University of East Anglia

CENTRE FOR COMPETITION POLICY

Grim Trigger or Cost Shifter: Dynamic Medicine Auctions in the Philippines

Farasat Bokhari
Loughborough Business School, Loughborough University and Centre for Competition Policy, University of East Anglia

Sean Ennis
Norwich Business School and Centre for Competition Policy, University of East Anglia

Timothy Salmon
Southern Methodist University

Carlos Vega
Philippine Competition Commission

CCP Working Paper 24-03
This version: 21 August 2024

Abstract: We look at the effect of a bid cap policy in procurement auctions for medicine. The policy of interest sets the reserve price for a given drug as the median or minimum of the winning bid prices across locations in a previous period. This can act as a mechanism to "harvest" downward pressure on price from more competitive markets and use their outcomes to keep prices low in markets with less intense competition. A consequence of the design could be that in some markets, competition actually suffers causing auctions to fail, bid caps to be abandoned, and prices not falling by very much. Alternatively, sellers sufficiently valuing future profits can engage in a grim trigger strategy opening up the possibility of sustained cooperation and higher prices. Using procurement data from 2012 to 2019, we estimate the policy's effect on transaction prices faced by government hospitals in the Philippines. A triple differences design is used to address potential parallel trends bias in a standard difference-in-differences design but estimates from both tell a similar story. We find that that the policy led to a statistically significant reduction in transaction prices as well as in price dispersion, on average.

Contact Details:
Farasat Bokhari, f.bokhari@lboro.ac.uk
Sean Ennis, s.ennis@uea.ac.uk
Timothy Salmon, tsalmon@mail.smu.edu
Carlos Vega, clvega@phcc.gov.ph

ISSN 1745-9648

Grim Trigger or Cost Shifter: Dynamic Medicine Auctions in the Philippines *

Farasat Bokhari[1,2], Sean Ennis[2], Timothy Salmon[3], and Carlos Vega[2,4]

[1]Loughborough Business School, Loughborough University, UK
[2]Centre for Competition Policy, University of East Anglia, UK
[3]Department of Economics, Southern Methodist University, USA
[4]Economics Office, Philippine Competition Commission, PHL

July 23, 2024

Abstract

We look at the effect of a bid cap policy in procurement auctions for medicine. The policy of interest sets the reserve price for a given drug as the median or minimum of the winning bid prices across locations in a previous period. This can act as a mechanism to "harvest" downward pressure on price from more competitive markets and use their outcomes to keep prices low in markets with less intense competition. A consequence of the design could be that in some markets, competition actually suffers causing auctions to fail, bid caps to be abandoned, and prices not falling by very much. Alternatively, sellers sufficiently valuing future profits can engage in a grim trigger strategy opening up the possibility of sustained cooperation and higher prices. Using procurement data from 2012 to 2019, we estimate the policy's effect on transaction prices faced by government hospitals in the Philippines. A triple differences design is used to address potential parallel trends bias in a standard difference-in-differences design, but estimates from both tell a similar story. We find that that the policy led to a statistically significant reduction in transaction prices as well as in price dispersion, on average.

Keywords: firm behaviour, auctions, government policy, regulation, public health
JEL Codes: D22, D44, I18

*We thank Francesco Decarolis for his guidance on related procurement mechanisms. Please do not cite or distribute without permission of the authors. As an usual disclaimer, the viewed expressed in this paper are solely those of the authors, and do not represent those of the Philippine Competition Commission

1 Introduction

Auctions are widely used by governments and companies to purchase goods and services. Bidders in this context compete in a first-price sealed bid auction for the right to sell instead of buy, and the auctioneer seeks the lowest price instead of the highest.

When identical objects are procured over time, a bidder considers the trade-off between earning a surplus in the current period and a larger but less likely surplus in subsequent periods. Competition can discipline bidders to increase the likelihood of winning, but with asymmetric costs, inefficient firms eventually exit the market, resulting in dampened levels of competition. With fewer sellers competing for the contract, bidding becomes less aggressive and prices would eventually rise. A heuristic solution with practical appeal to the government is to intervene using a bid cap, that is, regulated reserve price. The empirical question then is do they work. If done wrong, price controls can do more harm than good. In particular, a common concern is whether the focal-point hypothesis holds. The idea being that firms use the prominence of the regulated reserve price to tacitly collude in keeping prices high, but this is rarely seen in practise. From a game-theoretic perspective, theory predicts that for infinitely repeated games and given a sufficiently high discount factor, cooperation can be sustained in equilibrium. In the so-called grim trigger strategy, for instance, players choose to cooperate given a history of play where everyone cooperates and to deviate in any other history of play. This translates in our context as, when sellers sufficiently value future profits from repeated procurement auctions, the loss resulting from competing becomes a punishment such that in equilibrium bidding high instead of low can be sustained in equilibrium. If at some point, however, a seller decides to compete, cooperation breaks down, and competition would bring prices down.

Another version of the solution, albeit not as straight forward, is a dynamic variant of the bid cap, which harvests downward pressure from more competitive markets along temporal and spatial dimensions to keep prices low in less competitive ones. Consider first a static reserve price in a repeated setting, which essentially truncates the distribution of transaction prices and reduces the value to bidders of search over time. In first-price auctions, this means that bidders shade their bids less relative to their values in equilibrium, increasing the auctioneer's revenue. If we introduce the idea that competition is dampened by firm exit, shading increases, and gains to the auctioneer from the reserve price could be undone. Now suppose that the auctioneer's reserve price is set as the median or minimum of the transaction prices from different areas and in the previous period. In theory, this allows the auctioneer to take advantage of differences in relative competitiveness across areas and the level of competition in a previous period. The spatial and temporal dynamics introduced can therefore act as a countervailing feature of the environment and lead to an outcome where even if markets are left with fewer sellers, higher transaction prices are prevented over time. Alternatively, bidders can prevent the bid cap from coming down as much as it could by inflating their bids in earlier rounds.

We exploit quasi-experimental variation from imposing a bid cap in auctions and use controls

that allow us to isolate its effect. Specifically, we look at exemptions to the government mandate to purchase only essential medicines for our first control group and non-auction modes of procurement where the price cap is statistically nonbinding, as our second group. Our identification strategy uses difference-in-differences (DD) and triple differences (DDD) designs. An event study is used to verify the parallel trends assumption in the DD context but shows that pre-treatment period coefficients are positive and statistically significant. The second control group that uses the DDD design allows us to address this issue and identify the average treatment effect on the treated (ATT). Using a rich data set from the Department of Health (DOH) on medicine procurement by government facilities nationwide from 2012 to 2019, we estimate the effect of the Drug Price Reference Index (DPRI), which imposes a dynamic bid cap in auctions for essential medicines. The policy comes on the heels of government scrutiny for high procurement prices in public hospitals. Furthermore, the widely varied prices of the same seller for the same drug in different hospitals raised concerns of anti-competitive behaviour among participating firms. Evidence we gather suggests that for drugs that remain under regulation, we find that the policy was moderately successful, leading to an 11-15% reduction in transaction prices and a 26% reduction in price dispersion, on average. Because losing bids are not available in the data, it is not possible to determine whether there is a reduction in participants over time. However, we observe that the count of unique winning sellers increased by 7% on average, which can be indicative of greater competition among sellers who remain in the market. This gives indirect support for the story that the auctioneer is able to futureproof outcomes using a dynamic reserve price. We do, however, admit the possibility that there is at least some partial tacit collusion happening owing to clustering of prices observed near the bid cap. Taking into account the governing procurement guidelines, we can also infer that about 1 in 3 auctions fail under the bid cap policy, with some facilities much more likely to experience failed auctions than others. Our findings give clear motivation for an experimental investigation to shed light on issues that this paper does not explain due to limitations in our data. In controlled settings, multi-round low price auctions in the laboratory across different bid cap institutions can isolate the effect on bidding behaviour and entry.

The paper proceeds as follows. The next section looks at related work. Section 3 describes the institutional environment of the pharmaceutical sector in the Philippines and discusses the policy of interest. Section 4 gives details of our data and identification strategy. In section 5, we present and discuss our results. The last section concludes.

2 Related Literature

Price regulation is common in markets to address public policy questions. In a procurement auction market, standard partial equilibrium theory predicts that a nonbinding price control will not have an effect on price. However, the focal point hypothesis of Scherer (1967) argues that when a price ceiling is not binding, that is, above equilibrium, the regulated price can serve as a focal point, keeping prices higher than what they should be. The Folk Theorem sets out quite generally that

in a repeated game, any price level between the competitive one and some maximum sustainable level can be an equilibrium. Having multiple equilibria means that in the absence of direct communication, it is difficult for players to identify and sustain a collusive outcome. A focal point, through some salient feature of the price, can serve to facilitate coordination even without direct communication. Using a laboratory setting to study this hypothesis, Isaac & Plott (1981) came to two main conclusions. First, the behaviour of auction markets over several periods with static nonbinding price controls is better approximated by the competitive benchmark and therefore a rejection of the focal point hypothesis. Secondly, they found that a nonbinding price control does affect price but not necessarily create a focal point. The authors did not identify which feature of the environment induced such a result, but speculated that the additional uncertainty created by removing the price control could have played a role in encouraging additional search activity by participants. In another study that provided experimental evidence, Smith & Williams (1981) addressed the inconclusive nature of the second primary conclusion and present evidence that strongly supports the focal point hypothesis by controlling for the bargaining characteristics of the participants. In the empirical literature, we find examples where price regulation creates a focal point. Knittel & Stango (2003) suggests that tacit collusion at nonbinding price ceilings was prevalent in credit card markets during the 1980s. The authors note that although their findings do not deal with the dynamics of tacit collusion at focal points, it is a promising area for research. Zhang et al. (2020) provide evidence also suggesting that a government-regulated price ceiling for retail gasoline stations may have served as a focal point resulting in near-uniform pricing by most of the firms. Interestingly, the authors observe a jump in prices as they approach price levels that serve as focal points. There is a large body of literature[1] on how the prominence of certain patterns, such as odd-numbered pricing points, and pricing just below round numbers, are associated with coordination and price rigidity. Documented evidence of government regulation, particularly in auction markets, serving as a focal point is less available.

Bidders may learn to coordinate strategies in repeated auctions and find it more profitable to compete less aggressively against each other. If the threat of future punishment is strong enough to discourage deviating, collusion can be sustained. The importance of industry dynamics was recognised first by Stigler (1964) when he points out that the enforceability of collusive agreements depends on ease of entry, the ability to detect cheating and the number of buyers in the pool. The punishment regime in his repeated game is where the cartel responds to a price cut by cutting prices in return. Extending this work, Green & Porter (1984) models the game with imperfect information where firms use market price as the decision variable to follow the collusive output or not. As long as the price stays above a trigger price, a collusive arrangement is maintained. If the one-shot gain from cheating is greater than the expected reduction in profits during a reversionary episode in which profits are lower for everyone, then collusion will not be optimal. Comparing collusion levels in uniform and discriminatory auctions when tacit collusion is introduced, Fabra (2003)

[1]See Lewis (2015) for the odd numbered pricing point, as well as related papers mentioned there with their discussion on popular price endings. See Levy et al. (2011) for a discussion on retail price rigidity.

assumes that firms play a grim trigger strategy in response to cheating. In uniform auctions, where competition is more relaxed, asymmetric bidding can be optimal, as it reduces the profitability of defection and increases the value of cooperation in the future more than symmetric bidding. For discriminatory auctions, the model predicts that it is optimal for bidders to collude on symmetric equilibria.

An auctioneer's choice of reserve price can involve search-theoretic considerations similar to reservation wage offers in labour markets, that is, the highest bid in an auction will only be accepted by the auctioneer if it exceeds the reserve price, as observed by Ashenfelter (1989). In a sequential setting, it is favourable for bidders to shade their bids relative to their values because of the possibility of winning at more favourable prices in subsequent auctions. When a static reserve price is imposed, Carare (2012) finds that the distribution of transaction prices is truncated, lowering the expected surplus of the bidders. Because of a lower value of search over future auctions, he shows that bidders shade their bids by a lower amount. The implication of introducing dynamics is not included in the study. Recently, there has been renewed interest in behaviour-based pricing strategies driven by the rise of e-Commerce and online retailers motivating Kanoria & Nazerzadeh (2021)'s theoretical examination of auction markets with a dynamic reserve price. They find that in second price auctions, if the auctioneer updates a common reserve price based on bidding history, then this may create incentives for bidders to shade their bids. They then show that incentive compatibility can be restored by using personalised reserve prices based on historical bids of other bidders. An empirical study of first-price auctions with a dynamic reserve price mechanism may serve to motivate the investigation and testing of theory in this auction format.

Similar systems exist throughout procurement settings, but none, to our knowledge, is identical to our policy of interest. Bucciol et al. (2020) investigates changes in the procurement setting in Italy for medical devices where the buyer has discretion when establishing procedures for a public procurement tender. A reference price for classes of functionally equivalent devices was set using internal cost-effectiveness studies and served as a cap to standardise prices paid by different buyers. A similar mechanism is used by the US government through Medicare's average sales price (ASP) methodology for certain categories of drugs, Medicare Part B drugs, and devices. A key difference is that these procurement mechanisms do not feature the endogenous dynamic methodology like the one investigated here.

This paper thus contributes to the analysis of auctions by giving empirical evidence of the effect of a dynamic reserve price mechanism in procurement.

3 Background

3.1 Industry Overview

The Philippine pharmaceutical sector was estimated to be valued at 4.5 billion dollars in 2020, the second largest in ASEAN. Prescription and over-the-counter (OTC) sales were 60% and 40%, respectively. In terms of the channel used by manufacturers to reach consumers, retailers such

as pharmacies, drugstores, and supermarkets represent 91% of the sector's value while hospitals make up about 9%. Public funds allocated to government medicine procurement have increased significantly over the years, from about 160 million dollars in 2014 to about 400 million dollars in 2019[2] (Abrigo et al., 2021).

Healthcare in the Philippines has historically been an out-of-pocket (OOP) market. This means that consumers are more likely to pay for their own medical expenses than rely on insurance companies or health maintenance organisations (HMOs). According to the Philippines Statistics Authority, household out-of-pocket payments in 2019 made up 48% of the total health care expenditures in the country, even more than the expenses through government-led health insurance schemes. In previous years, this has been even greater. However, the start of 2019 saw the country's Universal Healthcare Act being signed into law, which could explain the slight expansion in contribution of government payment schemes compared to 5 years prior. In terms of spending per capita, there has been an increasing trend with growth rates of about 7-8% per year.

3.2 Government Interventions

Over the years, the government has implemented a number of interventions with the overarching objective of improving affordability and access to essential medicines.

The Generics Act of 1988 promotes the supply and use of generic counterparts by requiring manufacturers to carry out its production. This introduces more competition by making lower-priced generic drugs available in the market. In theory, because firms that manufacture drugs using off-patent molecules can use the clinical data of the innovator firm that prove the efficacy and safety of the API, generic medicines can be priced lower. The use of generics by consumers is promoted by requiring generic labelling to be used at the manufacturing level up to prescription and purchase.

The Philippine National Drug Formulary (PNDF) is a list of essential medicines prepared by the national government to be used by government health facilities and local government units as a basis for the purchase of medicines. The law is explicit about this mandate through administrative and executive orders, DOH Department Order 104, s. 1991, Executive Order No. 49, s. 1993, and the Cheaper Medicines Act of 2008, RA No. 9502, and its Implementing Rules and Regulations.

> Executive Order No. 49 of 1993- *"...all government entities concerned are mandated to use the current PNDF (Volume I) as the basis for procurement of drug products;"*
>
> RA No. 9502, IRR Rule no. 36- *"All government agencies, including local government units, shall procure drugs and medicines within the Philippine National Drug Formulary current edition in accordance with Republic Act No. 9184 and any other pertinent procurement reforms."*

Government facilities can still buy drugs not on the list *only if* they apply for and are granted exemption. Exemptions from the mandate to use the PNDF require extensive documentation of a

[2]Conversion of 50 PhP to 1 USD

proponent's justification on dimensions such as efficacy, safety, and cost, matched with the currently listed drug for the same therapeutic indication. *The Cheaper Medicines Act of 2008* recognises that the primary instrument to ensure access to affordable drugs is an effective competition policy, but in the event that full competition is not effective, price regulation can be used. Among the powers and measures that this law grants the government is the power to implement cost-containment measures for purposes of government procurement. The DPRI is one of those cost-containment measures. There are other interventions that stem from this aspect of this law, such as the 2009 Maximum Drug Retail Price (MDRP) and the Government Mediated Access Programme (GMAP) that were successful in reducing the prices of selected molecules directly, or through negotiations with the private sector, by at least 50% [3]. More recently, additional price regulation for medicines was taken to include both retail and wholesale prices through an executive order in 2021 expanding the coverage of the 2009 intervention. Attempts have been made to measure the impact of these regulations in the past, but there has not yet been a proper impact evaluation to establish a causal effect attributable to an intervention. Policies are often implemented simultaneously nationwide, and, as such, finding data covering a suitable control can be very challenging.

3.2.1 Public Procurement of Medicines

As a general rule, government facilities are supposed to use auctions or competitive bidding. However, under "highly exceptional circumstances" alternative methods are allowed by law. Conditions are established for the use of alternative methods of procurement, including limited source bidding (for specialised goods and consulting services), direct contracting (single source, proprietary, or critical goods), repeat orders (superior winning bids of prior bidding), shopping (emergency procurement under PHP50,000 [about USD1,000] or ordinary supplies under PHP250,000 [about USD5,000]), and negotiated procurement (following two failed biddings and other circumstances) Ball & Tisocki (2009). One of the circumstances under negotiated procurement is when there is an imminent threat to life, such as during a state of calamity. In particular, for goods that are essential to a service such as medicines for hospitals, exigency in responding to unanticipated needs is paramount. Situations like local epidemiological outbreaks or extreme weather conditions are independent of a facility's planned procurement activity, which takes into account prevailing regulations including those on price. Therefore, in these cases, it is plausible that a price cap will not have any binding effect. The guidelines for alternative modes of procurement are provided in Appendix A. In the event that there is a failure of bidding, due to no bids being received, or if all bids submitted exceed the limit, the auction is rerun with an adjusted bid limit of up to 20%. If the bid fails again, the facility can resort to negotiated procurement. These are provided for in the *Government Procurement Reform Act of 2003* and its implementing rules and regulations.

[3] Executive Order No. 821 ordered a fifty percent reduction for MDRP medicines while some manufacturers agreed to cut prices by half through the GMAP.

3.2.2 Devolution to Local Government Units

Through legislation in the early 1990s, the delivery of health services was shifted from a highly centralised system with DOH as the sole provider to one where local government units (LGUs) carry out functions previously done by the DOH. In the resulting setup, LGUs operate their own respective facilities, which involves procuring their own medicines according to the country's procurement laws (Cheng et al., 2020). Appendix C provides a map of the country and the locations of the DOH facilities covered by this study.

3.2.3 Drug Price Reference Index (DPRI)

Coverage of the policy is determined by what is included in the PNDF. The price cap is determined by past auction outcomes from government facilities across the country. Specifically, for the transaction up to 2019, if a drug was successfully sold to government facilities by a number of firms that exceeded a certain threshold in year $t-2$ then this drug has "sufficient" competition, and the regulated price for this drug in year t is the median (m) across the range of winning bid prices in $t-2$. If, however, the number of successful firms selling a drug falls below this threshold, then it has "limited" competition and the regulated price is set to the lowest. The threshold for this distinction was initially 3 firms, applying to 2014 and 2015 transactions but was then changed to 4 firms for 2016 to 2019 transactions. In the amendment to the guidelines, the definition of the firm used is no longer the seller, but the manufacturer [4]. We provide a copy of these rules in Appendix B. Equation 1 and Equation 2 describe the government's treatment of the sufficient and limited cases.

$$\overline{p}_{j,t} \sim F_P(p^m_{j,t-2}), \quad \text{where } P(X \leq p^m_{j,t-2}) = \frac{1}{2} \tag{1}$$

$$\overline{p}_{j,t} = min[p_{j,t-2}] \tag{2}$$

In general, the chronology of the DPRI is as follows. In year t = 0, the facilities conduct their respective auctions. They submit the purchase orders to the DOH Pharmaceutical Division who consolidates and determines in year t = 1, the price cap for each drug under the policy. The DPRI is published in a booklet and made public in the third quarter of t = 1. In t = 2, all government facilities are expected to use the price cap in all modes of procurement. The key point in the mechanism is that the levels of competition from other geographic markets and in a previous period are used to truncate the distribution of transaction prices for all auctions nationwide. Even with reduced levels of competition due to exit, the bid cap can serve as a counterveiling feature in the environment, preventing higher prices. If, however, cooperation among bidders can be sustained early in the policy's implementation, then transaction prices would persistently, albeit artificially, be high. The policy was signed into effect in the second half of 2014 using procurement data collected

[4] The guidelines were again amended in October 2019 changing the threshold in terms of the number of firms to the number of entries or successful procurement transactions, specifically 2 entries in the procurement data.

from 2012. Because of the policy's chronology, any effect would have happened to transactions in 2015 onwards.

4 Data and Identification

The study uses two data sets obtained from the Pharmaceutical Division of the DOH. The first data set is all the annual DOH booklets containing the specific drug under regulation, the maximum and minimum winning bid prices observed in the previous year, and the price cap for the same drug in the next year. The second data set is the actual procurement outcome database consolidated by the DOH Pharmaceutical Division from purchase order forms processed and submitted by regional hospitals across the country. Information on losing bids and negotiations done prior to award of a contract is not available. A drug in both data sets is expressed in terms of its active substance and presentation, which we use to define a unique drug j. An example would be "Amoxicillin 250 mg/5 mL, 60 mL Suspension". In the database, each drug has information on the winning price, units, supplier, manufacturer, procuring facility, and mode of procurement used. The series covers 2 years before the implementation of the price cap and 6 years post-implementation.

4.1 Drug Entry Matching

Because purchase orders are processed and encoded manually, discrepancies between data sets had to be addressed prior to our analysis. To match the drugs appearing in the published booklets with the entries in the procurement database, we use a combination of Damerau-Levenshtein distance methods to obtain candidate matches for each entry appearing in the booklet. This is implemented using the *stringdist* R package developed by van der Loo (2014). We then manually inspect each set of candidate matches and select those that reflect the same drug. We present the table of matched names and scores for the tests in Appendix D.

4.2 Study Coverage

The list of DPRI drugs may vary from year to year based on the changes made to the PNDF. The implication is that there can be multiple groups receiving treatment in different years, which introduces bias[5] in the estimates using a canonical difference-in-differences design. For the purposes of this paper, we restrict our analysis to include in our treatment group only those drugs that were subject to regulation starting 2014 and remained so until 2019. Although data for 2020 were generously made available, we excluded the year from the analysis due to policy changes made for certain months in response to the COVID-19 pandemic. During these months, the mechanism was changed so that facilities can set their reserve prices at the maximum of the range instead of the median or minimum. We use the same criteria to select our control group drugs, except that these are not covered by the price cap. This implies that each drug covered by the study has at least one

[5]Read Callaway & Sant'Anna (2021) and Sun & Abraham (2021) for a more detailed discussion of this issue.

procurement outcome per year and that the treatment and control groups stay the same throughout the covered periods. Summary statistics across years and across groups are given in Table 1 to Table 3. Looking at the number of drugs, although there are more varieties covered by the full dataset, the analysis looks at the same group across the series. This group represents at least 60% of the total number of drugs procured. We also cover a stable representation of auctions conducted by facilities at approximately 80%. This indicates that our drug matching and selection for analysis cover the majority of the drugs procured by the facilities through competitive bidding. The total revenue for all procurement methods goes up to 11 billion PhP in 2017. Auctions represent 45% of revenue and 60% of volume on average per year, the rest coming from other modes of procurement. This is important for our analysis because we use these non-auction transactions for our DDD identification strategy.

Table 1: Data Summary Statistics

	2012	2013	2014	2015	2016	2017	2018	2019
No. of Drugs								
Overall	744	985	949	1,030	1,069	1,032	961	1,009
Study	648	648	648	648	648	648	648	648
Rate	0.87	0.66	0.68	0.63	0.61	0.63	0.67	0.64
No. of Auctions								
Overall	7,924	11,539	13,164	14,520	15,119	16,991	24,458	20,608
Study	6,117	10,163	11,749	12,761	13,168	14,678	21,892	18,078
Rate	0.77	0.88	0.89	0.88	0.87	0.86	0.90	0.88
Total Revenue†								
Overall	2,989.71	2,964.12	5,645.72	8,025.81	8,126.04	11,125.25	8,574.52	2,959.80
Auctions	887.65	2,171.18	3,279.05	2,789.97	2,841.47	3,271.43	2,653.81	2,355.85
Rate	0.30	0.73	0.58	0.35	0.35	0.29	0.31	0.80
Total Volume‡								
Overall	293.64	859.53	763.97	2,248.33	2,426.12	2,337.63	251.46	107.57
Auctions	137.96	648.49	663.92	1,193.45	1,468.70	1,222.90	111.62	99.59
Rate	0.47	0.75	0.87	0.53	0.61	0.52	0.44	0.93

Note: †in Million PhP
‡in Million units

Table 2: Summary Statistics, Firms per Drug

	Supplier Count per Drug								Manufacturer Count per Drug							
	2012†	2013	2014	2015	2016	2017	2018	2019	2012	2013	2014	2015	2016	2017	2018	2019
Overall																
Ave	–	5.62	5.81	6.88	7.86	8.67	9.93	7.43	–	3.79	4.19	3.96	4.23	4.54	4.92	4.20
Min	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Max	–	51.00	49.00	52.00	77.00	76.00	77.00	52.00	–	25.00	30.00	39.00	39.00	37.00	40.00	27.00
Std Dev	–	7.70	7.13	9.07	10.58	11.43	13.05	9.00	–	3.63	3.87	3.94	4.48	4.39	4.78	3.61
Study																
Ave	–	5.40	5.33	6.00	5.90	6.43	7.06	7.14	–	4.62	5.08	4.50	4.66	4.77	5.02	4.69
Min	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Max	–	28.00	26.00	32.00	28.00	33.00	37.00	30.00	–	21.00	24.00	30.00	22.00	21.00	20.00	17.00
Std Dev	–	5.33	4.86	5.78	5.18	5.90	6.46	6.19	–	3.40	3.80	3.72	3.49	3.14	3.47	2.94
DPRI																
Ave	–	7.13	7.15	8.21	7.90	8.65	9.64	9.61	–	5.92	6.58	5.90	5.99	6.00	6.33	5.79
Min	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Max	–	28.00	26.00	32.00	28.00	33.00	37.00	30.00	–	21.00	24.00	30.00	22.00	21.00	20.00	17.00
Std Dev	–	5.75	5.12	6.23	5.44	6.32	6.82	6.45	–	3.47	3.92	4.05	3.68	3.24	3.59	3.01
Non-DPRI																
Ave	–	2.44	2.42	2.51	2.67	2.85	2.99	3.22	–	2.42	2.69	2.28	2.52	2.79	2.95	2.95
Min	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Max	–	24.00	22.00	13.00	19.00	20.00	20.00	19.00	–	14.00	16.00	8.00	10.00	9.00	11.00	9.00
Std Dev	–	2.59	2.38	2.25	2.37	2.42	2.65	2.81	–	1.72	1.91	1.35	1.60	1.60	1.91	1.74

Note: †Data does not have information on supplier and manufacturer

Table 3: Summary Statistics, Drugs per Firm

	Drug Count per Supplier								Drug Count per Manufacturer							
	2012†	2013	2014	2015	2016	2017	2018	2019	2012	2013	2014	2015	2016	2017	2018	2019
Overall																
Ave	–	19.55	18.11	20.47	22.30	23.66	24.72	24.60	–	5.72	5.96	7.08	6.96	6.79	6.57	5.81
Min	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Max	–	549.00	533.00	557.00	551.00	512.00	503.00	455.00	–	105.00	83.00	124.00	173.00	144.00	136.00	103.00
Std Dev	–	47.35	45.18	47.31	48.56	49.24	47.97	51.19	–	10.23	10.34	12.43	12.71	12.04	11.03	9.47
Study																
Ave	–	21.33	19.93	20.71	22.06	24.19	24.82	26.90	–	4.50	5.10	5.26	4.91	4.71	4.80	4.44
Min	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Max	–	322.00	335.00	324.00	296.00	255.00	283.00	249.00	–	61.00	63.00	76.00	90.00	70.00	71.00	63.00
Std Dev	–	43.27	43.65	42.79	43.70	44.11	43.69	47.15	–	7.25	8.22	8.62	8.39	7.63	7.72	6.77
DPRI																
Ave	–	18.60	17.49	19.15	19.40	21.23	21.60	23.69	–	4.03	4.56	4.73	4.35	4.14	4.21	3.81
Min	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Max	–	219.00	219.00	209.00	184.00	177.00	178.00	175.00	–	46.00	49.00	71.00	85.00	62.00	64.00	51.00
Std Dev	–	34.23	34.31	34.65	34.47	35.23	34.18	38.52	–	6.22	6.90	7.52	7.30	6.70	6.67	5.64
Non-DPRI																
Ave	–	6.10	6.44	6.90	6.55	6.93	7.03	6.91	–	2.18	2.48	2.36	2.32	2.21	2.43	2.20
Min	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00	–	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Max	–	103.00	116.00	115.00	112.00	105.00	121.00	98.00	–	28.00	30.00	27.00	27.00	25.00	28.00	26.00
Std Dev	–	13.80	14.78	14.77	14.57	14.31	15.24	13.13	–	2.77	3.22	3.09	3.15	2.62	2.88	2.67

Note: †Data does not have information on supplier and manufacturer

In Table 2, we see a wide range of supplier and manufacturer counts per drug. Contracts to sell some drugs can be to up to 77 suppliers and 40 manufacturers overall. This range is smaller for the drugs covered by the study. Breaking this down further to DPRI and Non-DPRI groups, there are more suppliers and manufacturers per drug under the DPRI on average, but the respective averages per group are not changing much over time. Table 3 show the average portfolio size by count per supplier and by manufacturer. Over time, we see that although the average portfolio size per supplier is going up, manufacturers portfolio size on average is relatively more stable. Manufacturers and suppliers of the drugs covered by the analysis on average keep their portfolio size the same over time. However, suppliers with contracts to sell DPRI drugs are slightly increasing their portfolio size on average. Because there are multiple dimensions along which these drugs and firms can be compared, we use regressions in the following sections to isolate the effect of the policy on prices.

To illustrate the evolution of the price before and after the DPRI, we plot the weighted mean price of the treatment and control groups in Figure 1. We first take a volume-weighted average across facilities per drug, and then average across drugs using revenue weights to derive a mean price measure for each group. It shows that the drugs in our treatment group have become cheaper in most of the post-period than in the pre-period. The divergence between the two groups became more apparent in 2017 and persisted in the following years.

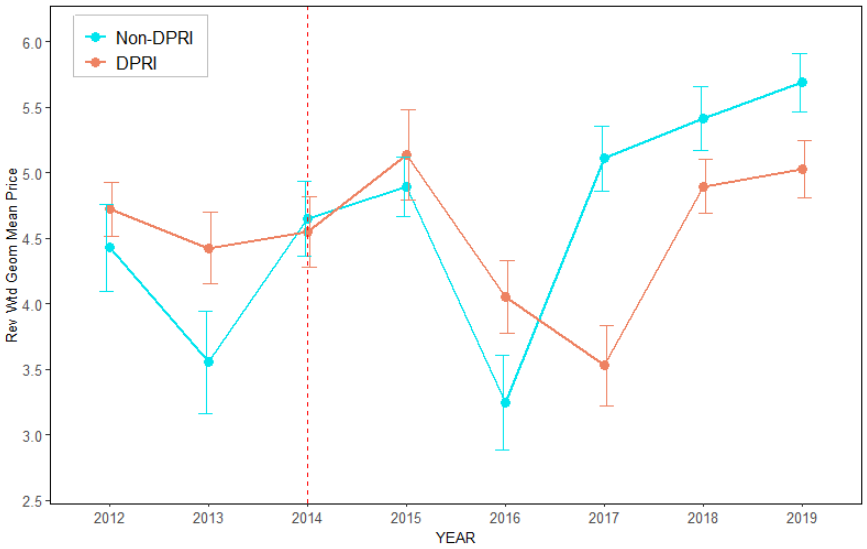


Figure 1: Revenue Weighted Mean Winning Bid Price Evolution

4.3 Market Power and Manipulation in Markets

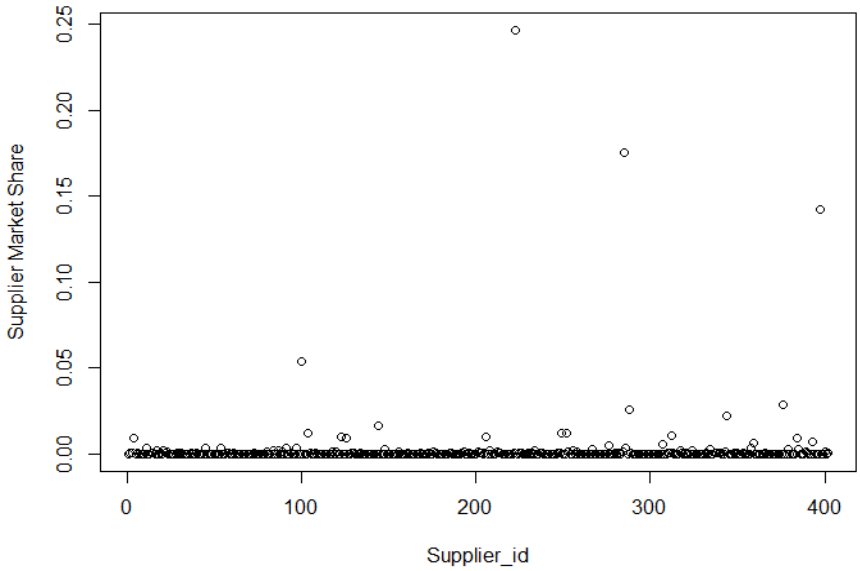
Without coordination among bidders, the theory of competitive markets predicts that price ceilings should have a negative effect if the ceiling is binding, or zero when the ceiling is set at or above the competitive level. However, when the ceiling is nonbinding, an alternative theory suggests that it can serve as a focal point for bidders to tacitly collude and prices end up higher than their efficient

levels. When competition is suppressed through some form of coordination, the surplus that should have accrued to government in a non-cooperative environment becomes captured rent. Here, we look at an overview of firm shares and from that the drug and facility portfolios of the top earning firms. Second, we estimate the distribution of transaction prices in terms of the distance of each to its respective bid cap.

4.3.1 Supplier Shares

A strategy of incurring losses in order to ease out competition and then raising prices is plausible when there are dominant players in the market. After competition is softened as inefficient firms are priced out of the market, prices are expected to increase. Incumbents should be able to withstand suboptimal pricing or at least pricing below the cost of competitors. Looking at the supplier shares of our selected DPRI drugs, we plot the overall revenue shares in Figure 2. A vast majority of suppliers represent vanishingly small shares, while just four make up 62%. This may be taken as evidence of dominance in these auction markets.

Figure 2: Supplier Revenue Shares, 2013-2019



We take a closer look at just the top four sellers of our selected DPRI drugs for the periods covered. In Table 4 we give a partial summary of the set of drugs and facilities that represent 80% of each firm's total revenue. A low count or a low percentage suggest concentration in the drug and facility aspects of competition. A portfolio gives a count and its corresponding share that make up 80% of the firm's revenue. A low count or contribution (% of Total) means that the firm derives the vast majority of its revenue from a few drugs or from just a few facilities. For example, Metro Drug Inc. was able to sell 3.90 Bn PhP worth of essential medicines included in our selected group, within the period of 2013 to 2019. This represents a quarter of the total revenues of all firms in the

period. Of this amount, 80% is from 14 kinds of medicines, which is 6% of the count of medicines sold. These 14 medicines were sold to 10 facilities, which is 14% of the number of facilities to which they were sold.

Table 4: Top Winning Suppliers 2013-2019

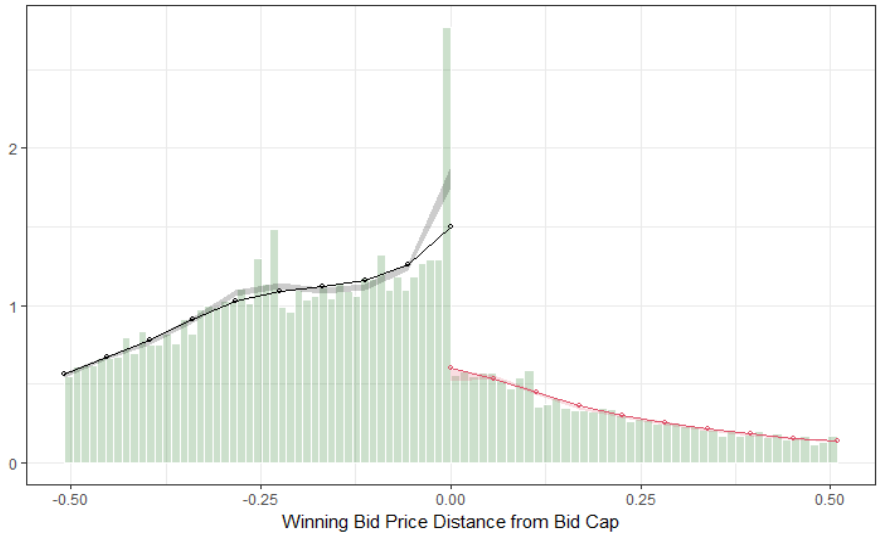
Supplier Name	Total Revenue (Bn PhP)	Share (%)	(80% of Revenue) Drug Portfolio Count	Drug Portfolio % of Total	Facility Portfolio Count	Facility Portfolio % of Total
Metro Drug Inc.	3.90	0.25	14	0.06	10	0.14
Phil Pharmawealth, Inc.	2.78	0.18	53	0.22	16	0.25
Zuellig Pharma Corporation	2.25	0.14	42	0.15	19	0.27
Endure Medical, Inc.	0.85	0.05	50	0.24	11	0.27

4.3.2 Policy Manipulation

Another possibility is that sellers can maximise their profits bidding just under the price cap. If in equilibrium, tacit cooperation among bidders can be sustained by bidding closely below the bid cap in some markets, then we should see a heaping of transactions just below the cap. This indicates that the value of search in subsequent auctions is substantially reduced by effectively competing and bidders will tend to shade their bids more rather than less. The mechanism may be a form of ratchet effect to try and avoid facing lower profits in expectation. In fact, increasing future profits in expectation would be through competing less from the very beginning and face as few periods of lowered profits as possible. This type of behaviour can be difficult to sustain if competition in markets is sufficiently strong such that the ability to manipulate the policy is overwhelmed by the short run gains of competing aggressively.

Borrowing logic used in a regression discontinuity design, we run a test to see if there is any indication of bidder manipulation of the policy. Figure 3 shows a plot of the test implemented on our data. The idea of the test is that those affected by the policy should not be able to select on either side of a running variable threshold (McCrary, 2008). In our case, we use the bid cap as the threshold, and the distance of each winning bid from this threshold as the running variable. The winning bids to the left of the threshold indicate that a previous auction was run but failed. The auction is rerun but with the maximum allowed bid adjusted higher than the bid cap. We want to test whether the distribution along this running variable is smooth, without any heaping just below or above the threshold. Our null hypothesis is that there is no manipulation and a discontinuity would be evidence that bidders are able to choose transaction prices just below the bid cap. Using data-driven bandwidth selection, we implement the test developed by Cattaneo et al. (2018) and find that there is a statistically significant discontinuity at the threshold by which we reject the null and infer that there is manipulation in some markets.

Figure 3: McCrary Density Test



4.4 Failed Auctions

We further note that there are about 1 in 3 transactions where prices are higher than the bid cap. These prices are likely set after an initial failure of the auction. In the event of a failure, e.g., no bids are submitted or all submitted bids are above the cap, the auction will be rerun with a higher reservation price. This event can occur twice before facilities can opt to use negotiations, at which point the transaction falls out of our sample. Those that are captured by our data as still using auctions but are above the price cap are transactions where the initial auction failed but succeeded in the rerun.

We run a probit regression with the dependent variable being whether or not the winning bid is from a failed auction and facility indicator variables on the right-hand side of the equation, and calculate the marginal effects from the standard probit regression with the same specification. The top five facilities that are most likely to have failed acutions are presented in Table 5 below. These numbers are not presented as having a causal interpretation, but as an estimate suggestive of correlation.

4.5 Econometric Specifications

To identify the effect of the dynamic bid cap on DPRI drugs, we control for any systematic shocks to the auction market outcomes of these drugs that may be correlated with, but not due to, the policy. We implement a canonical 2×2 DiD design and recover estimates of the treatment effect using the regression specification given by Equation 3. The pre-trend estimates and the persistence of the policy effect in the post-period are estimated using an event study model given by Equation 4. Finally, a triple difference design is implemented as an alternative design and robustness check using Equation 5.

Table 5: Regressions on Likelihood of Failure (Selected Coefficients)

	Binary for Failed Auction	
	(1)	(2)
Metro Manila Center for Health Devt	2.717***	0.707***
	(0.397)	(0.017)
Batanes General Hospital	2.079***	0.658***
	(0.135)	(0.018)
Region 1 Medical Center	1.859***	0.622***
	(0.136)	(0.025)
Amai Pakpak Medical Center	1.848***	0.621***
	(0.130)	(0.024)
Culion Sanitarium	1.784***	0.608***
	(0.146)	(0.029)
Observations	87,895	87,895

Note: Column (1) is a panel probit regression. Column (2) is the marginal effects from standard probit regression.
*p<0.1; **p<0.05; ***p<0.01

4.5.1 Difference-in-Differences and Event Study

Without the issue of heterogeneous treatment effects due to differential timing, we use the empirical design in Card & Krueger (1994) adding controls for the number of facilities that successfully procured a given drug through an auction. We also include facility fixed effects to control for unobserved idiosynchratic characteristics of facilities.

$$\ln p_{jlt} = \alpha_j + \gamma_l + \tau_t + \beta_1 D + \beta_2 P + \beta_3 \Big(D \times P \Big) + \delta_1 X_{jlt} + \varepsilon_{jlt}, \tag{3}$$

$$\ln p_{jlt} = \alpha_j + \gamma_l + \tau_t + \left(D \times \sum_{\substack{y=-2 \\ y \neq 0}}^{5} \beta_y I\left(t - t^* = y\right) \right) + \delta_1 X_{jlt} + \varepsilon_{jlt}. \tag{4}$$

In the equations above, D and P are indicator variables equal to 1 if the observation is for the selected DPRI drugs, and for years after the price cap has been implemented, respectively. α_j, γ_l, τ_t are drug, facility, and year fixed effects to control for unobserved invariant characteristics of each unique drug, facility and year covered in the study. X_{jlt} contains linear and quadratic time trend variables, the count of facilities, and dummies for each drug, facility, and year. For the event study model, $I(t - t^* = y))$ represents the periods being evaluated and where I represents the indicator variables to measure the time relative to the start of the policy. The reference year is 2014 considering that the policy was implemented only at the end of the year. The coefficients of interest are β_3 for the DiD design 2×2 and the β_y' in the event study for the lead and lag years.

4.5.1.1 Identifying Assumption, Diff-in-Diff and Event Study

By law, government facilities are restricted to buy only essential medicines listed in the PNDF. They

can only buy medicines outside of the PNDF after being granted exemption. These exemptions are based on justifications provided by the facility and match the counterpart drug listed in the PNDF. In other words, exemptions should be the closest available substitute in the market at the time of the procurement; otherwise, the facility should have defaulted to what is listed in the PNDF.

> DOH Admin Order 2012-0023, *"Sec. 5, General Guidelines, I. Only medicines listed in the PNF Manual (PNDF) shall be procured by all government entities (...) However, exemptions may be granted upon submission of a written request with justification and subject to the approval (...) based on prescribed criteria."*

Because the DPRI only covers those listed in the PNDF, these exemptions can be thought of as almost the same as DPRI drugs with the exception of the price cap. The post policy trend of these exemptions can therefore be a close approximation of the counterfactual trend of DPRI drugs. Formally, this kind of parallel trend assumption can be supported by a test of joint significance of the pre-trend coefficients. In the pre-period, if the coefficients are zeros or statistically not significant from zero, then statistically, the two groups are no different from one another. In our case, however, the data available in the pre-period is only for two years, and inference from any formal test may be misleading. We find that the institutional setup creating our control group through exemptions from the mandate lends credence to the parallel trends assumption in our context.

4.5.2 Triple Differences

In this design, we use the empirical strategy of Gruber (1994) and find a category of transactions which, despite involving treated units, are not affected by the policy. Although not very often used, primarily due to the difficulty of finding suitable data for the analysis, this design has the advantage of being able to address potential parallel trend bias. Satisfying the identifying assumption allows us to recover the causal effect of the policy given by E_D in Table 6.

The key attribute in the data set is the mode of procurement. This creates a category separating auction and non-auction purchases. Particularly, we find non-auction modes of procurement that are available only in extenuating circumstances. Covering both the DPRI and Non-DPRI drugs, these transactions serve as a second level of control with the same potential violation of parallel trends that we then exploit. The econometric model to implement is straightforward. In Equation 5, D, P, α_j, γ_l, τ_t, X_{jlt} take on the same interpretations and A is a 1/0 indicator variable equal to 1 if the drug is procured through an auction. We estimate the effect of the policy on drugs procured through auctions with the coefficient β_7.

$$\begin{aligned}\ln p_{jlt} = \alpha_j + \gamma_l + \tau_t + \beta_1 A + \beta_2 D + \beta_3 P + \beta_4\Big(A \times D\Big) + \beta_5\Big(D \times P\Big) \\ + \beta_6\Big(A \times P\Big) + \beta_7\Big(A \times P \times D\Big) + \delta_1 X_{jlt} + \varepsilon_{jlt}\end{aligned} \tag{5}$$

Table 6: Potential Outcomes and Identification in a Triple Differences Design

Mode	Drug Group	Period	Outcomes	Diff_1	Diff_2	Diff_3
Auctions, A	DPRI, D	After	$A_D + T + A_t + D_t + E_D$	$T + A_t + D_t + E_D$	$D_t - ND_t + E_D$	E_D
		Before	A_D			
	Non-DPRI, ND	After	$A_{ND} + T + A_t + ND_t$	$T + A_t + ND_t$		
		Before	A_{ND}			
Non-Auctions, NA	DPRI, D	After	$NA_D + T + NA_t + D_t$	$T + NA_t + D_t$	$D_t - ND_t$	
		Before	NA_D			
	Non-DPRI, ND	After	$NA_{ND} + T + NA_t + ND_t$	$T + NA_t + ND_t$		
		Before	NA_{ND}			

Note: Notation and table adapted from discussion in Cunningham (2021).

4.5.2.1 Identifying Assumption, Triple Differences

An alternative design is to use an additional control group to address parallel trend bias in the 2×2 DiD design. Table 6 sets out how identification is achieved using the non-auction group as a second level of control. The parallel trends necessary in a 2×2 DiD design for our context is $D_t = ND_t$ to isolate the effect on auction outcomes of DPRI drugs. If there is any violation to this, bias is introduced to the estimates. In a triple difference design, even if this equality does not hold, i.e. the time trajectories of DPRI and Non-DPRI groups are not the same, the divergence is differenced out by using the second control group. We require instead a different kind of parallel trend. In this design, we make the assumption that the gap $D_t - ND_t$ remains the same for auctions and non-auction groups across years. Because one of the potential outcomes is a sequence of counterfactuals, this cannot be tested directly. Indirect evidence is used to show that subgroups within the first control group are not differentially affected between the periods covered. We argue that for the period covered, and considering the conditions necessary for facilities to use the alternative modes of procurement we selected, it is plausible that the policy has a nonbinding effect on the nonauction group despite having the same DPRI drugs. We formally investigate the support for this assumption using indirect evidence discussed and implemented in section 5. If no differential effect is found within subgroups of the Non-DPRI group, then this lends credence to our assumption that the gap described above across procurement modes remains the same. Our estimates using this design could then have a causal interpretation and be used to validate our DD estimates.

4.5.2.2 Falsification Test: Non-Auction Group

Although DPRI drugs are procured using non-auction modes, we show that there are no spillovers in the non-auction group. By selecting only transactions using Emergency Procurement and Local Shopping into the non-auction group, we avoid issues of spillovers from the auction group. The reasoning is as follows. First, we note that the use of these non-auction modes is due to extenuating circumstances, which occur independently of whether the same drugs are procured by other facilities through an auction or not. Epidemiological and environmental shocks are likely idiosyncratic to the area of a facility and should not be influenced by other facilities that do not face these shocks, whether they are procuring drugs that are covered by the policy or not. Secondly, extenuating circumstances that require getting the drugs immediately is used to justify transaction prices higher than the cap. We formally check for contamination from this second control group by running a falsification test. If the policy does not have any effect on the non-auction group during the period covered, then the estimate we would get should be zero.

5 Results and Discussion

We first look at our main results comparing DPRI drugs and our first control group, drugs exempted from the PNDF mandate, procured through auctions, using a 2×2 Diff-in-Diff design and an event study model. We then discuss the results from our alternative design, using the non-auction group as a second control. We provide supporting evidence for its validity and compare the results with estimates from the initial design. Using a falsification test, we first confirm that there was no effect on the non-auction group. Second, we give indirect evidence in support of the identifying assumption. In expressing the effects on auction outcomes, we use the transformation $exp(\beta) - 1$ on the log value coefficient estimates. Finally, given the limitations of our data, we look at the trend in price and count of winning sellers of the DPRI drugs.

5.1 Diff-in-Diff and Event Study

Table 7 presents the estimate of our coefficient of interest, β_3. On average, transaction prices of DPRI drugs were reduced by 14.7% due to the bid cap. We also look at the effect of the bid cap on the spread of winning prices. Instead of the transaction price, we use the standard deviation of the transaction prices from their mean for a given drug in a given year. Controlling for the same shocks as in the previous specification, we find that the policy had a spread narrowing effect of 30.3%. Using the information available in the data, we avoid instances where a drug was procured by a single facility in a previous period and consider our estimate as an upper bound.

Figure 4 plots the event study. The coefficients for the two lead years are positive and significant, suggesting different pretrends. Although this is not supportive of the parallel trends, we note that a casual interpretation is not precluded. This is an important point to address and motivates our alternative design. In post-periods, estimates range from -24.1% in 2017 to -6.98% in 2015. All years after policy implementation show a significant reduction in transaction prices, on average.

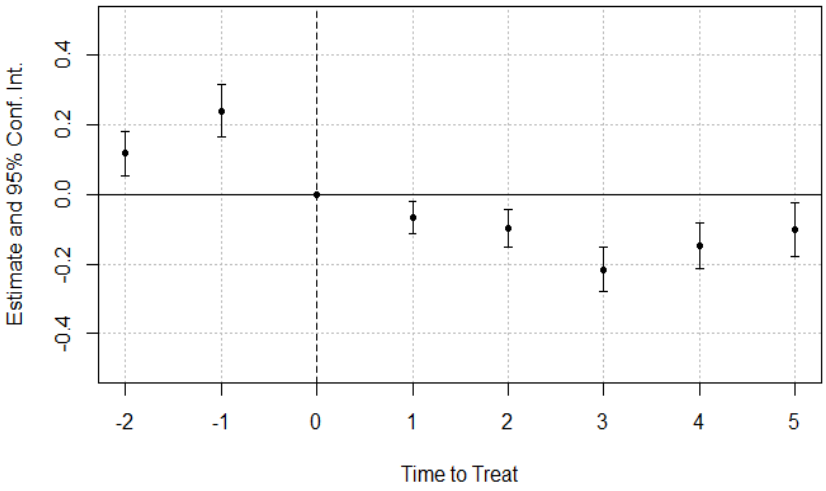
Table 7: Effect on Price, DD (selected coefficients)

	log(Price)	log(SD)†
DPRI (D)	0.962***	−0.437
	(0.069)	(0.418)
Post (P)	−2.147***	2.214
	(0.168)	(1.464)
D×P: β_3	−0.137***	−0.235***
	(0.026)	(0.068)
Drug FE	✓	✓
Year FE	✓	✓
Facility FE	✓	
Observations	108,590	4,456
Adjusted R^2	0.936	0.815

Note:†Single facility procurement are excluded
*p<0.1; **p<0.05; ***p<0.01

We provide these results in more detail in Table 12 of Appendix E. Suppose that parallel trends are violated in the two pre-treatment periods. We can address this by finding a second control group unaffected by the policy and estimating the treatment effect using a triple differences design. Once support for the identifying assumption in this secondary design is established, we can then use it to cross-validate our DD estimates.

Figure 4: Event Study Plots, Log Price



5.2 Triple Differences

Table 8 shows the estimated effect of the policy on the winning bid prices of our selected DPRI drugs β_7. If there is no contamination coming from the non-auction group and if our assumption of $D_t - ND_t$ being constant across procurement groups holds, then we can recover the policy's effect on auction outcomes for our selected DPRI drugs. The results of this model estimate a downward effect on prices on average of 11.2% because the bid cap is just slightly lower than our DD estimate. If our identifying assumption holds, then we show that either approach is capable of giving similar estimates of our parameter of interest.

Table 8: Effect on Price, DDD (selected coefficients)

	log(Price)
DPRI×Post (D×P)	-0.131^{***}
	(0.028)
Auction×DPRI (A×D)	0.136^{***}
	(0.035)
Auction×Post (A×P)	0.106^{***}
	(0.028)
A×D×P: β_7	-0.101^{***}
	(0.036)
Drug FE	✓
Year FE	✓
Facility FE	✓
Observations	124,607
Adjusted R^2	0.930

*p<0.1; **p<0.05; ***p<0.01

5.2.1 Falsification Test: Non-Auction Group

The purpose of testing if there is an effect on the non-auction group from the price cap is to ensure that there is no contamination from this second control group. The kind of parallel trends violation that may be present in the DD design is dealt with by differencing out D_t and N_t on the third difference, as discussed earlier, but we also want to make sure that the effect we are measuring is isolated to auctions. Table 9 shows the estimate of $\beta_{3,na}$ that is from the non-auction analogue of the specification given by Equation 3. From this specification and estimate, we do not find any significant effect due to the policy. This confirms the assumption that the non-auction group is not contaminated by the policy supporting the decision to use this group as a control.

Table 9: Falsification Test, DD (selected coefficients)

	log(Price)
$\text{DPRI}_{na}(\text{D}_{na})$	0.655^{**}
	(0.288)
Post (P)	-4.049^{***}
	(0.705)
$\text{D}_{na}\times\text{P}$: $\beta_{3,na}$	0.026
	(0.065)
Drug FE	✓
Year FE	✓
Facility FE	✓
Observations	16,017
Adjusted R^2	0.912

*p<0.1; **p<0.05; ***p<0.01

5.2.2 Differential Effect Across Procurement Groups

Our assumption for identification is that the gap with respect to price between our drug groups remains the same between the procurement groups. Although this cannot be directly tested, we provide indirect evidence that it is plausible. We create subgroups within the Non-DPRI drugs, ND_A and ND_B, as those below and above the mean price for this group in Auctions, respectively. We then look at the estimates for each subgroup θ_A and θ_B, given a hypothetical price cap policy imposed on ND_B, and test if they are equal. The estimates being equal gives indirect support for the assumption we make.

We implement this by estimating the following specification:

$$\begin{aligned}\ln p_{jlt} = \alpha_j + \gamma_l + \tau_t + \beta_1 A + \beta_2 ND_B + \beta_3 P + \beta_4\Big(A \times ND_B\Big) + \beta_5\Big(ND_B \times P\Big) \\ + \beta_6\Big(A \times P\Big) + \beta_7\Big(A \times P \times ND_B\Big) + \delta_1 X_{jlt} + \varepsilon_{jlt}\end{aligned} \tag{6}$$

In Equation 6, variables take on the same interpretation as in Equation 5, ND_B is an indicator variable 1 / 0 equal to 1 if the drug belongs to the ND_B subgroup, $\theta_A = \beta_6$, and $\theta_B = \beta_6 + \beta_7$. We check for equality between θ_A and θ_B by testing the significance of β_7. This coefficient has the interpretation of being the marginal effect over the baseline average effect on the ND_A subgroup. Since β_7 is not statistically different from zero, we have support for our assumption under the triple difference design.

Table 10: Effect on Non-DPRI Subgroups Across Procurement Methods (selected coefficients)

	log(Price)
A × P: β_6	0.102***
	(0.024)
ND_B× A × P: β_7	0.040
	(0.087)
Drug FE	✓
Year FE	✓
Facility FE	✓
Observations	21,620
Adjusted R^2	0.949

*p<0.1; **p<0.05; ***p<0.01

5.2.3 DPRI Drug Price Trend and Supplier Count

Outcomes of interest in these auction markets are prices and the level of competition. Although prices can be investigated straightforwardly, competition in auctions is harder because we do not observe all the bids of each auction. To try and gain some insight from what we observe, we regressed log prices of the DPRI drugs and the count of the winning bidders on linear and quadratic trend terms. We also include the contract volume and the log of contract revenue to control for the size of the transaction in terms of both the quantity of the transaction and the revenue. The results are shown in Table 11. We find that the average trend is decreasing for our selected DPRI drugs. By doing a similar exercise for the count of unique winning suppliers, we find an increasing trend. One interpretation is that there are slightly more different winners over time, and this can indicate increasing competition among sellers who have not exited these markets.

Table 11: Regression Estimates, DPRI Drugs (selected coefficients)

	log(Price)	log(Firm Count)
Post (P)	−0.046***	0.027
	(0.017)	(0.051)
Trend (T)	−0.069***	0.060**
	(0.009)	(0.026)
P × T	0.024**	−0.003
	(0.009)	(0.027)
Drug FE	✓	✓
Facility FE	✓	
Observations	102,913	2,681
Adjusted R^2	0.932	0.793

*p<0.1; **p<0.05; ***p<0.01

6 Conclusions

The high and widely varying prices of medications in the Philippines are some of the hurdles that the government needs to overcome to improve access to affordable healthcare. To this end, price cap policies, such as the DPRI, have been implemented. Because most policies are implemented simultaneously and nationwide, an evaluation that draws a causal link between intervention and market outcomes has never been done.

In this paper, we evaluate the effect of the DPRI on prices for a selected group of drugs under the regulation. Using a triple differences design, we find that the policy reduced prices by approximately 11.2% on average. We also find that the policy had no significant effect on DPRI drugs procured using alternative non-auction modes. This result allowed us to isolate the effect of the policy on auction prices of our selected DPRI drugs. The DD estimate is not far off at 14.7%. Furthermore, the spread of the transaction prices decreased by around 26%. However, we take these results with a grain of salt due to other findings in our investigation such as the presence of bidders that derive most of its sales from only a few products and facilities, evidence of possible policy manipulation, and indirect evidence of 1 in 3 auctions failing. There could be concerns if competition can be inhibited through inframarginal auctions which can be played with more or less aggressiveness to artificially raise the bid cap over time. The issue could be more serious when the auctioneer cannot commit credibly to its reserve price, resulting in artificially high prices over time.

In general, we find that the policy was moderately successful in lowering prices and narrowing their spread across facilities for essential drugs. Competition among firms that remain is increasing over time, although we cannot say if this includes those bidders who have not won but stayed in nonetheless. Our results are more consistent with bidders using a grim trigger strategy, where cooperation was not sustained. An investigation of auction markets in a controlled setting may provide complementary analyses of the features lacking from this study.

References

Abrigo, M. R. M., Opiniano, G. A., Tam, Z. C., Yee, S. A., & i M. Estopace, K. M. (2021). Public sector procurement of medicines in the philippines. Report 2021-44, Philippine Institute of Development Studies. http://hdl.handle.net/10419/256879.

Ashenfelter, O. (1989). How auctions work for wine and art. *The Journal of Economic Perspectives*, *3*(3), 23–36.

Ball, D., & Tisocki, K. (2009). Medicines Price Components in the Philippines. Tech. rep., Health Action International.

Bucciol, A., Camboni, R., & Valbonesi, P. (2020). Purchasing medical devices: The role of buyer competence and discretion. *Journal of Health Economics*, *74*, 102370.

Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230.

Carare, O. (2012). Reserve prices in repeated auctions. *Review of Industrial Organization*, *40*(3), 225–247.

Card, D., & Krueger, A. B. (1994). Minimum wages and employment: A case study of the fast-food industry in new jersey and pennsylvania. *The American Economic Review*, *84*(4), 772–793.

Cattaneo, M. D., Jansson, M., & Ma, X. (2018). Manipulation testing based on density discontinuity. *Stata Journal*, *18*(1), 234–261.

Cheng, K. J., Rivera, A., General, J. C., Asence-Mamporte, A., Ulitin, A., Miguel, R. T., Guerrero, A. M., Florentino-Fariñas, I., Sison, K., & Lam, H. (2020). Do local government units in the philippines procure medicines according to a set benchmark price? *World Medical & Health Policy*, *12*(1), 9–23.

Cunningham, S. (2021). *Difference-in-Differences*, (pp. 406–510). The Mixtape. Yale University Press.

Fabra, N. (2003). Tacit collusion in repeated auctions: Uniform versus discriminatory. *The Journal of Industrial Economics*, *51*(3), 271–293.

Green, E. J., & Porter, R. H. (1984). Noncooperative collusion under imperfect price information. *Econometrica*, *52*(1), 87–100.

Gruber, J. (1994). The incidence of mandated maternity benefits. *The American Economic Review*, *84*(3), 622–641.

Isaac, R. M., & Plott, C. R. (1981). Price controls and the behavior of auction markets: An experimental examination. *The American Economic Review*, *71*(3), 448–459.

Kanoria, Y., & Nazerzadeh, H. (2021). Incentive-compatible learning of reserve prices for repeated auctions. *Operations Research*, *69*(2), 509–524. Doi: 10.1287/opre.2020.2007.

Knittel, C. R., & Stango, V. (2003). Price ceilings as focal points for tacit collusion: Evidence from credit cards. *The American Economic Review*, *93*(5), 1703–1729.

Levy, D., Lee, D., Chen, H., Kauffman, R. J., & Bergen, M. (2011). Price points and price rigidity. *The Review of Economics and Statistics*, *93*(4), 1417–1431. (Allan).

Lewis, M. S. (2015). Odd prices at retail gasoline stations: Focal point pricing and tacit collusion. *Journal of Economics & Management Strategy*, *24*(3), 664–685.

McCrary, J. (2008). Manipulation of the running variable in the regression discontinuity design: A density test. *Journal of Econometrics*, *142*(2), 698–714.

Scherer, F. M. (1967). Focal point pricing and conscious parallelism economics. *Antitrust Bulletin*, *12*(2), 495–504.

Smith, V. L., & Williams, A. W. (1981). On nonbinding price controls in a competitive market. *The American Economic Review*, *71*(3), 467–474.

Stigler, G. J. (1964). A theory of oligopoly. *Journal of Political Economy*, *72*(1), 44–61.

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199.

van der Loo, M. P. J. (2014). The stringdist package for approximate string matching. *R Journal*, *6*(1), 111–122.

Zhang, X.-B., Fei, Y., Zheng, Y., & Zhang, L. (2020). Price ceilings as focal points to reach price uniformity: Evidence from a chinese gasoline market. *Energy Economics*, *92*, 104950.

Appendix A. Guidelines for Alternative Procurement Methods

1. Republic Act 9184, Government Procurement Reform Act link
2. Updated 2016 Revised Implementing Rules and Regulations of Republic Act 9184 link

These documents are available from the Government Procurement Policy Board website using the links above. Appendix documents are also available here.

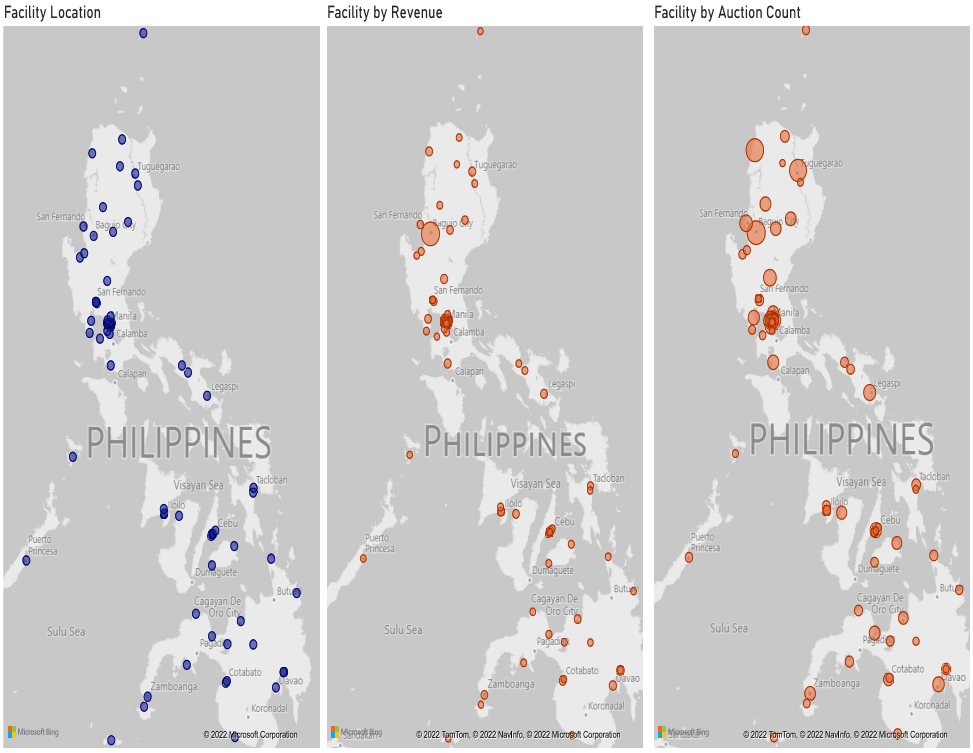
Appendix B. DPRI Implementing Rules and Regulations

1. Department Order 2014-0146, Implementing Guidelines on the Philippine Drug Price Reference Index (DPRI)
2. Administrative Order No. 2015-0051, Guidelines in the Implementation of the Philippine Drug Price Reference Index (DPRI) to All Public Hospitals and Health Facilities
3. Administrative Order No. 2015-0051-A, Amendment to Annex A of Administrative Order No. 2015-0051 regarding the Implementation of the Philippine Drug Price Reference Index (DPRI) to all Public Hospitals and Facilities
4. Administrative Order No. 2019-0040, Revised Guidelines in the Implementation of the Philippine Drug Price Reference Index (DPRI) to all Public Hospitals and Health Facilities

These documents are available from the DOH DPRI website.

Appendix C. Geo-mapping of Facilities

Figure 5: Facility Map, Department of Health Regional Offices and Hospitals



Appendix D. Drugname Match and Score

Appendix available online.

Appendix E. Additional Estimation Results

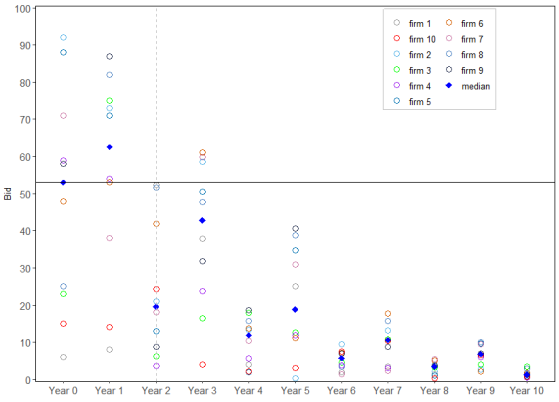
Table 12: Effect on Price, Event Study (selected coefficients)

Dependent Variable:	log(Price)
DPRI (D) × I ($y = -2$)	0.1183***
	(0.0331)
DPRI (D) × I ($y = -1$)	0.2408***
	(0.0392)
DPRI (D) × I ($y = 1$)	-0.0675***
	(0.0236)
DPRI (D) × I ($y = 2$)	-0.0968***
	(0.0275)
DPRI (D) × I ($y = 3$)	-0.2159***
	(0.0323)
DPRI (D) × I ($y = 4$)	-0.1476***
	(0.0343)
DPRI (D) × I ($y = 5$)	-0.1014***
	(0.0390)
Drug FE	✓
Year FE	✓
Facility FE	✓
Observations	108,590
Adjusted R^2	0.93652

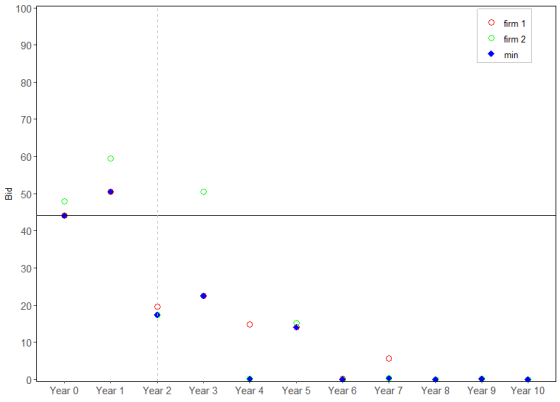
Clustered (Drug) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Appendix F. DPRI outcome simulations

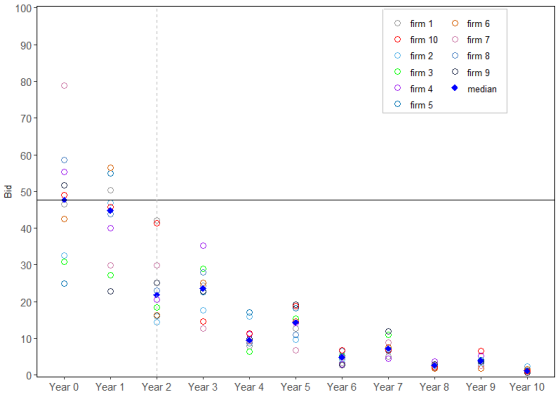
Figure 6: Simulations of Auction Outcomes



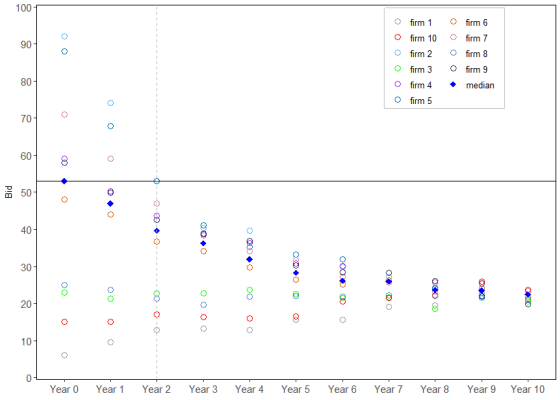
Uniform distribution, 10 firm



Uniform distribution, 2 firm



Normal distribution, 10 firm



Serial correlation, 10 firm