introduced—denoted by $\theta_{r(j,t)}$ for MSA j in a six-month period t. $\theta_{r(j,t)} = 0$ in the first six months MSA j enters competitive bidding. I use a six-month time increment because the second set of MSAs entered competitive bidding six months into the year.

For each competitive bidding MSA j in half-year t, I estimate the following difference-in-differences event study specification:

$$ln(y_{jt}) = \gamma_j + \tau_t + \Phi_r CB_j \times \theta_{r(j,t)} + \epsilon_{jt} \quad (1)$$

where γ_j and τ_t indicate MSA, and half-year fixed effects, respectively. CB_j is an indicator for MSAs subject to competitive bidding. $\theta_{r(j,t)}$ are indicators for relative half-years. The coefficients Φ_r quantify the impact of competitive bidding on the outcome of interest, $ln(y_{jt})$ in relative half year r. In the analysis of prices, y_{jt} the log of average price of competitive bidding DME in MSA j in half-year t, with different items weighted by their respective pre-competitive bidding utilization, measured in 2009; in the analysis of utilization, y_{jt} is either the share of beneficiaries residing in MSA j in half-year t who had a medical claim for any competitive bidding DME or the mean standardized DME utilization among beneficiaries residing in MSA j in half-year t.

To summarize the impact over the post-period, I also estimate a pre-post version of the same specification,

$$ln(y_{jt}) = \gamma_j + \tau_t + \Phi CB_j \times Post_t + \epsilon_{jt} \quad (2)$$

where $Post_t$ is an indicator for the period after competitive bidding was introduced.

The difference-in-differences regression specification relies on the identifying assumption that absent competitive bidding, the outcome of interest would have evolved in the same way across the different sets of MSAs. This assumption holds for prices by construction, as prices are otherwise administratively set and updated over time only by multipliers stipulated by law.[30] This assumption also appears to hold for utilization, given the lack of a pre-trends in the event studies, shown in the next section.

4.2 Results on Price and Utilization

Figure 4 plots the estimates from equation (1). The figure uses a panel of MSA-items that is balanced in relative half-years, focusing on the 24 months before and after competitive bidding was introduced. The coefficient on relative month -6 is normalized to zero. Relative half-years in MSAs that never introduced competitive bidding are also set to zero. The event study shows a flat pre-period trend, which is a mechanical result due to administratively set prices prior to competitive bidding. Similar to the raw trends, the event study shows an average reduction of about 0.6 in log price, which translates into a 45% reduction in price when competitive bidding was introduced. The reduction remains roughly constant in the 24 months following the introduction of competitive bidding, which is also mechanical because prices generated from auctions are in effect for three years. The estimates are fairly precise, shown by the 95% confidence intervals in the figure.

A pre-post analogue of the event study estimate in Figure 4 is summarized in Table 5 row (1), which reports estimates of Φ from equation (2). Column (2) of the table reports the implied percentage change based on the coefficient estimates reported in column (1). On average, competitive bidding in DME led to a 45% reduction in price. Row (2) reports a 36% reduction in price when I weight the items equally, regardless of their utilization prior to competitive bidding.

We expect the price to be lower since bidders must bid at or below the administrative fee schedule. An important question is whether the price falls below the market clearing price. Theoretical work by Cramton, Ellermeyer and Katzman (2015) and Merlob, Plott and Zhang (2012) suggests that an auction with non-binding bids and a median winning price would generate prices that fall below the market clearing price. To investigate this empirically, I examine the impact on quantity. Figure 5 plots estimates from equation (1) for the utilization of items subject to competitive bidding. The figure shows a statistically significant reduction of about 11% in the share of patients with any claims for the included items after competitive bidding was introduced. The decline in utilization remained

[30] https://www.ssa.gov/OP_Home/ssact/title18/1834.htm

roughly stable in the 24 months following the introduction of competitive bidding. As previously illustrated in Figure 2, although prices decreased by design, the impact on utilization was ex-ante ambiguous. The reduction in both price and quantity, however, suggests the creation of a supply shortage in the market and that the price fell below the market clearing price.[31]

Rows (3) through (6) of Table 5 report the impact of competitive bidding on utilization under different specifications, all of which show a statistically significant decline. The baseline specification is shown in row (3), which reports estimates from the pre-post analogue of the event study estimates in Figure 5: after competitive bidding was introduced for DME, the share of beneficiaries using the included items fell by 10.5%.

Row (5) of Table 5 repeats the analysis using an alternative utilization measure—log standardized utilization per beneficiary. This measure is constructed by computing the Medicare reimbursement assuming that each item was paid the mean fee schedule price among MSAs that were never subject to competitive bidding. Consistent with the primary utilization measure, there is a statistically significant decline of 7.2% in standardized utilization per beneficiary.[32]

Rows (4) and (6) of the table replicate rows (3) and (5) but weight the estimates by the number of beneficiaries residing in each MSA; the coefficient estimates can thus be interpreted as "per beneficiary" changes. The estimates show that 12.6% fewer beneficiaries were using DME as a result of competitive bidding and the per beneficiary standardized utilization declined by 11.6%.

As a robustness check, Appendix Figures A3 and A4 show very similar estimates when estimating the same event study figures on an unbalanced panel for price and quantity,

[31] An alternative interpretation of the reduction in utilization is a reduction in supplier-induced demand. However, this is unlikely to be the primary channel. First, one implication of supplier-induced demand is that the marginal units demanded should be lower value. As I will show in Section 4.3, this does not appear to be the case. Second, under a supplier-induced demand model, one might expect suppliers to increase the utilization of products that are not subject to competitive bidding, as well as to generate higher quantities in areas not subject to competitive bidding. As shown in Table 6 row (6) and in Figure 3 Panel (b), this also does not appear to be the case. Finally, as I will show through the model in Section 5, supply shortages appear to be a result of flaws in the auction design.

[32] There are two important differences between the two specifications. First, the two measures capture different margins of utilization – the primary outcome captures the extensive margin utilization at the beneficiary level, and the latter captures the average overall utilization. Second, the two measures also place different implicit weights on the different products. Share of beneficiaries weights all items equally; standardized utilization per beneficiary places more weight on items that have higher fee schedule prices. Therefore, one cannot directly back out the intensive vs. extensive margin response by comparing the two estimates.

respectively. As a further alternative specification, in Section B.2 of the Appendix, I estimate a version of the model at the item-MSA-half year level, rather than at the MSA-half year level. Unlike the model in equations (1) and (2), which captures the changes in price and utilization at the product category level, the alternative specification captures an average effect across different items within and across product categories and also shows a statistically significant reduction. Finally, the results are robust to the alternative estimator proposed by Sun and Abraham (2021) (Appendix Figures A8 and A9).

The result of reduced price and reduced quantity holds across different product categories. Table 6 replicates rows (1) and (3) of Table 5 separately for each product category, and the corresponding event studies figures are shown in Figures A10 and A11 in the Appendix. The magnitude of the decline varies across products, with walkers showing the largest price reduction (56%), and wheelchairs showing the smallest price reduction (36%). The largest decline in utilization is in walkers, which declined by 23%, and the smallest is in oxygen equipment, which declined by 5%. The heterogeneity in changes in utilization does not appear to be explained by the heterogeneity in price reductions alone—the correlation between changes in price and changes in utilization is 0.15[33]. The weak correlation between the reduction in price and the reduction in quantity at the product category level is perhaps not surprising, given that these products constitute different markets that vary in market characteristics, including their levels of competitiveness. Similar patterns are found using alternative specifications and outcome measures, shown in Appendix Tables A2 and A3. There appears to be little substitution toward non-competitive bidding products (Table 6 row (6)), which is expected since product categories are generally large and comprehensive.

In contrast, within a product category, it may be possible for suppliers to respond to price reductions by moving patients demanding a given type of product toward better reimbursed items of the same type. In fact, looking within product categories reveals a clear positive correlation between changes in price and quantity at the item level. Figure 6 shows that the correlation coefficient between changes in log price and log utilization is 0.42 across all competitive bidding items. The figure shows that items that saw a smaller decrease in price also had a smaller decrease in utilization, and in some cases, an increase in

[33] Author's calculation based on the Medicare claims data.

utilization. This pattern is consistent with suppliers disproportionately withdrawing from the sales of lower-priced items and substitution toward higher-priced items within product categories.

4.3 Allocation of DME Under Supply Shortage

The simultaneous reduction in price and quantity is consistent with a movement down the supply curve and the creation of a supply shortage. Under this regulation-produced supply shortage, a natural question concerns how the limited supply is rationed, and the efficiency of this rationing. To shed some light on this question, I explore heterogeneity in the impact of the quantity reduction across different types of users.

First, I estimate equation (2) separately by prior use, defined as whether the beneficiary received a DME of the same type in the first three years of the sample.[34] Reductions in claims among patients already in possession of the same DME likely represent reduced equipment upgrades or replacements, while reduction among those without a prior claim likely represents reduced new use. Table 7 reports the regression estimates. Across all five product categories, both beneficiaries with and without prior use are statistically significantly less likely to use DME following the introduction of competitive bidding, and the magnitude of the reduction appears comparable between the two groups. Assuming that new uses generate greater surplus than replacements and upgrades, these results may suggest inefficient distribution of DME among patients.

Second, Table 8 estimates the impact of competitive bidding on the average characteristics of patients receiving DME. Changes in the characteristics reflect the (endogenously) changing composition of beneficiaries who receive DME under competitive bidding with a supply shortage compared to administratively set prices. Interestingly, despite the 11% reduction in the share of beneficiaries using DME, the average patient receiving DME does not appear any sicker relative to the control group, as measured by the number of chronic conditions. The percent of DME recipients who are Medicare-Medicaid duals decreased by a statistically significant 1.5 percentage points, or 5.6% relative to a pre-competitive bidding mean of 26.9 percent among the treatment MSAs. This likely reflects the fact that

[34] For this exercise, I am focusing on the 91 MSAs that entered competitive bidding and the MSAs that never entered competitive bidding, because the first 9 MSAs that entered in 2011 do not allow for a long enough pre-period to establish prior use.

suppliers often face a lower "de facto" price with Medicare-Medicaid dually eligible beneficiaries, due to policies that allow Medicaid (which is responsible for the 20% patient cost-sharing for dually eligibles) to not pay the copayment.[35] Furthermore, those who receive DME are also more likely to be white as well as slightly younger and more likely to be male. These results suggest that the average beneficiary whose utilization is restricted is not healthier than the average DME user but does appear to come from a more disadvantaged socioeconomic background. The result appears consistent with the intuition that in a market where supply is limited, all else equal, those with fewer social resources are more likely to be excluded.

Finally, I find evidence of delays in DME use following an inpatient stay, presumably resulting from increased difficulties for patients and their physicians to obtain the required DME due to the shortage in supply. I focus on patients who are discharged from an inpatient setting as it provides a natural time frame for measuring delays in utilization and because patients are frequently prescribed DME upon discharge. Table 9 reports reduction in the share of patients who receive DME within 7, 14, and 30 days of discharge. The estimates show that relative to the control, patients affected by competitive bidding are 7.8% less likely to receive DME upon discharge by day 7, 6.4% less likely to receive DME upon discharge by day 14, and 4.2% less likely to receive DME upon discharge by day 30 after the discharge. The differences across the three estimates are statistically significant. The narrowing treatment-control gap in DME use over time is consistent with delays in receiving DME, conditional on ever receiving any. Appendix Table A4 further examines this pattern by product categories and the same appears to hold within each individual product category. This result could suggest temporal inefficiencies in allocation as patients experience delays in DME use.

[35] Many states have a "lesser of" policy under which Medicaid only pays based on the lesser of Medicaid and Medicare reimbursement rates. If 80% of Medicare reimbursement rate was higher than the Medicaid rate, then Medicaid no longer pays the copayment. https://www.cms.gov/Medicare-Medicaid-Coordination/Medicare-and-Medicaid-Coordination/Medicare-Medicaid-Coordination-Office/Downloads/Access_to_Care_Issues_Among_Qualified_Medicare_Beneficiaries.pdf

5 A Model of Supplier Bidding

The reduced form results suggest that the introduction of competitive bidding lowered both prices and quantities substantially, moving the market from excess supply (with administratively set prices) to excess demand. Given the goal of the reform, which was to reduce prices without reducing quantity, a natural question is whether alternative auctions could generate savings relative to the administratively-set prices while maintaining the existing quantities. Theoretically, the answer is a qualitative yes (Cramton, Ellermeyer and Katzman 2015, Merlob, Plott and Zhang 2012), but the quantitative impact of alternative designs is an empirical question.

The purpose of this model is two-fold. First, since the the auction design is a likely cause of the shortages observed in the market, the model can help confirm quantitatively whether the design could indeed rationalize a supply shortage of the observed size. Second, the model allows us to answer the question of whether alternative auctions can generate savings relative to the administratively-set prices and maintain the desired level of supply. To make counterfactual, quantitative inferences about what prices would look like under these alternative auction designs, I develop and estimate an equilibrium model of suppliers bidding for DME contracts in Medicare's median winning-price auction. In this model, suppliers bid for contracts that allow them to sell their entire capacity at the auction-generated price. The model highlights the two most unusual aspects of the auction design – that the contract is not binding, making it possible for bidders to refuse to supply after winning the auction, and that the winning bidders are paid the bid of the median winner.[36] I estimate the bidders' cost through the equilibrium model using data on the universe of DME bids and other observed parameters, and then simulate equilibrium outcomes under different auction designs.

[36]The model does makes an important simplification: it only models bidding at the product-MSA level. In practice, bidders submit separate bids for each individual item in a product category, and these bids are aggregated into one "composite bid" for the product-MSA based on a fixed set of weights (given to all bidders). Bidders are ranked and the winners are chosen based on their "composite bids", as I have specified in the model. However, this model as currently specified does not capture bid skewing at the items level, which, as shown in Athey and Levin (2001), can exist in 'scale sale' auctions where bidders submit unit bids but are scored based on their "composite bids."

5.1 Setting

For each product-MSA market j, let p^j denote the price and q^j the quantity. Since the model will be specified for a representative market, I will omit the superscript j in the rest of the section for simplicity.

Auction Rules: In each market, bidders compete for contracts that allow them to supply at the price determined by the auction. Bidder i submits bid $b_i \in [0, \bar{b}]$, which is the per-unit price at which she is willing to supply her full capacity κ_i, defined as the estimated number of units the supplier can sell in one year.[37] The bid ceiling is $\bar{b} = p^{admin}$, the administrative fee-schedule price. Medicare awards contracts starting with the lowest bidder. The number of contracts Medicare awards is given by the smallest W that satisfies $\sum_{i \in \{i: b_i \leq b_{(W:N)}\}} \kappa_i \geq q^*$, where q^* is the target quantity, i.e. the existing quantity in the market prior to competitive bidding. The notation $b_{(W:N)}$ denotes the W^{th} lowest bid among N bids. Medicare sets the price at the M^{th} lowest bid, the median winning bid, where M equals $\frac{W+1}{2}$ when W is odd and $\frac{W}{2}$ when W is even.[38] Importantly, bidders who win are not paid their own bids but instead, winners with bids above the bid of the median winner are paid below their own bids and winner with bids below the bid of the median winner are paid above their own bids.[39] For example, in the auction for walkers in Washington, DC, $W = 16$ winners were offered a contract, and the price was set at the bid of the $M = 8^{th}$ lowest bidder. After being offered the contract, the W winners can choose to supply their full capacity if they can make a positive profit at the final price, or to refuse to supply if they cannot.[40]

Bidders: Consider N risk-neutral bidders who vary along two dimensions: their capacity κ_i and their constant per-unit cost c_i up to capacity. Each bidder's capacity and cost

[37] Medicare estimates a bidder's capacity based on its past supply, adjusting upwards to account for increased market share after competitive bidding. See Appendix A for more details.

[38] Strictly speaking, the price is set at the (not capacity-weighted) median bid among the winners, which is not an order statistic when the number of winners is even. For simplicity, I have defined M as an order statistic although I expect this minor simplification to have negligible impact on the model predictions.

[39] This is different from the average price auction described in Decarolis (2014), where the bidder who bids closest to the average wins the auction but is paid their own bid (rather than the average).

[40] In practice, suppliers could either reject the contract outright or sign the contract but choose to not supply when contacted by the beneficiaries. Since they both result in a shortage, I do not distinguish the two in the model.

are drawn independently from a joint cumulative distribution $F_{\kappa c}(\cdot,\cdot)$ (with density $f_{\kappa c}(\cdot,\cdot)$ and marginal densities $f_{\kappa}(\cdot)$ and $f_c(\cdot)$). The information structure follows that of an independent private values (IPV) model where bidders know their own capacity (κ_i) and cost (c_i), the distribution of capacity and cost in the market ($F_{\kappa c}(\cdot,\cdot)$), the market-level parameters (N, q^*), but not other individual bidder's cost, capacity, or bid ($\kappa_{\neg i}$, $c_{\neg i}$, $b_{\neg i}$). Because the bidders know $F_{\kappa c}(\cdot,\cdot)$, N, and q^*, they form unbiased expectations about the number of winners (W) and the order statistic of the bid that sets the price (M).

5.2 Bidder's Problem

A bidder's objective is to choose a bid b_i that maximizes her expected payoff. Importantly, because the price is set at the median of the winning bids, it is necessary to take into consideration scenarios in which the bidder is above or below the price-setting bid, as well as scenarios where the bidder sets the price. Figure 7 illustrates the intuition behind the construction of the bidder's objective. Specifically, let $p_1(b_i)$ through $p_4(b_i)$ denote the probabilities that the bidder's bid ends up below the median winning bid, at the median winning bid, between the median and the highest winning bids, and above the highest winning bid (i.e. losing the auction), respectively. Let $x_1(b_i)$ through $x_4(b_i)$ denote the realized prices in each corresponding case. If the bidder wins and accepts the contract, the bidder receives payoff $\kappa_i(x_1(b_i) - c_i)$, $\kappa_i(x_2(b_i) - c_i)$, or $\kappa_i(x_3(b_i) - c_i)$, depending on which case the bidder falls into. If the bidder loses, they receive a payoff of 0. Note that since capacity is multiplicative in the payoff, we can remove it from the expression without affecting the optimization problem. Since contracts are non-binding and the bidder can refuse an offer upon seeing the final price and receive zero in payoff, the expected (per-unit) payoffs in each case where the bidder wins are given by $E(max\{x_i - c_i, 0\}|x_i = x_1(b_i))$ through $E(max\{x_i - c_i, 0\}|x_i = x_3(b_i))$, respectively. The bidder's objective is given by

$$\underset{b_i}{max} \quad \sum_{l=\{1,2,3\}} p_l(b_i) \cdot E(max\{x_i - c_i, 0\}|x_i = x_l(b_i)) \tag{3}$$

which maximizes the bidder's expected per-unit payoff across all possible scenarios where they win the auction. That the capacity drops out of the maximization problem is due to the assumption of constant per unit costs up to full capacity. Intuitively, the bidder's expected payoff is the product of two objects – the bidder's probability of winning (p_i's), which increases as the bidder lowers her bid, and the bidder's expected payoff conditional on winning ($E(max\{x_i - c_i, 0\}|x_i = x_l(b_i))$'s), which decreases as the bidder lowers her bid. The equilibrium bid optimally trades off these two opposing forces.

5.3 Discussion of Model Assumptions

The model makes several assumptions and simplifications. First, demand is exogenously determined, which follows from the fact that Medicare sets its procurement target based on pre-competitive bidding utilization. This assumption is likely valid since the majority of patients were not exposed to any price change due to supplemental insurance coverage (e.g. Medigap or Medicaid), hence there was unlikely to be much demand response. Second, supplier capacity is fixed in the model, which again follows from Medicare's procurement rules. While in the longer run, capacity would likely adjust, the model as currently specified captures the short-run effect of the introduction of the competitive bidding program and the immediate consequences of its flawed auction design. Furthermore, since most bidders only operate in one MSA (Table 3), there is limited scope for shifting capacity across markets. Third, bidders in the model are assumed to have private values (costs). This seems reasonable since there is a large number of manufacturers in the market and suppliers tend to contract with different manufacturers as shown in Table A7 Panel (a). Fourth, by dropping capacity κ from the objective, I have assumed that bidders do not play different strategies based on their κ. This assumption is necessary for identification: since I only observe one-dimensional bids, allowing strategy to vary by both cost and capacity is not feasible (Asker and Cantillon 2010). This assumption is also likely valid in practice, given the weak correlation between bid and capacity observed in the data ($\rho_{\kappa,b} = 0.03$). Finally, the model does not consider collusion. While collusion is often a concern in procurement auctions, the particular context of this program makes collusion less likely: I study the first interaction of a large number of bidders (mean = 68) in an auction that resulted in prices that were too low (as opposed too high, as one would expect from collusion). Collusive behavior may become more important in the longer term, although that is beyond the scope of the current paper.

5.4 Identification and Estimation

The goal of the estimation is to recover the distribution of bidder costs in each auction. With these distributions and the empirically observed market-level parameters, I can simulate counterfactual allocations under alternative auction rules. The structural estimation exploits the optimization of equation (3) to compute a mapping from observed bids to the inferred costs. Since auctions differ in N, q^*, and $F_{\kappa c}$, I estimate the model separately for each auction. Based on the assumptions of the model, the bidders have the correct expectation of W, which I set to be equal to the observed number of winners. Appendix Section C goes through the derivation that arrives at the final version of equation (3) that I take to the data.

To prepare the data for estimation, I normalize all bids as a fraction of the bid ceiling (administrative fee schedule price). This transforms all observed bids to a number between 0 and 1 and allows me to easily compare and aggregate results across markets[41]. The estimation steps follows the idea laid out in Guerre, Perrigne and Vuong (2000). The steps are as follows.

Step 1: Estimate the bid distribution F_b and f_b. I fit the observed bids in each market to a Beta distribution to obtain F_b and f_b. The reason for this parametric assumption is computational efficiency – since I estimate each auction separately, solving the objective using nonparametrically estimated kernel distributions can become very time-consuming. I use Beta distributions because they provide a good fit to the observed bids. Notably, they preserve the skewness that is observed in the bid distributions.

Step 2: Optimize the bidder's objective function to recover the mapping between b_i and c_i. Identification of c_i relies on the assumption that there exists a one-to-one mapping between b_i and c_i, and that all bids come from the the same equilibrium. Both conditions are assumed to hold, as is standard in the literature.[42] Using the estimated F_b, f_b, and the observed N and W in each auction as inputs, I numerically maximize equation (3) by search-

[41] See Table 4 for examples of prices before normalization.

[42] Prior theoretical work on median winning price auctions by Cramton, Ellermeyer and Katzman (2015) have found multiple equilibiria in their setting. For identification in my setting, uniqueness of the equilibrium is not required as long as all bidders are assumed to follow the same equilibrium strategy characterized by the profit maximization problem in equation (3).

ing over a 100-by-100 grid of evenly spaced values of $b_i \in [0, 1]$ and $c_i \in [0, 1]$. I recover c_i by minimizing the difference in expected payoffs between the observed bid and the optimal bid.

Step 3: Estimate F_c and f_c. Applying the estimated mapping in each auction to each observed bid b_i allows me to find the inferred cost c_i. Kernel estimation of the c_i's in each market yields the marginal distribution of cost (f_c). Kernel estimation of the c_i's and κ_i's yield the joint distribution of cost and capacity ($f_{\kappa c}$).

5.5 Model Estimates

Table 10 reports the observed parameters (N, W, M, b_i) across all auctions. The average auction has 68.2 bidders. The average bid is approximately 66% of the administrative fee schedule price. The average bidder has a capacity of 13.9% of the target quantity (normalized to 1 in each auction), although the distribution is skewed – the median bidder can only supply 3.6% of the market. The average auction has 20 winners, with the price set by the 10^{th} lowest bid. Following the estimation procedure described above, I estimate that the average cost is 62.6% of the administrative fee schedule price. The estimates suggest the presence of negative profit margins among winners: although the average winner makes an 8% profit, the 25^{th} percentile winner faces a margin of -2%. Appendix Figure A12 reports the share of winners facing negative profit margins across auctions, where the model predicts that profit-maximizing suppliers would refuse to supply.

Appendix Figure A13 illustrates the estimation procedure with the example of walkers in Washington, DC, which had $N = 70$ bidders and $W = 16$ winners (hence $M = 8$). Panel (a) shows the distribution of the observed bids (f_b) in this market (step 2 of the estimation procedure). The distribution of bids centers around 70% of the administrative fee schedule. Panel (b) illustrates in dots the equilibrium bid schedule obtained by optimizing equation (3) for different levels of cost (step 3). Superimposed on the bid schedule is the estimated cost distribution. As the bid schedule illustrates, the equilibrium bids in this market roughly follow the cost, with the exception of bidders with very low cost. Intuitively, bidders who have very low cost are able to shade-up their bids significantly to help raise the expected median winning bid without seriously jeopardizing their chance of winning. The bid schedule shows some bidders bidding below their cost; across all auctions, I estimate that approximately 1 in every 5 bidders submits a bid below their cost in equilibrium.

Table 11 Panel (a) reports the estimated price, quantity, and spending based on the model estimates as fractions of those under the administrative fee schedule. On average, across product-MSAs, I find that the median-winning-price auction generated price, quantity, and spending were 54%, 87%, and 46%, respectively of those under the existing fee schedule. This is equivalent to a reduction in spending by 54%, attributable to a 46% reduction in prices and a 13% reduction in quantities. These estimates closely match the difference-in-differences estimates from Table 5.

Appendix Figure A14 further compares the model-predicted quantity reductions with the reduced-form estimates across MSAs. The two distributions appear highly comparable, providing additional assurance that the auction design, as opposed to other factors, likely contributed to the reduction in DME utilization.

5.6 Counterfactuals

Having obtained cost estimates from the model, I perform a set of counterfactual exercises to examine price and quantity under alternative auction designs. All results are reported as fractions of those under the administrative fee schedule.

In Table 11, I consider two alternative auction designs frequently used in procurement auctions: a uniform price auction where winning bidders are paid the lowest losing bid, and a pay-as-bid auction where winning bidders are paid their own bids. These two auction designs are chosen because they have been widely used in other markets outside of health care (see, for example, Hortaçsu and McAdams (2010) on the Turkish treasury auctions, among many others), have straightforward rules that are easy for the bidders to understand and for the government to implement, and have good theoretical properties that should prevent them from generating shortages in this setting. Specifically, under the assumption of constant per-unit cost and fixed capacities, both designs are theoretically efficient.[43]

[43] Uniform price auctions where the bidder's per-unit cost is not constant are in general inefficient in theory because of incentives to shade up bids for the additional units. However, when bidders only supply a single unit (or as in this case, the full capacity at a constant per-unit cost), the auction becomes efficient

To generate these counterfactual allocations, I compute each bidder's optimal bid under each of the counterfactual auction designs. The optimal bid under the uniform price auction is given by the bidder's cost, as it is the dominant strategy; the optimal bid under the pay-as-bid auction is given by $b_i = E[c_{(W:N-1)}|c_i < c_{(W:N-1)}]$, where $c_{(W:N-1)}$ denotes the W^{th} lowest cost among the other $N-1$ bidders (Krishna 2009). Intuitively, in a pay-as-bid auction, bidders bid above their cost just enough to avoid losing their position to the bidder with the next lowest cost.

Table 11(a) reports the estimated price, quantity, and spending under these alternative auctions. By design, both auctions can deliver the target quantity. The uniform price auction would generate a price that is 58% of the fee schedule price, and the pay-as-bid auction would generate prices that are also on average 58% of the fee schedule price, with a standard deviation of 0.012 in the prices paid to different bidders. Focusing on the uniform price auction, the observed median winning price auction generated prices that were on average 4 percentage points (or 6.9%) below the prices required to generate Medicare's target quantity.

As a benchmark, in a first best allocation where all bidders are paid exactly their own cost, the average price paid out is only 45% of the administrative fee schedule price. This is of course unattainable in practice, as Medicare cannot directly elicit each bidder's cost. Figure 8 compares the different mechanisms in the same price-quantity space. The lowest average price is generated by the (unattainable) theoretical first best allocation. Pay-as-bid and uniform price auctions represent two of the best attainable allocations. The observed auction resulted in prices that were lower than these two auctions but also resulted in a significant shortage in quantity. Notably, all these prices are significantly below the administrative fee schedule price. Comparison of the different allocations allows us to decompose the price reduction generated by the DME competitive bidding program into two components: reducing the bidder margins above their costs resulted in 91% of the reduction in price (from 1 to 0.58), while the remaining 9% of the price reduction (from 0.58 to 0.54) resulted in negative profit-margins for some bidders and consequently generated a supply shortage. This comparison also makes clear that since administratively set prices have been vastly above the cost to supply, competitive bidding in this market is able to

in theory. The same is true for pay-as-bid auctions (Krishna 2009).

generate large savings.

Finally, I consider scenarios where the government wishes to increase or decrease the amount of DME supplied in the market. The results are reported in Table 11 Panels (b) and (c). Specifically, the table reports allocation when the government sets its target at 120% or 80% of the original target q^*. Note that prices generated under these counterfactuals are also equivalent to changing κ_i's, the estimated bidder capacity, downward by 17% (1/1.2) or upward by 25% (1/0.8), respectively. Target quantities can change over time as clinical guidelines and the population needs evolve; capacities can change due to technological changes in manufacturing and in the supply chain, or from consolidations and expansions; there could also be measurement and prediction errors in either or both, making it worthwhile to consider a range of possible values. In both scenarios, Medicare can continue to generate significant savings. In fact, because the administratively set prices have been so much higher than cost, Medicare can both raise its target quantity and achieve savings in overall spending.

6 Discussion and Conclusion

This paper studies the impact of using competitive bidding to set health care prices. Exploiting the staggered introduction of the Medicare DME competitive bidding program across different metropolitan statistical areas in the U.S., difference-in-differences estimates show that on average, the program led to a 45% reduction in price and a 11% reduction in the share of beneficiaries using DME. Several pieces of evidence suggest that the reduction in utilization was the result of a supply shortage following the introduction of competitive bidding.

One primary cause of this shortage appears to be the auction design. I investigate this hypothesis by estimating a stylized model of suppliers bidding in the DME auction and find that prices generated by the auction were on average 7% below the market clearing price, creating shortages in supply. Counterfactual simulations show that feasible alternative auctions could save 42% in government spending relative to the administratively set prices while maintaining the previous quantity in the market.

Competitive bidding has been widely touted as a solution to controlling health care costs and enhancing competition. However, analysis of the DME competitive bidding program shows that economic tools may not yield their intended results when improperly applied. The paper finds large pricing inefficiencies in the current administrative fee schedule. The results highlight the importance of auction design and the potential for well-designed competitive bidding to generate large savings in health care.

This paper leaves several open questions to be addressed in future work. First, the paper focuses on the immediate short-run effect of the competitive bidding program, which treats the set of products as fixed. This is likely to change in the longer run, when quality of products can respond. In fact, as documented by Decarolis (2014) in the context of Italian public works, quality deterioration could occur as prices fall. Also missing from the current analysis is the effect of the large price cut on product innovation. While the competitive bidding program has lowered spending on the existing set of products, cuts in reimbursement could affect the rate and quality of future innovation, and patient welfare in the long run. Finally, the paper has abstracted away from spillover effects onto the privately insured. As shown in Clemens and Gottlieb (2017), Medicare payment policy can have a large impact on private payers. An analysis of the privately insured market will help paint a more complete picture of the impact of Medicare price regulation.

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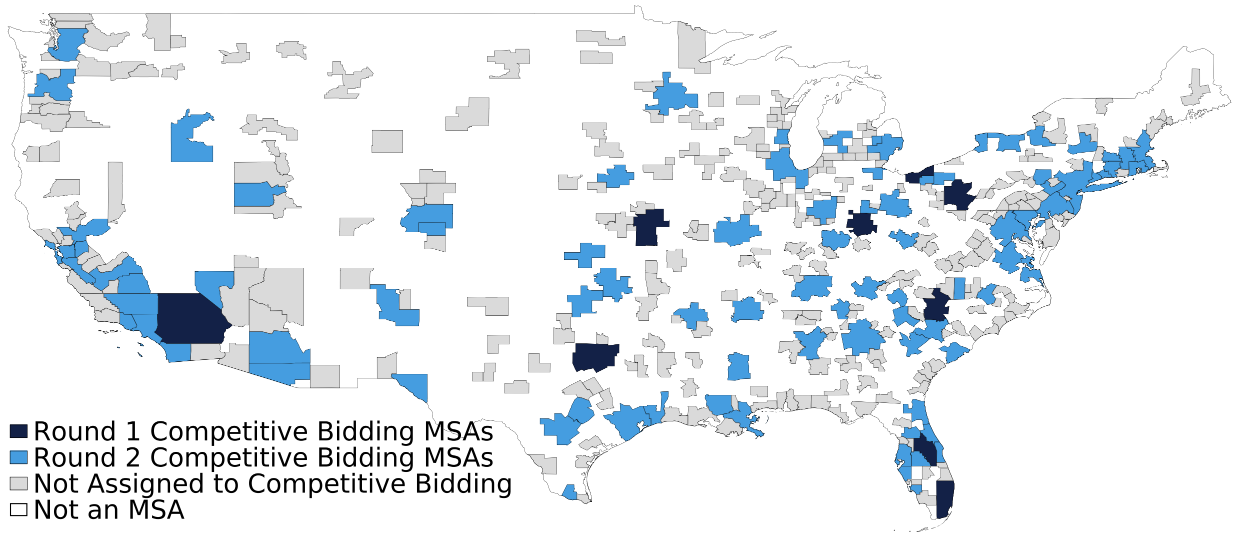
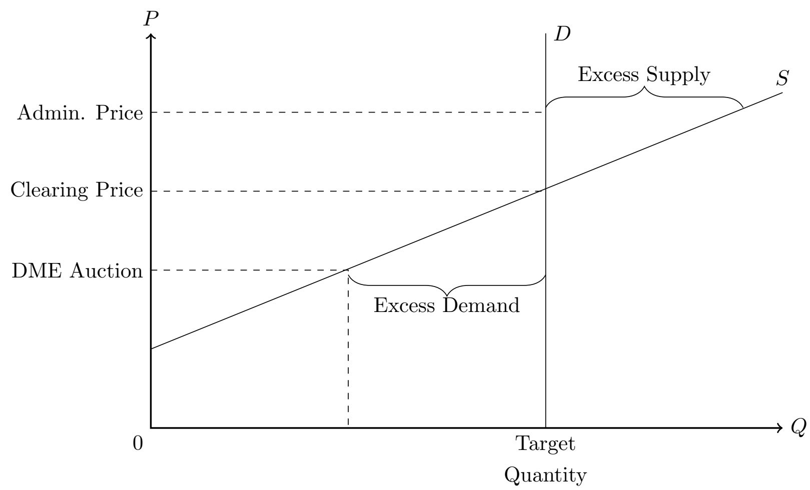
Figure 1. Map of MSAs Assigned to Competitive Bidding



Notes: Figure shows metropolitan statistical areas (MSAs) in the continental United States that were assigned to competitive bidding in either January 2011 (round 1) or July 2013 (round 2), or not assigned to competitive bidding by the end of the study period.

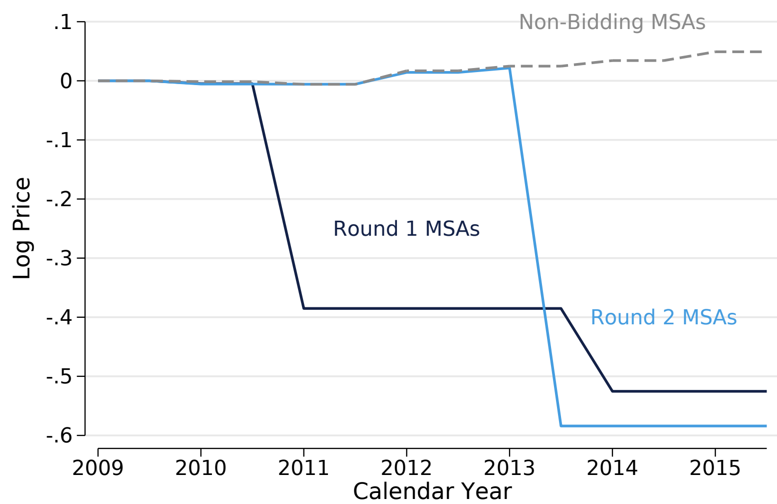
Figure 2. Price and Quantity Under Medicare Pricing Rules



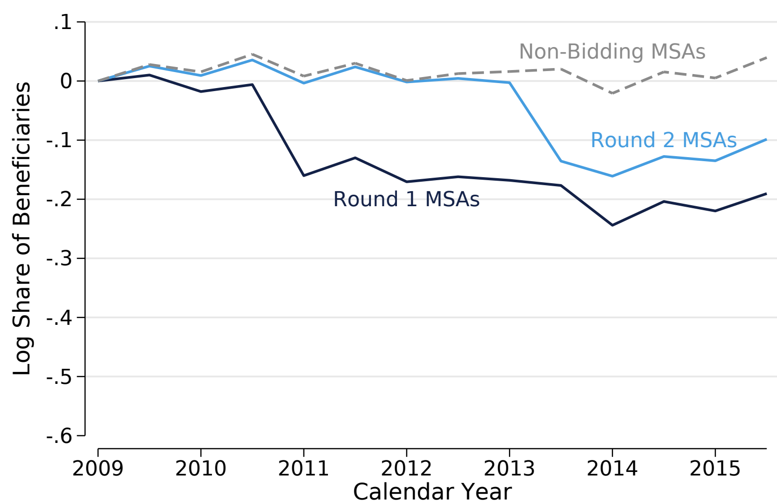
Notes: Figure illustrates the price and quantity under administrative pricing, the market clearing price, and the DME median winning price auction.

Figure 3. Raw Trends of Price and Utilization of Items Subject to Competitive Bidding

(a) Average Log Price

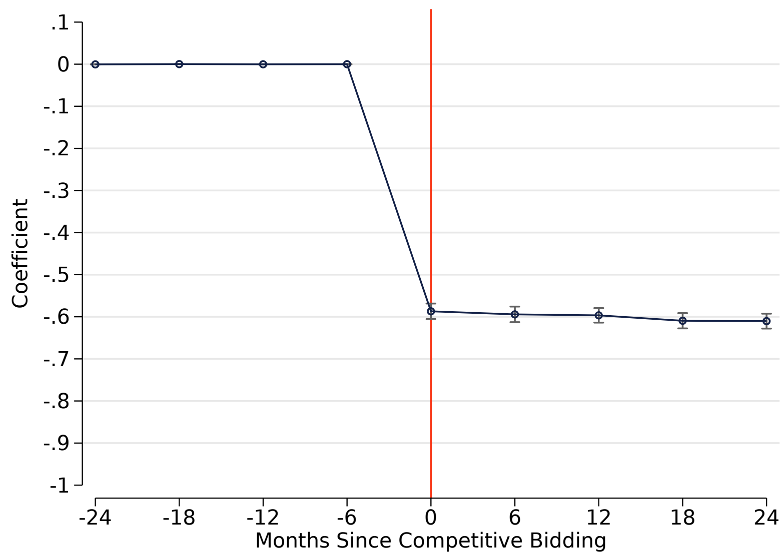


(b) Log Share of Beneficiaries Using Included DME



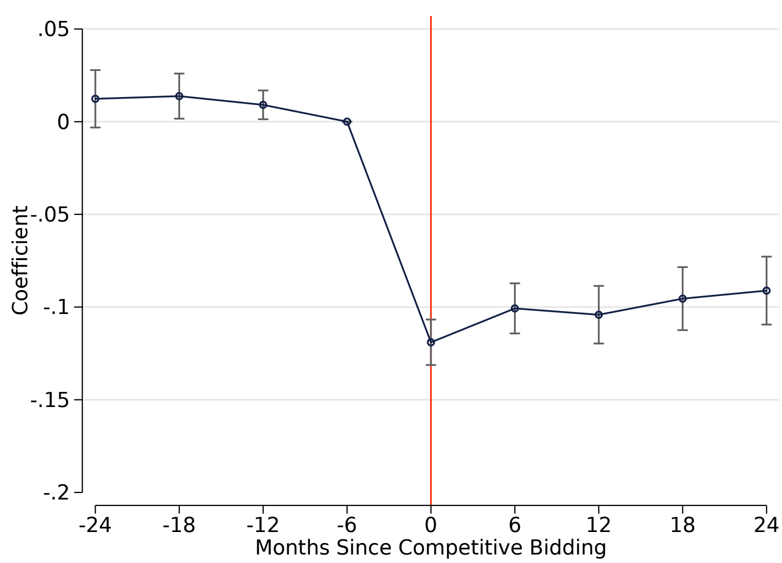
Notes: Panel (a) plots the simple average of log prices across items and MSAs separately for MSAs assigned to competitive bidding in January 2011, MSAs assigned to competitive bidding in July 2013, and MSAs paid using administrative fee schedules. Log prices for each MSA group in January-June 2009 are normalized to zero. Panel (b) plots the analogue of panel (a) for log share of beneficiaries using competitive bidding DME, defined as the number of beneficiaries in each MSA who have a Medicare claim for any DME that was eventually included in competitive bidding in each six-month period, divided by the total number of Medicare beneficiaries residing in that MSA. A simple average is taken across the MSAs.

Figure 4. Event Study: Log Price



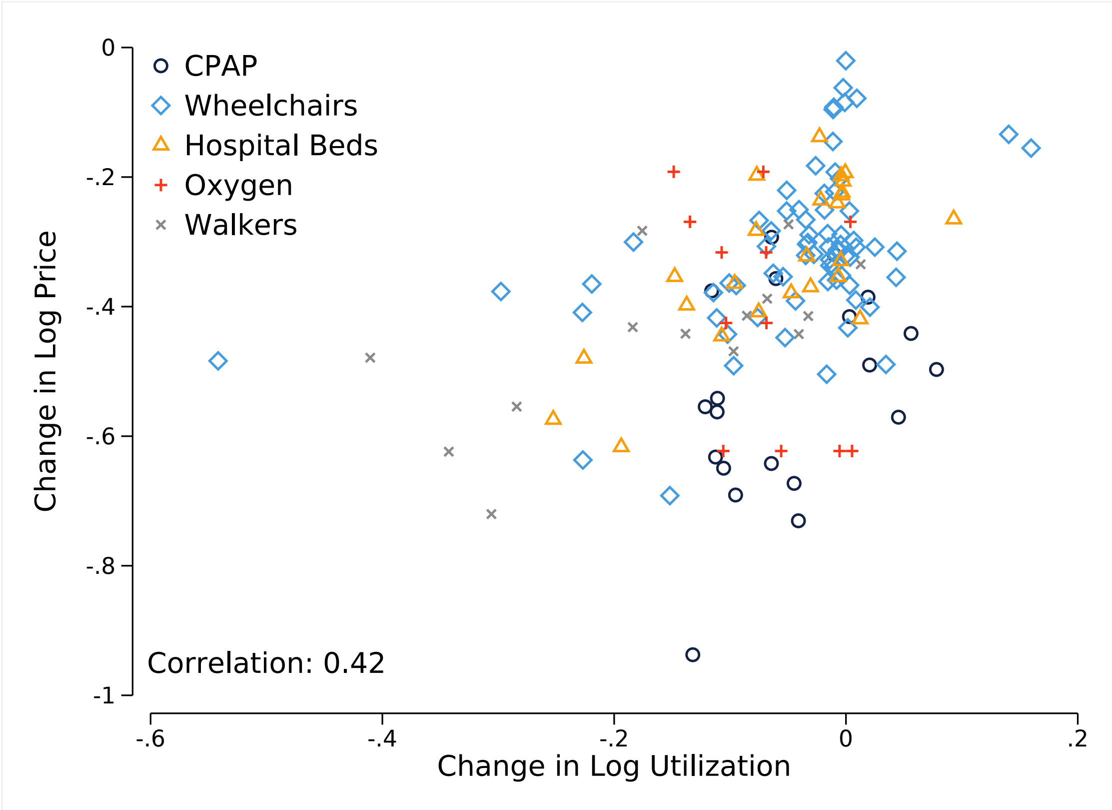
Notes: Figure shows estimates of Φ_r's from equation (1). The coefficient on the six months prior to the introduction of competitive bidding ($r(j,t) = -0.5$) is set to zero. 95% confidence intervals are based on standard errors clustered at the MSA level.

Figure 5. Event Study: Log Share of Patients with Any Competitive Bidding DME



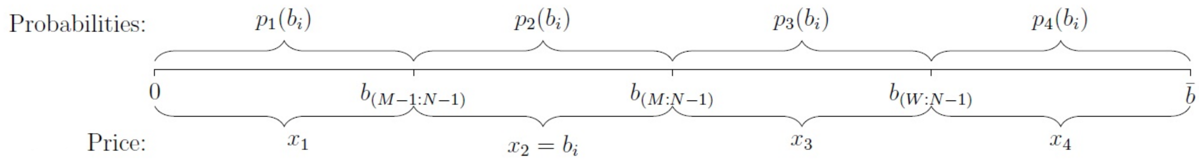
Notes: Figure plots estimates of Φ_r's from equation (1). The outcome is the log of share of patients with any claim on items that were included in competitive bidding. The coefficient for the six months prior to the introduction of competitive bidding ($r(j,t) = -0.5$) is set to zero. 95% confidence intervals are based on standard errors clustered at the MSA level.

Figure 6. Scatterplot: Change in Log Price and Change in Log Utilization



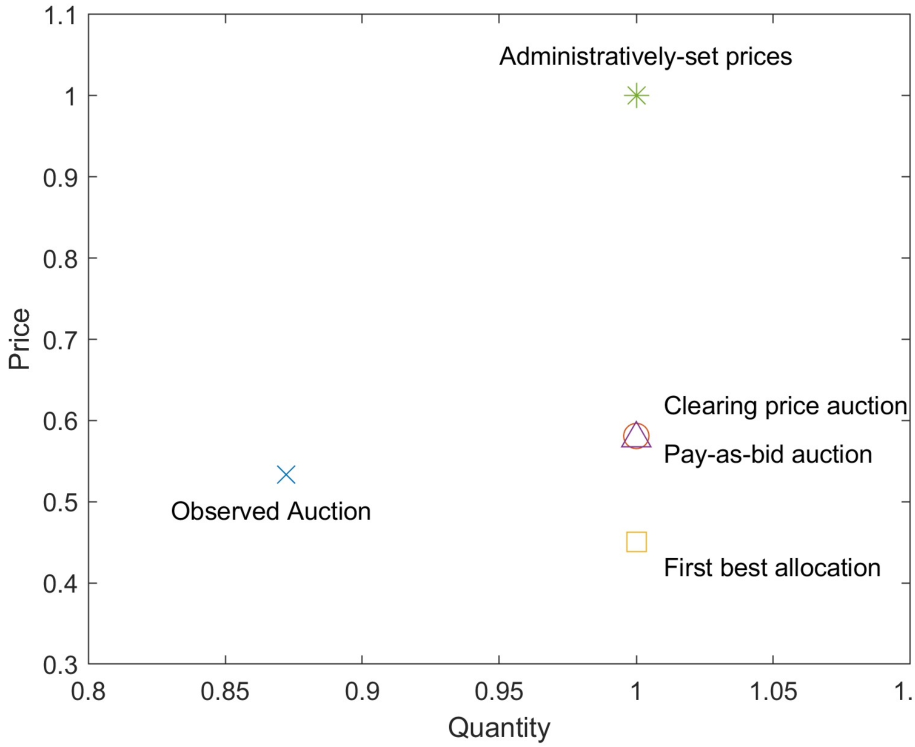
Notes: Each point in the figure represents a DME item (HCPCS code). The y-axis reports the changes in log price for that item based on estimates of equation (2). The x-axis reports the changes in log of share of patients in each MSA receiving that particular DME item, based on the same estimating equation. The correlation is an unweighted correlation across all items, regardless of their product category.

Figure 7. Bidder's Objective



Notes: Figure illustrates bidder i's problem. Bidder i's bid, b_i, can fall into one of four possible scenarios, shown on the line segment. The probabilities that b_i falls into each of the scenarios are shown above the line, and the realized prices (not observed at the time of the decision) conditional on being in each of these scenarios are shown below the line. When b_i is below $b_{(M-1:N-1)}$, the $(M-1)$-th lowest of the other $N-1$ bidders' bids, it wins the auction and is below the median winning bid; this happens with probability $p_1(b_i)$ and the final price is denoted by x_1. When b_i is between $b_{(M-1:N-1)}$ and $b_{(M:N-1)}$, it becomes the median winning bid and sets the price; this happens with probability $p_2(b_i)$. When b_i is between $b_{(M:N-1)}$ and $b_{(W:N-1)}$, it wins the auction and is above the median winning bid; this happens with probability $p_3(b_i)$ and the final price is denoted by x_3. Finally, b_i loses the auction when it is above $b_{(W:N-1)}$, that is, when there are at least W other bids below it.

Figure 8. Counterfactuals



Notes: Figure plots average allocations across different payment regimes. See notes to Table 11 for details. Price and quantity are shown as share of the price and quantity under administratively-set prices.

Table 1. Summary Statistics of Medicare Beneficiaries, 2009

	(1) All Medicare Beneficiaries	(2) Beneficiaries Using DME	(3) Beneficiaries Not Using DME
Panel (a) *Patient Characteristics*			
Average Age	71.1	72.8	70.5
White	83.4%	83.2%	83.5%
Female	54.7%	58.6%	53.3%
Medicaid	18.5%	26.3%	15.7%
Disabled	18.3%	17.8%	18.4%
End-Stage Renal Disease	0.7%	1.0%	0.6%
Number of Chronic Conditions[a]	2.99	4.99	2.29
$\geq$ 3 Chronic Conditions[a]	50.6%	80.4%	20.2%
$\geq$ 8 Chronic Conditions[a]	7.7%	19.0%	3.8%
Panel (b) *Health Care Utilization*			
Average Total Medicare Spending[b]	$8,284	$18,205	$4,828
Percent Beneficiaries with			
Inpatient Admissions	17.7%	35.7%	11.4%
Institutional Post-Acute Care Use[c]	4.5%	9.7%	2.4%
Home Health Use	8.6%	22.3%	3.5%
Panel (c) *DME Utilization*			
Product Types Used (S.D.)[d]	0.5 (1.0)	1.7 (1.1)	
Unique Items Used (S.D.)[e]	1.1 (2.6)	4.0 (3.5)	
Most Common Product Types[d]			
Glucose Monitor	10.5%	38.0%	
Oxygen Supplies/Equipment	4.3%	15.6%	
Nebulizers and Related Drugs	3.8%	13.6%	
Wheelchairs	3.3%	12.0%	
Continuous Positive Airway Pressure	3.0%	10.8%	
Walkers	2.6%	9.4%	
Diabetic Shoes	2.5%	9.1%	
Lower Limb Orthoses	1.8%	6.5%	
Lenses	1.5%	5.6%	
Hospital Beds/Accessories	1.5%	5.4%	
Number of Beneficiaries	36,861,647	9,523,409	27,338,238
% of All Beneficiaries		25.8 %	74.2%

Notes: Panel (a) reports the characteristics of beneficiaries. Panel (b) reports the share of Medicare beneficiaries who used health care services in different settings, as well as the most common conditions or services in each setting. Panel (c) reports the number of distinct DME product types used, the number of unique DME items used, as well as the most common product types by share of beneficiaries. In all panels, column (1) reports the mean for all Medicare beneficiaries enrolled in Traditional Medicare; columns (2) and (3) report the means for beneficiaries who did or did purchase durable medical equipment in 2009, respectively. All outcomes are based on the 100% Medicare enrollment and claims files in 2009.

[a] Based on the Chronic Conditions Segment of the 100% 2009 Medicare Beneficiary Summary File. End-of-year chronic condition indicators are used.

[b] Patient cost-sharing and non-Medicare payments excluded.

[c] Includes skilled nursing facilities, inpatient rehabilitation facilities, and long-term care hospitals.

[d] Defined based on the Durable Medical Equipment Coding System Product Classification and product categories used in the Durable Medical Equipment, Porsthetics, Orthotics, and Supplies Competitive Bidding program. These are collections of related items.

[e] Defined as unique Healthcare Common Procedure Coding System (HCPCS) codes, which are used for reimbursement.

Table 2. MSA Summary Statistics, 2009

	Competitive Bidding MSAs (Round 1)	Competitive Bidding MSAs (Round 2)	Non-Competitive Bidding MSAs
(1) Population†	3,129,132	1,850,855	210,469
	(1,727,962)	(2,663,610)	(173,751)
(2) Percent Female†	50.9	50.9	50.7
	(0.8)	(0.8)	(1.2)
(3) Percent White†	74.8	74.5	82.0
	(8.2)	(11.8)	(11.4)
(4) Percent Age 65 and Above†	12.5	12.7	13.3
	(3.0)	(3.3)	(3.3)
(5) Percent High School Graduate†*	85.7	85.6	85.2
	(4.0)	(5.2)	(6.6)
(6) Percent Home Ownership†	67.1	66.8	67.5
	(2.4)	(5.1)	(6.3)
(7) Percent on Medicare	15.2	16.0	18.1
	(3.1)	(4.0)	(4.6)
(8) Percent Medicare Dual**	13.2	13.8	12.9
	(4.0)	(5.2)	(5.7)
(9) Number of Chronic Conditions	2.1	2.2	2.4
	(0.5)	(0.5)	(0.6)
(10) Total Medicare Spending	6468.8	6345.9	6250.0
	(1450.6)	(1467.9)	(1599.7)
(11) Acute Spending	2039.7	2150.5	2147.3
	(336.6)	(561.9)	(613.9)
(12) Hospital Outpatient Spend	844.1	843.9	945.2
	(219.8)	(194.9)	(279.3)
(13) Skilled Nursing Spending	527.5	504.6	481.3
	(129.2)	(162.5)	(165.0)
(14) Home Health Spending	526.9	393.4	322.0
	(461.6)	(359.0)	(274.6)
(15) Hospice Spending	332.6	266.7	250.1
	(51.5)	(100.3)	(108.1)
(16) DME Spending	155.7	153.6	173.8
	(43.9)	(42.6)	(52.3)
(17) Percent Patients with DME	18.8	19.5	22.5
	(5.1)	(4.6)	(5.6)
Number of MSAs	9	91	271

Notes: Table reports summary statistics from 2009, the first year of the sample period, for MSAs that were assigned to competitive bidding in January 2011 (column (1)), MSAs that were assigned to competitive bidding in July 2013 (column (2)), and MSAs that were not assigned to competitive bidding during the sample period (column (3)). Unless otherwise noted, all outcomes are constructed from the 2009 Medicare master beneficiary summary file. All spending measures are Medicare spending, and do not include patient cost-sharing or third-party payment.

† Outcomes constructed from the 2009 American Community Survey, 3-Year estimates.

* High school graduation rate is computed among individuals aged 25 and above.

** Medicare patients who are also eligible for Medicaid.

Table 3. Auction Summary Statistics

	Mean	SD	P5	P25	P50	P75	P95
Panel (a): *Number of Bidders per Auction*							
All Auctions	68	30	33	48	62.5	80	126
Oxygen	58	21	31	44	53	70	98
CPAP	79	23	48	65	75	91	124
Wheelchair	67	33	25	47	61.5	79	133
Walker	71	33	34	49	60	83	132
Hospital Bed	66	33	30	45	58	79	126
N = 554 auctions							
Panel (b): *Bidder-level Summary Statistics*							
Number of MSAs*	3.6	11.1	1	1	1	3	10
Number of Product Categories	2.9	1.5	1	2	3	4	5
*N = 4,958 bidders representing 6,277 suppliers***							

Notes: Panel (a) reports summary statistics on the number of bidders across auctions. Panel (b) reports summary statistics on the number of MSAs and product categories for which each supplier participates in the auction. The sample is all auctions of the included product categories in 2011 and 2013.
*Reports the number of bidding areas—a small number of very large MSAs, such as New York, were further divided into several smaller bidding areas.
** Suppliers in the same MSA with the same ownership bid together.

Table 4. DME Prices Across MSAs and Items, January to June 2009

	Mean Across MSAs and Items (1)	SD Across MSAs (2)	SD Across Items (3)	Lowest Priced Item(s) (4)	Highest Priced Item(s) (5)	Number of Items (6)
(1) All Competitive Bidding DME	$157	$4	$253	$0.6 [Wheelchair bearings]	$2,139 [Power operated vehicle, 451-600 lbs capacity]	301
(2) Oxygen	$98	$0	$ 60	$28.8 [Portable gaseous or liquid oxygen system, rental]	$176 [Stationary compressed gaseous or liquid oxygen system, rental] [oxygen concentrator, rental]	12
(3) CPAP	$109	$4	$148	$1.8 [Replacement exhalation port]	$545 [RAD with backup invasive inteface, rental]	26
(4) Wheelchairs	$192	$5	$302	$0.6 [Wheelchair bearings]	$2,139 [Power operated vehicle, 451-600 lbs capacity]	185
(5) Walkers	$77	$3	$110	$1.7 [Brake for wheeled walker]	$522 [Walker with variable wheel resistance]	42
(6) Hospital Beds	$126	$5	$156	$3.6 [Bed cradle]	$699 [Hospital bed, extra heavy duty extra wide]	33

Notes: Table reports the distribution of prices across MSAs and items prior to competitive bidding, in the first six months of the study period. Each row is a category of DME that was subject to competitive bidding. For each category, column (1) reports the mean price across all MSAs and items in that category; column (2) reports the standard deviation across MSAs; column (3) reports the standard deviation across items; column (4) reports the lowest price and the lowest priced item(s) in that category; column (5) reports the highest price and the highest priced item(s) in that category; column (6) reports the number of items in the category.

Table 5. Impact of Competitive Bidding on DME Price and Utilization

	Change with Competitive Bidding	
	Estimate	% Change
	(1)	(2)
(1) Log Price	-0.600 (0.009) [<0.001]	-45.1%
(2) Log Price (Items Weighted Equally)	-0.445 (0.016) [<0.001]	-35.9%
(3) Log Share of Beneficiaries Using DME	-0.111 (0.010) [< 0.001]	-10.5%
(4) Log Share of Beneficiaries Using DME (Population Weighted)	-0.134 (0.015) [<0.001]	-12.6%
(5) Log Standardized Utilization Per Beneficiary	-0.074 (0.013) [<0.001]	-7.2%
(6) Log Standardized Utilization per Beneficiary (Population Weighted)	-0.124 (0.021) [<0.001]	-11.6%

Notes: Table reports results from estimating equation (1). Column (1) reports the coefficient estimates of Φ; robust standard errors clustered at the MSA and the p-value are reported in the parentheses and the square brackets, respectively. Column (2) reports the coefficient estimate in exponentiated form to represent a percentage change. The sample is all items that were subject to competitive bidding between 2009 and 2015. The outcome in row (1) is the simple average of log prices across items; the outcome in row (2) is the average log price across items, weighted by the number of beneficiaries with a claim for that item in the first six months of 2019.

Table 6. Heterogeneity in Impact Across Product Categories

	Change with Competitive Bidding			
	Log Price		*Log Share of Beneficiaries*	
	Estimate	% Change	Estimate	% Change
	(1)	(2)	(3)	(4)
(1) Oxygen Equipment	-0.585		-0.052	
	(0.009)	-44.3%	(0.011)	-5.0%
	[<0.001]		[<0.001]	
(2) CPAP	-0.647		-0.091	
	(0.010)	-47.7%	(0.009)	-8.7%
	[<0.001]		[<0.001]	
(3) Wheelchairs	-0.452		-0.134	
	(0.010)	-36.3%	(0.024)	-12.5%
	[<0.001]		[<0.001]	
(4) Walkers	-0.823		-0.262	
	(0.011)	-56.1%	(0.018)	-23.0%
	[<0.001]		[<0.001]	
(5) Hospital Beds	-0.586		-0.162	
	(0.008)	-44.4%	(0.031)	-15.0%
	[<0.001]		[<0.001]	
(6) Non-Competitive Bidding DME	0.003		-0.014	
	(0.003)	0.3%	(0.007)	-1.4%
	[0.274]		[0.052]	

Notes: Table replicates the main price and quantity results separately for each product category. Separately for each product category, columns (1) and (2) replicate row (1) of Table 5; columns (3) and (4) replicate row (4) of Table 5. Row (6) Non-Competitive Bidding DME includes all DME items that were never subject to competitive bidding during the sample period.

Table 7. Impact on Share of Beneficiaries Using DME, by Prior Use

	Change with Competitive Bidding			
	Sample: Prior Use		*Sample: No Prior Use*	
	Estimate (1)	% Change (2)	Estimate (3)	% Change (4)
(1) Oxygen Equipment	-0.053 (0.013) [<0.001]	-5.2%	-0.061 (0.016) [<0.001]	-5.9%
(2) CPAP	-0.101 (0.011) [<0.001]	-9.6%	-0.090 (0.016) [<0.001]	-8.6%
(3) Wheelchairs	-0.120 (0.030) [<0.001]	-11.3%	-0.115 (0.037) [0.002]	-10.8%
(4) Walkers	-0.410 (0.040) [<0.001]	-33.6%	-0.276 (0.029) [<0.001]	-24.1%
(5) Hospital Beds	-0.137 (0.055) [0.013]	-12.8%	-0.107 (0.043) [0.013]	-10.2%

Notes: Table replicates row (3) of Table 5, but separately for patients who had the same category of DME in the three year period between 2009 and 2011 (columns (1) and (2)), and those who did not have the same category of DME in those three years (columns (3) and (4)). The sample is all beneficiaries residing in the 91 MSAs that were assigned to competitive bidding in 2013, and all beneficiaries residing in MSAs that never entered competitive bidding. Beneficiaries residing in the 9 MSAs that entered competitive bidding in 2011 were excluded as the sample is not long enough to measure their prior use. The average share of beneficiaries with and without prior use in across MSAs are 4% and 96%, respectively, for oxygen equipment, 4% and 96% for CPAP, 4% and 96% for wheelchairs, 6% and 96% for walkers, 2% and 98% for hospital beds.

Table 8. Impact of Competitive Bidding on Characteristics of Patients Using DME

	Change with Competitive Bidding	
Outcome: Patient Characteristics	Pre-Period Mean (1)	Estimate (2)
Number of Chronic Conditions	5.7	0.005 (.015) [0.72]
Percent Over 80 Years Old	31.8	-0.58 (0.2) [0.004]
Percent Female	55.5	-0.81 (0.11) [<0.001]
Percent NonWhite	17.4	-1.0 (0.23) [<0.001]
Percent Medicaid	26.9	-1.5 (0.39) [<0.001]

Notes: Table reports results from estimating equation (2), except that outcomes are patient characteristics shown in each row. Column (1) reports mean in Round 1 and Round 2 MSAs prior to the introduction of competitive bidding. Columns (2) reports the coefficient estimates of Φ; robust standard errors clustered at the MSA and the p-value are reported in the parentheses and the square brackets, respectively. The sample is all MSA-half year combinations between 2009 and 2015 (N = 5,460 MSA-half years).

Table 9. Delay in DME Use After Inpatient Discharge

	Change with Competitive Bidding	
	Estimate (1)	% Change (2)
Outcome: Log Share of Patients Receiving DME		
(1) Within 7 Days of Inpatient Discharge	-0.081 (0.025) [0.001]	-7.8%
(2) Within 14 Days of Inpatient Discharge	-0.066 (0.022) [0.003]	-6.4%
(2) Within 30 Days of Inpatient Discharge	-0.043 (0.015) [0.004]	-4.2%

Notes: Table reports estimates of equation (2) for the row outcomes. The sample is all inpatient discharges in the treatment and control MSAs during the sample period.

Table 10. Model Parameters and Estimates

	Mean	SD	P25	P50	P75
Product-MSA Level Parameters:					
N	68.21	29.93	48	62.5	80
W	19.55	6.98	15	19	24
M	10.01	3.50	8	10	12
Supplier-Product-MSA Level Parameters:					
b_i	0.662	0.131	0.57	0.66	0.75
κ_i	0.139	0.263	0.008	0.036	0.131
c_i	0.626	0.200	0.55	0.65	0.74
Supplier Margins Conditional on Winning:					
$b_i - c_i$	0.084	0.168	-0.02	0.03	0.10

Notes: The top panel reports the distributions of bidders, winners, and the order statistic of the median across auctions. The middle panel reports the distributions of the observed bids, capacities, and the estimated bidder cost across all bidders and product-MSAs. The bottom panel reports the difference between bidders' bids and costs across all winners. Bids and costs are normalized to shares of the administrative fee schedule price (p^{admin}). Capacity is normalized to shares of quantity under administratively set prices (i.e. the target quantity).

Table 11. Counterfactuals

	Price	Quantity	Spending
Panel (a): Target Quantity = 1			
Existing Fee Schedule	1	1	1
Observed Auction[a]	0.54	0.87	0.46
Uniform-Price Auction[b]	0.58	1	0.58
Pay-as-bid Auction[ce]	0.58 (*s.d.* 0.012)	1	0.58
First Best[de]	0.45	1	0.45
Panel (b): Target Quantity = 1.2			
Uniform-Price Auction	0.60	1.2	0.72
Pay-as-bid Auction	0.61 (*s.d.* 0.011)	1.2	0.73
First Best	0.47	1.2	0.56
Panel (c): Target Quantity = 0.8			
Uniform-Price Auction	0.56	0.8	0.45
Pay-as-bid Auction	0.56 (*s.d.* 0.013)	0.8	0.45
First Best	0.43	0.8	0.34

Notes: Table reports the average price, quantity, and spending across all auctions under observed and counterfactual regimes. The price, quantity, and spending under the existing fee schedule is normalized to 1, and results for other regimes are reported as a share relative to the fee schedule. Panels (a), (b) and (c) report the allocation when target quantity is 1 (i.e. the quantity prior to competitive bidding), 1.2 (120% of prior quantity), and 0.8 (80% of prior quantity), respectively. With the exception of the observed auction, all auctions achieve the target quantity by design. The price generated under panel (b) is equivalent to the counterfactual where Medicare decreases its estimates of bidder capacity by 17%(= 1/1.2) while maintaining the target quantity. The price generated under panel (c) is equivalent to the counterfactual where Medicare increases its estimates of bidder capacity by 25%(= 1/0.8) while maintaining the target quantity.

[a] The average quantity across all auctions is reported.

[b] Price is set to the lowest losing bid.

[c] Price is set to each bidder's bid.

[d] Price is set to each bidder's cost.

[e] In each product-MSA, the mean and standard deviation of prices paid are computed across units and the average mean and standard deviation across product-MSAs is reported.

Online Appendix

A Rules of the DME Auction

Summary of the bidding process:[44]

1. To be eligible to participate in the competitive bidding program, suppliers must 1) have an active National Supplier Clearinghouse supplier number, 2) meet certain quality standards, and 3) be accredited or have their accreditation pending. Eligible suppliers may then submit bids in a sixty-day bidding period.

2. Bids are submitted separately for each product category in each MSA. Winning the bid grants the privilege to sell items in the given product category to beneficiaries residing in the MSA. Suppliers do not have to be physically located in an MSA to participate in competitive bidding.

3. Suppliers are provided with a bidding worksheet, which contains the list of HCPCS codes, the definition of a bidding unit (e.g. 1 unit = 100 calories of enteral formula), weights used to compute the composite bid, which are based on historical national volumes of the product relative to other products in that category, and the bid limit (maximum amount the supplier is allowed to bid), which is the administrative price that would have been paid absent competitive bidding. Figure A1 is an excerpt from a worksheet for the product category "standard power wheelchairs, scooters, and related accessories."

4. Suppliers must submit a bid for each product (defined as HCPCS code and applicable code modifiers) in the product category. CMS requires the bids to be "bona fide", which is determined based on the information the suppliers provide on cost to purchase the item, overhead, and profit. (e.g. the supplier may be required to submit invoices, and signed written quotes to prove that they can supply the product at the price they bid.) CMS rejects the entire bid if it determines that the bid for any product is not bona fide.[45]

5. Along with each bid, suppliers must also indicate how much volume they can provide at that price. Specifically, if a supplier does not plan to expand its capacity, it is asked to report the number of units it is currently providing in that market on a yearly basis; if a supplier is planning to expand, it should add any additional units it would be capable of supplying, and provide financial evidence for the proposed expansion.[46]

6. Based on the estimated capacity data reported by suppliers and historical claims data, CMS defines an estimated capacity for each supplier. Although the exact formula is not disclosed, it involves applying an upward adjustment of up to 20% to a supplier's historical capacity. For suppliers proposing to expand, if CMS deems that the financial evidence to be insufficient, it will only consider the number of units the supplier has supplied in the past to compute the supplier's capacity. Capacities for suppliers new to a market are computed based on a mixture of supplier's own estimate, historical trends for new suppliers in the market, and the capacities of other suppliers in the market.[47]

7. CMS computes a composite bid for each bidding supplier that is equal to a weighted average of the supplier's bids for each item in that product category.

[44] Based on https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/DMEPOSCompetitiveBid/downloads/DMEPOSRegSumm.pdf and Federal Register 2006 Vol. 71 No. 83

[45] 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

[46] See https://dmecompetitivebid.com/palmetto/cbicrd2.nsf/DocsCat/Home under "Bidding Suppliers" → "Bidding" → "Required Financial Documents."

[47] The methodology for estimating supplier capacity is guided by a panel discussion by the Program Advisory and Oversight Committee (PAOC) on February 28, 2005. The PAOC, "based upon their expertise and knowledge of the industry, suggested that most DMEPOS suppliers would be able to easily increase their total capacity to furnish items by up to 20 percent and the increase could be even larger for products like diabetes supplies that require relatively little labor." (Federal Register 2006 Vol. 71 No. 83)

8. CMS ranks all suppliers from lowest composite bid to highest and offers contracts in that order, until there are enough suppliers to reach the target quantity. To determine how many contracts to award, CMS uses the supplier capacity measure generated in the previous step, but caps each supplier at 20% target quantity (e.g. if a supplier claims to be able to satisfy 70% of the market, CMS disregards the 70% and uses 20% in its calculations) CMS also requires that small suppliers make up at least 30% of the awarded contracts. Small suppliers are defined as those with a annual gross revenue (Medicare and non-Medicare combined) of $3.5 million or below. If not enough small suppliers initially make the cut based on the composite bids, CMS continues down the list to make offers to additional small suppliers at the same price until the 30% number is reached.

9. The price paid to the suppliers is the median of all winning suppliers' bids for each item (HCPCS code and relevant modifiers). This price is paid out without adjustment for three years.

10. If a supplier does not enter a contract with CMS, either by failing to win the bidding process or rejecting the contract after winning, it cannot sell any of the products in question in that MSA. (For example, if a supplier failed to win a contract for "Oxygen Supplies and Equipment" in Pittsburgh, PA, it may not sell any item in that group to Medicare beneficiaries residing in the Pittsburgh, PA MSA for the next three years.)

11. A new round of competitive bidding is conducted every three years.

B Additional Results and Robustness

B.1 Event studies using the full panel of years

Due to the staggered introduction of competitive bidding across different MSAs, the main results in the paper use a panel that is balanced in relative months. This section shows the main results using the full panel of months. Figures A3 and A4 show event studies for log price and log share of beneficiaries using DME, respectively. Since the study period ends in 2015, I observe a different set of relative months in different MSAs, depending on when they entered competitive bidding. This imbalance in MSA-relative months causes compositional changes to show up at month 30, which is only defined for the set of MSAs that entered competitive bidding in 2011. To avoid confounding the result with compositional changes caused by the limited sample years, the results in the paper are based on a balanced panel of MSAs and relative months. Despite the issue with sample composition in later months, the results from the full panel are almost identical to those from the balanced panel for the period of interest (-24 to 24 months).

B.2 Event studies and model estimates at the item-MSA-half year level

The main regression specification in the paper estimates a difference-in-differences model at the MSA-half year level. This section reports results from an alternative specification at the item-MSA-half year level. For each competitive bidding item i in MSA j in half-year t, I estimate the following difference-in-differences event study specification

$$ln(y_{ijt}) = \gamma_j + \tau_t + \lambda_i + \Phi_r CB_j \times \theta_{r(j,t)} + \epsilon_{ijt} \tag{A1}$$

where $ln(y_{ijt})$ is log price or log share of beneficiaries using a competitive-bidding DME. λ_i, γ_j, τ_t indicate item, MSA, and half-year fixed effects, respectively. CB_j is an indicator for MSAs subject to competitive bidding, $\theta_{r(j,t)}$ are indicators for relative months. The coefficients Φ_r's quantify the effect of competitive bidding on price.

To summarize the impact over the post-period months, I also estimate a pre-post version of the same specification,

$$ln(y_{ijt}) = \gamma_j + \tau_t + \lambda_i + \Phi CB_j \times Post_t + \epsilon_{ijt} \tag{A2}$$

where $Post_t$ is an indicator for the period after competitive bidding was introduced.

Note that the interpretation of the result differs between the specification in equation (A2) and the main specification from equation (2) in the paper. The former is an average change across individual items, some of which experienced an increase in utilization and others a decrease. The latter captures the overall changes in the utilization of competitive bidding items in aggregate.
Figures A5 and A6, and Table A2 report event study and model estimates using this alternative specification. The figures and table show results that are very comparable with the baseline estimates.

B.3 Event studies by product categories

Figures A10 and A11 show event studies for price and quantity by product category, respectively.

C Deriving the Objective Function

This section contains the derivation of the version of equation (3) that I take to the data, which is a function of c_i, b_i, $F_b(\cdot)$, $f_b(\cdot)$, M, W, and N. Since N is observed, M, W, $F_b(\cdot)$, $f_b(\cdot)$ are estimated based on the observed bids, optimizing the objective can provide a mapping between c_i and b_i.
Starting with equation (3)

$$\max_{b_i} \sum_{l=\{1,2,3\}} p_l(b_i) \cdot E(max\{x_i - c_i, 0\}|x_i = x_l(b_i))$$

Note that $p_l(b_i) = Pr\{x_i = x_l(b_i)\}$. By Bayes' rule, I can rewrite the objective as as

$$\max_{b_i} \sum_{l=\{1,2,3\}} E(x_i - c_i|x_i > c_i, x_i = x_l(b_i)) \cdot Pr\{x_i > c_i, x_i = x_l(b_i)\}$$

When $b_i \geq c_i$, the objective is given by

$$\begin{aligned}
&E(b_{(M-1:N-1)} - c_i|b_i < b_{(M-1:N-1)}) \cdot Pr\{b_i < b_{(M-1:N-1)}\} \\
&+ (b_i - c_i) \cdot Pr\{b_{(M-1:N-1)} < b_i < b_{(M:N-1)}\} \\
&+ E(b_{(M:N-1)} - c_i|b_{(M:N-1)} > c_i, b_{(M:N-1)} < b_i < b_{(W:N-1)}) \cdot Pr\{b_{(M:N-1)} > c_i, b_{(M:N-1)} < b_i < b_{(W:N-1)}\} \\
=& \int_{b_i}^{\bar{b}} x f_{b_{(M-1:N-1)}}(x)dx - (1 - F_{b(M-1:N-1)}(b_i)) \cdot c_i \\
&+ (F_{b(M-1:N-1)}(b_i) - F_{b(M:N-1)}(b_i)) \cdot (b_i - c_i) \\
&\int_{b_i}^{\bar{b}} \int_{c_i}^{b_i} x f_{b(M,W:N-1)}(x,y)dxdy - c_i \cdot \int_{b_i}^{\bar{b}} \int_{c_i}^{b_i} f_{b(M,W:N-1)}(x,y)dxdy
\end{aligned}$$

When $b_i < c_i$, the objective is given by

$$\int_{c_i}^{\bar{b}} x f_{b_{(M-1:N-1)}}(x)dx - (1 - F_{b_{(M-1:N-1)}}(c_i)) \cdot c_i$$

In each of the expressions above, the PDF and CDF of order statistics, and the joint PDF of two order statistics are given by the following expressions:

$$f_{(k:n)}(x) = \frac{n!}{(k-1)!(n-k)!}(1 - F(x))^{n-k} F(x)^{k-1} f(x)$$

$$F_{(k:n)}(x) = \sum_{i=k}^{n} \frac{n!}{i!(n-i)!}(1 - F(x))^{n-i} F(x)^i$$

$$f_{(j,k:n)}(x,y) = \frac{n!}{(j-1)!(k-1-j)!(n-k)!} f(x)f(y)[F(x)]^{j-1}[F(y)-F(x)]^{k-1-j}[1-F(y)]^{n-k}$$

I take the objective function to the data by searching over a 100-by-100 grid of evenly sapced values of b_i and c_i, as described in Section 5. Estimation was conducted in MatLab R2021a.

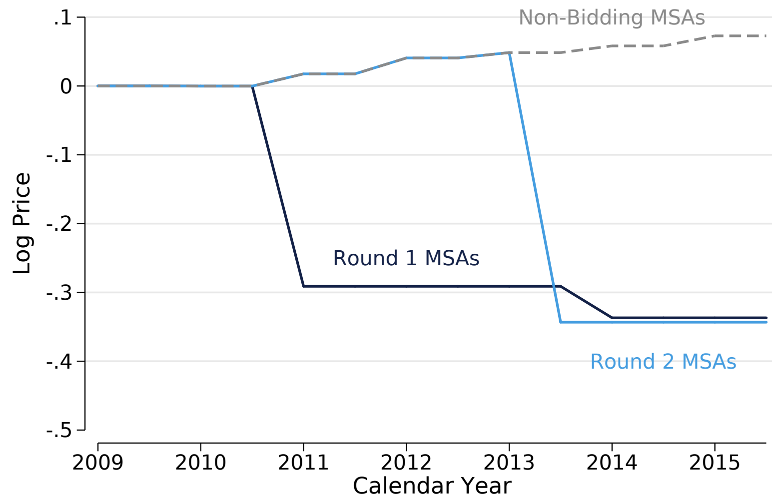
Figure A1. Bid Preparation Sheet Example

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

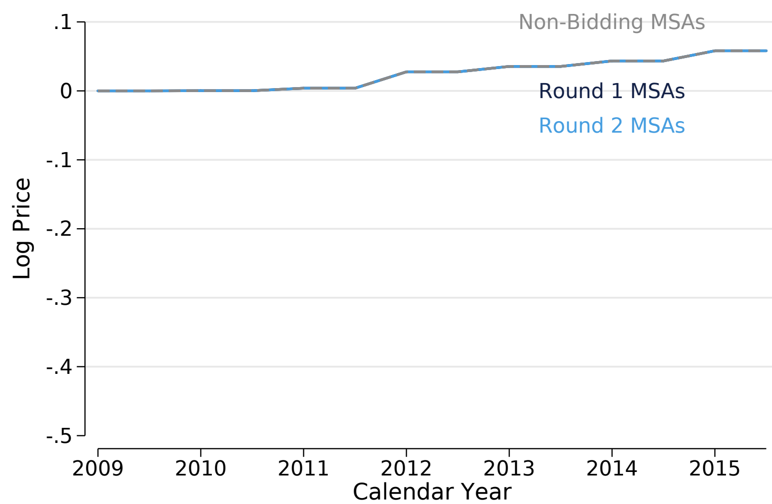
Notes: Excerpt from a bid preparation worksheet provided to suppliers, downloadable from https://www.dmecompetitivebid.com.

Figure A2. Raw Price Trends

(a) Average Log Price (Items Weighted Equally)

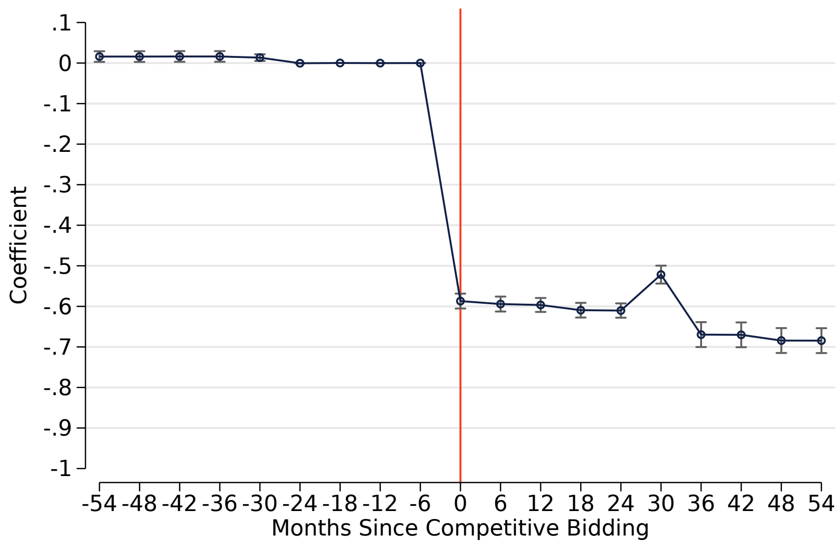


(b) Average Log Price (Items Not Included in Competitive Bidding)



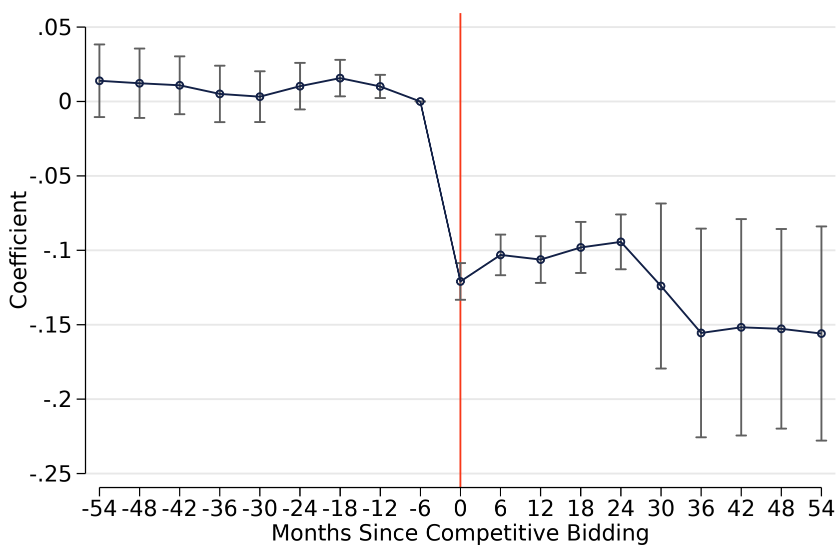
Notes: Panel (a) replicates Figure 3 panel (a), weighting each item equally, rather than by pre-period utilization. Panel (b) replicates the same figure for DME items that were never subject to competitive bidding throughout the study period; this figure serves as a placebo test that the price decline was a result of competitive bidding rather than system-wide price reductions.

Figure A3. Event Study: Log Price (Full Panel)



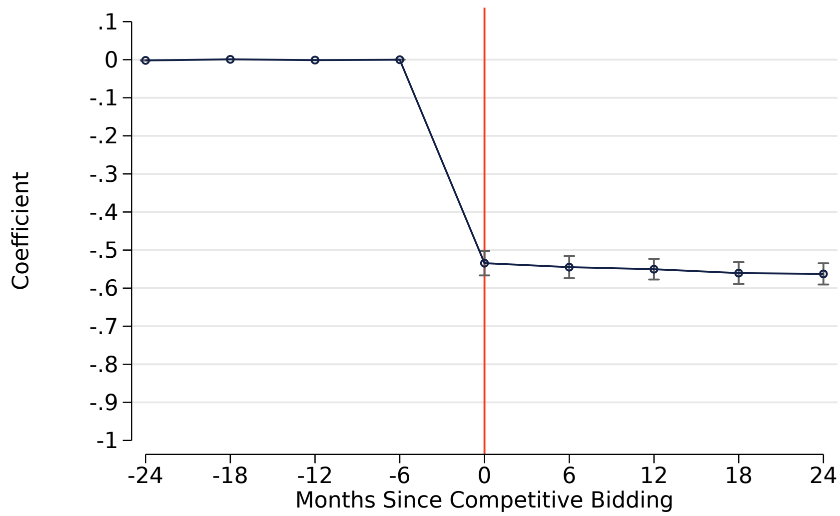
Notes: Figure replicates Figure 4 in the paper, except that it uses the full, unbalanced panel. The spike at month 30 is caused by the change in MSA compositionsince the study period ends in 2015, relative month 30 and later relative months are only defined for the set of MSAs that entered competitive bidding in 2011.

Figure A4. Event Study: Log Share of Beneficiaries Using DME (Full Panel)



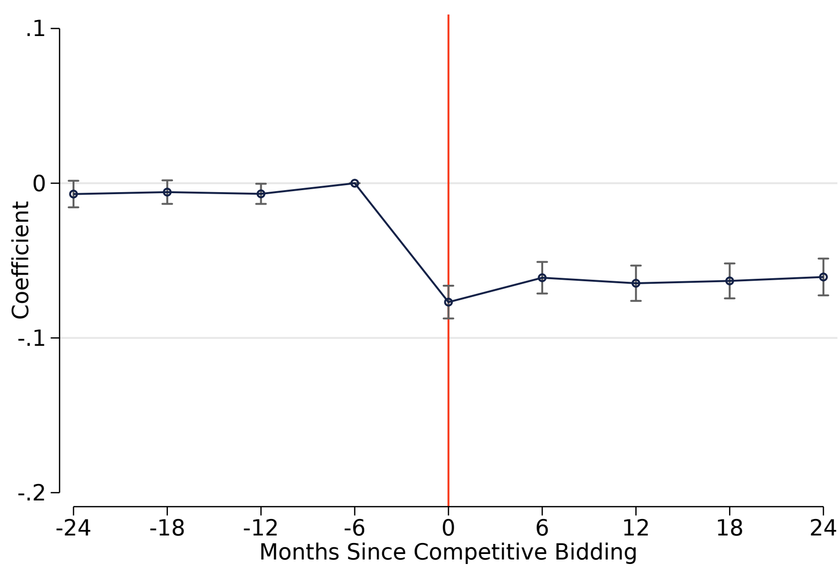
Notes: Figure replicates Figure 5 in the paper, except that it uses the full, unbalanced panel.

Figure A5. Event Study: Log Price (Item-MSA-Half Year Level Model)



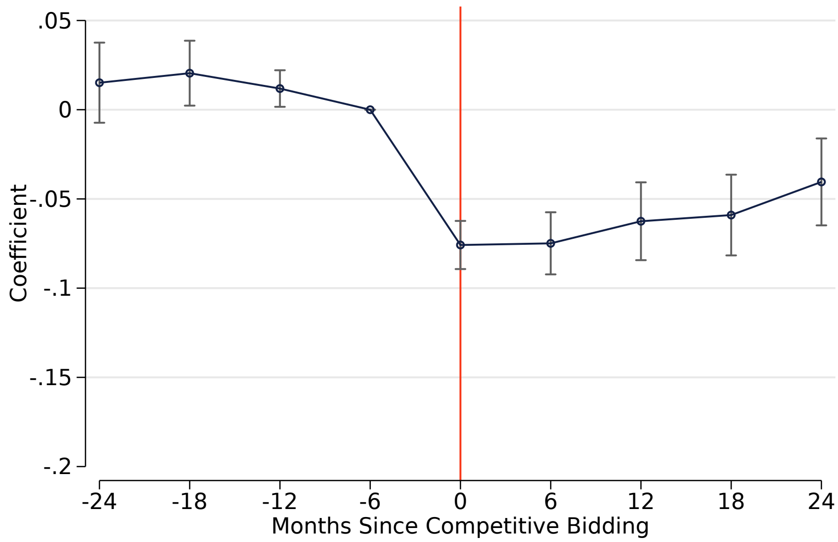
Notes: Figure plots coefficients from estimating equation (A1).

Figure A6. Event Study: Log Share of Beneficiaries (Item-MSA-Half Year Level Model)



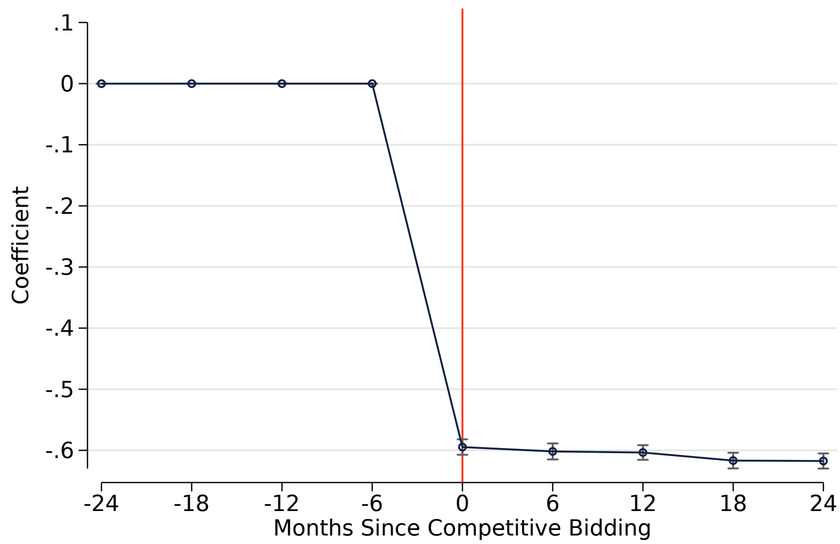
Notes: Figure plots coefficients from estimating equation (A1).

Figure A7. Event Study: Standardized Utilization



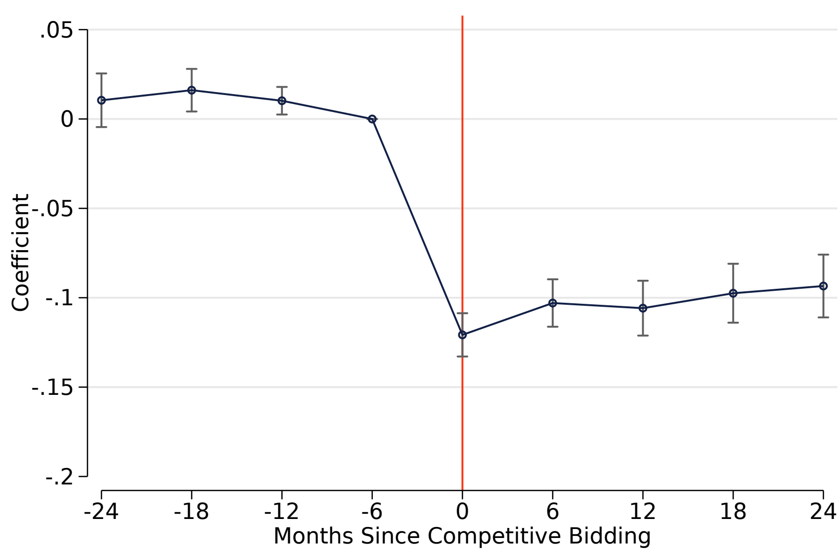
Notes: Figure plots coefficients from estimating equation (1) for log standardized utilization per beneficiary. This measure is constructed by computing the Medicare reimbursement assuming that each item was paid the mean fee schedule price among MSAs that were never subject to competitive bidding.

Figure A8. Event Study: Log Price (Sun and Abraham (2021))



Notes: Figure replicates Figure 4 using the Sun and Abraham (2021) estimator.

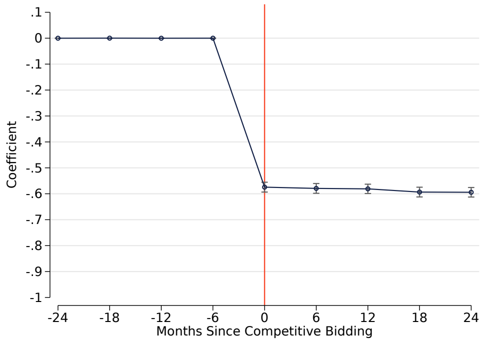
Figure A9. Event Study: Log Share of Beneficiaries (Sun and Abraham (2021))



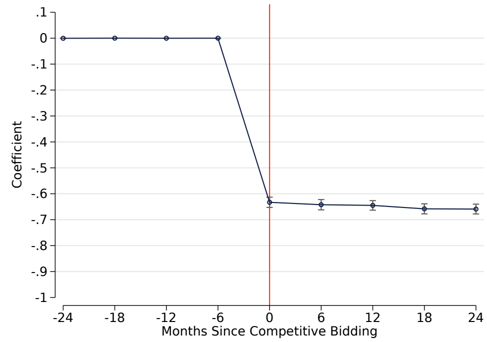
Notes: Figure replicates Figure 5 using the Sun and Abraham (2021) estimator.

Figure A10. Event Study: Log Price, by Product Category

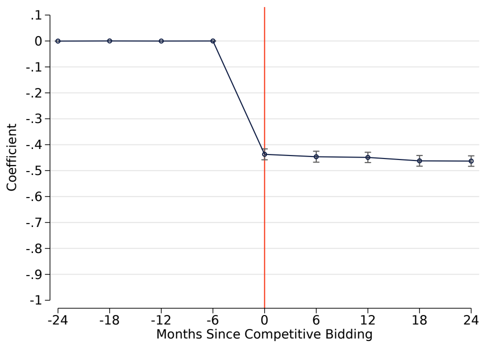
(a) Oxygen



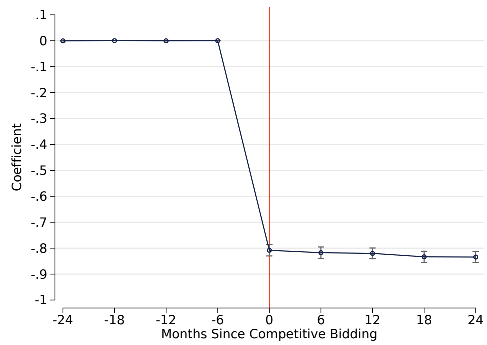
(b) CPAP



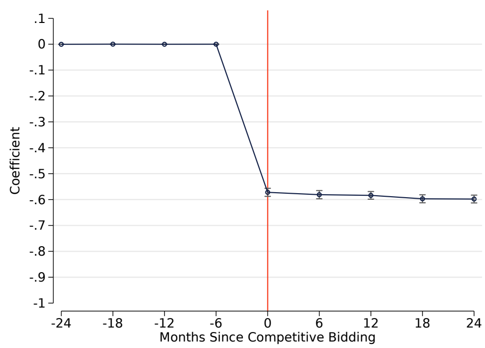
(c) Wheelchair



(d) Walker



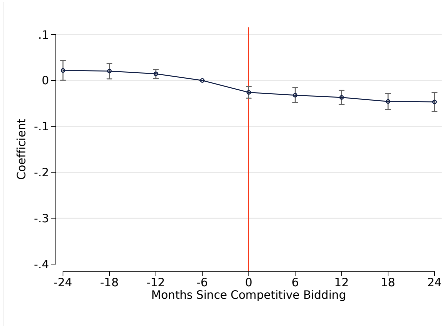
(e) Hospital Bed



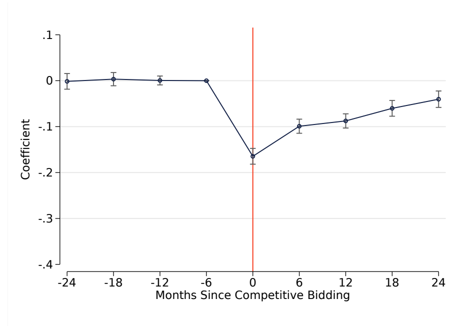
Notes: Figure replicates Figure 4 separately by each product category.

Figure A11. Event Study: Log Share of Beneficiaries with Any DME Claim, by Product Category

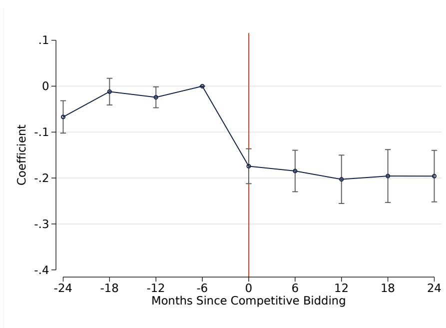
(a) Oxygen



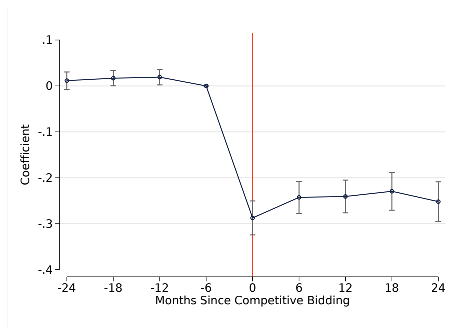
(b) CPAP



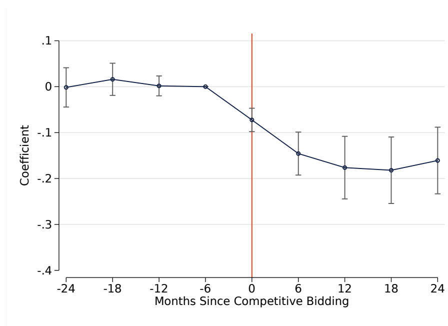
(c) Wheelchair



(d) Walker

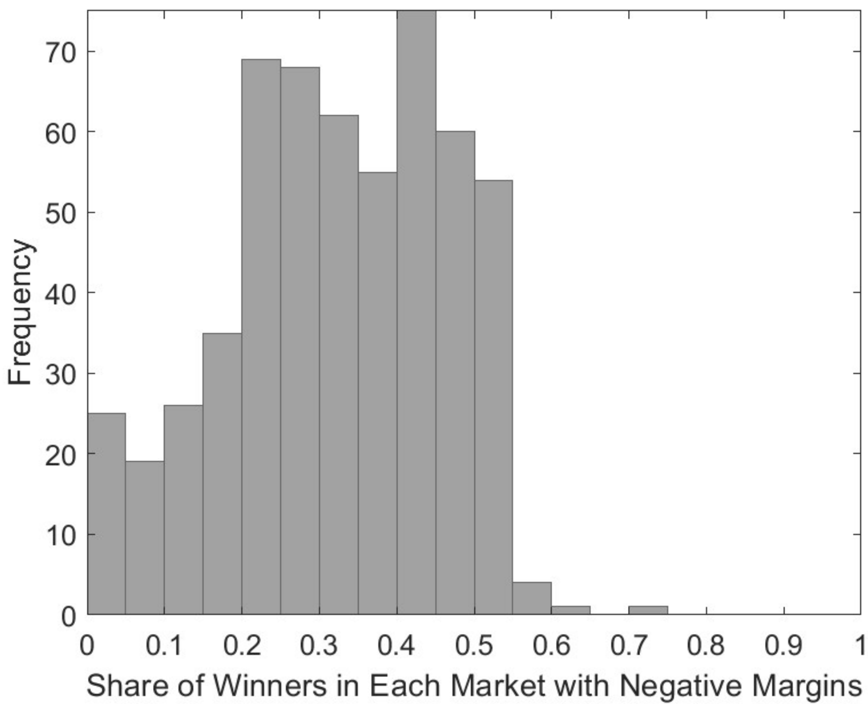


(e) Hospital Bed



Notes: Figures replicate Figure 5 separately by types of durable medical equipment.

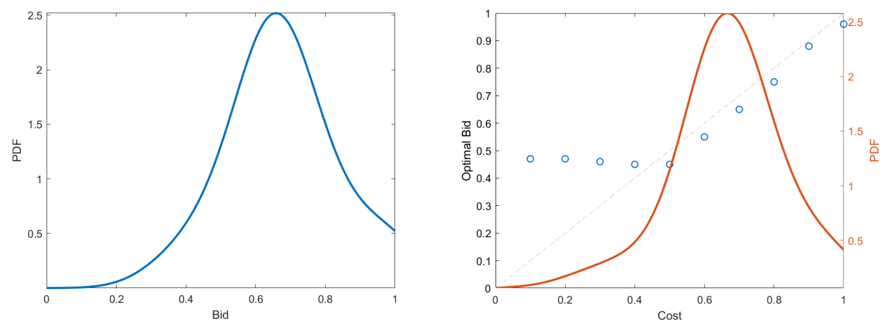
Figure A12. Share of Winners Facing Negative Margins



Notes: Figure shows the share of suppliers who win an auction but would incur a loss should they sell at the auction-generated price, based on the model estimates.

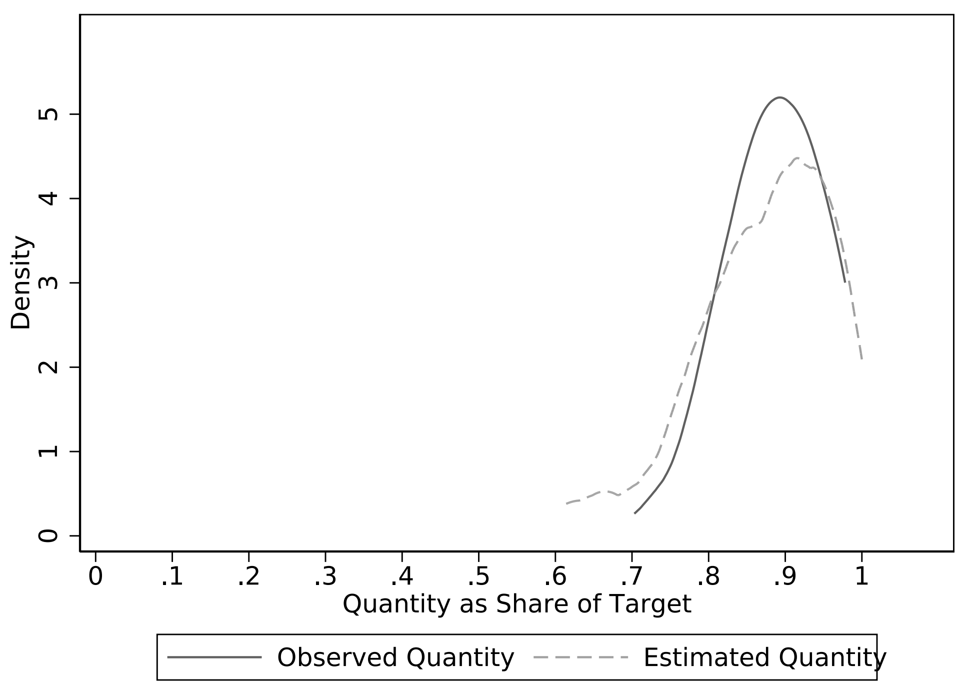
Figure A13. Model Estimates from Example Auction: Walkers in Washington, DC

(a) Bid Distribution **(b)** Estimated Cost Distribution



Notes: Panel (a) plots the observed bid distribution distribution using the example of the 2013 auction for walkers in the Washington, DC MSA. Panel (b) illustrates for the same example, the equilibrium bid schedule and the implied cost distribution. The dashed line is the 45-degree line.

Figure A14. Comparison with Reduced-Form Estimates



Notes: Figure shows the kernel densities of quantity as a share of quantity under administratively-set prices, based on the structural model and the reduced form analysis, respectively. The reduced form estimates are computed at the MSA level as differences between relative year 0 and relative year −0.5. The model estimates are generated by estimating the model in Section 5 using data on supplier bids and aggregating to the MSA level.

Table A1. Summary Statistics of Medicare DME Suppliers, 2009

	(1) Mean	(2) S.D.
Panel (a) *Supplier Level Summary Statistics*		
Number of Product Categories Sold	4.5	5.2
Number of MSAs Served	4.6	14.8
Number of Beneficiaries Served	168	2,945
Annual Medicare Reimbursement	\$114,069	\$1,008,617
Percent Medicare Reimbursement from Outside of an MSA	22.8%	36.8%
Panel (b) *MSA Level Summary Statistics*		
Number of Suppliers in MSA	402	548
Number of Suppliers in MSA by Product Category		
Glucose Monitor	193	286
Oxygen Supplies/Equipment	59	74
Nebulizers and Related Drugs	172	291
Wheelchairs	74	116
Continuous Positive Airway Pressure	55	61
Walkers	67	116
Diabetic Shoes	50	90
Lower Limb Orthoses	53	107
Lenses	29	47
Hospital Beds/Accessories	53	84

Notes: Panel (a) reports summary statistics at the supplier level. Panel (b) reports summary statistics at the MSA level. All measures based on the 2009 Medicare claims data. Suppliers are defined as unique NPIs. Panel (b) restricts to suppliers with at least 25 Medicare claims in the MSA.

Table A2. Impact of Competitive Bidding on DME Price (Item-MSA Level Model)

	Change with Competitive Bidding			
	Percent Change (1)	Estimate (2)	S.E. (3)	P-value (4)
Panel A Outcome: Log Price (Utilization Weighted)				
All Competitive Bidding DME	-42.4%	-0.552	0.015	<0.001
Oxygen Equipment	-41.6%	-0.538	0.007	<0.001
CPAP	-26.8%	-0.312	0.015	<0.001
Wheelchairs	-28.0%	-0.329	0.008	<0.001
Walkers	-33.5%	-0.408	0.006	<0.001
Hospital Beds	-36.1%	-0.448	0.006	<0.001
Panel B Outcome: Log Share of Beneficiaries				
All Competitive Bidding DME	-5.8%	-0.06	0.005	<0.001
Oxygen Equipment	-4.7%	-0.048	0.009	<0.001
CPAP	-4.2%	-0.043	0.007	<0.001
Wheelchairs	-5.7%	-0.059	0.009	<0.001
Walkers	-6.9%	-0.072	0.008	<0.001
Hospital Beds	-14.6%	-0.157	0.009	<0.001

Notes: Table reports model estimates from equation (A2), the item-MSA-half year level model.

Table A3. Heterogeneity in Impact Across Product Categories: Standardized Utilization

	Change with Competitive Bidding			
	Percent Change (1)	Estimate (2)	S.E. (3)	P-value (4)
Outcome: Log Standardized Utilization per Beneficiary				
(1) Oxygen Equipment	-4.9%	-0.050	0.011	<0.001
(2) CPAP	-1.2%	-0.012	0.012	0.307
(3) Wheelchairs	-16.0%	-0.174	0.048	<0.001
(4) Walkers	-20.4%	-0.228	0.019	<0.001
(5) Hospital Beds	-15.0%	-0.163	0.035	<0.001
(6) Non-Competitive Bidding DME	-1.6%	-0.016	0.009	0.069

Notes: Table replicates Table 6 using standardized utilization as the outcome.

Table A4. Heterogeneity in Delay in DME Use After Inpatient Discharge

	Change with Competitive Bidding			
	Percent Change (1)	Estimate (2)	S.E. (3)	P-value (4)
Outcome: Share of Beneficiaries Receiving Oxygen Equipment				
(1) Within 7 Days	-4.0%	-0.040	0.030	0.176
(2) Within 14 Days	-3.1%	-0.032	0.028	0.253
(3) Within 30 Days	-1.6%	-0.016	0.025	0.518
Outcome: Share of Beneficiaries Receiving CPAP				
(4) Within 7 Days	-23.5%	-0.267	0.051	<0.001
(5) Within 14 Days	-23.6%	-0.269	0.049	<0.001
(6) Within 30 Days	-16.8%	-0.184	0.042	<0.001
Outcome: Share of Beneficiaries Receiving Wheelchairs				
(7) Within 7 Days	-29.8%	-0.354	0.057	<0.001
(8) Within 14 Days	-30.0%	-0.356	0.054	<0.001
(9) Within 30 Days	-24.8%	-0.284	0.047	<0.001
Outcome: Share of Beneficiaries Receiving Walkers				
(10) Within 7 Days	-19.3%	-0.215	0.036	<0.001
(11) Within 14 Days	-16.3%	-0.178	0.032	<0.001
(12) Within 30 Days	-13.2%	-0.142	0.023	<0.001
Outcome: Share of Beneficiaries Receiving Hospital Beds				
(13) Within 7 Days	-16.4%	-0.179	0.048	<0.001
(14) Within 14 Days	-15.7%	-0.171	0.043	<0.001
(15) Within 30 Days	-12.4%	-0.133	0.038	0.001

Notes: Table replicates Table 9 separately for different product categories.

Table A5. Changes in DME Repair Rates

	Change with Competitive Bidding			
	Percent Change (1)	Estimate (2)	S.E. (3)	P-value (4)
Outcome: Share of DME Users Requiring Equipment Repairs				
(1) Within 30 Days of Use	4.5%	0.044	0.036	0.22
(2) Within 90 Days of Use	5.0%	0.049	0.034	0.14
(3) Within 1 Year of Use	5.6%	0.056	0.029	0.06

Notes: Table reports estimates of equation (2) for the row outcomes. The sample is all beneficiaries who had an DME claim in the treatment and control MSAs during the sample period.

Table A6. Patient Health Outcomes

	Change with Competitive Bidding			
	Percent Change (1)	Estimate (2)	S.E. (3)	P-value (4)
Outcome: Emergency Room Use				
(1) Within 7 Days	0.1%	0.001	0.002	0.542
(2) Within 30 Days	-0.2%	-0.002	0.002	0.164
(3) Within 90 Day	-0.2%	-0.002	0.001	0.144
Outcome: Readmission				
(4) Within 7 Day	-0.0%	-0.000	0.001	0.992
(5) Within 30 Day	-0.0%	-0.000	0.001	0.545
(6) Within 90 Day	-0.1%	-0.001	0.001	0.216
Outcome: Mortality				
(7) Within 30 Day	-0.1%	-0.001	0.001	0.074
(8) Within 90 Day	-0.1%	-0.001	0.001	0.139
(9) Within 1 Year	-0.1%	-0.001	0.001	0.125

Notes: Table reports estimates of equation (2) for the row outcomes. The sample is all patients discharged from an inpatient stay.

Table A7. Summary Statistics on Supplier-Manufacturer Contracting

	Oxygen	CPAP	Hospital Bed	Wheelchairs	Walkers
Panel (a) Manufacturers Level Summary Statistics					
Number of Suppliers Contracted					
P5	1	1	1	1	1
Median	3	9.5	6	1	2
P95	421	1162	555	176	211
Panel (b) Supplier Level Summary Statistics					
Number of Manufacturers Contracted					
P5	1	1	1	1	1
Median	6	4	2	1	2
P95	11	27	3	4	5
Number of Manufacturers Overall	133	60	29	74	93

Notes: Data collected by CMS in the first quarter after competitive bidding among all suppliers in competitive bidding MSAs.