ESSAYS IN INDUSTRIAL ORGANISATION AND AUCTIONS

by

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To my wife, Bianca.

Then the trav'ller in the dark,
Thanks you for your tiny spark,
He could not see which way to go,
If you did not twinkle so. (9-12)

-Jane Taylor, *The star*

ABSTRACT

This is a collection of three essays on industrial organisation and auctions involving pharmaceutical markets. The first chapter looks at markets in the Philippines affected by an actual acquisition that took place in 2019. Estimates suggest that a reduction in prices followed from the acquisition. Backing out marginal costs in the pre- and post-acquisition periods shows that the price reduction coincides with merger specific marginal cost efficiencies post-transaction of 2-3%. The next essay evaluates the effect of a procurement policy that imposes a dynamic bid cap on auction markets for essential medicines in the Philippines. Using a triple differences design, evidence indicates that the policy was moderately successful in reducing prices. Despite endogenous features, the mechanism led to a systematic reduction of prices by 11-15%. However, evidence also points to 1 in 3 auctions failing under the policy as well as possible policy manipulation. The last chapter investigates auction markets in a controlled laboratory setting. Performance of markets and bidder behavior using a dynamic bid cap is compared to the case without a bid cap. Even though the mechanism appears to be ill-suited from a theoretical perspective, the competition to win overwhelms the ability to manipulate the bid cap. Although transaction price outcomes are improved, bidder entry is severely affected, and failed auctions become far more likely with dynamic bid caps. Findings in the experiment are consistent with those of the reduced-form analysis of real-world auction data in the second essay.

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INTRODUCTION

The study of mergers and auctions involves investigating important economic activities that could have far-reaching effects on social welfare. Competition policy can be an effective tool to help ensure that these activities do not harm markets and that government social objectives are met. Looking at pharmaceutical markets makes it possible to study both mergers and auctions. Consolidation of firm ownership is commonplace in pharmaceuticals, and auctions are widely used by healthcare providers to buy medicines and medical products from sellers.

The evaluation of mergers by competition authorities is largely based on predictions of price effects. The default expected effect of a horizontal merger is a price increase, but this prediction can be reversed in the presence of merger-specific efficiencies. Detailed ex post modeling evidence on achievement of efficiencies for specific deals is nonetheless limited. In chapter 1, a direct examination of post-merger efficiency gains is performed using longitudinal price data on cough and cold remedy products in the Philippines[2]. A standard discrete choice model of demand is used to estimate baseline marginal costs prior to the acquisition. Post-acquisition marginal costs are then backed out using a novel combination of approaches, using actual data from periods after the transaction. The reduction in marginal costs is estimated to be about 2-3 percent. The evidence found confirms the theoretical possibility that a reduction in price (relative to a control) coincides with efficiency gains from lower marginal costs.

In the Philippines, government procurement of medicines represents a sizeable amount of public funds growing from 7.8 billion pesos in 2014 to 20.1 billion pesos in 2019 (Abrigo et al., 2021). Chapter 2 looks at the effect of a bid cap policy in procurement auctions for medicine on prices and competition. The policy 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 com-

[2]Chapter 1 was accepted at the 50th European Association for Research in Industrial Economics (EARIE) conference, and the 93rd Southern Economics Association (SEA) conference

petitive 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, the effect of the policy on transaction prices faced by government hospitals in the Philippines is estimated. 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. The evidence shows that the policy led to a systematic reduction in transaction prices as well as in price dispersion, on average. However, 1 in 3 auctions for regulated medicines failed after the policy was imposed. Evidence also points to possible policy manipulation by sellers winning just under the applicable bid cap. Although the mechanism makes the reservation price endogenous and possibly ill suited from a theoretical perspective, evidence suggests that price outcomes for the auctioneer are improved. We explore the properties of this mechanism using experimental methods in the last chapter[3].

In a procurement setting, when firms exit markets due to high costs, competition wavers, and the remaining bidders bid less aggressively, resulting in higher prices. The auctioneer's problem could conceivably be modulated by a reserve price mechanism that uses the lowest bid from the previous period. In a single market, when bidders set the cap in the next period, they can pull back their bids and keep that bid cap from biting. If instead bidders from another market set the cap, the incentive for strategic bidding is removed, and competition can potentially be restored. Using a controlled setting, we show how dynamics in reserve price setting influence bid shading and entry in multi-round low price auctions. Without a bid cap, empirical evidence from the experiment shows that dampened competition does lead to higher prices after bidders exit. Imposing a dynamic bid cap solves this issue of higher prices but knocks more people out of markets, leading to widespread failure of auctions. Surprisingly, bidding behaviour remains similar across

[3]Trials registered with the American Economic Association's registry for randomised controlled trials, AEA RCTR-0012049. Chapter 3 was accepted at the 14th International Conference of the French Association of Experimental Economics (ASFEE)

bid cap institutions during the first round. In subsequent rounds, bidding becomes deceptively more competitive in auctions with bid caps, but unexpectedly resulting in destroying markets.

The first chapter speaks to the ambit of competition authorities in assessing mergers and acquisitions and the importance of efficiency considerations. The combination of methodologies used to make the analysis is comprehensive and, at the same time, accessible to practitioners to implement. The second and third chapters deal with auctions as a policy tool and market modality. Because of the competitive nature of auctions and their widespread use in public procurement for a wide variety of goods and services, mechanisms may have unintended long term effects on markets and competition.The second essay establishes a causal effect of the policy on price outcomes. The third essay investigates the properties of the auction mechanism studied in the previous chapter with an experiment and evaluates the performance of markets that use them. Taken as a whole, rather than solely about pharmaceutical markets, these essays advance our broader understanding of industrial organisation and auctions, particularly as they relate to applications within a developing country setting.

CHAPTER 1

Efficiencies in Retrospective Merger Evaluation: GSK-Pfizer Consumer Health

Abstract

The evaluation of mergers by competition authorities is based largely on predictions of price effects. The default expected effect of a horizontal merger is a price increase, but this prediction can be reversed in the presence of merger-specific efficiencies. Detailed ex post modelling evidence on achievement of efficiencies for specific deals is nonetheless limited. We make a direct examination of post-merger efficiency gains using longitudinal price data on cough and cold remedy products in the Philippines. A standard discrete choice model of demand is used to estimate baseline marginal costs prior to the acquisition. In a novel combination of approaches, post-acquisition marginal costs are then backed out using actual data from periods after the transaction, with estimates of a reduction of marginal costs of about 2-3 percent. We provide evidence that confirms the theoretical possibility that a reduction in price (relative to a control) coincides with efficiency gains from lower marginal costs. This finding reinforces the importance that policymakers should consider potential efficiencies when evaluating mergers.

1.1 INTRODUCTION

Mergers are an important economic activity, representing an average of roughly $4 trillion in transaction value annually over the last 10 years. With so much economic value at stake, governments recognize the potential for higher prices to follow from concentration, with potentially negative effects on consumer and social welfare. Consequently, merger review is a common feature of competition authority oversight, with more than 120 authorities holding powers to prevent anti-competitive mergers. Among the tens of thousands of transactions per year, competition authorities face the difficult applied challenge of distinguishing the presumed small set of mergers that are expected to create harm from the others. While a default expectation may exist that horizontal mergers would raise prices, efficiencies can counteract negative impacts of mergers as shown by Williamson (1968), Farrell & Shapiro (1990), and Nocke & Whinston (2022). A full merger analysis will therefore consider the impact of efficiencies, a point further emphasised in competition authority guidelines for merger review. Yet among existing ex post studies of mergers, relatively little emphasis has been accorded, methodologically, to the potential countervailing impacts of efficiencies on price increases. This low emphasis is reflected in the common practice of assuming that marginal costs do not change between the pre- and post-merger state. This paper seeks to supplement our understanding of the countervailing impacts efficiencies by studying a particular merger and combining two common methods of modelling to provide an identified estimate of post-merger marginal costs.

The approach we use builds on that of ex post studies of individual mergers, which have grown increasingly common in recent times. One reason for these reviews is to refine competition authority approaches to merger review by assessing whether competition authorities appropriately allowed or blocked a merger. The interest in effective control of mergers has grown as studies were released suggesting that mergers have allowed for increasing concentration in markets leading to higher margins (De Loecker et al. (2020), Diez et al. (2018)) creating potential superstar firms with difficult to challenge positions (Autor et al. (2020)) and, ultimately, generating potential inequality impacts from greater concentration (Ennis et al. (2019)).

To allow a greater focus on techniques of measuring efficiencies occur from mergers, we focus on a single merger for which particularly detailed sales data is available. This relates to cough and cold medicines in the Philippines. The merger resulted in an aggregate market share of 13 percent, a relatively low figure, but the merging parties both provided differentiated products at the upper end of the price spectrum. We apply both (1) reduced-form regressions through difference-in-differences (DiD) designs, and (2) merger simulations using structural estimates of demand estimated using the random coefficients logit model. The former helps us to describe price patterns in the data, before and after the merger. The latter is used to estimating economic parameters and then simulating counterfactuals of interest. In particular, we calculate the implied marginal costs from the relative price changes in the DiD, by applying the structural model estimated with the pre-merger data. We find that the most reasonable interpretation of the data is that the merger was followed by a decline in marginal costs of 2-3 percent, suggesting that the merger of two firms was accompanied by efficiencies.

The primary contribution of this work is to separate out efficiencies and price effects from a merger with a careful selection of time period and modelling approach for the relevant variable estimates. In particular, we assume that demand does not change after the merger, but that the ownership matrix changes and, at the same time, marginal costs are able to change. Remarkably, provided a sufficiently robust estimate of demand conditions, this can allow an identified estimate of cost changes from a single transaction, without requiring the multiple transaction approach of Demirer & Karaduman (2022) and without requiring internal data on costs. This paper provides important practical tools for addressing the theoretical point that horizontal merger price increases can be counteracted by efficiencies. Its methods can be used with respect to an individual merger.

By freeing up cost conditions to vary post-merger, these findings add new evidence to the literature on ex post merger review, with a finding of substantial merger efficiency.[1]

[1]Merger control itself is an ex ante policy instrument. In order to ensure its appropriate application, it is valuable that decisions are subjected to rigorous ex post evaluation exercises (Mariuzzo & Ormosi, 2016). When done properly, the retrospective evaluation of economic model predictions can lead to a more efficient, objective and accurate merger review process (Ashenfelter et al., 2009). In jurisdictions where competition policy is still a new feature in the economy, empirical studies can have a significant impact by setting methodological precedence and potentially informing jurisprudence as its competition authority matures.

They particularly relate to the literature on event studies of efficiencies from mergers, such as Bjornerstedt & Verboven (2016), Friberg & Romahn (2012), Grieco et al. (2017), Miller & Weinberg (2017), Weinberg & Hosken (2013), and Zimmerman et al. (2019).

Other papers on retrospective evaluations of mergers follow two main alternative research designs to identify the parameters of interest, difference in differences (DiD) and structural models. [2] Using both reduced form and structural analyses can give a more complete picture of the merger's effect but can be quite involved. Papers that use this combination, typically look in one part, price patterns before and after the merger with reduced form estimates, and in another, use merger simulations to predict changes in price, and then check if they line up. Among the demand models used in the literature, the random coefficients logit model is often used. Despite the complexity in estimation, the model provides richer and more realistic substitution patterns, and allows the researcher to incorporate observed and unobserved individual valuation of product characteristics.

Rather than just comparing if estimates line up, factual patterns of price and market structure can inform the choice of merger counterfactuals to simulate, for instance changes in marginal cost and efficiency. We build on these insights to carry out an examination of marginal costs that combines a DiD and structural model approach. Allowing for a recalculation of marginal costs is fundamentally important, because a standard merger simulation that follows demand estimation keep marginal costs constant while changing the ownership matrix to give price predictions. This makes post-merger price increases higher by construction under well-specified elasticities and cross-elasticities. Our modelling approach relaxes a constraint and thus can be seen as more general that the approach generally used.

We look at experience from an acquisition in the pharmaceutical sector and use variation in both local and international markets to identify our parameters of interest. In the first part of the paper we find evidence that prices decreased relative to our control, while in the second part, we investigate how marginal costs evolved after the transaction. Using these two main approaches to evaluate mergers, we examine the impact of this acquisition on prices in the Cough and Cold Remedy (CCR) market and then show how marginal

[2] Reviews of these include Mariuzzo & Ormosi (2016) and Kwoka (2013).

costs evolved in the year after the transaction. Evidence from both approaches points to efficiency gains as a result of the acquisition and permits us to estimate welfare impacts.

The acquisition involves two relatively small sized product portfolios for cough and cold remedies in a country where five firms account for 95% of sales and the top firm alone accounts for more than 60% of sales. Because merger evaluation studies are typically done on transactions on the enforcement margin, smaller acquisitions are under-represented in the literature (and we are not aware of any).

Price effects are calculated relative to a chosen counterfactual group. In some cases, a price reduction is observed. There can be several sources of bias in the estimates. Even after satisfying classical parallel trends assumptions, merger impact estimates from a reduced form approach are not able to pin down changes in market primitives such as marginal cost and markup. Structural methods explicitly model these primitives and make possible predictive counterfactual exercises. With both pre- and post-merger data, a true ex-post evaluation is possible looking at both price effects and changes in marginal cost.

Ex post merger reviews have scant literature on their use in jurisdictions outside the EU or US, and particularly in lower or middle income countries, where competition policy and merger control may still be a nascent feature in the economy. Our paper focuses on the impact in such a jurisdiction, the Philippines, where the most prominent supplier of the product in question, but not a party to the acquisition, is locally owned.

The paper proceeds as follows. Section 1.2 looks at the relevant literature. Section 1.3 discusses the market, the merger, and the data. Section 1.4 contains the descriptive analysis. Section 1.5 discusses our structural approach, estimates, and predictions. Section 1.6 concludes.

1.2 RELATED LITERATURE

Other papers on retrospective evaluations of mergers follow two main alternative research designs to identify the parameters of interest, each with its own long-standing and well established corpus of work. Comprehensive reviews are made by Mariuzzo & Ormosi (2016) and Kwoka (2013). These are DiD and structural models.

The DiD design is more straightforward to implement and the more commonly used

approach in merger retrospectives. It involves a before-and-after analysis that compares the prices of merging firms with a control. Although seemingly simple, the challenge lies in selecting a valid comparison and addressing possible sources of bias in estimating the Average Treatment effect on the Treated (ATT). More recently, the pathology of DiD's most commonly used estimator, the two-way fixed effects (TWFE) estimator, has been given a closer look. Contributions of Callaway & SantAnna (2021), Sun & Abraham (2021), and de Chaisemartin & D'Haultfuille (2020) brought attention to issues coming from differential timing and heterogeneous treatment effects.

In merger simulations based on structural models, building on BLP approaches, the implementation and data requirements are much more involved, but the scope of a researcher's analysis with regard to a merger is increased. For example, given ex-ante and ex-post data, the kind that is typically used for DiD retrospectives, merger simulations can look at in-sample predictions and run counterfactual exercises, e.g. divestitures, remedies, and blocked mergers. Using both reduced form and structural analyses can give a more complete picture of the merger's effect, but can be quite involved. Papers that use this combination typically look in one part at price patterns before and after the merger with reduced form estimates, and in another, use merger simulations to predict changes in price, and then check if they line up. There is no consensus on this question, shown in Table 1.1. However, among the demand models used in the literature, the random coefficients logit model is considered as the most preferred. Despite the complexity in estimation, the model provides richer and more realistic substitution patterns and allows the researcher to incorporate observed and unobserved individual valuation of product characteristics.

The emergence of new empirical industrial organisation, particularly structural econometrics and merger simulation, was criticised by Angrist & Pischke (2010) and prescribed the wider use of quasi-experimental designs such as DiD to study the price effect of mergers. They cite the complexity of econometric modelling driving substitution patterns and question the validity of the instruments used. Nevo & Whinston (2010) gave a rejoinder to the critique giving their reasons favouring the use of merger simulations. In practise, however, there are certain circumstances where one method is preferred to the other, and in some, the use of both can give a more complete picture, as Mariuzzo & Ormosi (2016)

Table 1.1: Merger Retrospectives Using Descriptive Analysis and Merger Simulations

Paper, Market and Model	Merger	Evaluation
Peters (2006) US Airline Industry Nested logit	Northwest-Republic, TWA-Ozark, ContinentalPeople Express, Delta-Western and US Air-Piedmont	Simulations reasonably predict actual price effects
Ashenfelter & Hosken (2010) (in relation to Nevo (2000)) US RTE Breakfast Cereal RC logit	General Mills-Ralston Purina Kraft-Nabisco	Simulations do not line up with actual price effects
Weinberg (2011) US Feminine protection products Standard and Nested logit	Proctor&Gamble purchase of Tambrands	Simulations significantly underestimated price effects
Friberg & Romahn (2012) Swedish beer market RC logit	Carlsberg take over of Pripps	Diff-in-diff estimates are well matched by simulation predictions
Weinberg & Hosken (2013) US motor oil & breakfast syrup AIDS, linear, standard logit	Penzoil purchase of Quaker State, Aurora purchase of Log Cabin	Mixed results with simulations over predicting price effects of syrup merger while underpredicting those of the motor oil merger
Bjornerstedt & Verboven (2016) Swedish analgesics market Nested logit, RC logit	GSK and AZT	Nested logit model predicted actual average price increase but deviated in individual price effects. RC logit underpredicts average price
Doi & Ohashi (2019) Japanese Airline Industry Nested logit	Japan Airlines merger with Japan Air System	Simulations predict market outcomes farily accurately

Note: The list above only shows a sample of key or more recent papers and is by no means representative of the majority of the studies done

discusses in detail. When using both, Mahoney (2022) gives the guidance to make tight links from descriptive analysis (DiD) to model-based analysis (Merger Simulation).

Rather than just comparing if estimates line up, factual patterns of price and market structure can inform the choice of merger counterfactuals to simulate, for instance, changes in marginal cost and efficiency. We build on these insights to carry out an examination of marginal costs that combines a DiD approach and a structural model approach. Allowing for a recalculation of marginal costs is fundamentally important, because a standard merger simulation that follows demand estimation keeps marginal costs constant while changing the ownership matrix to give price predictions. This makes the post-merger price increase by construction under well-specified elasticities and cross-elasticities. Our modelling approach relaxes a constraint and thus can be seen as more general than the standard generally used.

We look at an acquisition in the pharmaceutical sector and use variation in both local and international markets to identify our parameters of interest. In the first part of the paper, we find evidence that prices decreased relative to our control, while in the second part, we investigate how marginal costs evolved after the transaction. Using these two main approaches to evaluate mergers, we examine the causal impact of this acquisition on prices in the Cough and Cold Remedy (CCR) market and then show how marginal costs evolved in the year after the transaction. Evidence from both approaches points to efficiency gains as a result of the acquisition. Most studies are typically done on transactions on the enforcement margin which means that smaller acquisitions are under represented in the literature (and we are not aware of any). Price effects are relative to a chosen counterfactual group, and in some cases, a price reduction is observed. Even after satisfying assumptions, causal estimates from a reduced form approach are not able to pin down changes in market primitives such as marginal cost and markup. Structural methods explicitly model these primitives and make possible predictive counterfactual exercises. With both pre- and post-merger data, a true ex-post evaluation is possible looking at both price effects and changes in marginal cost. Ex post merger reviews have scant literature on their use in jurisdictions outside the EU or US, and particularly in lower or middle income countries, where competition policy and merger control may still be a nascent feature in the economy. We provide

a comprehensive review of an acquisition that happened in the Philippines in 2019, three years after the country's competition authority was established. In the next section, we focus on the details of the acquisition, the market where it happened, and the data set we use for the analysis.

1.3 THE MARKET AND THE ACQUISITION

In June 2019, the Philippine Competition Commission (PCC) allowed the acquisition of Pfizer, Inc. Consumer Healthcare Business (Pfizer) by GlaxoSmithKline Consumer Healthcare Holdings, Ltd. (GSK). The following discussion provides relevant background information on the acquisition, industry, our market of interest, and data.

1.3.1 The Acquisition

GSK notified PCC of its proposed acquisition of Pfizer on 18 January 2019. As consideration for the transaction, GSK's ultimate parent entity, GlaxoSmithKline Plc. (GSKP) will issue non-controlling shares to Pfizer Inc. (PfizerP) representing 32% ownership interest in the global consumer healthcare joint venture. In the Philippines, this was implemented as a pure acquisition of assets. Before closing, it was necessary to secure approval from multiple countries, including the Philippines[3]. Therefore, approvals from competition authorities in smaller markets are just as important as those from key markets in terms of completing the transaction. In the Philippines, specifically, the acquisition was evaluated in terms of overlapping over-the-counter (OTC)[4] products in respiratory health, pain relief, and nutritive health. After undergoing Phase 1 and Phase 2 reviews, it was formally granted clearance on 27 June 2019.

In its official statement opening the Phase 2 review, PCC explains that a more detailed analysis will be undertaken:

The initial market investigation conducted by the MAO (Mergers and Acquisitions

[3]These countries are Australia, Austria, Brazil, Canada, China, Colombia, European Union, Germany, Israel, Japan, Philippines, Russia, Mexico, New Zealand, Serbia, South Africa, South Korea, Taiwan, Ukraine and the U.S.

[4]OTC medicines are defined as medicines used for symptomatic relief of minor ailments and which may be dispensed without prescription (Philippine Pharmacy Act of 2016).

> *Office) indicates that the transaction may affect the consumer healthcare industry, particularly the markets for antitussive and expectorants, analgesics, and nutritive health products.*
> *The commencement of Phase II Review does not mean that MAO has made a definitive finding of a substantial lessening of competition or has prejudged the result of the review. This only signifies that a more detailed analysis of the Transaction is required using additional information*

The transaction was eventually cleared citing, among other things, that there is sufficient competitive constraint post-merger, and so the acquisition will not likely result in substantial lessening of competition in the relevant markets. Interestingly, there was a finding in the decision that stated:

> *...the merged entity will gain ability to exercise market power, but will not have enhanced incentive to increase prices in the market for ACMs (Adult Cough Medicines)...*

There was recognition by PCC that the transaction could potentially affect markets in the healthcare sector with the opening of Phase 2 and explicitly indicated that the acquisition gives GSK increased ability to exercise market power, albeit incentive to do so will not change. This signals that the competition authority viewed the transaction to be initially of some concern but, after their investigation, has found it to be ultimately benign. The merger policy in the country has only been enforced since 2016 and only a handful of cases have gone through a phase 2 review, resulting in one prohibited merger. Retrospective studies of a consummated transaction can give evidence of what had actually happened to prices, marginal cost, and markups post merger and give guidance as to how similar mergers in the future can be assessed.

1.3.2 Cough and Cold Remedies in the Philippines

Although the acquisition can have a wider impact on other pharmaceutical sectors in the Philippines, we focus on over-the-counter cough and cold remedies (CCR) in this study. Respiratory Tract Infection (RTI) is consistently one of the leading causes of morbidity worldwide, and acute respiratory tract infection (ARTI) was one of the top 3 causes of

Table 1.2: Market Shares, Product and Active Substance Counts in 2018

Firm	Product	Prop Label	Non-Prop Label	Private Label	Active Substance	Share
United Lab	23	18	0	5	18	67.90%
Pfizer	4	4	0	0	4	8.34%
Sanofi Aventis	2	2	0	0	2	7.19%
GSK	3	3	0	0	2	6.02%
Pascual	2	2	0	0	2	4.97%
Others (47)	71	66	5	0	21	5.58%
Total	105	95	5	5	49	100%

Note:Table shows the largest firms, brands and active substances computed based on total values of sales in 2018

morbidity in 2018 in the Philippines. This runs parallel to the findings of the competition authority as one of the markets to be scrutinised in its Phase 2 review.

The Philippine pharmaceutical sector in 2020 was worth 4.5 billion USD with OTC products representing 38% or 1.7 billion USD. The other 62% is prescription or ethical drugs worth approximately 2.8 billion USD. Sales in the Philippine CCR market were approximately 160 million dollars in the same year, spreading across 52 firms. Despite this number of firms, the market is highly concentrated. Five of the firms and a third of the brands represent 94.4% of the market value, while the rest of the market is made up of 47 firms that capture the remaining 5.6%.[5] Table 1.2 shows the market shares of the top five companies in 2018, as well as the respective counts of their brands, the counts of their brands with *Proprietary label*, or *Non-proprietary label*, or *Private label*, and the number of active substances. The largest firm, United Lab, represents two thirds of the market, owning far more brands, and using more active substances than other relatively large firms. Pfizer and GSK were second and fourth, respectively, overlapping in a narrower range of medications. Their combined shares put them second overall and result in a market share that is twice as large as the next firm, Sanofi-Aventis.

The products in this segment can be differentiated along multiple dimensions. Drugs can be classified as *Proprietary label*, *Non-proprietary label*, or *Private label*. *Proprietary label* drugs have the same active substance as the originator drug that was first launched but are marketed under a different brand. *Non-proprietary label* refer to drugs that carry only the

[5]We define a brand to be the name given to a pharmaceutical product by the manufacturer, or the product's INN combined with the manufacturer name.

international non-proprietary name (INN) in conjunction with the manufacturer's name, while *Private label* drugs use a uniform brand for multiple active substances. As shown in Table 1.3, the vast majority of sales come from *Proprietary label* products, with less than 1% of annual sales and volume from 2008 to 2018 coming from the other two types. Products can also be classified as being produced by a firm that has presence outside of its country of origin, in which case the firm is classified as *Foreign*, otherwise the firm is labelled as *Local*. These *Foreign* products represent less than a third of sales on average, indicating that products from local firms are more popular.

Treatment of symptoms can vary in both pharmacological action and administrative formulation, but the choice of medication is likely driven by the symptoms to be treated and, therefore, the active substance that delivers the appropriate pharmacological action. Active substances in conventional pharmaceuticals and herbal medicines can be organised into therapeutic categories summarised and shown in Table A.1 of Appendix A.1. Products can be single-molecule drugs or a combination of two or more molecules in a single dose to address multiple symptoms. This type of product represents about half the sales in the segment on average. For this analysis, a combination of molecules will be considered as a unique molecule itself. Products can also be classified in terms of their formulation, whether they are in solid form or not. On average, about 63% of sales come from drugs in solid form, which is typically the form taken by drugs marketed to adult patients. Lastly, products can be differentiated in terms of whether the drug comes with flavours. The sales of these drugs represent about 8% of the total on average. A summary of product shares along these product attributes is shown in Table 1.3.

Table 1.3: Market Share by Product Attribute, 2008-2018

Attribute	mean	sd	min	max
Proprietary Label	99.57%	0.07%	99.41%	99.68%
Foreign	27.14%	3.29%	20.11%	35.30%
Combination INN	50.48%	3.49%	42.19%	58.52%
Solid Form	63.50%	3.35%	56.49%	72.94%
Flavoured	7.94%	1.54%	4.78%	10.07%

Note: Figures above are computed based on the total sales value

In terms of active substances or molecules, as Table 1.4 indicates, the largest firms tend

to focus on just a few active substances, and the share of the top 4 firms for products that have the same molecules as the products owned by the merging parties already accounts for 42% of the market. The figures also indicate that there are overlaps in active substances between the merging parties and their competitors. However, there are no overlapping product lines between the merging parties.

Table 1.4: Shares of Top 4 Firms in 2018 by Active Substance Shared with GSK or Pfizer

	Carbocisteine	Ambroxol	Butamirate	Dextromethorphan +Guaifenesin	Guaifenesin	Brompheniramine +Phenylephrine	Total
United Lab	18.52%	2.33%					20.85%
Pfizer	**0.92%**			**3.89%**	**3.29%**	**0.24%**	**8.34%**
GSK		**1.15%**	**4.87%**				**6.02%**
Sanofi-Aventis		6.61%					6.61%
Total	19.44%	10.09%	4.87%	3.89%	3.29%	0.24%	41.82%

Note: Figures are calculated based on sales value in 2018

Many OTC medications contain more than one active substance to address multiple symptoms. Using multiple products is strongly discouraged to avoid taking more than the prescribed dose. Pfizer products involve combinations of active substances that address the same symptoms as the GSK product line. Therefore, the behaviour of consumers taking more than one product from both the GSK and Pfizer product lines as complements, although possible, is largely unlikely.

1.3.3 Data

We use detailed longitudinal sales data from IQVIA (formerly IMS Health and Quantiles). Specifically, we use IQVIA's Philippine National Sales Audit (NSA) from Q1 2008 to Q4 2020, covering the Cough and Cold Remedies (CCR) and Pain and Fever Remedies (PFR) segments[6], and IQVIA's MIDAS World Review Pack (WRP) Database from Q4 2009 to Q4 2021, for Indonesia, Malaysia, Thailand, Singapore, and Philippines. From these sources, we used data on hypertension remedies (HTR) for the Philippines and CCR for the other countries. For consistency, we use the same therapeutic classes in other countries as those observed in the national sales audit data for the CCR segment in the Philippines. Both data

[6]The database comes from their Philippine Pharmaceutical Index (PPI) and the Philippine Hospital Pharmaceutical Audit (PHPA)

sets contain quarterly stock-keeping unit-level sales information, including both product and transaction characteristics. See Appendix A.2 for a complete list of attributes and definitions available for each data set. We define the product j as the unique corporation, brand, molecule, and the new form code (NFC). An example is the product *Pfizer Inc + Robitussin + Guaifenesin + ACA*. By this construction and further differentiating by submarket, that is, Adult or Paediatric, to be used in estimating the Nested Logit model, we observe 184 unique products in our data for the Philippine CCR market. One of these products included pack varieties with and without flavour. We break this out into two distinct products for purposes of using the flavour attribute in the structural estimation in the following sections. This brings the total number of products to 185. Considering that the market is concentrated within only a few firms, our final sample consists of 97% of the entire market in terms of revenue share. This helps isolate the effects to products and firms likely to be competing in markets and, at the same time, reduces computational complications when estimating parameters in our structural model. This gives us $J = 54$ products and 11 firms. See Appendix A.3 for details.

Although the data come at the regional level, drug prices are unified nationally across different regions. Therefore, we integrate drug sales into the national level for each quarter. Moreover, to avoid the confounding effects of COVID-19, we drop our data after Q3 2020. As a result, in our final data, each market t contains information on quarterly sales at the national level, r_{jt}, and the volume of sales measured in dosage units, q_{jt}, which we then use to derive the price per dose of product j in market t, $p_{jt} = r_{jt}/q_{jt}$.[7] Summary statistics for the set of products are shown in Table 1.5.

Figure 1.1 shows how drug prices of the top five firms evolve before and after the acquisition. Since cough and cold remedies are available in different pack varieties, i.e. presentation and form, and are sold at varying prices, this graph shows the average pack level prices of the top five firms across all of their respective products. Two points stand out. First, the prices of Sanofi and GSK seem to be significantly higher than those of other firms, and they move closely. On the other side, prices of Pascual Lab, Pfizer, and United Lab also move together. This pattern suggests product segmentation in the market. In-

[7] Defined as the standard unit or the smallest unit of the dosage form most commonly taken by the patient to allow comparison between different administrative formulations of different drugs. See Appendix A.3

Table 1.5: Summary Statistics PH CCR (Selected Products), 2008-2020

Corp + Brand + Mol + NFC	mean	sd	min	max
Sales Value, $(r_{jt} = p_{jt} \cdot q_{jt})$	581.1	923.5	0.001	7,034
Dosage Volume, (q_{jt})	4,912	9,172	0.012	85,063
Price per dose, (p_{jt})	0.138	0.094	0.008	0.792

Note: There are 2,291 observations (products, quarters). Sales value is in 1,000 USD (exclusive of VAT), Volume of dosage units is in 1,000. Price per dose is in USD, deflated by the Philippine Pharmaceutical Product Index .

terestingly, the merging parties are from different segments. Second, for three of the five firms, namely Pfizer, United Lab, and Pascual Lab, there are modest changes in the price of their products. At this level, it shows that average prices of GSK and Sanofi-Aventis rose within the first year after the acquisition. Defining a firm's product up to a certain level of aggregation allows us to calculate and compare measures of price more consistently across markets. However, without specifying a standard control for the comparison, this illustration would be insufficient to make any meaningful inference about the effect of the merger. In the next section, we apply two frameworks to identify merger-specific price effects.

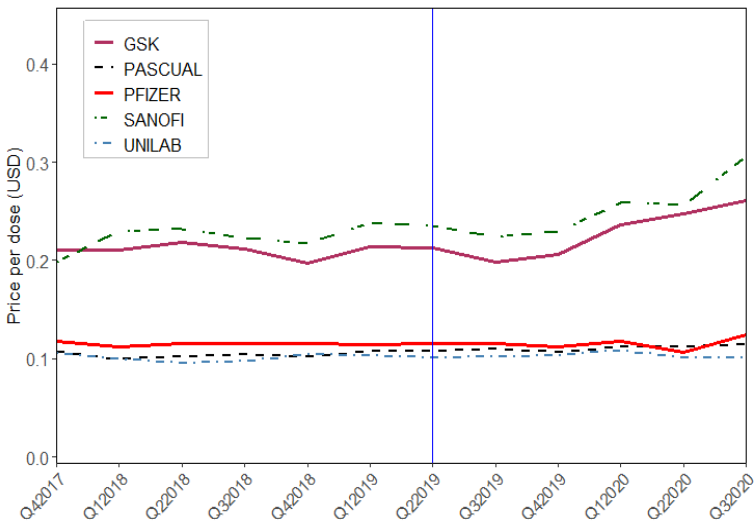


Figure 1.1: Price Evolution of Top 5 Firms in Philippine CCR, (Q1 2018 to Q3 2020)

1.4 DID MERGER RETROSPECTIVE

Merger control is an ex ante policy instrument, where the competition authority must assess the market effect of a transaction before it takes place. Because of this, despite using the best available information, there is inevitable uncertainty in the appropriateness of any intervention that follows.

A fundamental question for competition authorities is whether the current merger policy is too lax or too stringent. Carlton (2009) develops a model of government decision making on proposed mergers and offers guidance on how to measure its effectiveness in enforcing merger policy. He illustrates how the set of mergers that received a 'second request' for information, in particular those that were challenged, went to court but were allowed to proceed, can be used to assess governments systematic bias. Ashenfelter & Hosken (2010) used this idea in evaluating five consumer product mergers in the enforcement margin. They define these as mergers that posed a significant risk of anticompetitive harm but for which the risk was not large enough to cause the antitrust agency to block or substantially modify the transaction. They argued that, being on the enforcement margin, retrospective estimates of price effects from these mergers indicate a lower bound for prohibited mergers and an upper bound for mergers that were permitted. Rigorous review is, therefore, valuable as feedback to improve the authority's process.

Two modelling frameworks are commonly used in retrospective merger studies: event studies and a difference-in-differences design using the two-way fixed-effect (TWFE) estimator. We start by describing these two approaches, then the modelling details, and then the results.

Event Study Model. In this framework, we estimate the model using Equation 1.1 below:

$$\ln p_{jt} = \alpha_j + \gamma_t + \left(M_{jt} \times \sum_{\substack{y=-9 \\ y \neq -1}}^{5} \beta_y I\left(t - t^* = y\right) \right) + \sum_{q=1}^{3} \theta_q Q_{jt} + \varepsilon_{jt}, \tag{1.1}$$

where p_{jt} is the average price of the j^{th} product in market t, α is a product fixed effect, γ is a market fixed effect, β's are the mean differences between the treated and control group's price, $I(t - t^* = y)$ represents the periods being assessed, and where I represents

indicator variables to measure the time relative to the merger. M is an indicator equal to one if the product is owned by GSK or Pfizer, and zero otherwise. Q_{jt} indicates the quarter of the year to control for seasonal pricing. For the pre-acquisition period, we look at eight quarters, i.e. Q2 2017 to Q1 2019.

The event study can provide important insights about the segments being analysed. First, the parameter of interest is the effect of the acquisition on prices of GSK and Pfizer products. To make causal statements about the effect, we rely on evidence suggesting that the price dynamics of the control group is comparable to that of the treatment group. To do so, a common way is to check if the price of products involved in the acquisition evolved in the same way as the price of products in the control in pre-treatment periods. The idea is that, absent the acquisition, the trend in the treated group is expected to have evolved in the same way as the control group and, as such, serves as the counterfactual. The event study provides this kind of evidence. We use an F-test for joint significance to see if β_y's during periods before the merger are jointly not statistically different from zero. Failure to reject the null hypothesis, $H_0 : \beta_y = 0 \quad \forall \quad I\left(t - t^* = y\right)$ where $y < -1$, implies that the treatment and control groups are statistically the same before the merger and validates our assumption of parallel trends. The second insight from the event study is how prices evolved as a consequence of the acquisition. This can also be useful to see if the effects in the post-periods due to the transaction are persistent or not.

TWFE-DiD. In the standard difference-in-differences design, we estimate the following regression specifications to measure the price effect on the product lines of GSK and Pfizer. The first one estimates the combined average effects for the merging parties:

$$\ln p_{jt} = \alpha_j + \gamma_t + \beta^M \Big(M_j \times Post_t \Big) + \sigma_{jt} X + \varepsilon_{jt}, \tag{1.2}$$

and the second one below estimates the individual effect for each merging party:

$$\ln p_{jt} = \alpha_j + \gamma_t + \beta^G \Big(GSK_j \times Post_t \Big) + \beta^{Pf} \Big(Pfizer_j \times Post_t \Big) + \sigma_{jt} X + \varepsilon_{jt}. \tag{1.3}$$

In both specifications, $Post_t$ is an indicator equal to 1 after the acquisition. Equation 1.2 captures the price effect of the combined product lines of the merging firms with the other

variables taking the same meaning as in Equation 1.1. The specification given by Equation 1.3 allows an estimate of the specific price effects of the merging firm by using GSK_j, an indicator equal to 1 for GSK products and 0 otherwise, and $Pfizer_j$, an indicator equal to 1 for Pfizer products and 0 otherwise. Our coefficients of interest are β^M for Equation 1.2 and β^G and β^{Pf} for Equation 1.3. These give the DiD estimates of the combined and separate price effects of the acquisition, respectively.

1.4.1 Modelling

Before moving on to the results, there are a couple of estimation details that are to be discussed. The first is the measure of the price to use. We calculate three measures of price. The first is an average price that effectively uses contemporaneous quantity weights. The other two are variations of a Stone price index.[8] A standard average price has the advantage of containing information on all varieties of products available on the market. However, there may be pack varieties that were introduced later in the time series, so sales information of these would not be included in prices calculated at the start of the series. When limiting the products discussed above, this concern is mitigated because these products are present in almost all markets in the Philippines. Stone price indices allow the comparability of prices across markets by assuming a reference set of pack varieties for a given product and using the revenue weights derived from this set across other markets.[9] Our main analysis will use the standard average price, but we also look at Stone price indices as robustness.

The second issue is the selection of control groups. The control group is typically a set of drugs that are likely to share most of the same inputs as the GSK and Pfizer products or products that are very similar to those of GSK and Pfizer. This presents a challenge because these two designs rely on the stable unit treatment value assumption (SUTVA) to make any

[8] For each market t, the price of product j is calculated using the price of the k^{th} variation in that market, out of K_J and its corresponding revenue weight, ω_k^j, where $\sum_k^{K_j} \omega_k^j = 1$. We use the first and last period revenue weights.

$$p_{jt} = \sum_k^{K_j} \omega_k^j \times \ln p_{kjt}$$

[9] For other examples and discussion on the use of Stone indices, see Deaton & Muellbauer (1980) and Ashenfelter & Hosken (2010).

causal statements about the acquisition. This means that the control may share inputs as the treated or are very similar but they should not be involved in the acquisition or affected by it. We examine a number of possible control groups and consider each according to its merits.

First, we look at groups of products within CCR with the same molecules as those of Pfizer and GSK products, namely, private label and other proprietary label products. These groups likely share the same input to production as those involved in the acquisition and could therefore have a common trend in price. It is common practice in the literature to use private label products as controls because they share common costs with the proprietary label products while being relatively distant substitutes. However, this group contributes only 1-2% of the market in our sample, making it a less viable option. Other proprietary label products in the CCR segment might also be considered as a potential control group, since they directly share the same active substance as the merging firms' products, so that they can be good controls for both demand and cost shocks. However, since these could be fairly close substitutes, spillovers from the acquisition are possible.[10]

The third group we examine is proprietary label products in Pain and Fever Remedies (PFR) from the Philippines. These products are different from CCR products in that they address different symptoms, but they may also have similar marketing costs, being proprietary label and OTC products as well. This group could have less spillover issues and yet are similar to the products involved in the acquisition. However, products in PFR may experience indirect spillovers because patients are likely to consume CCR and PFR products as complements rather than substitutes.

Lastly, we consider products in the Hypertension Remedies (HTR) segment. Remedies for hypertension are ethical drugs, that is, they are provided only with a written order from a licenced physician. Since the acquisition occurred in OTC products, prices in CCR and HTR are likely to evolve orthogonally because these products are neither substitutes nor complements, and there is no conceivable supply-side substitution.

In order to make the analysis valid, the acquisition should be exogenous to the system;

[10] We also looked at CCR products from other countries, but because the consumer healthcare joint venture is global in nature, spillovers are also likely in these countries. The results using other country comparisons are presented in Table A.6 of Appendix A.4.

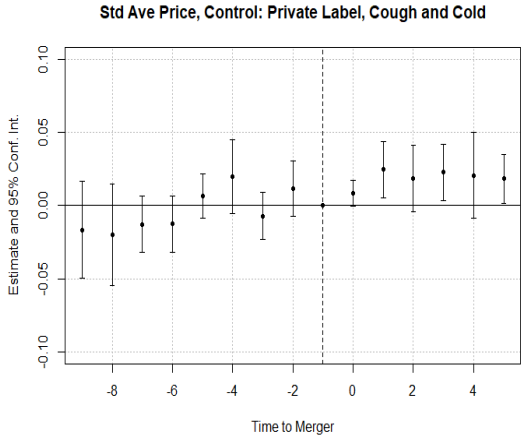
that is, the parties should not anticipate the merger in the defined pre-merger period. The decision to merge was made at an international level, that is, the transaction was global and the markets in the Philippines are relatively small; hence the merger is argued to be exogenous with regard to prices. In addition, we use product- and market-level fixed effects to account for the time-invariant part of the unobserved heterogeneity. Another important consideration is the selection of the period included in the analysis. To avoid changes in behaviour by the parties before a merger, i.e., no anticipation, we look at periods sufficiently close to the acquisition but not periods immediately before. Periods after the transaction should also consider price dynamics by not looking at periods immediately after or too far from the transaction (Mariuzzo & Ormosi, 2019). A sufficiently distant period following the transaction is good for allowing for market self-correction and for the effects to spread to other markets. However, longer-spanning data are more likely to be contaminated by other confounding effects. Therefore, to mitigate anticipatory and short-term effects, two quarters before the acquisition, i.e., Q4 2018 and Q1 2019, and the quarter immediately after the merger, Q3 2019, are excluded. We carefully choose 4 quarters before and 4 quarters after the acquisition to estimate the merger effect, i.e., Q4 2017 to Q3 2018 for the pre-period and Q4 2019 to Q3 2020 for the post-period. The pre- and post- time windows also share the same sequence of quarters, allowing us to control for potential seasonality in drug consumption and prices.

1.4.2 Results

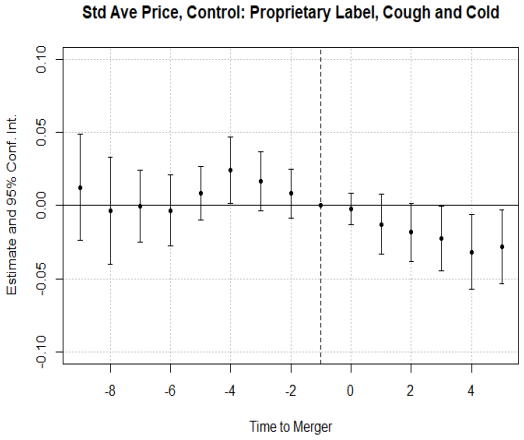
Figure 1.2 plots our estimates from the event study models, using the aforementioned control groups. The upper left panel plots the estimated coefficients when using private-label CCR drugs, and the upper right panel plots the estimates when using other proprietary-label CCR drugs. The bottom left panel uses proprietary label PFR drugs, and the bottom right panel uses all HTR drugs. The results are more reliable when the last control group is used, since it is the least likely group to get spillovers from the transaction. In each panel, the point estimate of the β_y's in Equation 1.1 and the associated 95% confidence intervals are plotted. The vertical dotted line indicates the merger. Post-merger point estimates using private-label CCR drugs are all positive, while we see a reversal of the effect when

Figure 1.2: Event Study Plots Using Different Control Groups

Philippine Cough and Cold Remedies

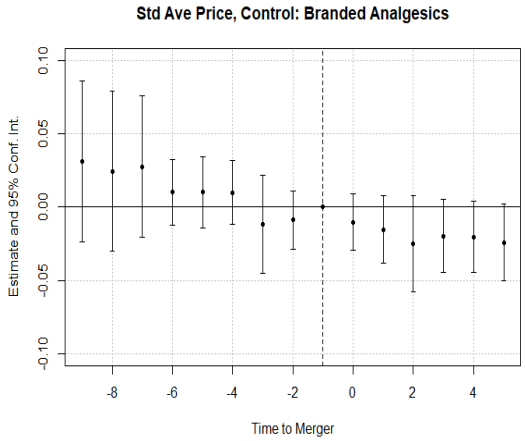


$F_{8,113} = 1.62237, p = 0.126105$

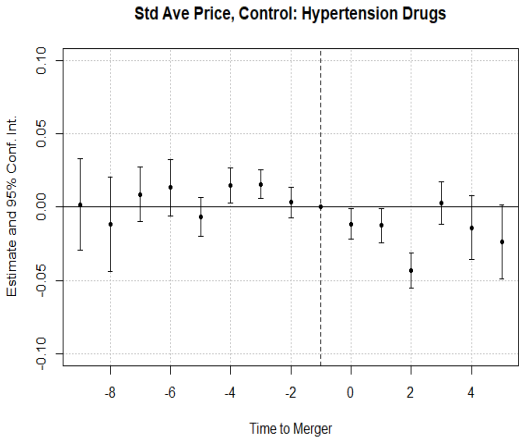


$F_{8,317} = 1.3657, p = 0.210777$

Philippine Analgesics and Hypertension Remedies



$F_{8,419} = 0.52251, p = 0.839675$



$F_{8,1314} = 0.562825, p = 0.808917$

using other proprietary-label CCR drugs. Specifications using PFR and HTR controls show a similar downward effect on parties' prices. The *F-stat* and the associated *p-value* show that the joint significance of β_y's before the merger. In all four cases, they are not statistically different from zero, suggesting that the product prices of the parties and that in the control groups are moving in parallel before the acquisition. Estimates suggest that when the appropriate control group is selected, the acquisition had a negative effect on GSK and Pfizer product prices.

We now turn to the estimates from the TWFE-DiD model. Table 1.6 summarises the results across control groups when using quantity weighted average prices. We find that compared to the counterfactual using HTR products, the acquisition resulted in a reduction in the price of approximately 3% for the combined product lines of GSK and Pfizer. Separately, GSK prices did not change, while Pfizer prices decreased about 4%. In the specification using private label products as the control group, an increase in prices of the merging parties' products by about 1.5% on average is suggested. Interestingly, estimates using specifications with proprietary label products in CCR and PFR as controls are both in the opposite direction, similar to the case with HTR products[11]. We note that in the cases where PFR and HTR products are used as the control, the estimates are closer to each other than either one is to the proprietary label CCR drugs. Both groups can be considered good controls. However, as discussed earlier, the estimates using PFR drugs, which suggests a decrease of approximately 2. 6% in the prices of the merging parties, may still be contaminated being complements to CCR drugs.

1.5 MERGER SIMULATION WITH EFFICIENCIES

Although the role of efficiencies should be considered in merger simulations, and is evident in the fact that competition authority guidelines for merger review include it, merger retrospectives rarely look into this issue. Even in practice, particularly in Europe, the efficiency defence in merger control is often not given due credit. This is also reflected in the fact that standard methodology involves assuming marginal costs to be the same between

[11] For robustness, we used the full product set and see that results do not change much. When using Stone prices, we also find a reduction in price among the control groups considered

Table 1.6: Merger Price Effects

	Cough & Cold†		Analgesics	Hypertension
Standard Average Price	Private Label	Proprietary Label	Proprietary Label	All
Aggregate Effect				
M×P	0.015**	−0.035***	−0.026***	−0.029*
	(0.007)	(0.007)	(0.010)	(0.015)
Separate Effects				
GSK×P	0.035***	−0.015	−0.007	0.009
	(0.008)	(0.010)	(0.016)	(0.025)
Pfizer×P	0.005	−0.045***	−0.036***	−0.038**
	(0.007)	(0.008)	(0.012)	(0.018)
Product FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Observations	132	327	477	1,420

Note: †Products with the same active substance as GSK and Pfizer products.

the pre- and post-periods.

In the next section of the paper, we show the reduction in marginal costs that rationalises the price changes described by the retrospective analysis in the previous section. We start this section by describing the demand models. We then move on to the estimation details and identification issues and finally discuss the results.

1.5.1 Demand Side Specification

To estimate demand, we look at two discrete choice models, namely the nested logit model and the random coefficients logit model. We consider $t = 1, ..., T$ markets, each with a mass M_t of patients who have symptoms similar to those of cough and cold during the period. The decision maker is an individual sensitive to prices and is concerned with his own well-being, as well as those in his household. The individual i faces the choice of $j = 0, 1, ..., J_t$ drugs (where 0 denotes the outside good or the non-purchase alternative) belonging to $G + 1$ groups $g = 0, 1, ..., G_t$ (where group 0 consists only of the outside good). Each group g is further divided into subgroups $h = 1, ..., H_{g_t}$. The subgroups in group g are denoted as $\mathcal{H}_{g_t}$ and the products in subgroup h of group g as $\mathcal{J}_{hg_t}$. The other groups are defined as *Pediatric* or *Adult* drugs, and subgroups are the molecules. The individual i in market t has his utility defined by

$$u_{ijt} = U(x_{jt}, \xi_{jt}, \epsilon_{ijt}; \boldsymbol{\beta}), \tag{1.4}$$

In Equation 1.4, x_{jt} is a $1 \times k$ dimensional vector of observed product characteristics that includes price such as the number of pack varieties, and drug dummies. Characteristics that are invariant across markets, e.g., corporation type (multinational/local), number of molecules, formulation (solid/not solid), and flavour (with/without flavour), enter only in the nonlinear part of the equation via the random coefficients. The term ξ_{jt} is a scalar that summarises the unobserved (to the econometrician) product characteristics. The term ϵ_{ijt} is an idiosyncratic error term for product j, assumed to be independently and identically distributed, over J and T, extreme value.

Nested Logit Model. For OTC drugs, it is natural that an individual first considers whether the drug is suitable for an adult or a child before deciding which particular molecule or combination of molecules to buy. On the basis of this, we employ a double nesting logit model, where the upper nest indicates if products are for adult or child use, and the lower nest indicates if they share the same molecule.

In the nested logit model, we assume that the random utility terms follow the extreme value distribution of a two-level nested logit model. For product $j \in \mathcal{J}_{hg_t}$, in market t, individual i maximizes her utility,

$$u_{ijt} = x_{jt}\boldsymbol{\beta} + \xi_{jt} + \zeta_{igt} + \zeta_{ihg_t}(1-\sigma_2) + (1-\sigma_1)(1-\sigma_2)\epsilon_{ijt} \tag{1.5}$$

The term ζ_{igt} is common to all drugs that are part of the same nesting group (Adult/Pediatric) and the same for ζ_{ihg_t} for drugs in the same subgroup (molecule). Each ζ_{igt} and ζ_{ihg_t} follow unique distributions such that $[\zeta_{ihg_t}+(1-\sigma_1)(1-\sigma_2)\epsilon_{ijt}]$ and $[\zeta_{igt}+(1-\sigma_2)\zeta_{ihg_t}+(1-\sigma_1)(1-\sigma_2)\epsilon_{ijt}]$ are both extreme value random variables. The nesting parameters σ_1 and σ_2 capture the correlation of utilities experienced by individuals across products of the same subgroup (σ_1) and group (σ_2), and should satisfy $1 \geq \sigma_1 \geq \sigma_2 \geq 0$ (McFadden, 1977). The model reduces to a simple logit model when σ_1 and σ_2 approach zero, that is, preferences are not correlated across products of the same group or subgroup. Let $\delta_{jt} = x_{jt}\boldsymbol{\beta} + \xi_{jt}$, given random utility maximisation, the unconditional selection probability of product j is

given by:

$$s_{jt} = s_{jt}(\boldsymbol{\delta}_t, \sigma) \equiv \underbrace{\frac{\exp\left(\frac{\delta_{jt}}{1-\sigma_1}\right)}{\exp\left(\frac{I_{hg_t}}{1-\sigma_1}\right)}}_{\overline{s}_{j|hg}} \quad \underbrace{\frac{\exp\left(\frac{I_{hg_t}}{1-\sigma_2}\right)}{\exp\left(\frac{I_{g_t}}{1-\sigma_2}\right)}}_{\overline{s}_{h|g}} \quad \underbrace{\frac{\exp\left(I_{g_t}\right)}{\exp\left(I_t\right)}}_{\overline{s}_g}, \tag{1.6}$$

where the first term is the selection probability of product j conditional on its subgroup being selected, the second term is the probability that subgroup h is selected conditional on its group being selected, and the last term is the probability that group g is selected. The terms I_{hg_t}, I_{g_t}, and I_t are inclusive values given by:

$$I_{hg_t} = (1-\sigma_1) \ln \sum_{k \in \mathcal{J}_{hg_t}}^{\mathcal{J}_{hg_t}} \exp\left(\frac{\delta_{k_t}}{1-\sigma_1}\right) \tag{1.7}$$

$$I_{g_t} = (1-\sigma_2) \ln \sum_{h \in \mathcal{H}_{g_t}}^{\mathcal{H}_{g_t}} \exp\left(\frac{I_{hg_t}}{1-\sigma_2}\right) \tag{1.8}$$

$$I_t = \ln\left(1 + \sum_g \exp(I_{g_t})\right). \tag{1.9}$$

Using the proposed approach of Berry (1994) to invert the system of choice probabilities $s_{jt} = s_{jt}(\boldsymbol{\delta}_t, \sigma)$ to solve for mean utilities $\delta_{jt} = \delta_{jt}(\mathbf{s}_t, \sigma)$, we obtain a closed form expression for shares:

$$\ln(s_{jt}) - \ln(s_{0t}) = x_{jt}\beta + \sigma_1 \ln(s_{j|hg_t}) + \sigma_2 \ln(s_{h|g_t}) + \xi_{jt}, \tag{1.10}$$

where the term $s_{j|hg_t}$ is the share of product j in subgroup hg_t and $s_{h|g_t}$ is the share of subgroup hg_t in group g.

Random Coefficients Logit Model. Substitution patterns from the nested logit model can be driven by the choice of nests. This can be seen as a limiting feature of the model, as it depends on what sometimes is an ad hoc decision by the researcher. We then consider a random coefficients logit model, which allows for more flexible substitution patterns by not imposing the restrictive assumption that the taste parameters $\boldsymbol{\beta}$ are the same for all individuals. The utility is given by:

$$u_{ijt} = x_{jt}\beta_i + \xi_{jt} + \epsilon_{ijt}. \tag{1.11}$$

The β_i are vectors of $(k \times 1)$ random coefficients and that can be expressed as the sum of means, β, and dispersion around these means. The dispersions are represented by $k \times 1$ unobservable random variables of individual heterogeneity v_i, drawn from a multivariate standard normal, and so $\beta_i = \beta + \Sigma v_i$ will also be a vector sampled from a multivariate normal distribution. The matrix Σ has a vector of standard deviations σ along its diagonal and where the off-diagonal elements of this matrix are zeros. In our model specification, we will account for three random coefficients (other than the constant) - price, corporation type, and formulation, to enter the nonlinear part of the model. The individual choice probability is given by:

$$\Psi_{ijt}(x_t, \xi_t, v_i, \beta, \sigma) = \frac{\exp(x_{jt}\beta_i + \xi_{jt})}{\Sigma_{j=0}^{J} \exp(x_{jt}\beta_i + \xi_{jt})}. \tag{1.12}$$

We recover the market share of product j in market t, s_{jt} by integrating Equation 1.12 with respect to the distribution of v_i, approximated by Monte Carlo simulations as shown by (Berry et al., 1995).

1.5.2 Supply Side Specification

For our supply side, we assume that the firms are multi-product price setting firms that have product and market-specific marginal costs, c_{jt}. Each firm $f = 1, ..., F$ controls the

set of prices p_{ft} that maximizes its profit , given prices of other firms' products, p_{-ft},

$$\max_{p_{ft}} \Pi_{ft}(p_{ft}, p_{-ft}) = \max_{p_{ft}} \sum_{l \in \mathcal{J}_{ft}} (p_{lt} - c_{lt}) q_{lt}(p_t) \tag{1.13}$$

where $\mathcal{J}_{ft}$ is the set of products marketed by firm f in market t. Total sales of product j a firm can be expressed as $q_{jt} = s_{jt} M_t$ and we can derive first order conditions for each firm available in the market to come up with a system of J_t equations per market t given by:

$$p_t = c_t + \underbrace{\Delta_t^{-1} s_t}_{m_t} \tag{1.14}$$

where m_t is a vector of mark-ups and Δ_t is the Jacobian whose elements j, k equal to $\frac{-\partial s_{kt}}{\partial p_{jt}}$ if j and k belong to the same firm and zero if they belong to other firms. We rewrite the pricing equation, re-expressed at the product and market level, and jointly estimate with the system of demand functions, discussed in the previous section, obtained by numerically deriving the market shares (s_{jt}),

$$\ln(p_t - \underbrace{\Delta_t^{-1} s_t}_{m_t}) \equiv \ln(c_t) = w_t \gamma + \xi_t, \tag{1.15}$$

As is standard in the literature, we assume that there exists a linear relationship between marginal costs and the observed and unobserved product characteristics. Also included in w_t are the exchange rates as cost shifters.

1.5.3 Potential Market and Outside Good

In defining the potential market for CCR medications in the Philippines, we rely on sources from the epidemiology and family medicine literature. We calculate this by getting an estimate of the proportion of the population with symptoms, multiplied by the average treatment days for a bout of illness, and a frequency of 3 doses per day, the common recommended frequency of treatment using antitussives (Dextromethorphan, Butamirate) and expectorants (Carbocisteine, Ambroxol). For the incidence of symptoms, we use the re-

sults of an active case finding programme conducted in the country by Lee et al. (2019), which examines how the presence of physical symptoms affects the probability of a successful testing for tuberculosis in local health units. The programme reports that 27.8% of the individuals screened were symptom positive. The mean duration of cough in the published literature is 17.8 days according to a meta-analysis of existing studies on acute cough illness Ebell et al. (2013). The total potential market in our model, M_t, is the Philippine population in period $t \times 27.8\% \times 17.8$ days $\times$ 3 dosage units per day. The share of each product j is relative to this potential market such that $s_{jt} = q_{jt}/M_t$ and the outside good is $s_{0t} = 1 - \Sigma_j s_{jt}$ where q_{jt} is the quantity measured in dosage units of product j.

1.5.4 Instruments and Identification

Table 1.7 provides a tabulation of descriptive statistics by variable. There is significant variation in the share variables and price of product j, as well as the instruments constructed. Random coefficients can be identified using repeated cross sections if there is sufficient variation in product characteristics or in the number of products over markets Ackerberg & Rysman (2005).

The mean share of a product is 0.003 and the mean price per dose is 0.139 USD. The outside good has a mean share of 0.829, varying from 0.767 and 0.903. Table 1.7 shows the between (across products) and within (across markets) variation of variables. Characteristics vary less across markets than over products, with pack variety count standard deviation of 1.157 across markets and 0.405 across products, and an overall standard deviation of 1.231. The count of molecules and dummy variables are time invariant with variation coming only from differences between products. Variations in these characteristics are important in identifying their coefficients.

In the nested logit model, identification of our nesting parameters σ_1, σ_2 is possible due to the variation generated when individuals shift shares within subgroups and groups. To address the endogeneity of these within nest shares, we use the count of brands, molecules, and packs of other products by the reference firm and competitor firms within groups. The random coefficients model uses the nonlinear method of moments estimator, which relies on orthogonal conditions between observed product characteristics and the demand error

Table 1.7: Summary of Between and Within Variation of Variables

Variable	Description	mean	min	max	s_O^2	s_B^2	s_W^2
Share variables							
s_{jt}	Share of product j	0.003	0.000	0.066	0.006	0.006	0.002
s_{0t}	Share of outside good	0.829	0.767	0.903	0.032	0.002	0.032
$\ln(s_{jt}/s_{0t})$	Dependent variable	-6.468	-18.445	-2.455	1.614	1.362	0.953
$\ln(s_{jt}/s_{hg})$	Within subgroup log share	-1.236	-15.953	0.000	1.522	1.430	0.666
$\ln(s_{hg}/s_g)$	Within group log share	-2.523	-13.482	-0.418	1.333	1.262	0.654
Product characteristics							
p_{jt}	Price (USD) per dose	0.139	0.008	0.792	0.095	0.093	0.015
x_{1jt}	# of pack varieties	1.811	1.000	12.000	1.231	1.157	0.405
x_{2jt}	# of molecules	1.769	1.000	11.000	1.494	1.497	0.000
x_{3jt}	Dummy (Foreign/Local)	0.477	0.000	1.000	0.500	0.503	0.000
x_{4jt}	Dummy (Flavor/No Flavor)	0.096	0.000	1.000	0.294	0.293	0.000
x_{5jt}	Dummy (Solid/Not Solid)	0.413	0.000	1.000	0.492	0.499	0.000
Instruments							
w_{1t}	Exchange rate	0.022	0.019	0.024	0.002	0.000	0.002
z_{2jt}	# of prod (other firms)	92.057	62.000	134.000	16.009	12.682	9.988
z_{3jt}	# of molecules (other firms)	64.001	43.000	105.000	13.458	10.247	8.862
z_{4jt}	# of molecules (other firms, within same group)	5.698	0.000	23.000	6.809	6.726	1.925
z_{5jt}	# of molecules (other drugs by same firm,within same group)	24.102	11.000	42.000	5.794	4.803	3.216
z_{6jt}	# of brands (other firms, within same group)	26.502	11.000	50.000	9.337	7.038	6.179
z_{7jt}	Price of product j in other ASEAN countries	0.089	0.001	0.770	0.097	0.086	0.044

term. Using the suggestion from Berry et al. (1995) and Bjornerstedt & Verboven (2016), we construct instruments using non-price characteristics of products and markets, including those using nests. Here we use the full set of products, i.e. 185, to exploit relevant variation across products and markets. Furthermore, we use the type of instrument suggested by Hausman et al. (1994) and Hausman (1996). The logic is that products sharing common costs have prices that are correlated across geographic areas but are uncorrelated to the market-specific product valuation. We use pricing data from neighbouring ASEAN countries (Indonesia, Malaysia, Thailand, and Singapore) to construct a vector of price of products that share common costs with product j (see Table A.8 of Appendix A.5 for details). Lastly, we generate the optimal instruments for the estimation as described by Reynaert & Verboven (2014).

1.5.5 Model Estimates

Table 1.8 shows the selected demand parameter estimates from our demand models. The first two columns show the improvement of the simple logit OLS model by using price instruments. Using nesting parameters and price instruments shows further improvements in the third column. Results from the random coefficients logit model are reported in the last three columns, where the demand side is jointly estimated with supply side moment conditions and using optimal instruments. This model is our preferred specification.

Looking at the nested logit model in column (3), the nesting parameters are consistent with $1 \geq \sigma_1 \geq \sigma_2 \geq 0$. This means that products that have the same molecule and belong to the same group (Adult/Pediatric) are the closest substitutes, products with different molecules but belong to the same group as weaker substitutes, and those that are from different groups are the weakest substitutes. This is an intuitive result considering that products are OTC, which means patients make decisions for themselves rather than rely on a physician. An individual is likely to first consider whether the drug is suitable for an adult or a child before deciding on which particular molecule or combination of molecules to buy. The nests are also important considering that they are closer to 1 than to 0 and the fact that these estimates are close to each other indicate that products in the same group but with different molecules are fairly close substitutes to those products with the same molecule as long as they belong to the same group. In line with Bjornerstedt & Verboven (2016), the results from the random coefficients logit model are of larger magnitudes and the dispersions from the mean valuation are statistically significant. There is consumer heterogeneity in the valuation of Solid form and Foreign with a standard deviation of about 0.93 and 1.63 times (in absolute value) the mean valuation, respectively.

Table 1.9 reports a summary of the price elasticities and mark-ups implied by our preferred specification. Mean values are weighted by product market shares. The own-price elasticity for a given product in CCR is on average -3.09 with a standard deviation of 1.40, while the cross-price elasticity is 0.01 on average with a standard deviation of 0.04. To get a sense of the substitution patterns across the segment, we look at cross-price elasticities according to groups of products involved in the acquisition or not, and by groups of products made by foreign or local corporations. A 1% increase in the price of a product

Table 1.8: Demand and Supply Parameter Estimates

	Logit	Logit	N-Logit	RCL		
	OLS	IV	IV	*Demand* β	σ_β	*Supply*
Constant	-8.186^{***}	-7.258^{***}	-3.649^{***}	6.5025^{***}	0.0000	-0.0270
	(0.207)	(0.356)	(0.205)	(0.835)	(0.026)	(0.022)
Price	10.518^{***}	-15.662^{*}	-4.134^{**}	-23.609^{***}	13.213^{***}	
	(1.715)	(8.121)	(1.647)	(0.085)	(0.074)	
Subgroup (σ_1)			0.851^{***}			
			(0.043)			
Group (σ_2)			0.844^{***}			
			(0.045)			
No. of Packs	0.615^{***}	0.541^{***}	0.091^{***}	0.494^{***}		-0.0029
	(0.051)	(0.059)	(0.023)	(0.021)		(0.014)
No. of INN†	0.0439	0.0472	-0.0263	0.8447^{***}		
	0.1241	0.1243	0.0543	(0.224)		
Foreign†	-0.8048^{***}	-0.8351^{***}	-0.1869^{*}	-3.743^{***}	3.469^{***}	
	0.2692	0.2641	0.129	(1.072)	(0.030)	
Solid Form†	-0.1493	-0.0165	0.822^{***}	-3.586^{***}	5.836^{***}	
	0.2588	0.2723	0.134	(0.746)	(0.052)	
Flavored†	-0.4672	-0.4016	-0.1782	4.877^{***}		
	0.4508	0.4168	0.1925	(2.279)		
PH Exchange rate						1.010^{***}
						(0.0003)

Notes: 1,985 observations were used from the period Q4 2009 to Q1 2019. Demand side specifications include 38 quarter fixed effects and 54 product fixed effects. Supply side specification includes 18 molecule fixed effects and controls for country specific currency cross rates in USD. †Mean utility coefficients of time invariant variables are computed via the second stage minimum distance projection of estimated product fixed effects on characteristics.

Table 1.9: Price Elasticity and Markups

Product level, Price Elasticity†	mean	sd	min	max
Own price elasticity	−3.0948	1.3951	−14.9117	−0.1754
Cross price elasticity	0.0125	0.0412	4.1136^{-10}	1.4705
Acquisition Products (MP) v Non-Acquisition Products(NMP)				
$\%\Delta MP_s/\%\Delta MP_p$	0.0245	0.0918	3.1490^{-08}	1.0822
$\%\Delta NMP_s/\%\Delta MP_p$	0.0083	0.0266	6.9434^{-10}	1.0521
$\%\Delta MP_s/\%\Delta NMP_p$	0.0299	0.0908	3.6800^{-08}	1.4706
$\%\Delta NMP_s/\%\Delta NMP_p$	0.0105	0.0271	4.1136^{-10}	1.0825
Foreign (F) v Local(L)				
$\%\Delta F_s/\%\Delta F_p$	0.0316	0.0994	4.1136^{-10}	1.0822
$\%\Delta L_s/\%\Delta F_p$	0.0069	0.0152	8.1827^{-08}	1.0521
$\%\Delta F_s/\%\Delta L_p$	0.0275	0.0797	8.8559^{-10}	1.4706
$\%\Delta L_s/\%\Delta L_p$	0.0089	0.0138	4.4710^{-08}	0.9501
Markups $(p-c)/p\,\%$				
GSK	25.69	4.98	15.87	33.98
Pfizer	27.79	5.20	17.24	39.88
Pascual Lab	56.59	22.35	21.89	82.97
Sanofi Aventis	26.36	10.14	7.00	55.92
United Lab	66.13	18.21	24.48	99.13

Note: †Subscripts s and p denote share and price, respectively

involved in the acquisition is associated with a 0.025% increase in the share of other products involved in the acquisition, and an increase of 0.008% in the share of non-acquisition products, a difference of about 3 times lower in magnitude. Interestingly, 1% increase in the price of non-acquisition products is associated with a 0.030% increase in the share of products involved in the acquisition and an increase of just 0.011% in the share of other non-acquisition products. This pattern suggests that the products involved in the acquisition are closer substitutes to each other than to products outside the acquisition. This also suggests that substitution away from acquisition products to non-acquisition products (0.008%) is lower than the substitution away from non-acquisition products to other non-acquisition products (0.011%). A possible explanation is that GSK and Pfizer are multinational firms whose products are perceived to be better quality. The estimated margins reported Table 1.9 also show an interesting pattern. Foreign firms, i.e., GSK, Pfizer, and Sanofi have relatively lower marginal cost compared to local firms. The margin of the foreign firms is around 25-27% with relatively small standard deviations, while that of the local firms is around 56-66% and with large standard deviations.

1.5.6 Post Merger Market Equilibrium

Using our estimates obtained from the preferred demand specification, we generate predictions of the post-merger market equilibrium. We assume Nash-Bertrand price competition for the post-merger market conduct to simulate the effect of the acquisition on price and marginal cost. Each firm owns a portfolio of products $\mathcal{F}_f$, and the profit of each firm is represented by defining a profit function of the firm f as follows:

$$\Pi_f(p;\theta) = \sum_{k \in \mathcal{F}_f} (p_k - c_k) D_k(p;\theta) \tag{1.16}$$

In Equation 1.16, demand is given by D_k, where $\mathbf{p}$ is the vector of price and $\boldsymbol{\theta}$ is the set of demand parameters. The profit maximising price $\forall\ j = 1, ..., J$ should satisfy the following first-order condition:

$$D_k(p;\theta) + \sum_{k \in \mathcal{F}_f} (p_k - c_k) \frac{\partial D_k(p;\theta)}{\partial p_j} = 0 \tag{1.17}$$

Define the product ownership matrix of firms $\boldsymbol{\Upsilon}^F$ as a matrix with elements $\Upsilon^F(j,k)$ equal to 1 if both j and k are products of the same firm and 0 otherwise. Let the matrix of partial derivatives be denoted by $\boldsymbol{\Delta}$ with $\Delta_{jk} \equiv -\frac{\partial D_k(p;\theta)}{\partial p_j}$. The Hadamard product $\boldsymbol{\Upsilon}^F \odot \boldsymbol{\Delta}$ gives,

$$\Omega = \begin{cases} -\frac{\partial D_k(p;\theta)}{\partial p_j} & \text{if } \exists\ f : \{k,j\} \subset \mathcal{F}_f; \\ 0 & \text{otherwise.} \end{cases} \tag{1.18}$$

The system of J first order conditions can then be concisely written as:

$$D(p;\theta) - \Omega(p-c) = 0 \tag{1.19}$$

The system given by Equation 1.19 can then be inverted to give the expression:

$$p = c + \Omega^{-1} D(p;\theta) \tag{1.20}$$

The convention in predicting post-merger market equilibrium is to simulate prices under the new ownership structure, Ω_{Post}, where the products of the two merging parties belong to one firm, and the demand parameters estimated using the pre-merger data. In this approach, the estimated marginal costs are assumed to remain unchanged in the pre- and post- merger periods. By construction, this approach will predict an increase in prices in the post-merger equilibrium with only a few exceptions where multi-product firms may adjust the price of a single product to maximise the joint profit of their entire portfolio. Thus, the prediction from this conventional approach will not align with the analysis from the DiD merger retrospective in the previous section. To fully estimate merger-specific efficiencies, we use observed post-merger prices, i.e. the actual post-merger prices observed in the data. Specifically, by holding demand parameters constant, we search for the changes in marginal cost associated with ex-post prices such that the distance between the model-simulated equilibrium prices after the acquisition and post-merger prices is minimised. The change in marginal cost is then $\Delta\mathbf{c} = (\mathbf{c}_{Post}/\mathbf{c}_{Pre}) - 1$.

1.5.7 Predicted Cost Efficiency

Looking at Figure 1.3 we see the evolution of marginal costs and markups for GSK and Pfizer during the entire time series, that is, Q4 2009 to Q3 2020. GSK's marginal costs were rising at the start of the series, starts a downward trend, and then levels before the acquisition. Pfizer's costs, on the other hand, have mostly been going down, and then levels also before the acquisition. In the post, the marginal costs of both exhibit a very similar trend. The product mark-ups of both firms were relatively stable at the beginning of the series and started climbing at about the same periods that the marginal cost of both firms began to decline. Similarly, markups in the post-periods show an almost synchronised trend between the two firms.

Figure 1.3: Marginal Costs and Mark ups Pre and Post Merger

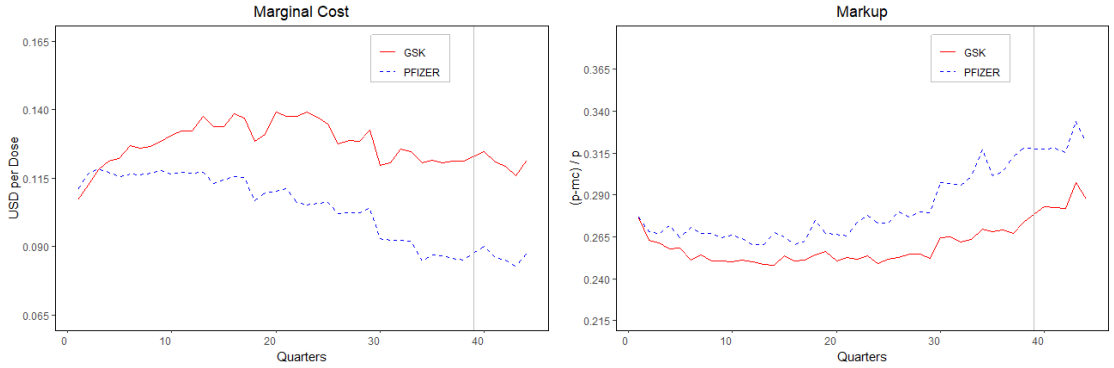
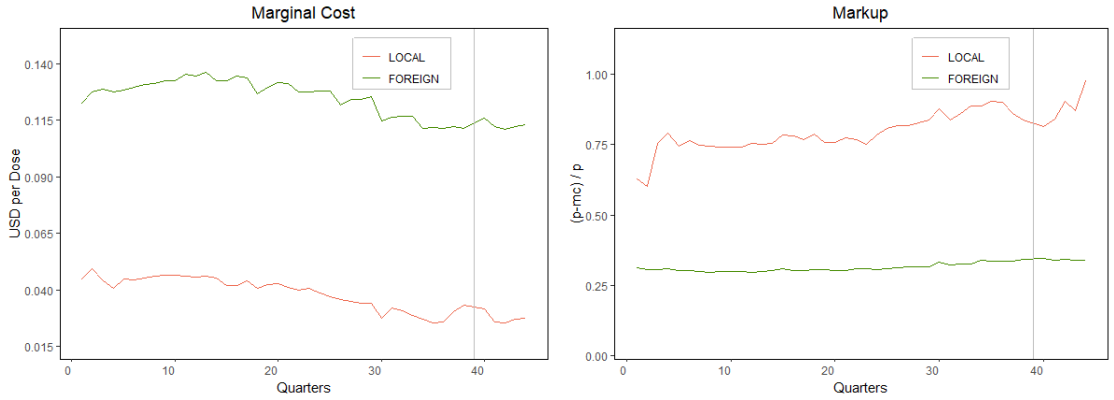


Figure 1.4 shows the evolution of costs and mark-ups by the partition of Foreign vs Local firms. Marginal costs between groups have a non-trivial gap throughout the series. Foreign firm products are 3 times more costly to make than those by local firms. In the periods just before the acquisition, marginal costs were increasing, and drops back to previous levels in the periods shortly after. Interestingly, a similar non-trivial gap exists for markups, but the positions are reversed. Products from local firms have a higher mark-up than those from foreign firms. The price margins are more stable for foreign firms compared to those of local firms. This suggests that foreign firms are less able to pass on their cost efficiencies to get a higher margin compared to local firms. The breakdown plots for each firm are shown Figure A.2.

Our results are summarised in Table 1.10. To be consistent with the TWFE-DiD model,

Figure 1.4: Marginal Costs and Mark ups Pre and Post Merger



we limit our data to the 4 quarters before the merger (Q4 2017 to Q3 2018). We first predict the hypothetical equilibrium post-merger prices assuming no cost change. Without considering any changes in efficiency, relative to prices before the change in the structure of the market, the prices of the GSK products increase by 2.29% and those of Pfizer products increase by 1.68%, with an average effect of 1.88% on the combined product lines. The marginal costs backed out is 0.12 \$/dose for GSK and 0.09 \$/dose for Pfizer. These figures are shown in the first two columns of Table 1.10.

When we search for the marginal cost changes that would align acquisition-simulated post-merger equilibrium prices to actual observed post-merger prices in Q4 2019 to Q3 2020, we find a reduction of GSK's marginal cost by 2.11% and a reduction of 2.6% for Pfizer. For the combined product lines, a reduction of 2.4% in marginal cost is estimated. Intuitively, the change in marginal costs for non-merging firms is very low since they are unlikely to have any efficiency gains resulting from the acquisition. However, we note that the change in the actual observed pre- and post-merger prices could also have been affected by merger-irrelevant factors. The backed-out marginal costs may then include nonspecific changes as a consequence. To try and address this, we use a DiD design to partial out potentially acquisition-irrelevant factors. In turn, the changes to the marginal cost that we find can be viewed as specific to the acquisition.

We check the robustness of our results and directly estimate the change in marginal costs of GSK and Pfizer as a result of the acquisition using a DiD design and a TWFE esti-

Table 1.10: Comparison of Predicted Outcomes

Product Line	Merger simulation, assuming constant mc		Estimated %Δmc using post-merger price	
	%Δprice	mc($)	mc($)	%Δmc
	(1)	(2)	(3)	(4)
GSK	2.2869	0.1219	0.1193	-2.1073
Pfizer	1.6835	0.0877	0.0854	-2.5997
Combined	1.8846	0.0991	0.0967	-2.3978
Non-merging	0.0656	0.0589	0.0588	-0.1563

mator. Given our simulated pre- and post-merger marginal costs in the previous section, we can access information of other firms in the CCR sector to use for our control group. Although spillovers may be a concern for the analysis of prices, marginal costs of other firms are independent of the acquisition. The set of other CCR products can, therefore, be a valid control for this analysis. We present our results in Table 1.11 and find evidence to support our finding that there was a reduction in marginal costs specific to the transaction.

Table 1.11: Regressions on Marginal Cost

Product Line	(1)	(2)
GSK		-2.568***
Pfizer		-2.279***
Combined	-2.376***	
Obs	416	416
R-squared	0.997	0.997

Note: *p<0.1; **p<0.05; ***p<0.01
Coefficients are adjusted by 100*(beta/avg.mc)

We find that as a result of the acquisition, the marginal costs of the combined product lines were about 2.4% lower. Specifically, the marginal costs for GSK products were about 2.6% and for Pfizer products, 2.3%, lower. Although the figures are not a precise match for each group, we see that even after isolating the effect to only the transaction, we find similar estimates. This allows us to separate out efficiencies and price effects from the merger, providing evidence that merger-specific efficiencies can counteract price increases.

1.6 CONCLUSIONS

In this paper, we evaluate the acquisition of Pfizer by GSK in 2019 in the Philippines, which affected the markets for cough and cold remedies. Specifically, we use aggregate level sales data before and after the transaction to first estimate a causal parameter of the acquisition's price effect via a DiD design and then estimate discrete choice models of demand to predict price and back out marginal costs before and after the acquisition. TWFE estimates suggest that relative to our controls, there was a 3% reduction in the price of the GSK and Pfizer product lines. Parameters from the joint estimation of a random coefficients logit model and a supply-side specification reveal significant consumer heterogeneity in their valuations of cough and cold remedies in terms of the corporation type and form. Increases in price of a product of either GSK or Pfizer lead to significant substitution toward their other products. While substitution towards products outside the acquisition is three times less likely possibly due to the perceived difference in quality of products made by multinational firms. This pattern implies that spillovers are unlikely and lend credence to the group of Proprietary Label products as a plausible control for the DiD analysis alongside HTR products.

Finally, using the estimated demand parameters and data from both sides of the transaction, we find that relative to own prices before the acquisition, the GSK and Pfizer products are predicted to be 1.88% more expensive afterward. Furthermore, the marginal costs associated with the actual observed prices have decreased by an average of 2.4%. Regulation of mergers happens ex ante, which requires authorities to evaluate a transaction prior to its consummation. Decisions taken by authorities should be given rigorous scrutiny, ex post, to determine whether actual outcomes are aligned with those explicitly predicted by economic models and are fleshed out as interventions. The results of these studies are important to inform regulators and lead to a more efficient, objective and accurate merger review process Ashenfelter et al. (2009).

CHAPTER 2

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

Abstract

We examine the effect of a bid cap policy on drug procurement auctions. 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 effect of the policy 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 the policy led to a statistically significant reduction in transaction prices as well as in price dispersion, on average.

2.1 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 equilib-

rium, 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 2.3 describes the institutional environment of the pharmaceutical sector in the Philippines and discusses the policy of interest. Section 2.4 gives details of our data and identification strategy. In section 2.5, we present and discuss our results. The last section concludes.

2.2 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

[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.

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) 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.

2.3 BACKGROUND

2.3.1 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.

[2]Conversion of 50 PhP to 1 USD

2.3.2 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 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.

2.3.2.1 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.

[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.

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 B.1. 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.

2.3.2.2 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 B.2 provides a map of the country and the locations of the DOH facilities covered by this study.

2.3.2.3 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.3. Equation 2.1 and Equation 2.2 describe the government's treatment of the sufficient and limited cases.

$$\overline{p}_{j,t} \sim F_P(p^m_{j,t-2}), \quad \text{where } P(X \leq p^m_{j,t-2}) = \frac{1}{2} \tag{2.1}$$

$$\overline{p}_{j,t} = min[p_{j,t-2}] \tag{2.2}$$

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

2.4 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

[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.

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.

2.4.1 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 B.4.

2.4.2 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

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

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 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 2.1 to Table 2.3. 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 2.1: 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 2.2: 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 2.3: 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 2.2, 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 2.3 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 2.1. 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.

2.4.3 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 two salient outcomes from this policy environment, other than the change in price. First, we look at an overview of firm

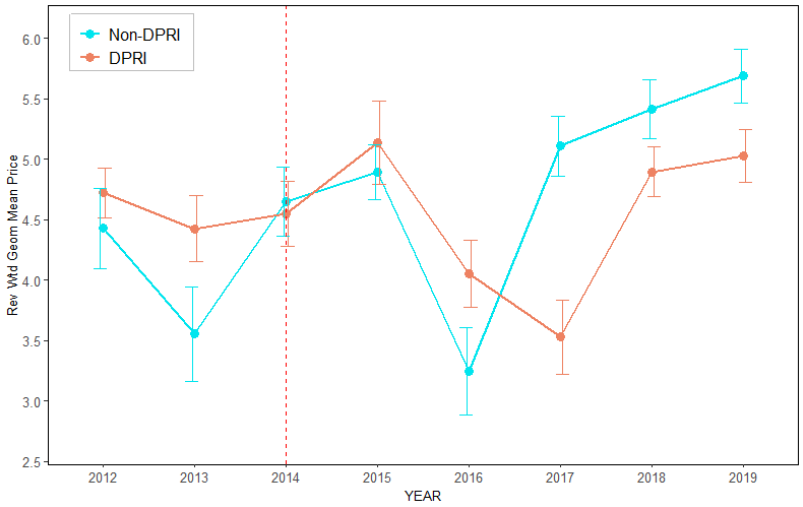


Figure 2.1: Revenue Weighted Mean Winning Bid Price Evolution

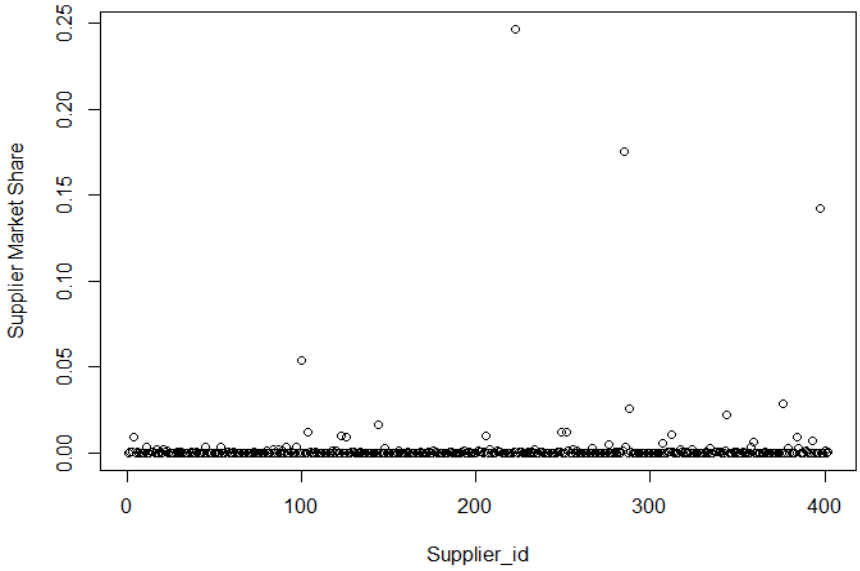
shares and from that the drug and facility portfolios of the top earning firms. Second, we estimate the distribution of transaction prices in terms of the distance of each to its respective bid cap.

2.4.3.1 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 2.2. 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.

We take a closer look at just the top four sellers of our selected DPRI drugs for the periods covered. In Table 2.4 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

Figure 2.2: Supplier Revenue Shares, 2013-2019



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 2.4: Top Winning Suppliers 2013-2019

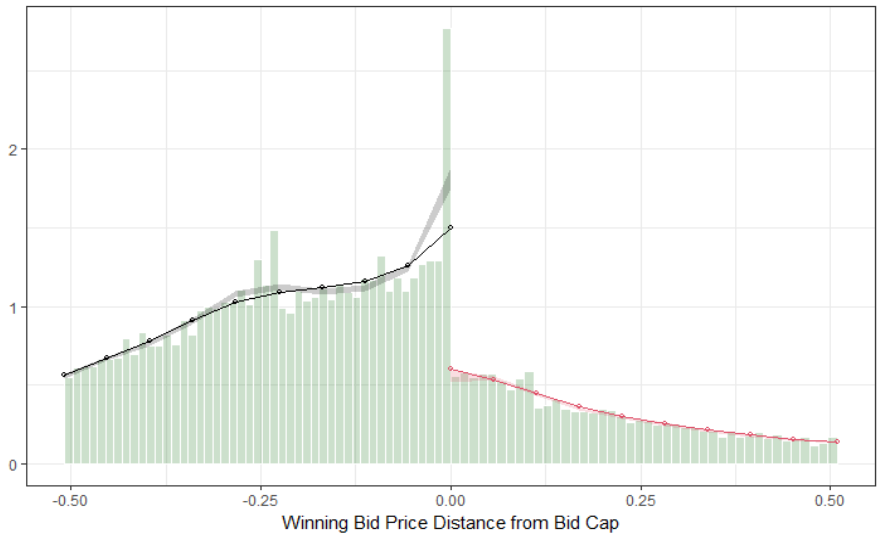
Supplier Name	Total Revenue	Share	(80% of Revenue)			
			Drug Portfolio		Facility Portfolio	
	(Bn PhP)	(%)	Count	% of Total	Count	% of Total
Metro Drug Inc.	3.90	0.25	14	0.06	10	0.14
Phil Pharmawealth, Inc.	2.78	0.18	53	0.22	16	0.25
Zuellig Pharma Corporation	2.25	0.14	42	0.15	19	0.27
Endure Medical,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

2.4.3.2 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 2.3 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 2.3: McCrary Density Test



2.4.4 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 2.5 below. These numbers are not presented as having a causal interpretation, but as an estimate suggestive of correlation.

Table 2.5: 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

2.4.5 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 2.3. 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 2.4. Finally, a triple difference design is implemented as an alternative design and robustness check using Equation 2.5.

2.4.5.1 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.

$$\ln p_{jlt} = \alpha_j + \gamma_l + \tau_t + \beta_1 D + \beta_2 P + \beta_3 \Big(D \times P \Big) + \delta_1 X_{jlt} + \varepsilon_{jlt}, \tag{2.3}$$

$$\ln p_{jlt} = \alpha_j + \gamma_l + \tau_t + \left(D \times \sum_{\substack{y=-2 \\ y \neq 0}}^{5} \beta_y I\left(t - t^* = y\right) \right) + \delta_1 X_{jlt} + \varepsilon_{jlt}. \tag{2.4}$$

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.

2.4.5.1.1 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.

2.4.5.2 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 2.6.

Table 2.6: 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).

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 2.5, 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.

$$\begin{aligned}\ln p_{jlt} = \alpha_j + \gamma_l + \tau_t + \beta_1 A + \beta_2 D + \beta_3 P + \beta_4\Big(A \times D\Big) + \beta_5\Big(D \times P\Big) \\ + \beta_6\Big(A \times P\Big) + \beta_7\Big(A \times P \times D\Big) + \delta_1 X_{jlt} + \varepsilon_{jlt}\end{aligned} \tag{2.5}$$

2.4.5.2.1 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 2.6 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 2.5. 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.

2.4.5.2.2 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.

2.5 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.

2.5.1 Diff-in-Diff and Event Study

Table 2.7 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.

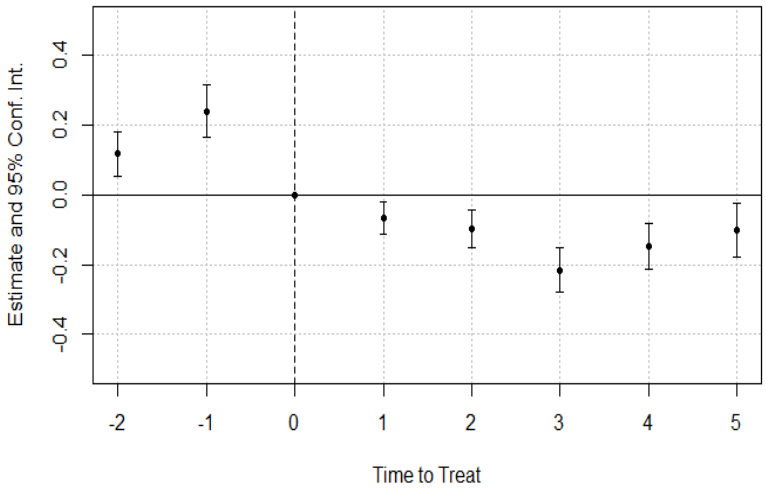
Table 2.7: Effect on Price, DD (selected coefficients)

	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

Figure 2.4 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. We provide these results in more detail in Table B.1 of Appendix B.5. Suppose that parallel trends are violated in the two pretreatment 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 2.4: Event Study Plots, Log Price



2.5.2 Triple Differences

Table 2.8 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.

2.5.2.1 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 2.9 shows the estimate of $\beta_{3,na}$ that is from the non-auction analogue of the specification given by Equation 2.3. From this specification and estimate, we do not find any significant effect due to the policy. This

Table 2.8: 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

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 2.9: Falsification Test, DD (selected coefficients)

	log(Price)
$DPRI_{na}(D_{na})$	0.655^{**}
	(0.288)
Post (P)	-4.049^{***}
	(0.705)
D_{na}×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

2.5.2.2 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:

$$\begin{aligned}\ln p_{jlt} = \alpha_j + \gamma_l + \tau_t + \beta_1 A + \beta_2 ND_B + \beta_3 P + \beta_4\Big(A \times ND_B\Big) + \beta_5\Big(ND_B \times P\Big) \\ + \beta_6\Big(A \times P\Big) + \beta_7\Big(A \times P \times ND_B\Big) + \delta_1 X_{jlt} + \varepsilon_{jlt}\end{aligned} \tag{2.6}$$

In Equation 2.6, variables take on the same interpretation as in Equation 2.5, 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.

2.5.2.3 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 2.11. 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

Table 2.10: Effect on Non-DPRI Subgroups Across Procurement Methods (selected coefficients)

	log(Price)
A $\times$ P: β_6	0.102***
	(0.024)
$ND_B \times$ A $\times$ 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

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 2.11: 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 $\times$ 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

2.6 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.

CHAPTER 3

Dynamic Reserve Prices in Procurement: An Experiment

Abstract

In a procurement setting, when firms exit markets due to high costs, competition wavers, and the remaining bidders bid less aggressively, resulting in higher prices. The auctioneer's problem could conceivably be modulated by a reserve price mechanism that uses the lowest bid from the previous period. In a single market, when bidders set the cap in the next period, they can pull back their bids and keep that bid cap from biting. If instead bidders from another market set the cap, the incentive for strategic bidding is removed, and competition can potentially be restored. Using a controlled setting, we show how dynamics in reserve price setting influence bid shading and entry in multi-round auctions. We find that, without a bid cap, dampened competition does lead to higher prices after bidders exit. Imposing a dynamic bid cap solves this issue of higher prices but knocks more people out of markets, leading to widespread failure of auctions. Surprisingly, bidding behaviour remains similar across bid cap institutions during the first round. In subsequent rounds, bidding becomes deceptively more competitive in auctions with bid caps, but unexpectedly resulting in destroying markets.

3.1 INTRODUCTION

Auctions are widely used by governments to buy different types of goods and services. The main feature of this mechanism is competition, which should drive discipline among bidders to keep procurement costs low for the buyer. The most common format used is the sealed bid, first price auction, or low price (LP) auction. Here, bidders compete for the contract to sell, and the seller with the lowest asking price wins, getting paid their winning bid. In order to maximise profit, sellers need to consider the trade-off between the cost of bidding aggressively and its increased probability of winning. However, when bidding to sell the same object is done repeatedly, inefficient firms tend to exit the market over time, resulting in a dampened level of competition. With fewer sellers competing for the contract, bidding becomes less aggressive and prices are expected to rise.

Consider the case of government hospitals, spread across different locations, keeping a certain set of essential drugs in their inventory at all times. The hospitals would then regularly ask for competing offers from suppliers for each of these drugs. Sellers are heterogeneous, and some are relatively more efficient than others. These sellers have idiosyncratic costs that can change from year to year. It is likely that over time some firms will realise that they are not competitive. These firms leave, and the number of bidders participating in auctions drops. Sellers who stay quickly find out that they need not bid as aggressively as before, resulting in higher auction prices. A way to possibly mitigate this effect is to use a reserve price mechanism to keep prices low even when there are fewer sellers competing. Suppose that the auctioneer's reserve price is set as the lowest bid in the previous period. One can imagine that this bid cap can put a strong downward pressure on prices over time. This approach imposes a bid cap endogenously by making it a function of bidder behaviour. This type of bid cap can be vulnerable to manipulation and can inadvertently help bidders tacitly collude in order to keep prices high. An alternative approach would be to set the bid cap as the lowest bid in the previous period in a different market. The idea is to address the issue of endogeneity and restore prices to competitive levels, as if there were no bid caps. Examining these two institutions against the case where there is no bid cap is motivated by policy questions encountered by Bokhari et al. (2023).The authors find

that the average prices were, in fact, lower due to the bid cap, but also find evidence that at least 1 in 3 auctions for regulated drugs failed. They also present evidence of significant heaping of prices just below the bid cap, indicating some ability to manipulate the policy. This policy mechanism is not common in practice, if used at all [1].

Imposing a static reserve price in repeated first-price auctions improves auctioneer revenue. In a static setting, because the distribution of transaction prices is truncated with a reserve price, the search over subsequent auctions becomes less valuable, and bidders shade their bids less with respect to their values. However, the introduction of dynamics into the mechanism may leave markets vulnerable to strategic bidding by sellers Kanoria & Nazerzadeh (2021). The salience of a regulated price has been speculated to serve as a focal point that allows bidders to tacitly collide, a common issue associated with such an intervention Scherer (1967). In this version of the story, sellers can bid less aggressively to keep prices high. They shade their bids more to maximise their expected utility across periods, making the contract more expensive for the auctioneer. When endogeneous dynamics are introduced, one would expect bidders to pull back their bids to improve their profits in subsequent auctions. When this happens, the downward pressure on prices is less severe, keeping more sellers in the market, and reducing the likelihood of failed auctions. When bidders fail to collectively inflate bids and instead compete aggressively to win the current auction, they end up pricing themselves out of subsequent periods and winning in auctions only when they get a favourable cost draw. Seller attrition can end up being more severe than when there is no bid cap, and failures become more likely. Although the system can have favourable price outcomes, the implication is that markets end up being destroyed.

Our study examines how the dynamics in setting the reserve price affects bidder entry and exit in markets, the likelihood of failed auctions, and bidding behaviour over time. We examine the implications of two bid cap institutions in controlled settings using laboratory auction markets. We compared and contrast outcomes against the case where there is no bid cap imposed in the markets, and between institutions. Surprisingly, we find that our results show that bidders compete aggressively despite the endogenous bid cap and end

[1] Similar mechanisms exist throughout procurement settings, see Bucciol et al. (2020), the average pricing system (APS) in Medicare for Group B drugs and medical devices, but none with a dynamic feature

up pricing themselves out of subsequent rounds. Over time, bidding behaviour becomes less competitive, as expected from the no bid cap case resulting in higher prices, and both institutions effectively address this issue. As a general result, we observed a clear trade-off between lower auction prices and extensive auction failure. Our choice of studying the behaviour of laboratory auction markets reflects an attempt at continuity with previous experimental studies, as well as previous empirical work evaluating a closer related policy regulating auction markets for medicines.

This paper proceeds as follows. Section 3.2 discusses related work. Section 3.4 looks at the theoretical predictions for the static case and our behavioural predictions when dynamics are introduced. Section 3.3 discusses our experimental design. Section 1.5.5 present the data from the experiment and analysis of the results. The last section concludes.

3.2 RELATED LITERATURE

In auction markets, standard partial equilibrium theory predicts that a non-binding 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 the equilibrium, the regulated price can serve as a focal point, keeping prices higher than what they should be. Using a laboratory setting to study this issue, Isaac & Plott (1981) found that the behaviour of auction markets over several periods with “static" price controls is better approximated by standard predictions than by the focal point hypothesis. However, they also found that a non-binding price control does affect price but not necessarily creating a focal point. The authors did not identify which feature of the environment induced such a result, but speculate that additional uncertainty created by removing the price control could have played a role in encouraging additional search activity by participants. An auctioneer’s choice of reserve price can involve search theoretic considerations similar to reservation wage offers in labour markets, i.e., the highest bid in an auction will only be accepted by the auctioneer if it exceeds the reserve price, as observed by Ashenfelter (1989). From the bidder’s perspective, it is optimal to bid up to their values in a one-shot auction, but in a sequential setting, bidders shade their bids relative to their values because of the possibility of winning at more favourable prices in subsequent auctions. Carare (2012) finds

that imposing a static reserve price truncates the distribution of transaction prices, lowering bidders' expected surplus and because of a lower value of search over future auctions, bidders will shade their bid by a lower amount. Renewed interest in behaviour-based pricing strategies driven by the rise of e-commerce and online retailers motivated 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 reservation prices based on historical bids from other bidders.

In the literature on independent private value auctions, wide-spread deviations from the risk-neutral Nash equilibrium (RBNE) are well documented. This puzzle of overbidding in experiments, initially observed by Coppinger et al. (1980), has been explored and debated over the years. General bidding models using risk aversion (Cox et al. (1983, 1985, 1988)), regret theory (Rabin (2000)), quantal response equilibrium (Goeree et al. (2002)), and level-k behaviour (Crawford & Nagore (2007)) have been proposed to explain this finding. Common knowledge of rationality, that is, when all bidders believe that they are competing with similarly rational subjects, can plausibly contribute to such behaviour among bidders. The competition to win could then overwhelm the ability to manipulate the bid cap.

A real world application of a dynamic reserve price mechanism in pharmaceutical markets is studied by Bokhari et al. (2023). They conducted an empirical investigation of a procurement policy in the Philippines for essential drugs. Using a triple difference design, they found a causal effect that the policy reduced prices. In other dimensions of competition, their findings are not as rosy. The dataset they used recorded only winning bids, and one can infer that the auction failed and was re-run at an inflated reserve price if the transaction price recorded is higher than the applicable bid cap. They found that about 1 in 3 auctions resulted in the winning bid higher than the bid cap, and inferred that failed auctions could be widespread. Bidders in auctions for regulated drugs have won significantly more at prices just under the applicable bid cap. Due to the limitation of their data, this finding could be conditioned on the number of bidders. Such an insight could be use-

ful to better understand if this was due to coordination among the sellers or a severely diminished level of competition in the markets because there are no sellers willing to bid.

We hope to contribute to the existing literature in the following ways. First, we extend the findings of Isaac & Plott (1981) and Carare (2012) by looking at the behaviour of laboratory auction markets with a dynamic reserve price rather than the static version. Second, our experiment provides evidence relevant to the theoretical predictions of Kanoria & Nazerzadeh (2021) and extends their findings on second-price auctions to first-price sealed bid auctions. Lastly, we contribute to the literature insight about the trade-off between auction price regulation and the likelihood of failed auctions. By doing so, we add to the growing body of knowledge related to the regulation of auction markets, where a strong link between evidence and policy is needed, but often lacking.

3.3 EXPERIMENTAL DESIGN

Real-world procurement auctions and their outcomes before and after imposing a dynamic bid cap policy motivate our choices in designing the experiment. Bokhari et al. (2023) studies such auctions, finding a systematic reduction in prices and evidence of widespread auction failures. We want to look at the behaviour of laboratory auction markets with a dynamic bid cap to measure changes in transaction prices and bidder entry relative to a baseline of auctions without a bid cap. We explore two variants of the mechanism, one with endogenous features and another that delinks the bid caps from behaviour of bidders in a market. Therefore, the experiment requires three treatments using the Low Price (LP) auction: one without a dynamic reserve price, i.e. no bid cap, (NBC), one using a dynamic reserve price in a single market (SBC), and the third using a dynamic reserve price with multiple markets (MBC). Participants will interact through a computerised system. The winner of these auctions will be determined by the lowest bid submitted. Using a between-subjects design, each participant is exposed to only one of the three conditions and plays multi-round auctions. Each treatment will have 3 sessions. In each session, there is a hypothetical buyer and up to 5 competing sellers. In each session, subjects participate in 10 sequences of up to three auction rounds per sequence. In each sequence, each participant will receive a fundamental cost to provide the product to the buyer. In each auction round,

the actual cost will be equal to this fundamental cost plus a round-specific random draw. The fundamental cost will be redrawn for each sequence from a uniform distribution in the range [100, 200]. Then in each auction round, the second component is then redrawn from a uniform distribution in the range [-15, 15]. Participants will only be told their actual cost for the round.

In round 1 of each sequence, everyone is told their realised cost and everyone participates. In each subsequent round, participants are told their realised cost for that round and will be allowed to choose whether or not to participate in the auction for that round. If they choose to participate, they will pay a 2 ECU fee to do so, whether they win or not. If they choose not to participate in a round, they will not be able to participate for the remaining rounds in that sequence, but they will be able to rejoin in the subsequent sequence. If they choose not to participate, there will be an alternative uncompensated activity for them to engage in while waiting for the experiment to continue. After deciding to participate, subjects are informed of the number of competitors participating. Each competitor will have received a realised cost using the same method, with all draws being independent.

In the first treatment, there is no bid cap imposed between rounds. In the second treatment, inside a sequence, there will be a bid cap on possible bids that can be submitted based on the winning bid in the prior round. There will be no cap placed on bids in round 1 of a sequence, but there will be in rounds 2 and 3. This cap will be reset between sequences, so after one sequence ends and a new one begins, in the first auction round of a new sequence, there will be no bid cap.

For the third treatment, each participant will be randomly assigned to a group. Each group will be randomly matched with another group. Inside a sequence, there will be a bid cap on possible bids that can be submitted based on the winning bid in the matched group in the prior round. This means that there will be no cap placed on bids in round 1 of a sequence, but there will be in rounds 2 and 3. This cap will be reset between sequences, so after one sequence ends and a new one begins, in the first auction round of a new sequence, there will be no bid cap.

In addition to a 200 Philippine Peso (PhP) fee for showing up, participants will be paid after adding the earnings from all rounds at the conversion of 1 ECU to 10 PhP. Overall,

subjects earned an average of PhP 967.91 in NBC sessions, PhP 517.74 in SBC sessions, and PhP 562.21 in MBC sessions, inclusive of a PhP 200 show-up fee. Bankruptcy rules were put in place to deal with the possibility of bidders going bankrupt. First, all subjects start the experiment with an initial balance of 50 ECUs. If they lose so much money that their balance reaches zero, then they were declared bankrupt and asked to leave the experiment with only their show-up fee. Alternate participants were recruited for each session who went through the instuctions at the same time as the other subjects and replaced those who were declared bankrupt. Alternates are given 50 ECUs upon replacing bankrupt subjects. Participants were recruited through online ads posted in public access student social media groups and invited to sign up for a session. No demographic information was asked of the participants. The software for the experiment was programmed using oTree Chen et al. (2016).

3.4 EQUILIBRIUM PREDICTIONS

We consider n sellers competing for a contract to sell a good or provide a service to a buyer. Each seller $i \in 1, ..., n$ gets a fundamental cost draw c_i from uniform $[\underline{f}, \overline{f}]$. In each round $t \in 1, ..., T$, a seller receives a second draw from uniform $[-\delta, \delta]$ to form their actual private cost s_{it}. In effect, the actual cost in each round is independently drawn from a trapezoidal distribution over the interval $[c_i - \delta, c_i + \delta]$. This means that a given seller will know the actual cost of winning in any given period, but only knows that it is within δ above or below the fundamental cost. This also means that in each round, a seller cannot be certain but can draw inference if they have likely drawn a higher or lower cost than others. In each round, sellers try to win the contract such that they maximise their expected payoffs. They pay a nominal participation fee to submit a bid in each round but can decide to withhold participation after the first round.

3.4.1 Low Price (LP) Auction

In period t, each seller i submits a price bid of b_i, and given these bids, the ex post payoff function of seller i is

$$\Pi_i(b_i, b_{-i}) = \begin{cases} b_i - c_i & \text{if} \quad b_i < b_j \quad \forall j \neq i, \\ 0 & \text{otherwise.} \end{cases} \tag{3.1}$$

3.4.1.1 Equilibrium with n sellers

We look at the case where bidders are symmetric in expectation in that the actual costs are independently drawn from the same distribution, $F_i = F, \forall i$. First, suppose that bidder i's signal $S_i \sim F(\cdot)$ with realization $s_i \in [\underline{s}, \overline{s}]$, where $F(\cdot)$ is continuous, and her cost is $c_i(s_i) = s_i$. Assume that bidders $j \neq i$ use identical bidding strategies $b_j = b(S_j)$ that are strictly increasing, continuous, and differentiable functions of cost, then we consider the problem facing bidder i. Bidder i's expected payoff, as function of her bid b_i, and her signal s_i is:

$$U(b_i, s_i) = (bi - s_i) \cdot Pr[b_j = b(S_j) \geq b_i, \forall j \neq i] \tag{3.2}$$

Bidder i then chooses b that solves:

$$\max_{b_i} (b_i - s_i)\big(1 - F(b^{-1}(b_i))\big)^{n-1}$$

The first order condition is:

$$(b_i - s_i)(n-1)\big(1 - F(b^{-1}(b_i))\big)^{n-2}\big(-f(b^{-1}(b_i))\big)\frac{1}{b'(b^{-1}(b_i))} + \big(1 - F(b^{-1}(b_i))\big)^{n-1} = 0$$

At the symmetric equilibrium, $b_i = b(s_i)\ \forall i$ so the FOC reduces to a differential equation:

$$b'(s) = \big(b(s) - s\big)(n-1)\frac{f(s)}{1 - F(s)} \tag{3.3}$$

Using the boundary condition $b(\overline{s}) = \overline{s}$, this can be solved to obtain:

$$b(s) = s + \frac{\int_s^{\overline{s}} \big(1 - F(\tilde{s})\big)^{n-1} d\tilde{s}}{\big(1 - F(s)\big)^{n-1}} \tag{3.4}$$

Given signal s, bidders use strategy $b(s)$, where it is optimal to bid some positive value above cost. Observe further that this deviation from cost is decreasing in the number of bidders. The formal derivation and examples are given in Appendix C.4 and Appendix C.5. When bidders are asymmetric with costs drawn from independent, but not necessarily identical distributions, it is possible for a bidder to have the lowest cost and another to have the lowest willingness to pay [2].

3.4.1.2 Equilibrium Bid Functions with a Trapezoid Distribution

Now suppose that the bidders are still symmetric in that $F_i = F, \ \forall \ i$, but $S_i \sim F(r)$ where bidder i's signal has realisation drawn from $[c_i - \delta, c_i + \delta]$. Given that both c_i and δ are uniformly distributed with different supports, the resulting probability distribution is trapezoidal. The shape is illustrated in Figure 3.1.

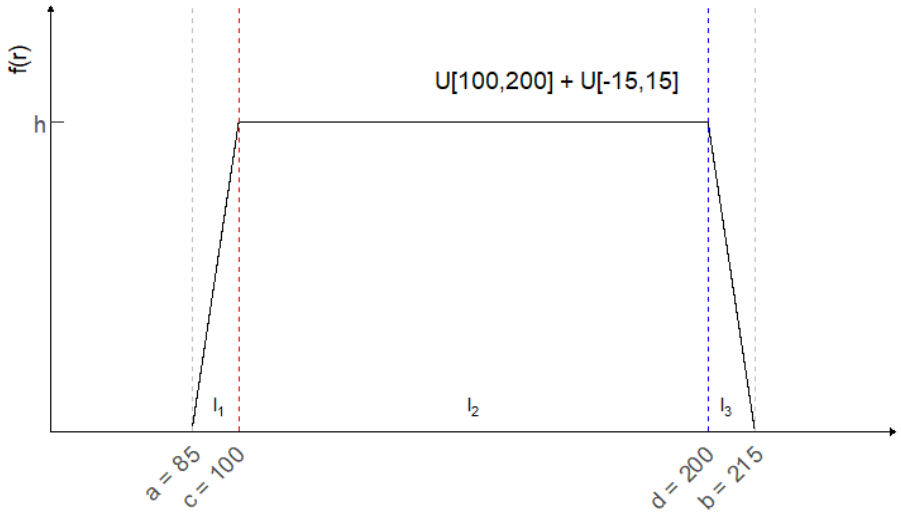


Figure 3.1: Trapezoid probability density function

The distribution is defined by four parameters, the minimum a, the maximum b, the lower mode c, and the upper mode d, where $a \leq c \leq d \leq b$. Substituting the expression for the cdf derived by Kacker & Lawrence (2007) into Equation 3.4, we get the equilibrium bid function for our environment as Equation 3.5. We simplify the expression by defining line segments between a, c, d, b as $l_1 = (c - a)$, $l_2 = (d - c)$, and $l_3 = (b - d)$, where $w \equiv l_1 + l_2 + l_3 = (b - a)$. The formal derivation of the pdf and cdf are given in Ap-

[2] For more details on this, see Myerson (1981).

pendix C.6. All relevant cases are consistent with the standard theory that bidders choose to bid some positive amount above cost in equilibrium. We provide worked out examples in Appendix C.7.

$$b(r) = \begin{cases} r + \dfrac{\int_r^c \left(1 - \dfrac{(\tilde{r}-a)^2}{l_1(w+l_2)}\right)^{n-1} d\tilde{r}}{\left(1 - \dfrac{(r-a)^2}{l_1(w+l_2)}\right)^{n-1}} & \text{if} \quad a \le r < c, \\ r + \dfrac{\int_r^d \left(1 - \dfrac{l_1 + 2(\tilde{r}-c)}{w+l_2}\right)^{n-1} d\tilde{r}}{\left(1 - \dfrac{l_1 + 2(r-c)}{w+l_2}\right)^{n-1}} & \text{if} \quad c \le r < d, \\ r + \dfrac{\int_r^b \left(\dfrac{(b-\tilde{r})^2}{l_3(w+l_2)}\right)^{n-1} d\tilde{r}}{\left(\dfrac{(b-r)^2}{l_3(w+l_2)}\right)^{n-1}} & \text{if} \quad d \le r \le b. \end{cases} \tag{3.5}$$

3.4.2 Behavioral Response to Dynamic Reserve Price

Without any restriction to the auctioneer's reserve price, bids become less competitive as high-cost bidders exit and fewer bidders are left in the market to compete. Using a mechanism where the reserve price is made endogenous by setting it equal to the winning bid of the same auction market in the previous period, we consider two possible outcomes. The first is that bidders learn to bid less aggressively to prevent the bid cap from closing them out of the subsequent auction. Sellers end up shading their bids more and inflating the price.

Suppose that this is the outcome. Another bid cap mechanism can address the endogeneity by setting the reserve price of a market as the winning bid in the previous period of a different auction. Here bidders in an auction should have no ability to manipulate

the bid cap they will face in the subsequent auction, and we expect sellers to compete aggressively and prevent the increase in auction prices over time.

There may be an alternative outcome from the endogeneous bid cap. For the collusive outcome to be sustained, the participating bidders must be convinced that this is a sustainable strategy for everyone. If this tacit coordination is not maintained and at least one bidder decides to bid aggressively and compete, then the other sellers would switch to competing as well. This leads to the other possible outcome, which is that sellers end up bidding at least as aggressively as if there were no bid caps. If everyone believes that all other players understand that the tacit collusive strategy is unlikely to be sustained, the increased bid shading will not be observed.

3.5 RESULTS

A set of summary statistics for key variables of interest is given in Table 3.1. Average values are provided by session and treatment. For auction prices, entry of bidders, and failure rates, we present averages by round. When comparing the average bids and costs of round 1, the similarity between treatments is striking. Average costs are similar by construction. Round 1 average bids in NBC and MBC auctions are similar as expected. However, sellers in NBC auctions were expected to be bidding higher under the collusive prediction. Instead of increased shading in bids, we find bidders competing aggressively.

In subsequent rounds, auction prices rise in the NBC auctions, while in both the SBC and MBC cases, prices have stayed low. Prices in the no bid cap case increase up to 148 on average by round 3. In contrast, both SBC and MBC auction prices are much lower and stay below 120 in subsequent rounds. Looking at the average number of bidders, we see attrition in all three treatments. This is because high cost sellers exit the market after round 1. However, the loss of bidders in the SBC and MBC auctions is much more pronounced. When there is no bid cap, the bidder count drops to about 3 bidders in round 2 and in the last round, 2 bidders on average. For both bid cap institutions, an average of just one bidder remains in the auction immediately after round 1. We get a better understanding of this attrition and average bidder counts when we look at the auction failure rates. Examining the auctions in rounds 2 and 3 where subjects are given the option of entering

Table 3.1: Summary Statistics

Treatment†	Session	*Avg Cost‡*	*Avg Bid‡*	Avg Price			Avg Bidder #			Failed (%)		
				r1	r2	r3	r1	r2	r3	r1	r2	r3
NBC	3	*149.54*	*153.79*	120.10	128.35	157.65	5.00	2.73	2.56	-	3.33	3.33
	8	*152.27*	*156.62*	117.65	124.11	139.95	5.00	3.00	2.50	-	0.00	0.00
	10	*151.87*	*153.77*	114.35	130.88	150.16	5.00	2.57	2.33	-	0.00	5.00
	All	*151.27*	*155.04*	117.73	126.99	147.98	5.00	2.82	2.49	-	1.11	2.22
SBC	2	*148.47*	*148.92*	118.17	106.31	105.75	5.00	1.31	0.74	-	20.00	50.00
	4	*152.37*	*157.79*	119.93	113.18	113.22	5.00	0.97	0.77	-	43.33	70.00
	5	*152.25*	*156.31*	122.40	122.64	123.40	5.00	1.01	0.79	-	30.00	50.00
	All	*151.30*	*155.01*	120.19	113.72	114.27	5.00	1.08	0.76	-	32.86	58.57
MBC	1	*149.33*	*152.33*	117.60	107.57	116.46	5.00	0.92	0.56	-	43.33	73.33
	7	*151.70*	*155.54*	124.57	114.55	116.48	5.00	1.36	0.89	-	20.00	56.67
	9	*148.83*	*152.23*	118.17	115.80	120.75	5.00	1.03	0.59	-	33.33	73.33
	All	*149.95*	*153.37*	120.11	113.03	117.69	5.00	1.11	0.71	-	32.22	67.78

Note: †NBC- No bid cap, SBC- Single market dynamic bid cap , MBC- Multi-market dynamic bid cap
‡Averages of round 1 auctions. Costs and bids are of all participating sellers.

the auction, we find, quite surprisingly, that a large proportion of auctions end up failing with a dynamic bid cap. In NBC auctions, only about 1-2% on average fail. With the SBC, about 33% of the auctions fail in round 2 and 59% end up failing in round 3. We initially get the same proportion of auctions that fail in the MBC institution, but a larger number of auctions fail in round 3 at about 68%.

3.5.1 Bidding Behaviour

Figure 3.2 gives a scatter plot of bids and their corresponding costs across the three treatments with nonlinear regression lines fitted through the respective data sets. Reference lines are provided as the 45 degree line and the equilibrium bid function in the LP auction. We show round 1 auctions where the environments can be compared along these two dimensions. Bidding in rounds 2 and 3 becomes also a function of the level of competition. For these we use our regressions to gain insight to bidders' behaviour. Trend lines show a visually obvious similarity of bidding behaviour in all three institutions. Throughout the range of cost draws, trend lines stay very close to each other, overlapping in most parts. Bids are clustered above the cost and below the predicted levels for the LP auction. This means that bids are more aggressive relative to standard equilibrium predictions. We note

that the observed behaviour in NBC auctions is consistent with overbidding among subjects in other laboratory experiments with independent private valuations. A long series of experiments find that bidders tend to bid more aggressively than the risk neutral equilibrium predictions[3]. General bidding models such as risk aversion, regret theory, level-k, and quantal response equilibrium have been proposed to rationalise such a finding. The tacit collusion prediction that would have resulted in higher round 1 bids with the SBC treatment did not show up in the results. Instead, behaviour that is identical to that in NBC auctions comes clearly through the summary table and figure. A possible explanation is that subjects have common knowledge of rationality, expecting that competing sellers also form beliefs that, despite the endogenous feature of the mechanism, a collusive equilibrium is not easily sustained. Such level-k thinking of what opponents expect other players to bid can drive up competition to win, overwhelming the ability to influence the bid cap. Under conditions where coordination is easier to maintain, strategic behaviour would be more likely. The robustness of this explanation needs to be further investigated and is one of the ways forward for extensions of this study. In the MBC mechanism, we see what is expected in that bidding is similar to the NBC bids, since there is no ability to influence bid caps by shading bids more.

Table 3.2 gives the results of several regression specifications on bids in each round to determine the overall structure of bidding behaviour. Variables used include the realised cost of the bidder, dummies for auctions using the single market bid cap (SBC) and the multimarket bid cap (MBC), and a dummy for whether the round is in the second half of the experiment. Specifications examine differences in behaviour between institutions over time. These regressions support our first result.

[3]See Sections 1.1 and 1.2 of Kagel & Levin (2017) for a survey of experiments exploring this finding

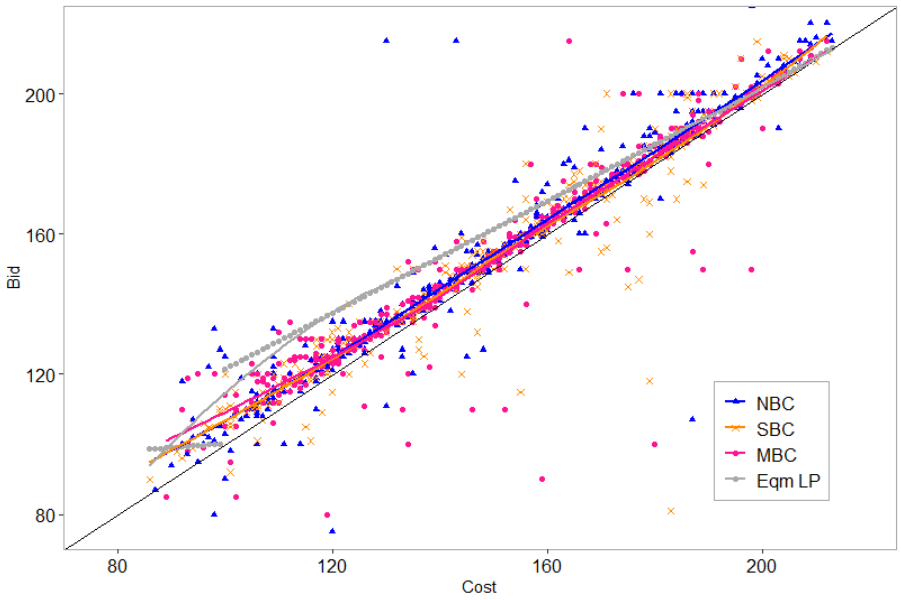


Figure 3.2: Scatterplot of Bids vs Cost (Round 1 Auctions)

RESULT 1. There is no significant statistical difference across treatments for round 1 bidding. In rounds 2 and 3, we find that bidding behaviour in NBC auctions becomes increasingly less competitive relative to both SBC and MBC auctions.

We find a clear break in the nature of bid functions between round 1 and the other rounds. For NBC, the bid function in round 1 is approximately $0.9s_i + 9$ shown in column (1). In round 2, it becomes $0.5s_i + 68$, shown in column (3), and in round 3 it is $0.5s_i + 86$, shown in column (6). This break holds after controlling for the number of bidders. The slope and intercept are different in round 1 but only the intercept is different between rounds 2 and 3. Bidding behaviour under the bid cap institutions becomes increasingly more competitive than in NBC seen in the coefficients of indicator variables SBC and MBC in columns (3)-(5) and (6)-(8).

3.5.2 Seller Earnings

Reported statistics in Table 3.1 show that the average price in NBC auctions starts around 118 on average in round 1 but rose to 147 in round 3. Prices in SBC and MBC auctions begin with a slightly higher level of about 120 on average but do not go up in rounds 2 and 3,

Table 3.2: Regressions on Bidding Behaviour

	Bid							
	Round 1		Round 2†			Round 3†		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cost	0.964***	0.964***	0.549***	0.569***	0.582***	0.484***	0.524***	0.519***
	(0.013)	(0.013)	(0.040)	(0.041)	(0.041)	(0.069)	(0.066)	(0.066)
No. of Bidders				−2.932**	−2.458**		−11.012***	−11.383***
				(1.174)	(1.166)		(2.048)	(2.066)
SBC	−0.069	−0.033	−21.993***	−25.448***	−24.017***	−34.408***	−50.997***	−50.979***
	(1.021)	(1.017)	(3.139)	(3.413)	(3.392)	(6.112)	(6.572)	(6.563)
MBC	−0.403	−0.403	−19.375***	−22.391***	−21.489***	−25.278***	−39.731***	−40.436***
	(0.947)	(0.944)	(2.870)	(3.098)	(3.068)	(6.022)	(6.318)	(6.333)
H2		2.440***			7.982***			4.873
		(0.804)			(2.266)			(3.758)
Constant	9.157***	7.936***	68.458***	75.199***	67.833***	86.268***	110.390***	109.327***
	(2.126)	(2.157)	(5.822)	(6.385)	(6.639)	(9.668)	(10.217)	(10.237)
Observations	1,240	1,240	428	428	428	259	259	259

Note: †Failed auctions are excluded.
*p<0.1; **p<0.05; ***p<0.01

ending lower than the initial average levels. The rise in auction prices for NBC auctions is consistent with what theory tells us. A seller's bidding function would predict higher bids with fewer competing sellers. Markets become less competitive, and sellers who remain in the markets realise that they can bid less aggressively. This gives us the expected problem faced by the auctioneer in these multi-round auctions. With the imposition of a dynamic bid cap, both the SBC and MBC cases seem to resolve this issue. Table 3.3 shows that the expected surplus of participants in both variants of the bid cap is almost always a loss, while participants earn a surplus in the NBC auctions. Table 3.4 shows that conditional on winning the auction, bidders in the NBC earn more than both SBC and MBC. Between the bid cap variants, winners tend to earn more in the MBC case. The number of subjects who lost their endowment in NBC sessions was 8, 12 in SBC sessions and 10 in MBC sessions. These subjects were removed from their sessions and replaced by alternate participants. Our second result summarises the findings on auction prices and seller surplus.

Table 3.3: Summary of Participant Surplus

Treatment	Session	Avg Surplus		
		All	1st Half	2nd Half
NBC	3	46.69	1.21	53.05
	8	24.04	10.71	14.55
	10	34.50	34.36	0.17
	All	34.58	12.94	24.56
SBC	2	-8.80	-4.07	-7.10
	4	-8.16	-5.26	-3.67
	5	-2.38	-3.13	0.80
	All	-6.50	-4.22	-2.85
MBC	1	-1.60	-2.90	1.73
	7	-4.08	-4.79	0.85
	9	-3.19	-1.81	-1.45
	All	-3.03	-3.25	0.25

Note: Figures are inclusive of participation fee.

RESULT 2. On average, prices are lower with SBC and MBC than in NBC auctions. Seller surplus is lower for both bid cap cases with those with the SBC losing more than those with the MBC.

We provide statistical support for this result in Table 3.5, which contains regressions on auction price for each round. The variables in these regressions include dummy variables indicating whether the bid cap is SBC or MBC, the lowest and second lowest cost among participating bidders in a group, and a dummy variable indicating whether the round is in the second half of the experiment. Round 1 regression, column (1), confirms that, indeed, prices across treatments are not statistically different, as shown by the coefficients of the SBC and MBC indicator variables. In the regressions for rounds 2 and 3, specifically columns (2) and (4), we see that prices in the SBC and MBC are different from NBC. In round 2, prices in both bid caps institutions are similarly lower by 11 than NBC. In round 3, surprisingly, prices in SBC are even lower than those in MBC. Despite the endogenous feature of the mechanism, bidders in SBC auctions are competing more aggressively than in MBC auctions. These statements are true even after controlling for the number of bidders in the auction, seen in columns (3) and (5). Because bidding behaviour becomes increasingly less competitive in NBC auctions over time, auction prices increase. This is consistent with the analysis on bidding behaviour. Similarly, because bidding behaviour

Table 3.4: Summary of Winner Surplus

Treatment	Session	Avg Surplus		
		All	1st Half	2nd Half
NBC	3	86.03	14.34	95.58
	8	52.20	35.93	29.71
	10	81.33	101.17	15.63
	All	70.05	37.17	48.03
SBC	2	2.89	6.20	-0.71
	4	5.59	3.33	5.00
	5	13.20	4.50	16.00
	All	7.03	4.28	6.08
MBC	1	14.38	6.91	15.40
	7	10.20	2.64	10.33
	9	13.13	7.67	8.75
	All	12.61	5.79	11.26

Note: Figures are inclusive of participation fee.

in the SBC and MBC auctions grows more competitive in subsequent rounds because of the bid caps, auction prices fall. The summary statistics in Table 3.1, clearly show that immediately after round 1, bidder attrition is more severe in both the SBC and MBC auctions. Without any bid caps, this level of competition would have resulted in bids from remaining sellers being much higher, as standard theory predicts.

However, there is a monotone, inverse relation between the average auction price and the number of bidders, which can be problematic for both sellers and auctioneer. Sellers who stay could take advantage of the low level of competition and charge a high price. If in the limit entry is so severely impacted that all bidders stay out of the market, the auctioneer is faced with a failed auction and is not able to acquire the object. We discuss this in the following sections.

3.5.3 Entry

In Figure 3.3, we see a visualisation of the average prices and bidder counts presented in Table 3.1. The difference between NBC and the other treatments is clearly seen in rounds 2 and 3 for both prices and bidder counts. Lower prices resulting from the bid caps forced more sellers out of the markets. In the NBC auctions, bidder attrition is as expected with high cost bidders exiting in subsequent rounds. When bid caps are imposed endogenously,

Table 3.5: Regressions on Auction Price

	Auction price				
	Round 1	Round 2		Round 3	
	(1)	(2)	(3)	(4)	(5)
SBC	1.266	−11.264***	−20.129***	−28.029***	−53.643***
	(1.903)	(4.127)	(4.551)	(7.730)	(7.401)
MBC	2.235	−11.024***	−19.549***	−21.932***	−48.251***
	(1.778)	(3.820)	(4.251)	(7.678)	(7.407)
Lowest Cost (LC1)	0.875***	0.805***	0.796***	0.656**	0.750***
	(0.066)	(0.151)	(0.145)	(0.252)	(0.214)
2nd Lowest Cost (LC2)	0.040	0.101	0.038	0.331*	0.131
	(0.057)	(0.119)	(0.116)	(0.194)	(0.166)
H2	4.989***	8.648***	7.337**	2.839	8.646*
	(1.510)	(3.265)	(3.161)	(5.839)	(5.013)
No. of Bidders			−6.933***		−22.962***
			(1.734)		(3.079)
Constant	8.563	16.410	46.149***	26.119	90.025***
	(6.153)	(13.465)	(14.948)	(25.214)	(23.038)
Observations	250	197	197	146	146

Note: *p<0.1; **p<0.05; ***p<0.01

the winning bid in the previous period, which is likely from a bidder with a low cost draw, priced out all bidders that have higher cost draws in subsequent rounds. Imposing price caps somewhat reverses the standard prediction. Even with fewer bidders competing, bids stay low. This outcome is misleading because the auctioneer should also consider the rate at which the auctions fail. In some procurement settings, failed auctions are dealt with a re-run of the failed auction with the reserve price adjusted upward.

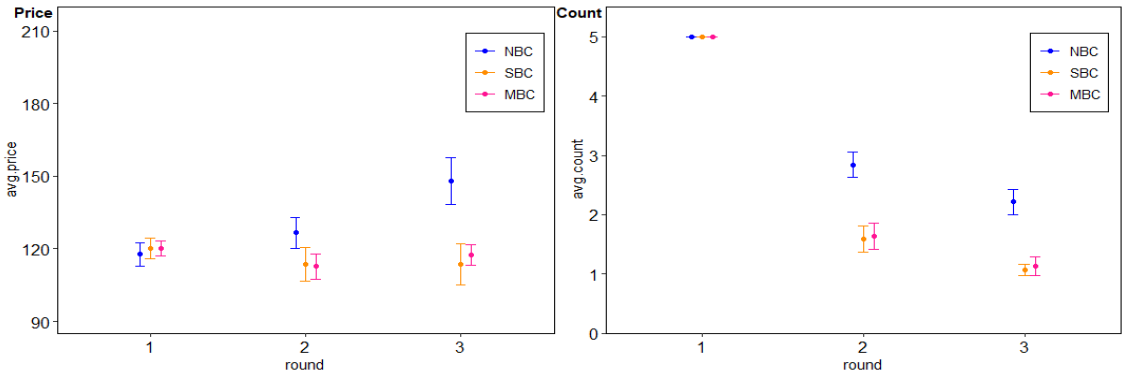


Figure 3.3: Price and Bidder Count Outcomes by Treatment, Round

RESULT 3. The auctioneer's problem of high prices is addressed, but bidders are more likely to exit markets with the SBC and MBC than in NBC auctions.

Table 3.6 provide statistical support for this result. Here, we present a series of probit regressions in columns (1)-(4), with the dependent variable being whether or not the bidder decided to join the auction, as well as a set of marginal effects in columns (5)-(8), which were calculated from standard probit regressions with the same specifications. We find that the probability of entry is significantly reduced by the SBC and MBC dummies. Looking at the magnitudes of the marginal effects, we see that the probability of entry is lower for MBC than for SBC relative to the NBC case.

Table 3.6: Regressions on Likelihood of Entry

	Binary for Entry†							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Cost	−0.021***	−0.021***	−0.027***	−0.028***	−0.006***	−0.006***	−0.007***	−0.007***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)
Bid Cap			0.027***	0.028***			0.007***	0.007***
			(0.004)	(0.004)			(0.001)	(0.001)
SBC	−1.197***	−1.198***	0.117	0.111	−0.387***	−0.388***	0.031	0.030
	(0.094)	(0.094)	(0.100)	(0.101)	(0.024)	(0.024)	(0.027)	(0.027)
MBC	−1.272***	−1.272***			−0.425***	−0.425***		
	(0.087)	(0.087)			(0.024)	(0.024)		
Round 2 (R2)	−0.291***	−0.291***	−0.211*	−0.215*	−0.113***	−0.113***	−0.060	−0.060
	(0.082)	(0.082)	(0.125)	(0.126)	(0.032)	(0.032)	(0.038)	(0.038)
H2		−0.028		−0.261***		−0.011		−0.069***
		(0.071)		(0.100)		(0.027)		(0.026)
Constant	3.671***	3.688***	−0.045	0.056	1.035***	1.040***	−0.011	0.014
	(0.208)	(0.212)	(0.407)	(0.410)	(0.060)	(0.061)	(0.101)	(0.100)
Observations	1,648	1,648	953	953	1,648	1,648	953	953

Note: Columns (1)-(4) are panel probit regressions. Columns (5)-(8) are marginal effects from standard probit regressions. † Only rounds 2 and 3 are considered.
*p<0.1; **p<0.05; ***p<0.01

In Figure 3.4, we check whether subjects make the decision to leave if the current cost exceeds the current bid cap. Similarly, subjects should make the decision to enter the auction when there is a positive surplus to be had by staying in. In round 2 we find that some subjects are deciding to enter even though the surplus expected by staying is negative. We take this as evidence of some subjects expecting to have a lower cost draw in round 3 and therefore staying in. The figures show that the mass of subjects leaving are found on the left of zero and those that stay on the other side. This suggests that subjects are leaving or entering the auctions when they should.

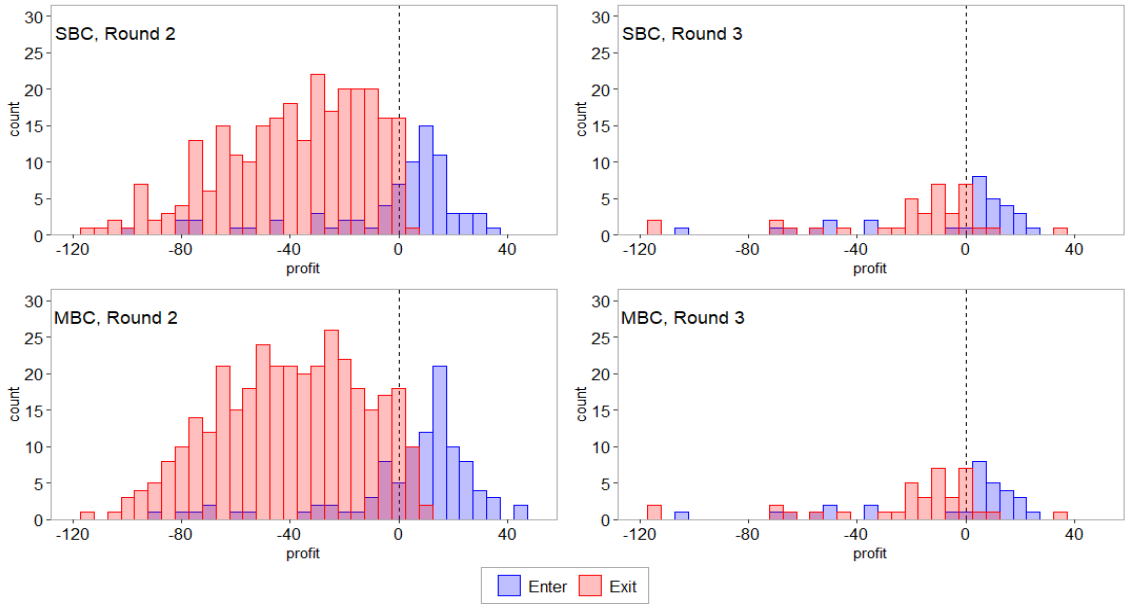


Figure 3.4: Seller Entry Decision by Surplus

3.5.4 Failed Auctions

Dynamic bid caps put such strong downward pressure on prices that failure becomes widespread. Even sellers with low cost draws end up exiting markets over time. The competition to win drives down the bid cap such that subjects end up staying out of the market.

RESULT 4. Auction markets are more likely to fail with SBC and MBC auctions.

Table 3.7 provide statistical support for this result. Here, we present a series of probit regressions in columns (1)-(4), with the dependent variable being whether or not the auction failed, as well as a set of marginal effects in columns (5)-(8), which were calculated from standard probit regressions with the same specifications. We find that the probability of failure is significantly affected by the SBC and MBC dummies. On average, both bid cap institutions make failure 56% more likely than without a bid cap, seen in columns (5) and (6). Including a variable for bid cap, coefficients are now with reference to the MBC auctions. In columns (7) and (8), after controlling for round 2 and second half auctions, for every unit higher of the bid cap, auctions are 0.9% less likely to fail.

Table 3.7: Regressions on Likelihood of Failure

	Binary for Failed Auction†							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SBC	1.911***	1.912***	−0.155	−0.150	0.559***	0.559***	−0.058	−0.056
	(0.296)	(0.296)	(0.165)	(0.166)	(0.072)	(0.072)	(0.061)	(0.061)
MBC	2.051***	2.050***			0.557***	0.557***		
	(0.290)	(0.290)			(0.060)	(0.060)		
Bid Cap			−0.025***	−0.025***			−0.009***	−0.009***
			(0.006)	(0.006)			(0.002)	(0.002)
R2	−0.271*	−0.271*	−0.198	−0.192	−0.058*	−0.058*	−0.074	−0.072
	(0.155)	(0.155)	(0.167)	(0.168)	(0.034)	(0.034)	(0.063)	(0.063)
H2		0.032		0.146		0.007		0.055
		(0.152)		(0.165)		(0.032)		(0.061)
Constant	−2.163***	−2.180***	2.741***	2.745***	−0.506***	−0.510***	0.950***	0.949***
	(0.274)	(0.285)	(0.660)	(0.661)	(0.033)	(0.038)	(0.232)	(0.231)
Observations	442	442	263	263	442	442	263	263

Note: Columns (1)-(4) are panel probit regressions. Columns (5)-(8) are marginal effects from standard probit regressions. † Only rounds 2 and 3 are considered.
*p<0.1; **p<0.05; ***p<0.01

We find that this is a key result since auction prices could be deceptively low, despite a lower number of participating bidders in the auctions that are observed to have succeeded. A closer examination of auction outcomes reveals that these low prices come at the expense of destroying markets. In the context of real-world auctions, this means that hospitals cannot acquire essential drugs. If these auctions can be re-run after relaxing the bid cap, then the situation could be similar to NBC auctions where prices rise over time. This then places the auctioneer in its original predicament with the added cost of multiple auctions.

In Table 3.8, conditional on auctions failing, we look at the frequency of subjects making the decision to leave even when there is a positive surplus from winning in the current auction. We find that for both bid cap variants, this is quite rare. Subjects in the auctions that eventually failed are largely deciding to leave when the surplus from staying in and winning the current auction is negative.

Table 3.8: Exit Decisions in Failed Auctions

Treatment	Round 2	Round 3	All
SBC	0.89%	1.54%	0.98%
	(1/112)	*(3/195)*	*(3/307)*
MBC	2.76%	2.68%	2.70%
	(4/145)	*(8/299)*	*(12/444)*
All	1.91%	2.18%	2.09%
	(5/262)	*(11/504)*	*(16/766)*

Note: In parenthesis, the numerator is the count of exit when a subject could have earned a positive surplus by staying in and the denominator is the count of exit in auctions that failed.

3.5.5 Efficiency

We look at the efficiency properties of the bid cap institutions by computing two measures that we present in Table 3.9 and Table 3.10. First, we look at efficiency in the sense that the lowest cost bidder wins in the auction. This notion of efficiency reflects how often an auction awards the object to the most cost efficient bidder. SBC auctions are on average more efficient at 84.25% than MBC auctions at 80. 00%, and NBC auctions are the least efficient at 77.53%. These figures suggest that in multi-round auctions, a dynamic bid cap, particularly the SBC, offers an improvement from the NBC.

Table 3.9: Efficiency of Auctions

Treatment	Session	Efficient Seller Wins		
		All	1st Half	2nd Half
NBC	3	79.55	75.56	83.72
	8	78.33	78.33	78.33
	10	72.29	75.86	70.00
	All	77.53	76.87	78.20
SBC	2	82.61	78.26	86.96
	4	84.93	80.00	88.46
	5	86.36	83.33	90.00
	All	84.25	80.52	88.41
MBC	1	70.91	73.08	68.97
	7	80.60	75.00	85.71
	9	87.93	89.29	86.67
	All	80.00	79.07	80.85

Table 3.10: Ratio of Winning Cost to Optimal Cost

Treatment	Session	Winner Cost / Lowest Cost			
		All	1st Half	2nd Half	M†
NBC	3	1.04	1.04	1.03	1.26
	8	1.04	1.05	1.02	1.30
	10	1.04	1.03	1.05	1.28
	All	1.04	1.05	1.03	1.28
SBC	2	1.06	1.11	1.02	1.23
	4	1.07	1.09	1.05	1.32
	5	1.05	1.03	1.07	1.29
	All	1.06	1.08	1.04	1.28
MBC	1	1.07	1.11	1.04	1.32
	7	1.03	1.05	1.01	1.26
	9	1.02	1.02	1.03	1.28
	All	1.04	1.06	1.03	1.29

In Table 3.10 we measure a notion of efficiency that looks at the deviation of the winning bidder's cost to the lowest possible cost among participating bidders in an auction. Figures in the table suggest that the lowest cost subjects tend to win at these auctions and the deviation of the winning bidder's cost is not very large. Our hypothetical benchmark M is calculated as the expected cost of bidders participating in the round divided by the lowest cost in that round for that group. This indicates that institutions are improvements over the case where the winners are simply selected at random.

3.6 CONCLUSIONS

Auctions are common modalities for public procurement because they use the competitive nature of auctions to keep government costs low. If we introduce the issue of a weakened state of competition in these markets over time, the auctioneer faces the problem of rising auction prices. Regulating the reserve price can be an option to resolve this issue, but regulators need to be careful in designing a reserve price mechanism to try and minimise unintended consequences, some of which could be harder to correct than the original problem. In multi-round auctions, the issue of rising prices can conceivably be controlled by imposing a dynamic bid cap that prevents price increases even when there are only a few bidders participating. An example of this is studied by Bokhari et al. (2023) and their

results indicate some degree of success in reducing prices. Although a mechanism that endogenizes the reserve price in subsequent periods may appear to be ill-suited from a theoretical perspective, competition to win in earlier auctions can overwhelm the ability to manipulate the policy resulting in price outcomes favourable to the auctioneer. When the collusive equilibrium is not sustained, the bidders end up competing with each other the rest of the time. Even with dampened competition, the bid caps put a strong downward pressure on prices, and the level of shading predicted by standard theory does not happen.

The unintentional consequence of this reserve price mechanism is that in subsequent auctions, bidder entry is adversely affected. Although bidder attrition is also expected even in there are no bid caps, it is on average 39-43% more likely that bidders leave the markets with a dynamic bid cap. We find that bidders exit markets so much that auctions are almost 60% on average more likely to fail with bid caps. Compared to NBC auctions, with an average failure rate of up to 2% in round 3, for SBC and MBC, about 1 in 3 auctions fail in round 2 and up to 2 in 3 auctions fail in round 3. When the policy for failed auctions is to allow a re-run of the auction with an inflated reserve price, the governments can find themselves faced with prices that are increasing rather than decreasing because of the bid cap. The resulting trade-off between price and entry is that by controlling prices, bidders are pushed out, markets are left without any bidders participating, resulting in a widespread failure of these auctions. Although the choice of reserve price is important, it is better to attract an additional bidder than to run the perfect auction. The auctioneer gains more by increasing competition than by holding the “perfect" auction Bulow & Klemperer (1996).

The results of our experiment show that an endogeneous dynamic reserve price can be effective in addressing high prices in our benchmark case. Bidders were unable to use this mechanism as a focal point to tacitly collude and keep prices high. Due to the strong downward pressure on prices, bidders leave and a large number of auctions fail. There are likely other reserve price mechanisms that prevent these failed auctions while keeping prices low. The way forward for research is to determine the solution to the auctioneer’s problem, as well as the seller’s problem of being priced out of markets.

APPENDIX A

Efficiencies in Retrospective Merger Evaluation: GSK-Pfizer Consumer Health

A.1 ADDITIONAL MARKET DETAILS

A.1.1 Cough and Cold Therapeutic Categories

Table A.1: Therapeutic Categories of Active Substances in Cough and Cold Remedies

Therapeutic Category	Active Substance	ATC3
Stomatologicals	Echinacea Purpurea + Eucalyptus Globulus + Melaleuca Alternifolia + Mentha Piperita + Menthol + Propolis + Thymus Vulgare	A1A
Topical Nasal Preps	Oxymetazoline, Sodium, Sea Water, Potassium + Sodium	R1A
Systemic Nasal Preps	Diphenhydramine + Phenylpropanolamine, Chlorphenamine + Phenylephrine, Chlorphenamine + Phenylpropanolamine, Brompheniramine + Phenylephrine, Phenylpropanolamine, Brompheniramine + Phenylpropanolamine, Pseudoephedrine	R1B
Pharyngeal Preparations	Benzydamine + Cetylpyridinium, Hexetidine, Povidone-Iodine, Dequalinium, Fucus Vesiculosus + Povidone-Iodine, Anethole + Mentha Piperita + Menthol + Pimpinella Anisum	R2A
Chest Rubs and Inhalants	Camphor + Menthol, Camphor + Menthol + Salicylic Acid, Camphor + Eucalyptus Globulus + Menthol, Aloe Barbadensis + Eucalyptus Globulus + Lavandula Angustifolia + Parafin Oil + Rosmarinus Officinalis, Camphor + Cedar Wood Oil+ Eucalyptus Globulus + Menthol + Myristica Fragrans + Thymol+Turpentine Oil	R4A
Cold Preparations	Chlorphenamine + Paracetamol + Phenylephrine, Ibuprofen + Phenylephrine, Paracetamol + Phenylephrine, Paracetamol + Phenylpropanolamine, Chlorphenamine + Paracetamol + Phenylpropanolamine, Dextromethorphan + Paracetamol + Phenylephrine Dextromethorphan + Paracetamol + Phenylpropanolamine Chlorphenamine + Dextromethorphan + Guaifenesin + Paracetamol + Phenylpropanolamine, Caffeine + Chlorphenamine + Paracetamol + Phenylephrine, Chlorphenamine + Dextromethorphan + Paracetamol + Phenylpropanolamine	R5A
Expoectorant	Ambroxol, Bromhexine, Carbocisteine, Guaifenesin Chlorphenamine + Guaifenesin + Phenylpropanolamine Guaifenesin + Phenylpropanolamine, Carbocisteine + Zinc Guaifenesin + Sodium, Hedera Helix + Honey + Mentha Piperita + Phyllanthus Ninuri	R5C
Antitussive	Butamirate, Dextromethorphan, Dextromethorphan + Guaifenesin, Dextromethorphan + Guaifenesin + Sodium	R5D
Other Cough and Cold Preps	Vitex Negundo	R5F
All Oth. Therapeutic Prds	Andrographis Paniculata + Echinacea Purpurea + Selenium + Zinc	V3X

A.2 DATA ATTRIBUTES AND DEFINITIONS

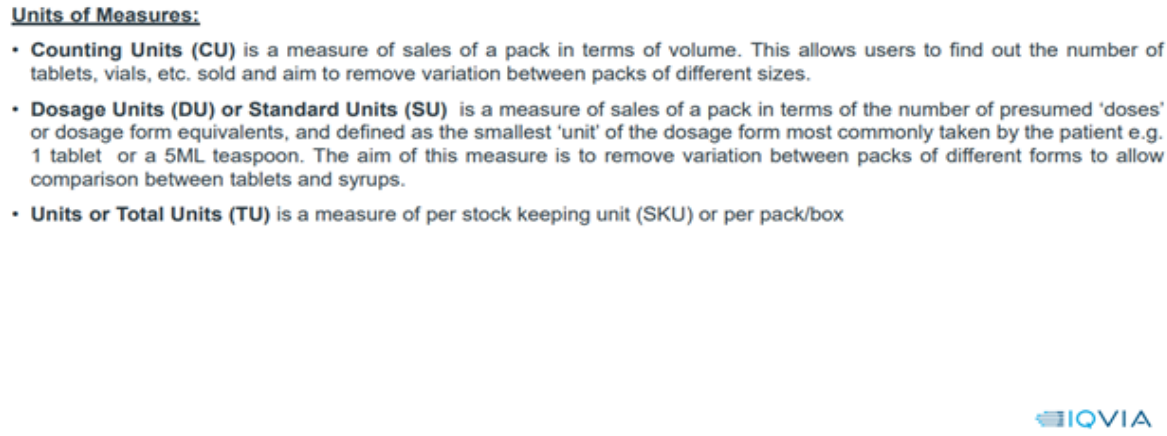
A.2.1 IQVIA Philippine National Sales Audit

Variables	Definition
Channel	IQVIA National Sales is subdivided into two main audits mainly **Retail/Drugstore** and **Hospital**
Market	General grouping or description of the use of the drug (e.g. cough and cold, pain, hypertension)
IQVIA Region	Composed of four (4) Philippine main island groups (Metro Manila, Luzon, Visayas, Mindanao)
Political Region	Refers to the 17 geo-political regions in the Philippines i.e., Region 1 to BARMM
Manufacturer	Means any legal person or entity engaged in the manufacture of a product subject to license under the act
Anatomical Therapeutic Classification (ATC)	A classification system devised by the European Pharmaceutical Market Research Association (EPhMRA) and International Pharmaceutical Market Research Group (IPMRG) which groups drugs of similar action, for the purposes of comparison and the establishment of competitive markets within the total pharma market
New Form Code (NFC)	A classification used by IQVIA to describe the form in which a product is supplied.
Ethical Status	Classification of the product based on the CPR and indication/s (Ethical – prescription drugs, Proprietary – over the counter drugs)

Variables	Definition
License Type	Indicates if the pharmaceutical product is Originator (first launch), Branded Generic, or Unbranded Generic
Product	Brand name
Pack	Stock keeping unit (SKU) level of each brand
Pack Form	Presentation of the product (e.g. capsule, tablet, syrup)
Pack Size	Represents the quantity of each product in a given pack type (ex. 1's, 100's)
Pack Strength	Refers to the potency/strength of a particular molecule/active ingredient in a drug
Additional Strength	Refers to the potency/strength of another molecule/active ingredient in a drug. A drug may or may not have an additional strength information
Pack Volume	This represents the total volume of liquid/solution or weight of product contained in each pharmaceutical product (e.g. 2ml, 0.5 ml, 50G)
Pack Molecule String	Active therapeutic ingredients of the product. A product may be composed of single or multiple molecules.

IQVIA

A.2.1.1 Definition of Measures



Units of Measures:

- **Counting Units (CU)** is a measure of sales of a pack in terms of volume. This allows users to find out the number of tablets, vials, etc. sold and aim to remove variation between packs of different sizes.
- **Dosage Units (DU) or Standard Units (SU)** is a measure of sales of a pack in terms of the number of presumed 'doses' or dosage form equivalents, and defined as the smallest 'unit' of the dosage form most commonly taken by the patient e.g. 1 tablet or a 5ML teaspoon. The aim of this measure is to remove variation between packs of different forms to allow comparison between tablets and syrups.
- **Units or Total Units (TU)** is a measure of per stock keeping unit (SKU) or per pack/box

A.2.2 IQVIA Customized Insights World Review Pack

Appendix available online.

A.3 PRODUCT SET SELECTION

A.3.1 Product Market Shares

For the estimation, we select products with average shares of 0.2% or greater in the pre-merger period of our data set, 2008-2018. This limits the product set to $J = 54$, representing 97% of the market. Shares are computed using IQVIA dosage units. This benefits the estimation in the following ways.

Table A.2: Product Set Average Shares (2008-2018)

Count	Product ID	Share	CumSum	Count	Product ID	Share	CumSum
1	160	0.2085	0.2085	28	22	0.0080	0.8561
2	138	0.1076	0.3162	29	84	0.0076	0.8637
3	168	0.0808	0.3970	30	171	0.0074	0.8711
4	173	0.0372	0.4341	31	159	0.0073	0.8785
5	77	0.0323	0.4665	32	118	0.0057	0.8842
6	178	0.0317	0.4982	33	20	0.0054	0.8895
7	89	0.0283	0.5264	34	24	0.0051	0.8946
8	143	0.0271	0.5536	35	114	0.0047	0.8993
9	78	0.0265	0.5800	36	109	0.0046	0.9040
10	161	0.0246	0.6046	37	86	0.0046	0.9086
11	150	0.0243	0.6289	38	76	0.0046	0.9132
12	185	0.0188	0.6477	39	153	0.0044	0.9176
13	149	0.0180	0.6657	40	112	0.0043	0.9219
14	44	0.0175	0.6833	41	155	0.0041	0.9260
15	144	0.0175	0.7008	42	116	0.0040	0.9300
16	91	0.0172	0.7180	43	172	0.0039	0.9339
17	23	0.0169	0.7349	44	108	0.0039	0.9378
18	163	0.0144	0.7493	45	179	0.0038	0.9417
19	90	0.0129	0.7621	46	133	0.0034	0.9450
20	170	0.0129	0.7750	47	88	0.0031	0.9482
21	162	0.0121	0.7871	48	145	0.0031	0.9512
22	146	0.0113	0.7984	49	68	0.0031	0.9543
23	9	0.0104	0.8088	50	115	0.0028	0.9571
24	82	0.0102	0.8190	51	8	0.0024	0.9595
25	87	0.0102	0.8292	52	85	0.0024	0.9618
26	106	0.0098	0.8391	53	113	0.0023	0.9641
27	117	0.0090	0.8481	54	70	0.0022	0.9663

A.3.2 Firm Market Shares

After defining our product set, we observe 11 firms out of 52 observed in the Cough and Cold Philippine data set. The other 41 smaller firms collectively represent less than 3.4% of the market.

Table A.3: Firm Average Shares (2008-2018)

Count	Firm	Share	CumSum
1	UNITED LAB	0.6655	0.6655
2	PFIZER INC	0.0862	0.7517
3	PASCUAL LAB	0.0822	0.8339
4	GLAXOSMITHKLINE	0.0354	0.8693
5	SANOFI-AVENTIS	0.0328	0.9021
6	JOHNSON	0.0175	0.9196
7	BAYER PHILIPPINES	0.0128	0.9325
8	PEDIAPHARMA	0.0102	0.9427
9	PROCTER & GAMBLE	0.0098	0.9525
10	RECKITT BENCKISER	0.0085	0.9611
11	NEW MARKETLINK PH	0.0052	0.9663

A.4 ADDITIONAL DESCRIPTIVE RESULTS

Table A.4: Summary Statistics for Philippine CCR Segment (All Products), 2008-2020

variable	mean	sd	min	max
Corp + Brand + Molecule + NFC				
Sales Value, $(r_{j,t} = p_{j,t} \cdot q_{j,t})$	169.24	548.00	0.00	7,033.70
Dosage Volume, $(q_{j,t})$	1,405.93	5,273.04	0.00	85,062.85
Price per dose, $(p_{j,t})$	0.15	0.14	0.00	3.38

Note: There are 5,489 observations (products, quarters). Sales value is in 1000 USD (exclusive of VAT), Volume of dosage units is in 1000. Price per dose is in USD. Philippine Pharmaceutical Product Index was used to deflate prices.

A.4.1 Results using Complete Cough and Cold Product Set

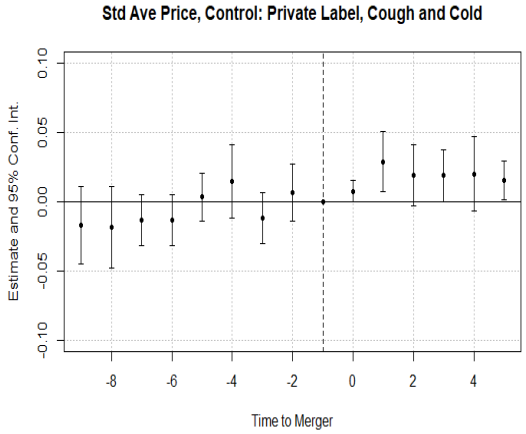
Table A.5: Merger Price Effect, Philippine Comparisons

	Cough & Cold[a]		Analgesics	Hypertension
	Private Label	Proprietary Label	Proprietary Label	All
Standard Average Price				
Aggregate Effect				
M×P	0.018**	−0.032***	−0.023***	−0.026*
	(0.007)	(0.006)	(0.009)	(0.013)
Separate Effects				
GSK×P	0.032***	−0.018**	−0.009	0.011
	(0.007)	(0.008)	(0.012)	(0.019)
Pfizer×P	0.005	−0.045***	−0.036***	−0.038**
	(0.007)	(0.008)	(0.012)	(0.017)
Stone Price Index, Q4 2017 weights				
Aggregate Effect				
M × P	−0.064***	−0.147***	−0.007	−0.020*
	(0.016)	(0.071)	(0.053)	(0.011)
Separate Effect				
GSK×P	−0.082***	−0.165*	−0.025	−0.037**
	(0.017)	(0.093)	(0.072)	(0.016)
Pfizer×P	−0.049***	−0.132	0.008	−0.004
	(0.017)	(0.089)	(0.068)	(0.015)
Stone Price Index, Q3 2020 weights				
Aggregate Effect				
M × P	0.014	−0.189**	−0.259***	−0.307***
	(0.195)	(0.091)	(0.061)	(0.033)
Separate Effect				
GSK×P	0.111	−0.065	−0.134	−0.182***
	(0.217)	(0.119)	(0.083)	(0.046)
Pfizer × P	0.123	−0.298***	−0.368***	−0.416***
	(0.212)	(0.113)	(0.078)	(0.044)
Product FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Observations	168	363	513	1,456

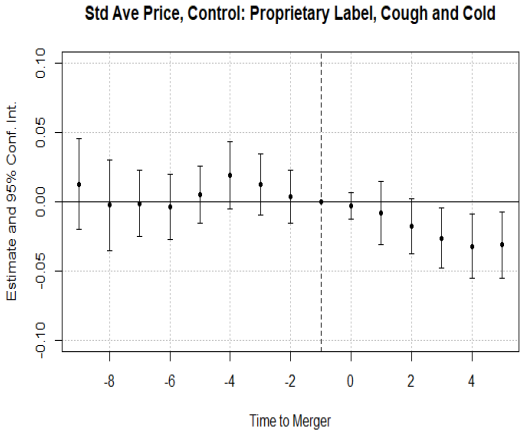
Note:[a] Products with the same active substance as GSK and Pfizer products;

Figure A.1: Event Study Plots Using Different Control Groups

Philippine Cough and Cold Remedies

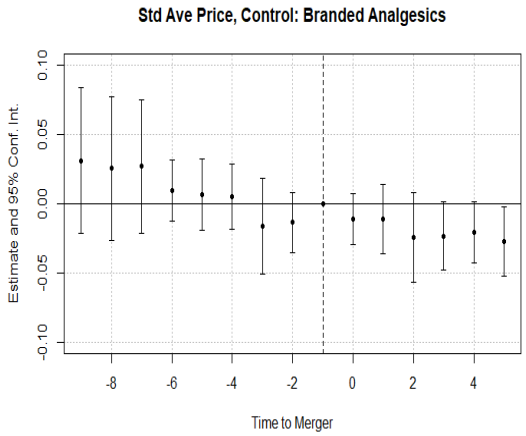


$F_{8,137} = 1.4350, p = 0.1872$

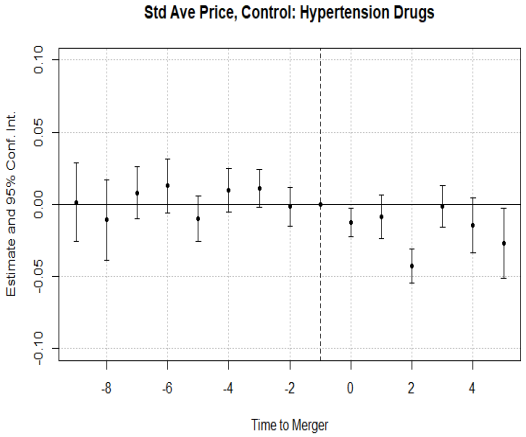


$F_{8,341} = 1.1243, p = 0.3461$

Philippine Analgesics and Hypertension Remedies



$F_{8,443} = 0.7913, p = 0.6106$



$F_{8,1338} = 0.5761, p = 0.7982$

Table A.6: Merger Price Effect, ASEAN Comparisons

	Indonesia	Malaysia	Singapore	Thailand
		Clough & Cold[a]		
Standard Average Price				
Aggregate Effect				
M×P	0.271***	0.229**	0.319**	0.153***
	(0.039)	(0.093)	(0.140)	(0.019)
Separate Effects				
GSK×P	0.248***	0.207**	0.297**	0.131***
	(0.043)	(0.095)	(0.142)	(0.017)
Pfizer×P	0.296***	0.253***	0.344**	0.178***
	(0.043)	(0.095)	(0.142)	(0.017)
Stone Price Index, Q4 2017 weights				
Aggregate Effect				
M × P	0.482***	0.424	0.499	0.362*
	(0.130)	(0.355)	(0.429)	(0.203)
Separate Effect				
GSK×P	0.614***	0.557	0.631	0.494**
	(0.143)	(0.369)	(0.441)	(0.217)
Pfizer×P	−0.356**	0.296	0.370	0.235
	(0.142)	(0.368)	(0.441)	(0.216)
Stone Price Index, Q3 2020 weights				
Aggregate Effect				
M × P	0.555***	0.476	0.425	0.393*
	(0.134)	(0.357)	(0.442)	(0.210)
Separate Effect				
GSK×P	0.773***	0.695*	0.642	0.611***
	(0.147)	(0.370)	(0.453)	(0.224)
Pfizer × P	0.345**	0.267	0.214	0.184
	(0.146)	(0.369)	(0.452)	(0.224)
Product FE	✓	✓	✓	✓
Time FE	✓	✓	✓	✓
Observations	2,719	933	843	1,424
Adjusted R^2	0.988	0.963	0.890	0.997

Note:[a]Products with the same active substance and formulation as GSK and Pfizer products

A.5 INSTRUMENT CONSTRUCTION

A.5.1 Product and Market Characteristics

Competitors share the same pricing equation as the merging firms. Decisions on product and market characteristics are made prior to the revelation of consumer valuation and shares.

Table A.7: BLP Type Instrument

Product characteristics	Count of molecules
Market characteristics	Count of proprietary and non-proprietary label (brand)
	Count of unique product j

A.5.2 Prices in Other Geographic Areas

We construct our Hausman Instrument by using prices of the same products in other ASEAN countries, namely, Indonesia, Malaysia, Singapore, and Thailand. Products in our product set are not observed in all T markets in each country. Similarly, an exact product match is not always available. We systematically broaden our matching criteria given in Table A.8 per country and combine resulting country vectors to fill in missing values. This gives us a vector of prices. When contemporaneous product prices are still unavailable, we look to the nearest market t for a proxy until the entire vector is filled in.

Table A.8: Hausman Instrument Product Matching Criteria

level 1	Corporation + Proprietary Label + Active Substance + NFC3
level 2	Corporation + Active Substance + NFC3
level 3	Corporation + Active Substance
level 4	Active Substance + NFC3
level 5	Active Substance
level 6	Corporation

A.6 FURTHER EMPIRICAL RESULTS

A.6.1 First Stage Demand Estimates

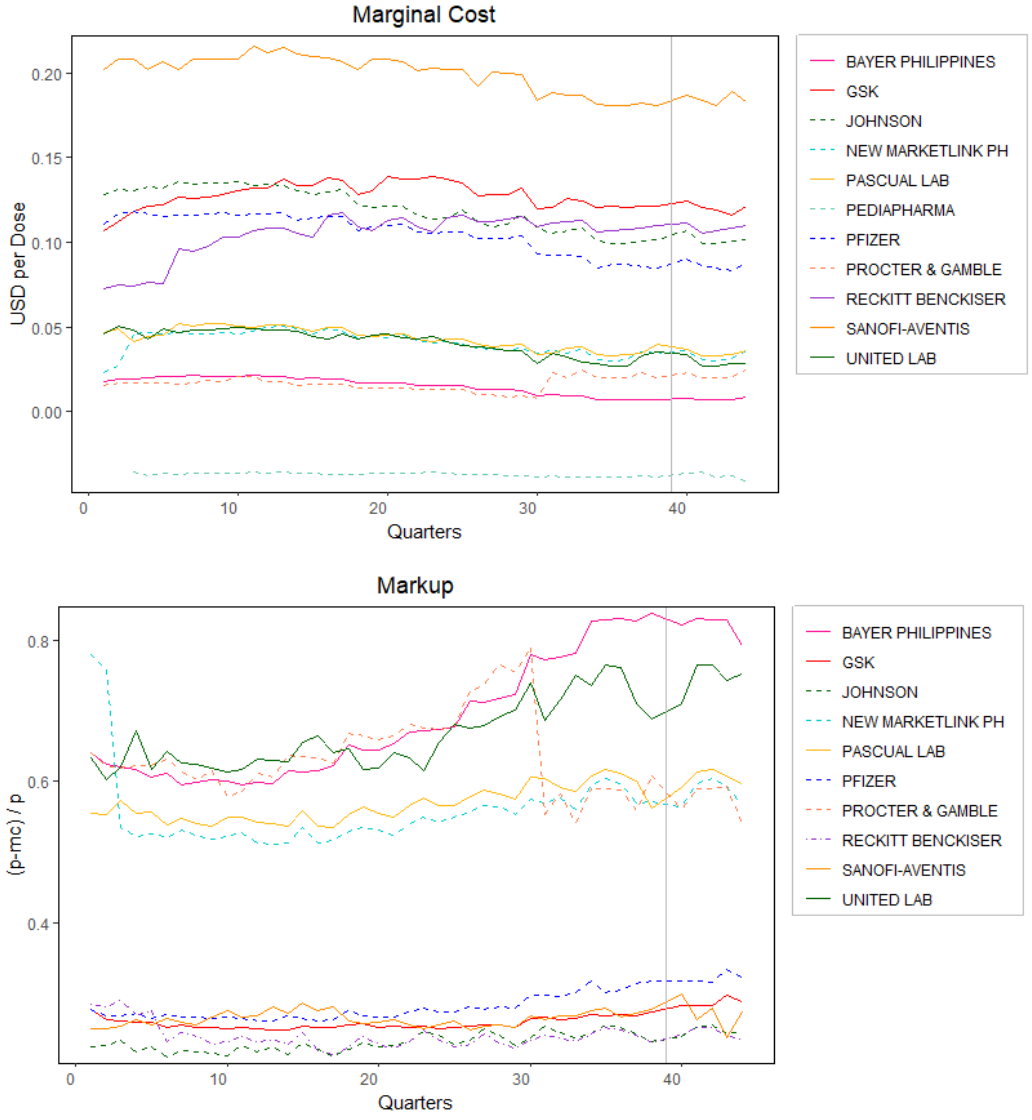
Table A.9: Logit and Nested Logit, First-Stage Estimates

	Logit	Nested Logit		
	$log(p_j)$	$log(p_j)$	$log(s_{jhg})$	$log(s_{hg})$
Number of prod (comp)	0.002^{***}			
	(0.0003)			
Number of mol (comp)	-0.001^{***}			
	(0.0002)			
Number of brand (k not j, group)		0.002^{***}	-0.014	0.159^{***}
		(0.001)	(0.029)	(0.029)
Number of pack (k not j, group)		-0.002^{***}	-0.091^{***}	0.043^{***}
		(0.0002)	(0.014)	(0.014)
Number of mol (k not j, group)		0.001^{***}	0.042^{***}	-0.055^{***}
		(0.0002)	(0.011)	(0.011)
Number of brand (comp, group)		0.00005	-0.001	0.045^{***}
		(0.0003)	(0.014)	(0.014)
ASEAN price	0.045^{***}	0.070^{***}	-0.425	-1.115^{***}
	(0.007)	(0.007)	(0.408)	(0.409)
F-test excluded instruments	33.2274	23.6265	11.6272	11.3548

Notes: 1,985 observations were used from the period Q4 2009 to Q1 2019. Demand side specifications include 38 market fixed effects and 54 product fixed effects.

A.7 ADDITIONAL SIMULATION RESULTS

Figure A.2: Marginal Costs and Mark ups Pre and Post Merger



APPENDIX B

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

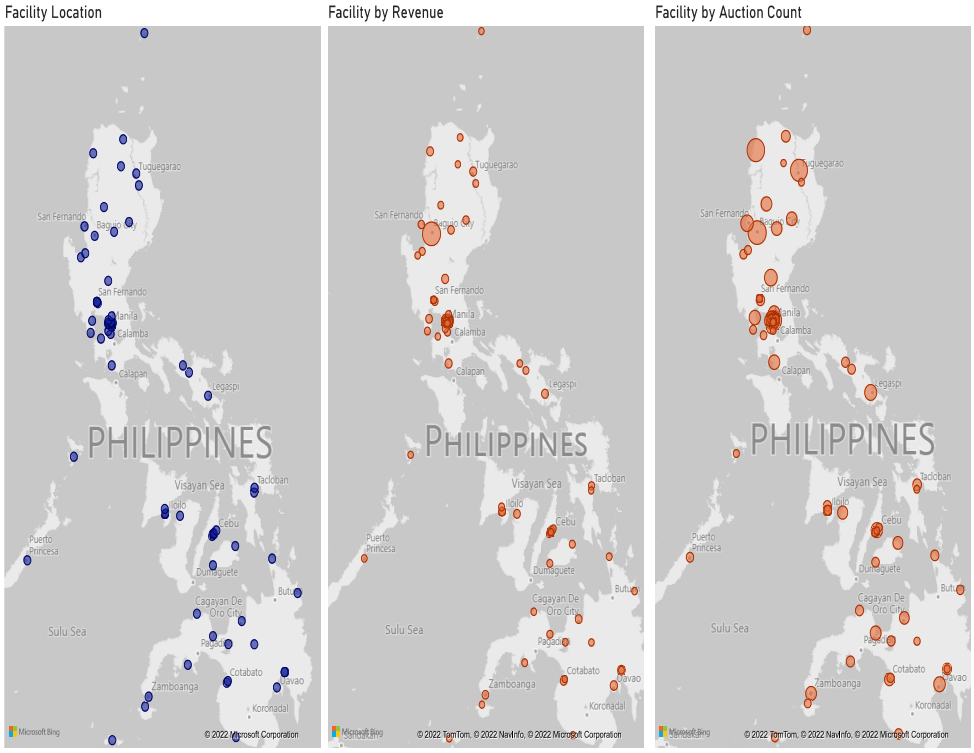
B.1 GUIDELINES FOR ALTERNATIVE PROCUREMENT METHODS

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.

B.2 GEO-MAPPING OF FACILITIES

Figure B.1: Facility Map, Department of Health Regional Offices and Hospitals



B.3 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.

B.4 DRUGNAME MATCH AND SCORE

Appendix available online.

B.5 ADDITIONAL ESTIMATION RESULTS

Table B.1: Effect on Price, Event Study (selected coefficients)

Dependent Variable:	log(Price)
DPRI (D) $\times$ I $(y = -2)$	0.1183***
	(0.0331)
DPRI (D) $\times$ I $(y = -1)$	0.2408***
	(0.0392)
DPRI (D) $\times$ I $(y = 1)$	-0.0675***
	(0.0236)
DPRI (D) $\times$ I $(y = 2)$	-0.0968***
	(0.0275)
DPRI (D) $\times$ I $(y = 3)$	-0.2159***
	(0.0323)
DPRI (D) $\times$ I $(y = 4)$	-0.1476***
	(0.0343)
DPRI (D) $\times$ 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 C

Dynamic Reserve Prices in Procurement: An Experiment

C.1 EXPERIMENT INSTRUCTIONS, TREATMENT 1

General information

Thank you for participating in todays experiment. I will read you a script to explain the nature of todays experiment and how to navigate the computer interface with which you will be working. I will be using this script to ensure that all sessions of this experiment receive the same information. This is an experiment in decision-making. In addition to a 200 Philippine Peso (PhP) fee for showing up on time, you will have the opportunity to earn more money through your decisions and the decisions of others, which we will explain soon. You will be paid in PhP at the end of the experiment after adding earnings from all rounds to your balance. All monetary amounts you will see in this experiment will be denominated in ECUs or Experimental Currency Units. They will translate into PhP at the rate of 1 ECU = 10 PhP therefore 15 ECU = 150 PhP. You will start with a balance of 50 ECUs. In each round of the experiment, you will have the opportunity to make additional earnings which will increase this balance but it will be possible to make losses as well. Your total earnings will increase with profits and decrease with losses. Should you lose so much money that your total earnings become negative, you will be declared bankrupt and asked to leave the experiment receiving only your show-up fee. At that time, one of the participants in the role of alternate will replace you. The alternate will begin participating with a balance of 50 ECUs and will have the same opportunities to gain or lose money in the experiment. If you have any questions during the experiment, raise your hand and wait for an experimenter to come to you. Do not talk, exclaim, or try to communicate with other participants during the experiment. Participants intentionally violating the rules may be asked to leave the experiment with only your show-up payment.

Outline of the Experiment

Before we go through the computer interface for the experiment, we will explain the struc-

ture of the decisions you will be making. You will be participating in a series of multiple round procurement auctions in which you will be attempting to sell a product to a buyer. There will be 10 sequences in todays experiment with each sequence giving you the opportunity to participate in up to 3 auction rounds.

In each sequence you will have some fundamental cost for providing the product to the buyer, let us call this F. In each auction round, your actual cost will be equal to this fundamental cost F plus a random draw D. So your actual cost C in a round will be C = F + D. F will be redrawn for each sequence from a uniform distribution in the range [100, 200], meaning that each value is equally likely. Then in each auction round, D will be redrawn from a uniform distribution on the range [-15, 15]. What you will be told in a round is your actual value of C=F+D. This means that from one round to another in the same sequence, your fundamental cost, F, will not change, but your realized cost, C,will as D will change from round to round. Your fundamental cost F, will change between sequences. We will take you through some examples later to make it clear how this works.

In the first round of each sequence, you will be told your realized cost for that round and everyone will participate. In each subsequent round, you will be told your realized cost for that round and will be allowed to choose whether or not to participate in the auction for that round. If you choose to participate, you will pay a cost of 2 ECUs to do so, whether you win or not. If you choose not to participate in a round, you will not be able to participate for the remaining rounds in that sequence, but you will be able to rejoin in the subsequent sequence. If you choose not to participate, there will be an alternative uncompensated activity for you to engage in while you wait for the experiment to continue. If you join an auction, then you will compete to sell the product to a hypothetical buyer with the other participants in your group who also elect to participate. You will begin a sequence in a group of five bidders, you and four others, meaning the largest possible auction will consist of five total bidders.

In the actual auction, you will know the number of competitors who are participating. Each competitor will have received a realized cost using the same method with all draws being independent. This means that all bidders will have different costs with a possible range between [85, 215]. Each bidder will submit a bid indicating the price they would be

willing to sell the item at. The seller who submitted the lowest price will win the auction and receive earnings equal to the difference between the price they submitted, P and their realized cost for that auction, C, less the 2 ECU participation cost. Therefore, the earnings from the auction will be $P - C - 2$, if you win. If you entered and lost the auction, your earnings are -2 ECU while if you do not enter the auction your earnings are 0.

Examples

We will now go through several examples to show you how all this works. Please go to your computer now and follow along. Let us examine potential auction rounds inside of a sequence. What you can see now are the realized costs for all five bidders in the first auction round of a sequence. In an actual auction, you would see only your own cost, but for this example, we will show you what is happening with all five competitors. These competitors have realized costs of 187, 125, 136, 178 and 152.

	Bidder 1	Bidder 2	Bidder 3	Bidder 4	Bidder 5
Realized Cost	187	125	136	178	152
Participate ?	Yes	Yes	Yes	Yes	Yes
Bid	225	150	145	204	190
Earnings	-2	-2	7	-2	-2

In the first auction round, everyone participates. The next line in the table shows you what bids each chose to submit. Note that these bid values were chosen randomly and are not meant to indicate suggested bids.

In this case, bidder 3 would win since they submitted the lowest price. You can then see the earnings for each bidder. The bidders who did not win all receive a -2 earnings for the auction as they paid the entry fee. Bidder 3 won the auction and therefore receives the earnings of 145-136 = 9 less the entry fee of 2 ECU, which produces a net pay-off of 7 ECU. After this auction round ends, the bidders see the results and the second round of the sequence begins.

All bidders would see their new realized costs. Each bidder must then choose whether to participate and pay the 2 ECU fee. Note that each bidder has a new realized cost. Given your cost in the first auction round, your new cost could potentially be anything in the

range of 30 ECU above or 30 ECU below that previous cost realization. You should keep this in mind as it means that your cost can shift substantially from one auction to the next.

	Bidder 1	Bidder 2	Bidder 3	Bidder 4	Bidder 5
Realized Cost	168	120	140	195	160
Participate ?	Yes	Yes	Yes	No	No
Bid	145	138	143	–	–
Earnings	-2	16	-2	0	0

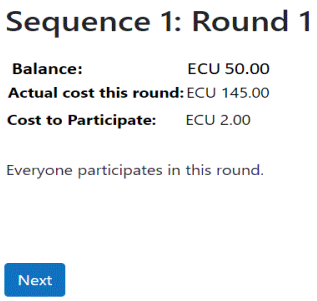
Let us assume that after seeing their new realized costs, bidders 4 and 5 decide that they no longer wish to participate, but the three others do. Bidders 1, 2, and 3 then submit the bids, meaning that bidder 2 now wins with a bid of 138 ECU. Given that their cost realization for this auction was 120 ECU, they earn an auction profit of 18 ECU less the 2 ECU participation fee, leading to total earnings of 16 ECU. The other two participants make an earnings of -2 ECU each while those staying out earn 0 for the round.

After the second round has concluded, the bidders would see the results, and there will now be one additional round in this sequence, where bidders 1, 2, 3 could participate. See the next table for their new cost draws. Assume now that bidder 1 no longer wishes to participate but bidders 2 and 3 remain in. Bidder 2 bids 138 ECU while bidder 3 bids at 135 ECU and wins. This yields a net profit to bidder 3 of 3 ECU and to bidder 2 of -2 ECU.

	Bidder 1	Bidder 2	Bidder 3	Bidder 4	Bidder 5
Realized Cost	175	137	130	–	–
Participate ?	No	Yes	Yes	–	–
Bid	–	138	135	–	–
Earnings	0	-2	3	0	0

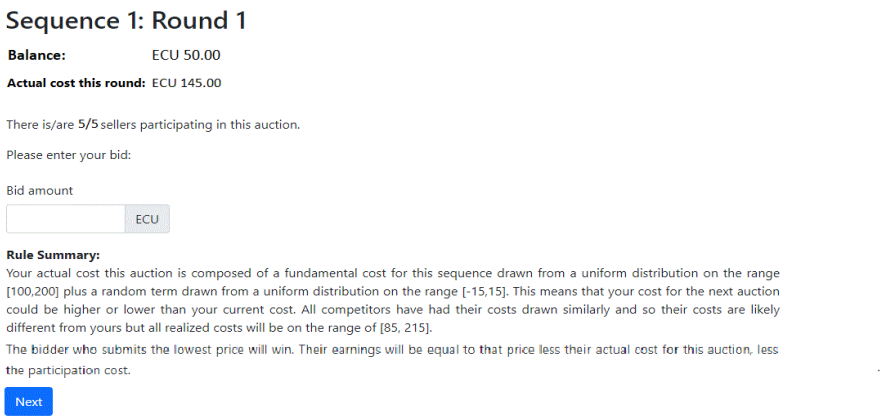
We went through this extended example to make it clear to you how the cost realizations for each participant might change across auctions and the number of competitors might also shift. Of course, in an actual round, you will see only your own cost realization and not that of the other bidders. It is important to remember that your realized cost in a sequence will shift between rounds and can go up or down. When a new sequence begins, you will have a new fundamental cost draw that will be unrelated to the one from the prior sequence. We will now take you through the actual bidding interface to show you how a sequence of auctions would unfold from the perspective of an actual bidder.

In this first screen, you are told that this is the first auction round in a sequence. You are told your realized cost for this auction round. For this example, it has been set to 145. You are also told that the cost to participate is 2 ECU. In round 1 everyone participates. You then click 'Next' to go to the next screen.

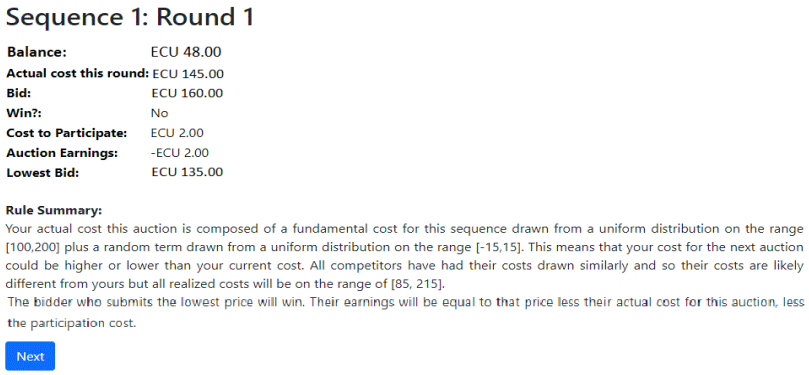


After all players in the group clicks 'Next' you will again see your cost which is 145. You are reminded how many sellers are participating in this auction. You are then asked to enter your bid. The bidder who submits the lowest bid will win the auction and will receive as earnings the difference between their bid and their realized cost less the participation fee. All other participants will receive -2 ECU earnings from the auction. A rule summary is given at the bottom of the screen. Suppose you enter 160 and then click 'Next'.

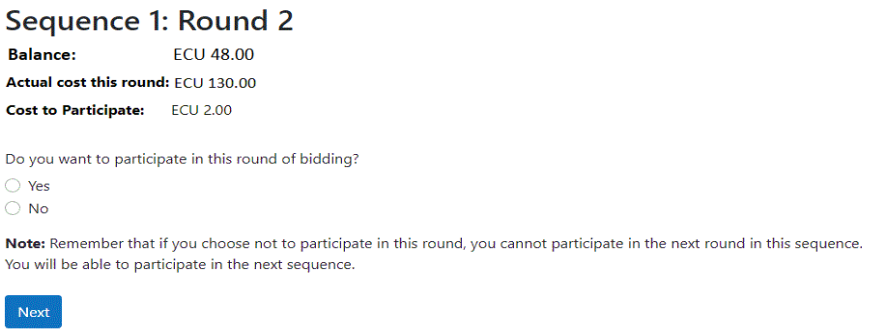
After all bidders enter their bids and click 'Next', you will see the results screen for an auction round. In this case, we presume that a bid of 160 was entered. You see that you did not win this auction and so your earnings for this round are -2 ECU due to paying



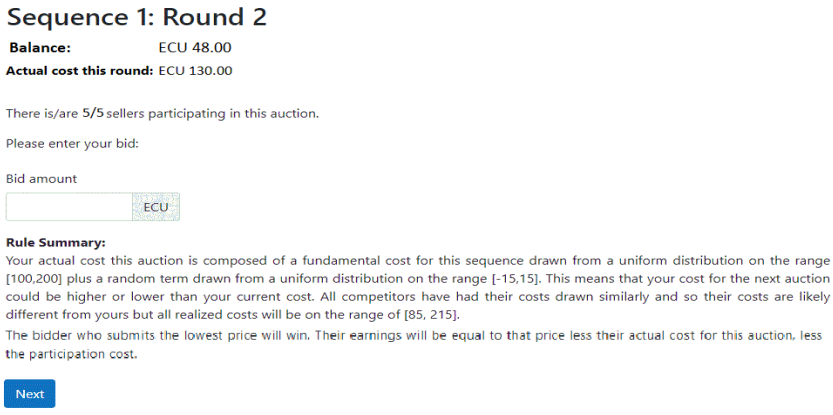
the participation cost. The lowest bid was 135 submitted by some other bidder. A rule summary is again given at the bottom of the screen.



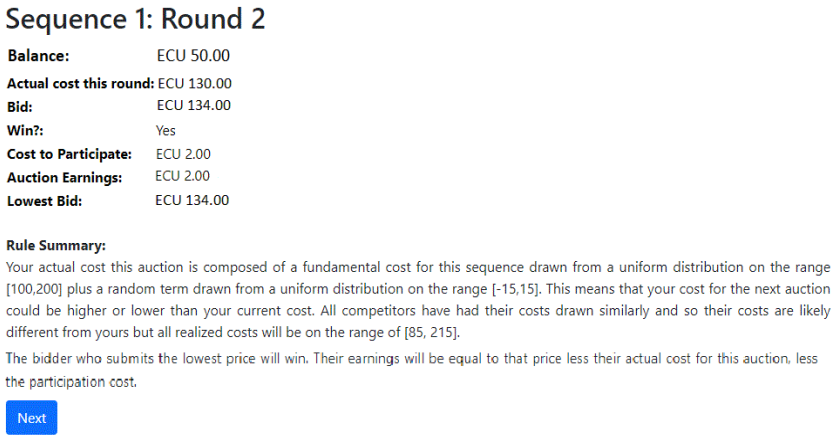
When you click 'Next' you will see what might be a second round for this sequence. You are told your new realized cost which is now 130 for this example. It was 145 in the previous round but as we explained, this value will shift up or down between rounds in a sequence. In this case, it has shifted down to 130. Seeing this information, you would be able to choose to participate and pay the 2 ECU fee or not. If you choose 'Yes', then you will be able to participate in this auction round and have the option to participate in the subsequent round in this sequence. If you choose 'No', then you will participate in no more auctions this sequence, but you will be able to participate in a future sequence. Suppose you choose 'Yes'.



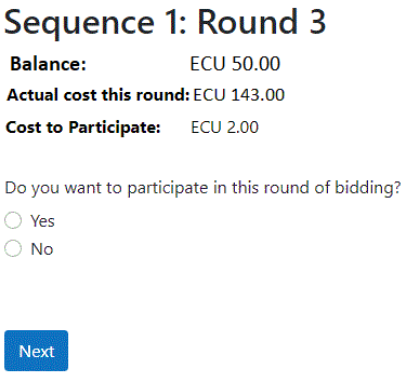
You then see a screen identical to the previous bidding screen except note that the auction round is now 2 as this is the second of this sequence. As noted on the last screen, your realized cost is now 130. Suppose you enter a bid of 134 and click 'Next'.



This takes you to the results screen for this auction. Here we represented this results screen with you winning with your bid of 134. Given that your realized cost is 130, you have auction earnings of 4 less the 2 ECU participation cost. Yielding net earnings of 2 ECUs. Clicking 'Next' will take you to the last auction round in this sequence.



You see a screen asking you if you wish to participate in the last auction for this sequence. You see that your realized cost is now 143. In the real auctions, you would make a choice and then compete in the auction or not as you choose. We skip this last round for this example.



There will be 10 sequences of these three round auctions. Remember that in each sequence, you will get a new fundamental cost draw on the range [100, 200]. This fundamental cost will then be shifted by an amount in the range [-15, 15] in each auction round for that sequence. For each auction you enter and earn a profit, your total earnings will rise. If you enter and make a loss your total earnings will fall. Remember that you will all begin with an initial balance of 50 ECUs. If you lose enough such that your total earnings reach 0, then you will be declared bankrupt and be asked to leave receiving only your show-up fee. The experiment will continue for the other participants with an alternate subject taking your place in future auctions.

If you have questions about how this experiment works, kindly raise your hand. If there are none, we will begin the first auction sequence.

C.2 EXPERIMENT INSTRUCTIONS, TREATMENT 2

General information

Thank you for participating in todays experiment. I will read you a script to explain the nature of todays experiment and how to navigate the computer interface with which you will be working. I will be using this script to ensure that all sessions of this experiment receive the same information. This is an experiment in decision-making. In addition to a 200 Philippine Peso (PhP) fee for showing up on time, you will have the opportunity to earn more money through your decisions and the decisions of others, which we will explain soon. You will be paid in PhP at the end of the experiment after adding earnings from all rounds to your balance. All monetary amounts you will see in this experiment will be denominated in ECUs or Experimental Currency Units. They will translate into PhP at the rate of 1 ECU = 10 PhP therefore 15 ECU = 150 PhP. You will start with a balance of 50 ECUs. In each round of the experiment, you will have the opportunity to make additional earnings which will increase this balance but it will be possible to make losses as well. Your total earnings will increase with profits and decrease with losses. Should you lose so much money that your total earnings become negative, you will be declared bankrupt and asked to leave the experiment receiving only your show-up fee. At that time, one of the participants in the role of alternate will replace you. The alternate will begin participating with a balance of 50 ECUs and will have the same opportunities to gain or lose money in the experiment. If you have any questions during the experiment, raise your hand and wait for an experimenter to come to you. Do not talk, exclaim, or try to communicate with other participants during the experiment. Participants intentionally violating the rules may be asked to leave the experiment with only your show-up payment.

Outline of the Experiment

Before we go through the computer interface for the experiment, we will explain the structure of the decisions you will be making. You will be participating in a series of multiple round procurement auctions in which you will be attempting to sell a product to a buyer.

There will be 10 sequences in todays experiment with each sequence giving you the opportunity to participate in up to 3 auction rounds.

In each sequence you will have some fundamental cost for providing the product to the buyer, let us call this F. In each auction round, your actual cost will be equal to this fundamental cost F plus a random draw D. So your actual cost C in a round will be C = F + D. F will be redrawn for each sequence from a uniform distribution in the range [100, 200], meaning that each value is equally likely. Then in each auction round, D will be redrawn from a uniform distribution on the range [-15, 15]. What you will be told in a round is your actual value of C=F+D. This means that from one round to another in the same sequence, your fundamental cost, F, will not change, but your realized cost, C,will as D will change from round to round. Your fundamental cost F, will change between sequences. We will take you through some examples later to make it clear how this works.

In the first round of each sequence, you will be told your realized cost for that round and everyone will participate. In each subsequent round, you will be told your realized cost for that round and will be allowed to choose whether or not to participate in the auction for that round. If you choose to participate, you will pay a cost of 2 ECUs to do so, whether you win or not. If you choose not to participate in a round, you will not be able to participate for the remaining rounds in that sequence, but you will be able to rejoin in the subsequent sequence. If you choose not to participate, there will be an alternative uncompensated activity for you to engage in while you wait for the experiment to continue. If you join an auction, then you will compete to sell the product to a hypothetical buyer with the other participants in your group who also elect to participate. You will begin a sequence in a group of five bidders, you and four others, meaning the largest possible auction will consist of five total bidders.

In the actual auction, you will know the number of competitors who are participating. Each competitor will have received a realized cost using the same method with all draws being independent. This means that all bidders will have different costs with a possible range between [85, 215]. Each bidder will submit a bid indicating the price they would be willing to sell the item at. The seller who submitted the lowest price will win the auction and receive earnings equal to the difference between the price they submitted, P and their

realized cost for that auction, C, less the 2 ECU participation cost. Therefore, the earnings from the auction will be $P - C - 2$, if you win. If you entered and lost the auction, your earnings are -2 ECU while if you do not enter the auction your earnings are 0.

Price Cap rule

Inside a sequence, there will be a bid cap on possible bids that can be submitted based on the winning bid from the prior round. This means that there will be no cap placed on bids in round 1 of a sequence but there will be in rounds 2 and 3. This bid cap will limit what bids competitors can submit, as bids must be no higher than the cap. This means that the bid cap will be the highest price that a bidder can receive in an auction. This cap will be reset between sequences, so after one sequence ends and a new one begins, in the first auction round of a new sequence, there will be no bid cap.

Examples

We will now go through several examples to show you how all this works. Please go to your computer now and follow along. Let us examine potential auction rounds inside a sequence. What you can see now are the realized costs for all five bidders in the first auction round of a sequence. In an actual auction, you would see only your own cost, but for this example, we will show you what is happening with all five competitors. These competitors have realized costs of 187, 125, 136, 178 and 152.

	Bidder 1	Bidder 2	Bidder 3	Bidder 4	Bidder 5
Realized Cost	187	125	136	178	152
Participate ?	Yes	Yes	Yes	Yes	Yes
Bid	225	150	145	204	190
Earnings	-2	-2	7	-2	-2

In the first auction round, everyone participates. The next line in the table shows you what bids each chose to submit. Note that these bid values were chosen randomly and are not meant to indicate suggested bids.

In this case, bidder 3 would win since they submitted the lowest price. You can then see the earnings for each bidder. The bidders who did not win all receive a -2 earnings

for the auction as they paid the entry fee. Bidder 3 won the auction and therefore receives the earnings of 145-136 = 9 less the entry fee of 2 ECU, which produces a net pay-off of 7 ECU. After this auction round ends, the bidders see the results and the second round of the sequence begins.

All bidders would see their new realized costs. Each bidder must then choose whether to participate and pay the 2 ECU fee. Note that each bidder has a new realized cost. Given your cost in the first auction round, your new cost could potentially be anything in the range of 30 ECU above or 30 ECU below that previous cost realization. You should keep this in mind as it means that your cost can shift substantially from one auction to the next.

	Bidder 1	Bidder 2	Bidder 3	Bidder 4	Bidder 5
Realized Cost	168	120	140	195	160
Participate ?	Yes	Yes	Yes	No	No
Bid	145	138	143	–	–
Earnings	-2	16	-2	0	0

Since bidder 3 won the first auction with a bid of 145, that is the cap in bids allowed in this second auction. Let us assume that after seeing their new realized costs and the bid cap for this auction round, bidders 4 and 5 decide that they no longer wish to participate, but the three others do. Bidders 1, 2, and 3 then submit their bids, meaning that bidder 2 now wins with a bid of 138 ECU. Given that their cost realization for this auction was 120 ECU, they earn an auction profit of 18 ECU less the 2 ECU participation fee, leading to total earnings of 16 ECU. The other two participants make earnings of -2 ECU each while those staying out earn 0 for the round.

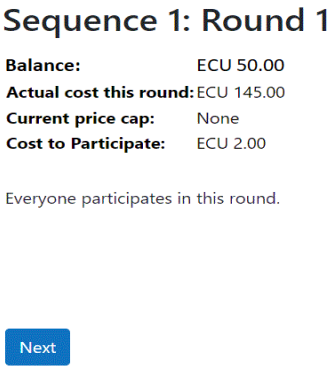
After the second round has concluded, the bidders would see the results, and there will now be one additional round in this sequence, where bidders 1, 2, 3 could participate, and the bid cap will now be 138 ECU. See the next table for their new cost draws. Assume now that bidder 1 no longer wishes to participate but bidders 2 and 3 remain in. Bidder 2 bids at the cap of 138 ECU while bidder 3 bids at 135 ECU and wins. This yields a net profit to bidder 3 of 3 ECU and to bidder 2 of -2 ECU.

We went through this extended example to make it clear to you how the cost realizations for each participant might change across auctions and how the bid cap and number of competitors might also shift. Of course, in an actual round, you will see only your own

	Bidder 1	Bidder 2	Bidder 3	Bidder 4	Bidder 5
Realized Cost	175	137	130	–	–
Participate ?	No	Yes	Yes	–	–
Bid	–	138	135	–	–
Earnings	0	-2	3	0	0

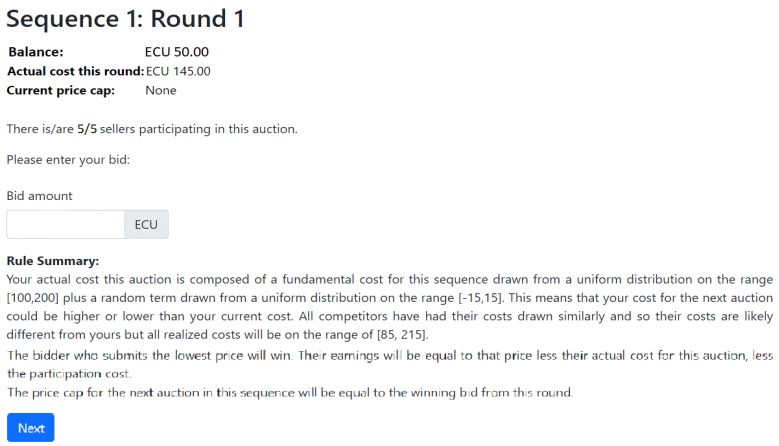
cost realization and not that of the other bidders. It is important to remember that your realized cost in a sequence will shift between rounds and can go up or down. When a new sequence begins, you will have a new fundamental cost draw that will be unrelated to the one from the prior sequence. We will now take you through the actual bidding interface to show you how a sequence of auctions would unfold from the perspective of an actual bidder.

In this first screen, you are told that this is the first auction round in a sequence. You are told your realized cost for this auction round. For this example, it has been set to 145. You are also told about the current price cap. Since this is the first auction in this sequence, there is none. You are told the cost to participate, 2 ECU, and that in round 1 everyone participates. You then click 'Next' to go to the next screen.

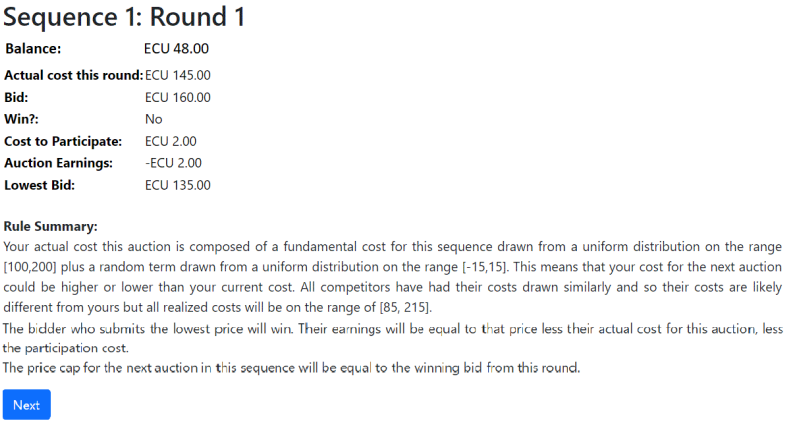


After all players in the group clicks 'Next' you will again see your cost which is 145. You are reminded of the current price cap and told how many sellers are participating in this auction. You are then asked to enter your bid. The bidder who submits the lowest bid will win the auction and will receive as earnings the difference between their bid and their realized cost less the participation fee. All other participants will receive -2 ECU earnings

from the auction. A rule summary is given at the bottom of the screen. Suppose you enter 160 and then click 'Next'.

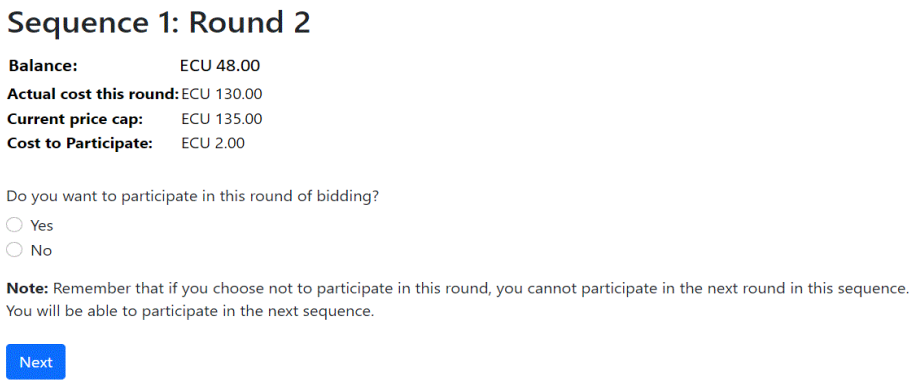


After all bidders enter their bids and click 'Next', you will see the results screen for an auction round. In this case, we presume that a bid of 160 was entered. You see that you did not win this auction and so your earnings for this round are -2 ECU due to paying the participation cost. The lowest bid was 135 submitted by some other bidder. They won this round and the new bid cap will now be 135 in the next auction. A rule summary is again given at the bottom of the screen.

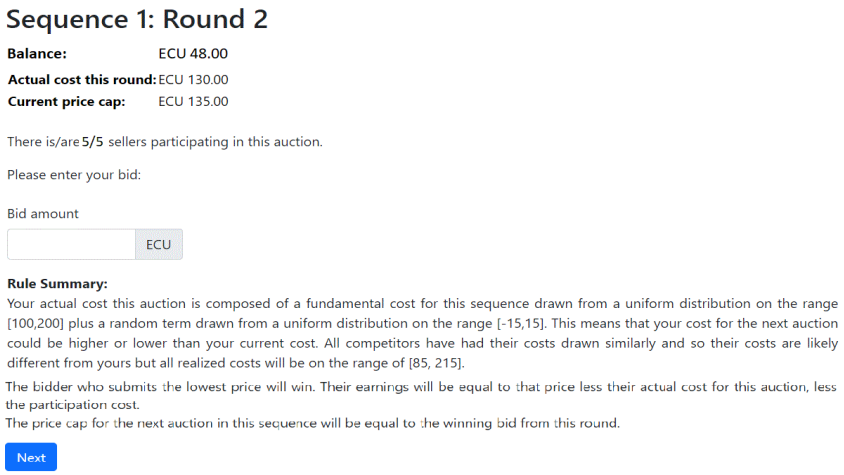


When you click 'Next' you will see what might be a second round for this sequence. You are told your new realized cost which is now 130 for this example. It was 145 in the

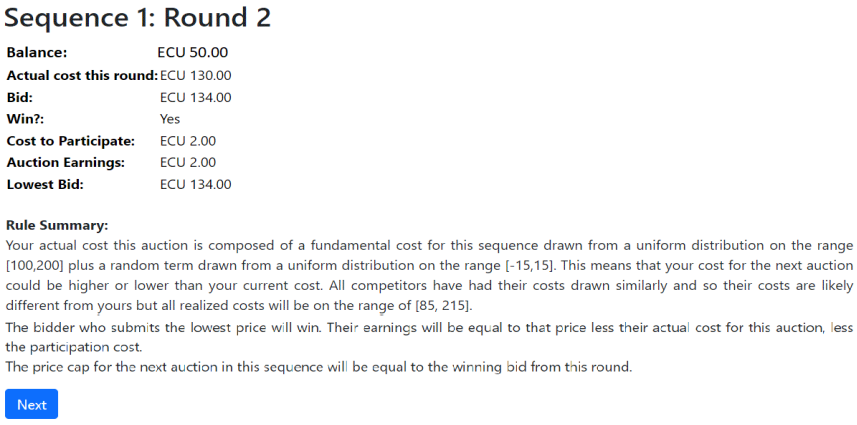
previous round but as we explained, this value will shift up or down between rounds in a sequence. In this case, it has shifted down to 130. Notice that the bid cap is 135 meaning the highest price you can bid in this round is 135. Seeing this information, you would be able to choose to participate and pay the 2 ECU fee or not. If you choose 'Yes', then you will be able to participate in this auction round and have the option to participate in the subsequent round in this sequence. If you choose 'No', then you will participate in no more auctions this sequence, but you will be able to participate in a future sequence. Suppose you choose 'Yes'.



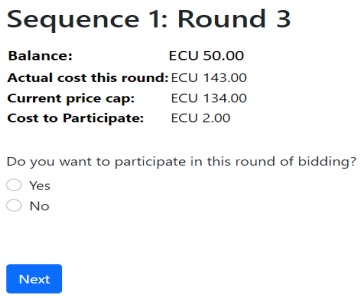
You then see a screen identical to the previous bidding screen except note that the auction round is now 2 as this is the second of this sequence. As noted on the last screen, your realized cost is now 130 and the bid cap is 135. Suppose you enter a bid of 134 and click 'Next'.



This takes you to the results screen for this auction. Here we represented this results screen with you winning with your bid of 134. Given that your realized cost is 130, you have auction earnings of 4 less the 2 ECU participation cost. Yielding net earnings of 2 ECUs. As your bid was the lowest, your bid sets the cap for the third and final auction of this sequence. Clicking 'Next' will take you to that one.



You see a screen asking you if you wish to participate in the last auction for this sequence. You see that your realized cost is now 143. The bid cap as set by your winning bid in the last round is 134 meaning that you would have to bid at most 134 if you entered the auction. In the real auctions, you would make a choice and then compete in the auction or not as you choose. We skip this last round for this example.



There will be 10 sequences of these three round auctions. Remember that in each sequence, you will get a new fundamental cost draw on the range [100, 200]. This fundamental cost will then be shifted by an amount in the range [-15, 15] in each auction round for that sequence. For each auction you enter and earn a profit, your total earnings will rise. If you enter and make a loss your total earnings will fall. Remember that you will all begin with an initial balance of 50 ECUs. If you lose enough such that your total earnings reach 0, then you will be declared bankrupt and be asked to leave receiving only your show-up fee. The experiment will continue for the other participants with an alternate subject taking your place in future auctions.

If you have questions about how this experiment works, kindly raise your hand. If there are none, we will begin the first auction sequence.

C.3 EXPERIMENT INSTRUCTIONS, TREATMENT 3

General information

Thank you for participating in todays experiment. I will read you a script to explain the nature of todays experiment and how to navigate the computer interface with which you will be working. I will be using this script to ensure that all sessions of this experiment receive the same information. This is an experiment in decision-making. In addition to a 200 Philippine Peso (PhP) fee for showing up on time, you will have the opportunity to earn more money through your decisions and the decisions of others, which we will explain soon. You will be paid in PhP at the end of the experiment after adding earnings from all rounds to your balance. All monetary amounts you will see in this experiment will be denominated in ECUs or Experimental Currency Units. They will translate into PhP at the rate of 1 ECU = 10 PhP therefore 15 ECU = 150 PhP. You will start with a balance of 50 ECUs. In each round of the experiment, you will have the opportunity to make additional earnings which will increase this balance but it will be possible to make losses as well. Your total earnings will increase with profits and decrease with losses. Should you lose so much money that your total earnings become negative, you will be declared bankrupt and asked to leave the experiment receiving only your show-up fee. At that time, one of the participants in the role of alternate will replace you. The alternate will begin participating with a balance of 50 ECUs and will have the same opportunities to gain or lose money in the experiment. If you have any questions during the experiment, raise your hand and wait for an experimenter to come to you. Do not talk, exclaim, or try to communicate with other participants during the experiment. Participants intentionally violating the rules may be asked to leave the experiment with only your show-up payment.

Outline of the Experiment

Before we go through the computer interface for the experiment, we will explain the structure of the decisions you will be making. You will be participating in a series of multiple round procurement auctions in which you will be attempting to sell a product to a buyer.

There will be 10 sequences in todays experiment with each sequence giving you the opportunity to participate in up to 3 auction rounds.

In each sequence you will have some fundamental cost for providing the product to the buyer, let us call this F. In each auction round, your actual cost will be equal to this fundamental cost F plus a random draw D. So your actual cost C in a round will be C = F + D. F will be redrawn for each sequence from a uniform distribution in the range [100, 200], meaning that each value is equally likely. Then in each auction round, D will be redrawn from a uniform distribution on the range [-15, 15]. What you will be told in a round is your actual value of C=F+D. This means that from one round to another in the same sequence, your fundamental cost, F, will not change, but your realized cost, C,will as D will change from round to round. Your fundamental cost F, will change between sequences. We will take you through some examples later to make it clear how this works.

In the first round of each sequence, you will be told your realized cost for that round and everyone will participate. In each subsequent round, you will be told your realized cost for that round and will be allowed to choose whether or not to participate in the auction for that round. If you choose to participate, you will pay a cost of 2 ECUs to do so, whether you win or not. If you choose not to participate in a round, you will not be able to participate for the remaining rounds in that sequence, but you will be able to rejoin in the subsequent sequence. If you choose not to participate, there will be an alternative uncompensated activity for you to engage in while you wait for the experiment to continue. If you join an auction, then you will compete to sell the product to a hypothetical buyer with the other participants in your group who also elect to participate. You will begin a sequence in a group of five bidders, you and four others, meaning the largest possible auction will consist of five total bidders.

In the actual auction, you will know the number of competitors who are participating. Each competitor will have received a realized cost using the same method with all draws being independent. This means that all bidders will have different costs with a possible range between [85, 215]. Each bidder will submit a bid indicating the price they would be willing to sell the item at. The seller who submitted the lowest price will win the auction and receive earnings equal to the difference between the price they submitted, P and their

realized cost for that auction, C, less the 2 ECU participation cost. Therefore, the earnings from the auction will be $P - C - 2$, if you win. If you entered and lost the auction, your earnings are -2 ECU while if you do not enter the auction your earnings are 0.

Treatment Specific Instructions

Price Cap rule

Each participant will be randomly assigned to a group. Each group will be randomly matched with another. Inside a sequence, there will be a bid cap on possible bids that can be submitted based on the based on winning bid in matched group in the prior round. Note that this means your bids do not effect the bid cap in your group. This means that there will be no cap placed on bids in round 1 of a sequence but there will be in rounds 2 and 3. This bid cap will limit what bids competitors can submit, as bids must be no higher than the cap. This means that the bid cap will be the highest price that a bidder can receive in an auction. This cap will be reset between sequences, so after one sequence ends and a new one begins, in the first auction round of a new sequence, there will be no bid cap.

Examples

We will now go through several examples to show you how all this works. Please go to your computer now and follow along. Let us examine potential auction rounds inside a sequence. What you can see now are the realized costs for all five bidders in the first auction round of a sequence. In an actual auction, you would see only your own cost, but for this example, we will show you what is happening with all five competitors. These competitors have realized costs of 187, 125, 136, 178 and 152.

	Bidder 1	Bidder 2	Bidder 3	Bidder 4	Bidder 5
Realized Cost	187	125	136	178	152
Participate ?	Yes	Yes	Yes	Yes	Yes
Bid	225	150	145	204	190
Earnings	-2	-2	7	-2	-2

In the first auction round, everyone participates. The next line in the table shows you

what bids each chose to submit. Note that these bid values were chosen randomly and are not meant to indicate suggested bids.

In this case, bidder 3 would win since they submitted the lowest price. You can then see the earnings for each bidder. The bidders who did not win all receive a -2 earnings for the auction as they paid the entry fee. Bidder 3 won the auction and therefore receives the earnings of 145-136 = 9 less the entry fee of 2 ECU, which produces a net pay-off of 7 ECU. After this auction round ends, the bidders see the results and the second round of the sequence begins.

All bidders would see their new realized costs. Each bidder must then choose whether to participate and pay the 2 ECU fee. Note that each bidder has a new realized cost. Given your cost in the first auction round, your new cost could potentially be anything in the range of 30 ECU above or 30 ECU below that previous cost realization. You should keep this in mind as it means that your cost can shift substantially from one auction to the next.

	Bidder 1	Bidder 2	Bidder 3	Bidder 4	Bidder 5
Realized Cost	168	120	140	195	160
Participate ?	Yes	Yes	Yes	No	No
Bid	145	138	143	–	–
Earnings	-2	16	-2	0	0

The winning bid in the matched group from round 1 is 165. That is the cap in bids allowed in this second auction. Let us assume that after seeing their new realized costs and the bid cap for this auction round, bidders 4 and 5 decide that they no longer wish to participate, but the three others do. Bidders 1, 2, and 3 then submit their bids, meaning that bidder 2 now wins with a bid of 138 ECU. Given that their cost realization for this auction was 120 ECU, they earn an auction profit of 18 ECU less the 2 ECU participation fee, leading to total earnings of 16 ECU. The other two participants make earnings of -2 ECU each while those staying out earn 0 for the round.

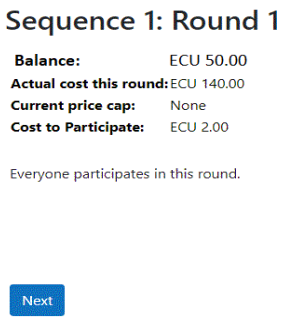
After the second round has concluded, the bidders would see the results, and there will now be one additional round in this sequence, where bidders 1, 2, 3 could participate. The winning bid in the matched group in round 2 is 153 so that will be the bid cap in this last round. See the next table for their new cost draws. Assume now that bidder 1 no longer wishes to participate but bidders 2 and 3 remain in. Bidder 2 bids 138 ECU while bidder 3 bids at 135 ECU and wins. This yields a net profit to bidder 3 of 3 ECU and to bidder 2 of -2 ECU.

	Bidder 1	Bidder 2	Bidder 3	Bidder 4	Bidder 5
Realized Cost	175	137	130	–	–
Participate ?	No	Yes	Yes	–	–
Bid	–	138	135	–	–
Earnings	0	-2	3	0	0

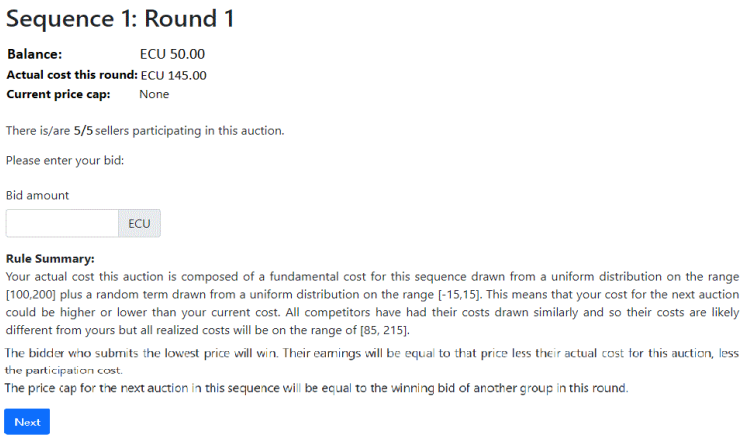
We went through this extended example to make it clear to you how the cost realizations for each participant might change across auctions and how the bid cap and number of competitors might also shift. Of course, in an actual round, you will see only your own cost realization and not that of the other bidders. It is important to remember that your realized cost in a sequence will shift between rounds and can go up or down. When a new sequence begins, you will have a new fundamental cost draw that will be unrelated to the one from the prior sequence. We will now take you through the actual bidding interface to show you how a sequence of auctions would unfold from the perspective of an actual bidder.

In this first screen, you are told that this is the first auction round in a sequence. You are told your realized cost for this auction round. For this example, it has been set to 145. You are also told about the current price cap. Since this is the first auction in this sequence, there is none. You are told the cost to participate, 2 ECU, and that in round 1 everyone participates. You then click 'Next' to go to the next screen.

After all players in the group clicks 'Next' you will again see your cost which is 140. You are reminded of the current price cap and told how many sellers are participating in this auction. You are then asked to enter your bid. The bidder who submits the lowest bid will win the auction and will receive as earnings the difference between their bid and their realized cost less the participation fee. All other participants will receive -2 ECU earnings

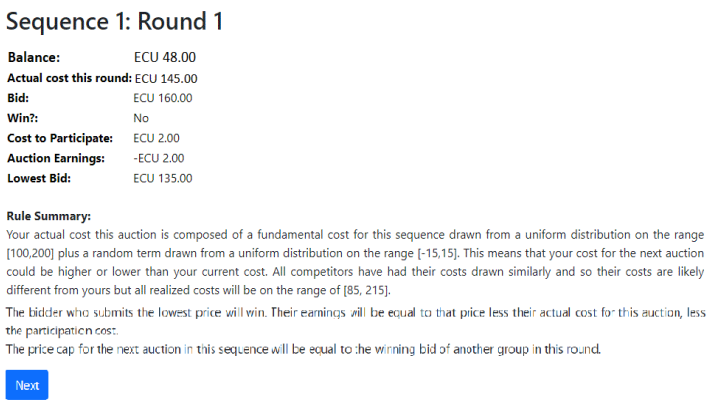


from the auction. A rule summary is given at the bottom of the screen. Suppose you enter 160 and then click 'Next'.



After all bidders enter their bids and click 'Next', you will see the results screen for an auction round. In this case, we presume that a bid of 160 was entered. You see that you did not win this auction and so your earnings for this round are -2 ECU due to paying the participation cost. The lowest bid was 135 submitted by some other bidder in your group. Suppose the lowest bid in another group was 150. The new bid cap in your group in the next round will be 150. A rule summary is again given at the bottom of the screen.

When you click 'Next' you will see what might be a second round for this sequence. You are told your new realized cost which is now 126 for this example. It was 145 and as



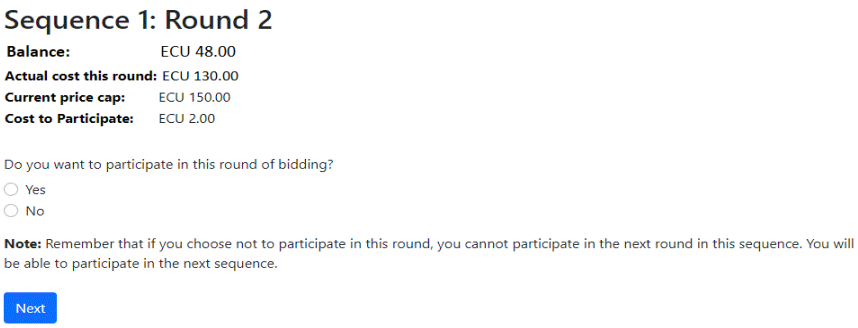
Sequence 1: Round 1

Balance: ECU 48.00
Actual cost this round: ECU 145.00
Bid: ECU 160.00
Win?: No
Cost to Participate: ECU 2.00
Auction Earnings: -ECU 2.00
Lowest Bid: ECU 135.00

Rule Summary:
Your actual cost this auction is composed of a fundamental cost for this sequence drawn from a uniform distribution on the range [100,200] plus a random term drawn from a uniform distribution on the range [-15,15]. This means that your cost for the next auction could be higher or lower than your current cost. All competitors have had their costs drawn similarly and so their costs are likely different from yours but all realized costs will be on the range of [85, 215].
The bidder who submits the lowest price will win. Their earnings will be equal to that price less their actual cost for this auction, less the participation cost.
The price cap for the next auction in this sequence will be equal to the winning bid of another group in this round.

Next

we explained in each round your cost will shift up or down. In this case, it has shifted down to 130. Notice that the bid cap is 150 meaning the highest price you can bid in this round is 150. Seeing this information, you would be able to choose to participate and pay the 2 ECU fee or not. If you choose 'Yes', then you will be able to participate in this auction round and have the option to participate in the subsequent round in this sequence. If you choose 'No', then you will participate in no more auctions this sequence, but you will be able to participate in a future sequence. Suppose you choose 'Yes'.



Sequence 1: Round 2

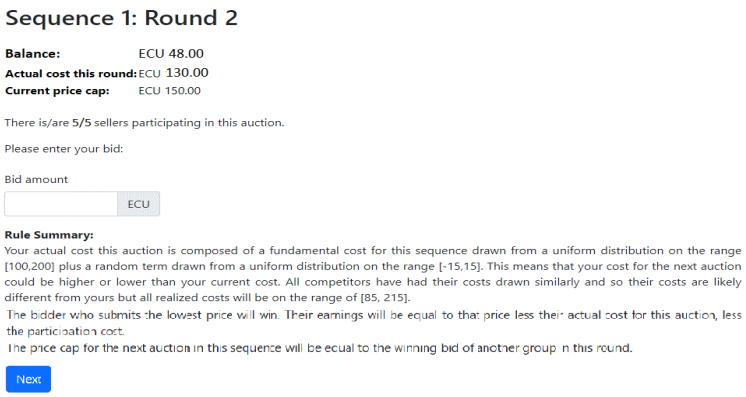
Balance: ECU 48.00
Actual cost this round: ECU 130.00
Current price cap: ECU 150.00
Cost to Participate: ECU 2.00

Do you want to participate in this round of bidding?
Yes
No

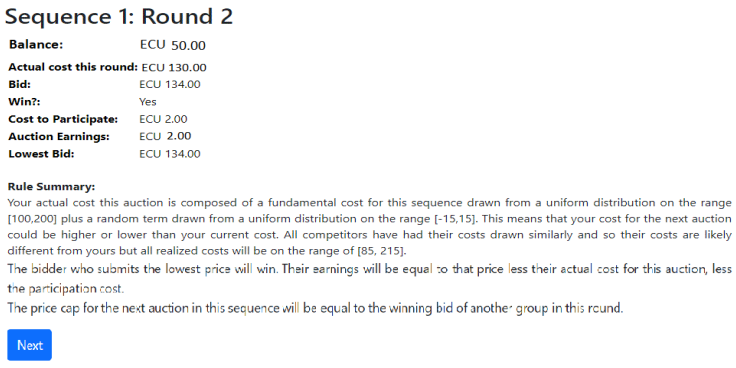
Note: Remember that if you choose not to participate in this round, you cannot participate in the next round in this sequence. You will be able to participate in the next sequence.

Next

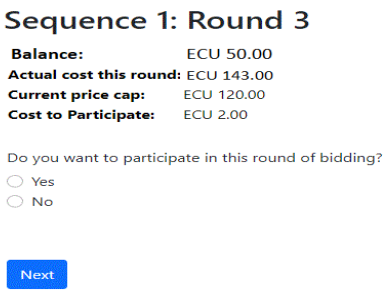
You then see a screen identical to the previous bidding screen except note that the auction round is now 2 as this is the second of this sequence. As noted on the last screen, your realized cost is now 130 and the bid cap is 150. Suppose you enter a bid of 134 and click 'Next'.



This takes you to the results screen for this auction. Here we represented this results screen with you winning with your bid of 134. Given that your realized cost is 130, you have auction earnings of 4 less the 2 ECU participation cost. Yielding net earnings of 2 ECUs. Suppose that the lowest bid in the other group in this round is 120. The bid cap for your group in the third and final auction of this sequence will be 120. Clicking 'Next' will take you to that one.



You see a screen asking you if you wish to participate in the last auction for this sequence. You see that your realized cost is now 143. The bid cap as set by the winning bid in another group last round is 120 meaning that you would have to bid at most 120 if you entered the auction. In the real auctions, you would make a choice and then compete in the auction or not as you choose. We skip this last round for this example.



There will be 10 sequences of these three round auctions. Remember that in each sequence, you will get a new fundamental cost draw on the range [100, 200]. This fundamental cost will then be shifted by an amount in the range [-15, 15] in each auction round for that sequence. For each auction you enter and earn a profit, your total earnings will rise. If you enter and make a loss your total earnings will fall. Remember that you will all begin with an initial balance of 50 ECUs. If you lose enough such that your total earnings reach 0, then you will be declared bankrupt and be asked to leave receiving only your show-up fee. The experiment will continue for the other participants with an alternate subject taking your place in future auctions.

If you have questions about how this experiment works, kindly raise your hand. If there are none, we will begin the first auction sequence.

C.4 STANDARD BID FUNCTION

From Equation 3.3, multiply both sides by $(1 - F(s))^{n-2}$,

$$\big(1 - F(s)\big)^{n-1} b'(s) - b(s)(n-1)\big(1 - F(s)\big)^{n-2} f(s) = -s(n-1)f(s)\big(1 - F(s)\big)^{n-2}$$
$$\frac{d}{ds}\Big[\big(1 - F(s)\big)^{n-1} b(s)\Big] = -s(n-1)f(s)\big(1 - F(s)\big)^{n-2}$$

Let $s = \tilde{s}$, rewrite and integrate both sides from s to $\overline{s}$,

$$\int_s^{\overline{s}} \frac{d}{d\tilde{s}}\Big[\big(1 - F(\tilde{s})\big)^{n-1} b(\tilde{s})\Big] = \int_s^{\overline{s}} -\tilde{s}(n-1)f(\tilde{s})\big(1 - F(\tilde{s})\big)^{n-2}$$

Since F is continuous, and integrating the right hand side by parts, this reduces to,

$$b(\tilde{s}) - \big(1 - F(s)\big)^{n-1} b(s) = \tilde{s} - s\big(1 - F(s)\big)^{n-1} - \int_s^{\overline{s}} \big(1 - F(s)\big)^{n-1} d\tilde{s}$$

Using the boundary condition $b(\overline{s}) = \overline{s}$ and re-arranging terms, we get Equation 3.4 in section 3.4.

C.5 STANDARD BID FUNCTION EXAMPLES

From Equation 3.4, symmetric equilibrium with $c = s$, F is uniform, continuous on $[100, 200]$

$$b(s) = s + \frac{\int_s^{\bar{s}} \big(1 - F(\tilde{s})\big)^{n-1} \, d\tilde{s}}{\big(1 - F(s)\big)^{n-1}}$$

Example 1.1.1 Suppose $c = 110$ and $n = 5$

$$\begin{aligned} b(s) &= 110 + \frac{\int_{110}^{200} \big(1 - F(\tilde{s})\big)^{4} \, d\tilde{s}}{\big(1 - F(110)\big)^{4}} \\ &= 110 + \frac{11.8090}{0.6561} \\ &= 128 \end{aligned}$$

Example 1.1.2 Given same $c = 110$ but with less competitors, $n = 4$

$$\begin{aligned} b(s) &= 110 + \frac{\int_{110}^{200} \big(1 - F(\tilde{s})\big)^{3} \, d\tilde{s}}{\big(1 - F(110)\big)^{3}} \\ &= 110 + \frac{16.4025}{0.729} \\ &= 132.5 \end{aligned}$$

C.6 BID FUNCTION WITH TRAPEZOIDAL DISTRIBUTION

From Figure 3.1, define line segments between a, c, d, b as $l_1 = (c - a)$, $l_2 = (d - c)$, and $l_3 = (d - b)$, where $w \equiv l_1 + l_2 + l_3 = (b - a)$. The expression for the area of the trapezoid is $h(c - a)/2 + h(d - c) + h(b - d)/2$. Equating this expression to one, to represent a pdf, we can solve for the height, $h = 2/(l_1 + 2l_2 + l_3)$. The pdf $f(x)$ is then given by,

$$f(r) = \begin{cases} \dfrac{(r-a)}{(c-a)}h & \text{if} \quad a \le r \le c, \\ h & \text{if} \quad c \le r \le d, \\ \dfrac{(b-r)}{(b-d)}h & \text{if} \quad d \le r \le b. \end{cases} \tag{C.1}$$

The cdf is obtained by integrating the pdf within the limits $-\infty$ to r. We can therefore express the cdf of the trapezoid distribution as,

$$F(r) = \begin{cases} \dfrac{h(r-a)^2}{2(c-a)} & \text{if} \quad a \le r \le c, \\ \dfrac{h}{2}(c-a) + h(r-c) & \text{if} \quad c \le r \le d, \\ 1 - \dfrac{h(b-r)^2}{2(b-d)} & \text{if} \quad d \le r \le b. \end{cases} \tag{C.2}$$

Substituting the cdf in the standard equilibrium bid function we arrive at Equation 3.5.

C.7 TRAPEZOID DISTRIBUTION BID FUNCTION EXAMPLES

From Equation 3.5, symmetric equilibrium with $c + \delta = s = r$, F is trapezoid, continuous on $[85, 100, 200, 215]$

For cost realizations, $a \leq r \leq c$

$$b(r) = r + \frac{\int_{r}^{c} \left(1 - \frac{(\tilde{r} - a)^2}{l_1(w + l_2)}\right)^{n-1} d\tilde{r}}{\left(1 - \frac{(r - a)^2}{l_1(w + l_2)}\right)^{n-1}}$$

Example 2.1.1 Suppose $c = 90, \delta = 5$ and $n = 5$

$$\begin{aligned} b(r) &= 95 + \frac{\int_{95}^{100} \left(1 - \frac{(\tilde{r} - 90)^2}{10(120 + 10)}\right)^{4} d\tilde{r}}{\left(1 - \frac{(95 - 90)^2}{10(120 + 10)}\right)^{4}} \\ &= 95 + 4.5055 \\ &= 99.5055 \end{aligned}$$

Example 2.1.2 Suppose $c = 90, \delta = 5$ and $n = 4$

$$\begin{aligned} b(r) &= 95 + \frac{\int_{95}^{100} \left(1 - \frac{(\tilde{r} - 90)^2}{10(120 + 10)}\right)^{3} d\tilde{r}}{\left(1 - \frac{(95 - 90)^2}{10(120 + 10)}\right)^{3}} \\ &= 95 + 4.6222 \\ &= 99.6222 \end{aligned}$$

For cost realizations, $c \leq r \leq d$

$$b(r) = r + \frac{\int_{r}^{d} \left(1 - \frac{l_1 + 2(\tilde{r} - c)}{w + l_2}\right)^{n-1} d\tilde{r}}{\left(1 - \frac{l_1 + 2(r - c)}{w + l_2}\right)^{n-1}}$$

Example 2.2.1 Suppose $c = 150, \delta = 5$ and $n = 5$

$$\begin{aligned} b(r) &= 155 + \frac{\int_{155}^{200} \left(1 - \frac{10 + 2(\tilde{r} - 100)}{120 + 100}\right)^{4} d\tilde{r}}{\left(1 - \frac{10 + 2(155 - 100)}{120 + 100}\right)^{4}} \\ &= 155 + 9.9999 \\ &= 164.9999 \end{aligned}$$

Example 2.2.2 Suppose $c = 90, \delta = 5$ and $n = 4$

$$\begin{aligned} b(r) &= 155 + \frac{\int_{155}^{200} \left(1 - \frac{10 + 2(\tilde{r} - 100)}{120 + 100}\right)^{3} d\tilde{r}}{\left(1 - \frac{10 + 2(155 - 100)}{120 + 100}\right)^{3}} \\ &= 155 + 12.4988 \\ &= 167.499 \end{aligned}$$

For cost realizations, $d \leq r \leq b$

$$b(r) = r + \frac{\int_{r}^{b} \left(\frac{(b-\tilde{r})^2}{l_3\big(w+l_2\big)} \right)^{n-1} d\tilde{r}}{\left(\frac{(b-r)^2}{l_3\big(w+l_2\big)} \right)^{n-1}}$$

Example 2.2.1 Suppose $c = 200, \delta = 5$ and $n = 5$

$$\begin{aligned} b(r) &= 205 + \frac{\int_{205}^{210} \left(\frac{(210-\tilde{r})^2}{10\big(120+100\big)} \right)^{4} d\tilde{r}}{\left(\frac{(210-205)^2}{10\big(120+100\big)} \right)^{4}} \\ &= 205 + 1 \\ &= 206 \end{aligned}$$

Example 2.2.2 Suppose $c = 90, \delta = 5$ and $n = 4$

$$\begin{aligned} b(r) &= 205 + \frac{\int_{205}^{210} \left(\frac{(210-\tilde{r})^2}{10\big(120+100\big)} \right)^{3} d\tilde{r}}{\left(\frac{(210-205)^2}{10\big(120+100\big)} \right)^{3}} \\ &= 205 + 1.25 \\ &= 206.25 \end{aligned}$$

C.8 DYNAMICS BY FIRST AND SECOND HALF

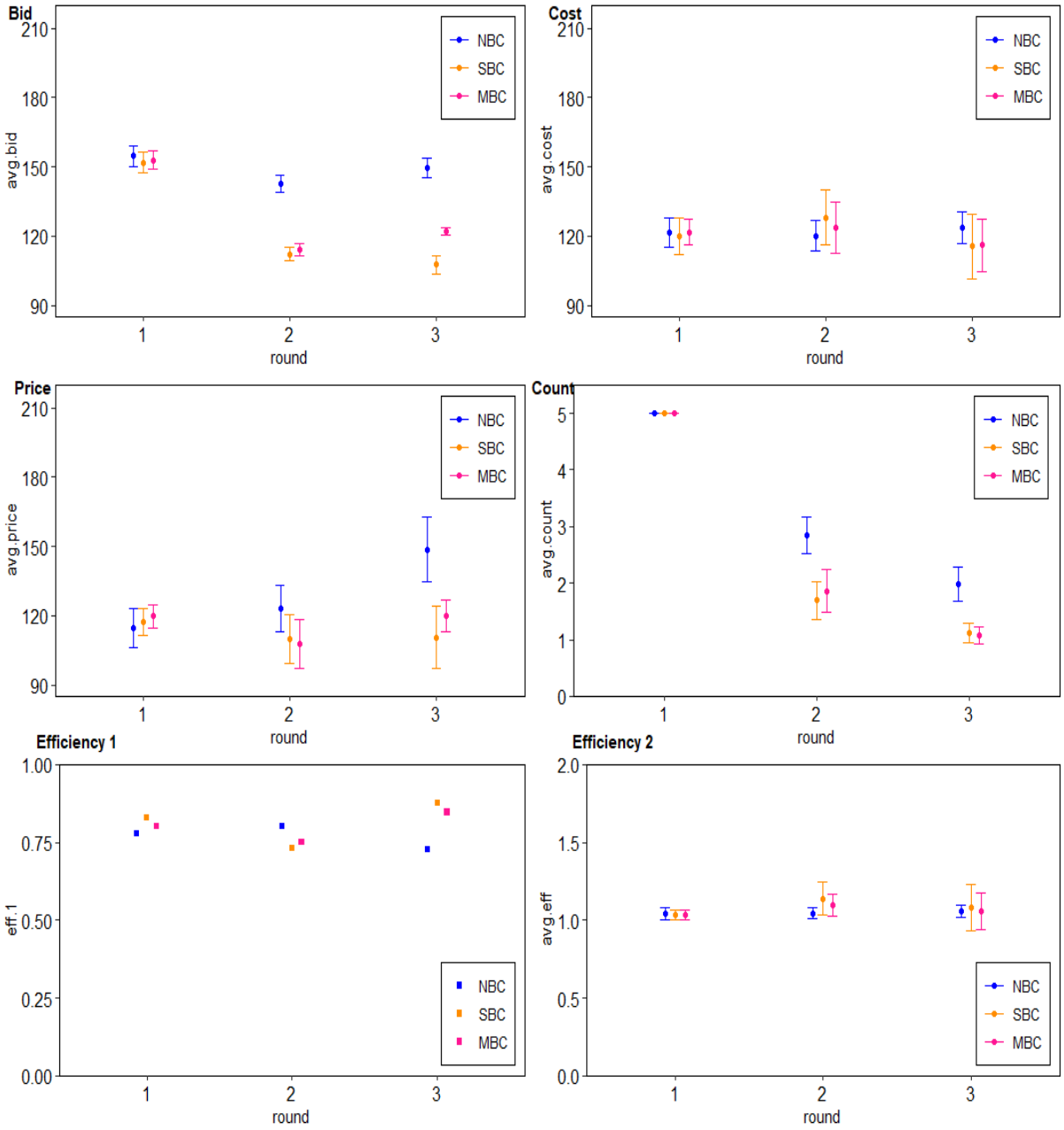


Figure C.1: Experiment Dynamics (First Half) by Treatment and Round

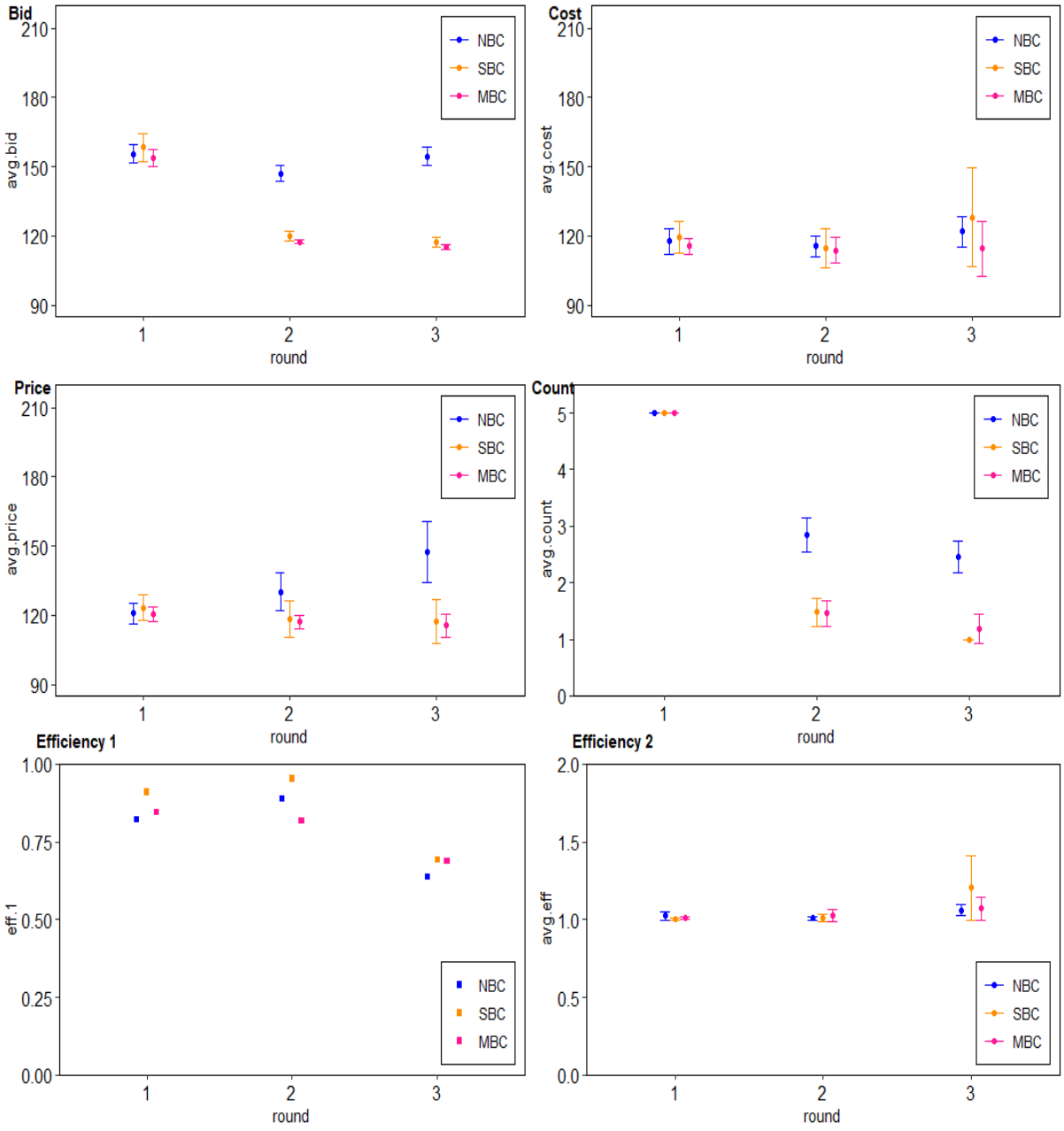


Figure C.2: Experiment Dynamics (Second Half) by Treatment and Round

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