Drivers of Public Procurement Prices: Evidence from Pharmaceutical Markets*

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Abstract. This paper examines the determinants of public procurement prices using comprehensive data on pharmaceutical purchases by the public sector in Chile. We first document sizable price differences between buyers for the same product and quantity purchased: the difference between the average prices paid by buyers at the 90*th* and 10*th* percentiles of the distribution is 16 percent. Our main results are related to the importance of market structure in explaining the dispersion in procurement prices. We find that market structure explains three times more dispersion than buyer effects. Moreover, we leverage exogenous variation in market structure due to patent expirations to estimate that the entry of an additional seller decreases average procurement prices by 11.7 percent, which is 72 percent of the price differences implied by the gap between the 90*th* and 10*th* percentiles of estimated buyer effects. These results suggest that supply-side factors are relevant determinants of public procurement prices and that their quantitative importance may exceed that of demand-side factors previously emphasized in the literature.

Keywords: procurement, bureaucracy, competition, drugs

JEL Codes: D44, D73, H57

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1 Introduction

What determines the prices that different public agencies pay for goods or services? Given that a substantial share of public spending is devoted to public procurement, the answer to this question has first-order economic implications, not only for government finances but also for the quantity and quality of public sector delivery. At least since Bandiera, Prat and Valletti (2009), a growing body of literature has attempted to identify the drivers of public procurement prices and the degree to which these vary between different purchasing units within the government. Two broad lessons have emerged: (i) there is substantial dispersion across agencies in prices paid for narrowly defined goods, and (ii) this variation is systematically related to demand-side drivers such as observable characteristics of the buyer and the institutions that govern the procurement process. However, there is less evidence about the contribution of supply-side drivers to the dispersion in procurement prices.

This paper examines the relative roles of demand- and supply-side drivers of procurement prices. We employ detailed administrative data on the universe of procurement purchases of pharmaceutical products by the public sector in Chile. In this setting, public procurement operates mainly through auctions. The data cover hundreds of thousands of procurement auctions by 436 public agencies. For each auction, the data provide detailed information about seller participation in these auctions and their bids, a description of the products ultimately purchased by these agencies down to the barcode level, and the prices paid for them.

We start by revisiting some of the core results of the previous literature by measuring the dispersion in public procurement prices and assessing the role of demand-side factors. We do so by improving on the measurement and methodological fronts. In terms of measurement, our data allow us to compare prices between buyers within the same product barcode, largely alleviating concerns of unobserved quality differences present in most previous work. In terms of methodology, we apply empirical Bayes methods to account for noise when estimating the buyer fixed effects on procurement prices. Our analysis finds broad agreement with the established stylized facts: we estimate that an agency at the 90*th* percentile of the distribution of buyer effects pays 16.2 percent more than an agency at the 10*th* percentile of such distribution. Accounting for measurement error in product attributes and estimation noise is consequential, as we would overestimate dispersion in buyer effects by 44 percent otherwise. Moreover, we show that buyer fixed effects are systematically correlated with buyer characteristics such as institutional sector, geography, size, and complexity.

The second part of the analysis focuses on documenting the role of supply-side drivers of procurement prices, which is the main contribution of the paper. In previous work, supply-side factors have received substantially less attention than demand-side drivers, yet we show that they explain a sizable share of the variation in procurement prices. We build this evidence through two separate analyses. First, we combine regressions with a variance decomposition to show that market structure has significant explanatory power for procurement prices. Market structure explains three times more of the variation in procurement prices than the buyer effects. We complement these results with a second analysis that exploits patent expiration events as exogenous shifters of market structure. This strategy allows us to provide a more causal interpretation of the relationship between market structure and procurement prices. We find that patent expirations, on average, increase the number of sellers by 2.4 and decrease prices by 28 percent after four years, such that a marginal seller decreases its prices by 11.7 percent. This impact is equivalent to 72 percent of the gap between the 10*th* and 90*th* percentiles of the distribution of buyer effects.

Our results highlight that market structure is a crucial driver of procurement prices. In addition to enacting policies that improve buyer efficiency, policymakers should also pay particular attention to the determinants of the competitive environment in procurement auctions and assess the need for policies that foster market competition.

Our paper adds to a growing recent literature documenting dispersion in public procurement prices and studying its sources, focusing mainly on the role of the buyer. Starting with Bandiera, Prat and Valletti (2009), there has been work focusing on bureaucratic competence (Decarolis *et al.* 2020; Best, Hjort and Szakonyi 2023; Liscow, Nober and Slattery 2023), bureaucratic discretion (Coviello, Guglielmo and Spagnolo 2018; Bosio *et al.* 2022; Carril 2022; Szucs 2023; Celhay *et al.* 2024), bureaucratic workload (Warren, 2014), the role of demand pooling (Dubois, Lefouilli and Straub 2021; Allende *et al.* 2024; Wang and Zahur 2023), the use of electronic platforms (Lewis-Faupel *et al.*, 2016), and the tenure of politicians in office (Coviello and Gagliarducci, 2017), among others.[1]

We make two contributions to this literature. First, on the methodological front, we quantify the importance of accounting for unobserved differences across products and estimation noise in estimating buyer effects in procurement prices, and we show that these are quantitatively relevant. Second, while prior research predominantly emphasized the demand-side factors influencing procurement prices, we examine their supply-side drivers by analyzing the impacts of shifts in market structure following patent expiration events and comparing them to the role of demand-side drivers. By doing so, we contribute to a small body of recent work that focuses partially on the supply-side drivers of procurement prices (e.g., Dubois, Lefouilli and Straub 2021, Liscow, Nober and Slattery 2023, Best, Hjort and Szakonyi 2023). Our analysis on the effects of patent expiration on procurement prices is complementary to recent work that leverages mergers (e.g., Carril and Duggan 2020; Atella, Ceschin and Decarolis 2021) or the adoption of competitive bidding (e.g.,

[1]Relatedly, there is also a large literature studying the consequences of market design choices on procurement outcomes. This includes both the role of the awarding mechanism (e.g., Bajari, McMillan and Tadelis 2009, Athey, Levin and Seira 2011, Lewis and Bajari 2011, Marion 2007, Krasnokutskaya and Seim 2011, Decarolis 2014, Branzoli and Decarolis 2015), as well as contractual form (e.g., Crocker and Reynolds 1993, Bajari and Tadelis 2001). Instead, our paper studies differences in procurement prices between buying units holding fixed these market design features.

Ding, Duggan and Starc 2021; Ji 2023) as sources of exogenous variation in market structure and competition to study its effects on procurement outcomes.[2]

The remainder of the paper is organized as follows. We start by describing the institutional setting and the data in Section 2. We examine demand-side factors in Section 3, and then proceed with our analysis of supply-side factors in Section 4. Finally, we conclude in Section 5.

2 Setting

2.1 Institutional Framework

The public procurement system in Chile is organized around the online platform *Mercado Público*. Approximately 1,350 public agencies use this platform to buy goods and services from more than 100,000 private firms through auctions and other mechanisms (ChileCompra, 2012). We restrict our sample to purchases of pharmaceutical products by any public entity, including hospitals and other primary healthcare facilities, municipalities, universities, and other agencies. In addition, we restrict our attention to purchases made through auctions, which account for more than two-thirds of government purchases. These are scoring auctions, where the buyer specifies the quantity requested for the product and the rule under which the bids are evaluated.[3] The attributes included in the scoring rule and their weights are known in advance to sellers, and, in essence, reflect buyer preferences over product characteristics. The most common non-price attributes relate to technical characteristics, delivery capabilities, and seller experience. Procurement auctions operate at the drug level, where there is room for substitution between specific barcodes or sellers, but not between molecules, strength, or pharmaceutical dosage forms. Auction participants are either drug manufacturers or wholesalers who purchase from domestic or international manufacturers.

2.2 Data

Procurement. Our primary data source is an online platform called *Mercado Público*, which is where public agencies post and run procurement auctions. We observe all auctions posted by all buyers for the years 2011–2020. For each auction, we observe detailed information about the product and the quantity requested, some information about the auction scoring rule, bidder identities and bids, the winner's identity, and the details of the purchase order that stems from the

[2] We also contribute to a recent literature focused on the role of bargaining power, information, and lobbying in the context of hospital procurement (Grennan 2013; Craig, Grennan and Swanson 2021; Grennan and Swanson 2020). We complement this literature by analyzing the drivers of price dispersion in a context of procurement in health care that operates through auctions.

[3] Procurement purchases via framework agreements or through a public intermediary dependent on the Ministry of Health (*Central Nacional de Abastecimiento*, CENABAST) are the main alternative to auctions. These channels consist of a catalog of drugs that varies over time. We exclude auctions for drugs available in the intermediation catalog in the same quarter to avoid selection problems in the analysis.

auction. These data include over 800,000 auctions that amount to roughly one billion dollars in purchases.

We classify products using the regulator's drug registry (equivalent to the US Orange Book), which contains the universe of drug marketing licenses. This registry includes information on drug therapeutic use, active ingredient, manufacturer, strength, dosage form, and whether it is a prescription drug. We make the following distinction for our analysis. We refer to *drugs* as the combination of an active ingredient, strength, and dosage form, but without specifying a laboratory or the brand name. We refer to *products* as narrowly defined varieties of a drug that a seller offers, namely a barcode. Hence, there may be multiple products that correspond to the same drug. Products are classified into either *innovator*—the product initially patented by the innovator laboratory—or *generics*, which are products created to have the same molecule and strength as the innovator drug after the expiration of the patent.[4] An example of a drug is "Ibuprofen Oral Suspension 100 MG per 5 ML". Two examples of different products within the same drug described above are a branded generic called "Ibuflam Oral Suspension 100 MG per 5 ML" by SCM PHARMA Chile, and an unbranded generic called "Ibuprofen Oral Suspension 100 MG per 5 ML" by Laboratorio Chile.[5]

Our sample includes 432 buyers who purchased drugs in 2011–2020.[6] The sample includes 828,514 purchases of 6,859 distinct products in 2,115 drugs. We classify buyers by their type and geographic location. In particular, we identify three types of buyers in our analysis: healthcare buyers that consist mostly of hospitals, municipalities that buy for small local health services and public pharmacies, and the central government and the army, which collect all residual buyers. Furthermore, we group buyers in five regions of the country: North, Center-North, Metropolitan, Center-South, and South. Table 1 presents summary statistics of the data. Most buyers are in the healthcare sector, located in the country's metropolitan or otherwise central areas. The average drug has 11 distinct sellers, of which 4.4 are laboratories. Moreover, the average auction has almost four bidders, and the innovator product wins the auction 37 percent of the time.

Retail. We complement our procurement data with data on retail market outcomes from IQVIA for 2010–2019. These data include monthly retail prices and sales at the product level. We use these data to identify market characteristics and to measure product availability outside the procurement market.

[4]In our setting, some generic drugs are marketed as branded generics under a fantasy name that differs from the active ingredient's name. Throughout the paper, we lump both branded and unbranded generics into a broad category of generics.

[5]For more details about these distinctions, see Atal, Cuesta and Sæthre (2022).

[6]We excluded a few buyers that seldom appear in our dataset. In particular, we exclude buyers who purchased pharmaceutical products less than 200 times in the ten-year window of our sample.

Table 1: Summary statistics

	Mean	Min	p25	p50	p75	Max
A - Buyer characteristics						
Geographic location						
In North	0.07	0.00	0.00	0.00	0.00	1.00
In Center-North	0.15	0.00	0.00	0.00	0.00	1.00
In Metropolitan	0.17	0.00	0.00	0.00	0.00	1.00
In Center-South	0.36	0.00	0.00	0.00	1.00	1.00
In South	0.24	0.00	0.00	0.00	0.00	1.00
Institutional						
Healthcare	0.45	0.00	0.00	0.00	1.00	1.00
Municipality	0.49	0.00	0.00	0.00	1.00	1.00
Central government and army	0.06	0.00	0.00	0.00	0.00	1.00
Size						
Log spending	19.27	15.53	17.87	18.94	20.48	24.39
Log number of different drugs purchased	5.43	2.71	4.96	5.32	5.87	7.19
B - Market characteristics						
Sellers						
Number of sellers in the market	5.97	1.00	2.00	4.00	8.00	67.00
Number of labs in the market	2.32	0.00	1.00	2.00	3.00	25.00
Products						
Number of products in market	4.31	1.00	1.00	3.00	5.00	68.00
Number of generics in market	0.84	0.00	0.00	0.00	1.00	21.00
C - Procurement auctions						
Number of bidders	4.68	1.00	2.00	4.00	7.00	24.00
Number of labs in the auction	2.56	0.00	1.00	2.00	3.00	16.00
Purchase innovator product	0.37	0.00	0.00	0.00	1.00	1.00

Notes: This table displays summary statistics for the main sample in the analysis. Panel A includes observations at the buyer-year level. Panel B includes observations at the drug-region-year level. Panel C includes observations at the auction level.

Drug patents. We match our data to patent expiration dates by molecule using the NBER Orange Book Dataset (Durvasula *et al.*, 2023). We focus on generic-preventing exclusivity and substance-protecting patents. We discuss the construction and use of these data in Section 4.2 and Appendix B.1.

3 Demand-side Drivers of Procurement Prices

The starting point of our analysis of procurement prices is a version of Bandiera, Prat and Valletti (2009)'s main regression specification:

$$\log p_{ijt} = X'_{ijt}\beta + \eta_i + \mu_{jt} + \varepsilon_{ijt}, \tag{1}$$

where p_{ijt} is the unit price that buyer i paid for product j in period t; X_{ijt} is a set of auction-specific covariates: dummies for within-drug deciles of purchased quantity, and dummies for the type of auction that originated the contract;[7] η_i is a buyer fixed effect that captures average price differences across buyers conditional on contract observables and product-time, and μ_{jt} is a product-by-quarter fixed effect that controls for shocks to product prices in a quarter that are common across buyers.

Throughout our analysis, we consider the product definition j to be either a *drug* or a specific *product*, as defined in Section 2. By estimating this regression at the product level, we make particularly precise comparisons between buyers who purchase drugs with the exact same barcode. This allows us to improve upon most previous studies, which cannot rely on this level of granularity.[8] This is important because precise product definitions help us alleviate concerns about price differences being driven by unobserved product characteristics.[9]

3.1 Buyer effects

We start by examining the distribution of estimated buyer fixed effects $\hat{\eta}_i$ from equation (1). We begin by comparing the results of this exercise when estimated at the drug or product level. Coarser product definitions will lead to an artificial increase in within-product price dispersion across buyers since the estimated buyer effects will group together barcodes that may have cost and (real or perceived) quality differences. By explicitly comparing our two product definitions,

[7] Procurement auctions are classified based on their expected amount. In our data, auctions are classified into eight types. The auction format is the same across types (score auctions); however, the ones that involve higher amounts are subject to stricter rules regarding the number of days they should be open and the requirements of warranties to back up each bid.

[8] Best, Hjort and Szakonyi (2023) argue that three standard approaches have been applied to deal with imperfect product classification: using hedonic regressions to partial out the effects of different product attributes, using product codes provided by customs agencies, or restricting attention to products that are expected to be homogeneous. These authors add a fourth approach using machine learning and text analysis methods to infer product classifications from the text of the contracts.

[9] Despite the precise definition of products in our setting, we are unable to fully rule out the presence of unobservables. For example, a particular agency might pay a premium for a product in return for a credible guarantee of continuous and uninterrupted supply. This is unlikely to be a first-order concern in our setting, as regulation leaves little room for agencies to customize their purchase mechanism and procurement contract terms, resulting in relatively homogeneous contracts across buying units. However, it is possible that even with our measurement improvements, some overestimation of the price dispersion remains.

we can quantitatively gauge the extent to which price dispersion could be overestimated due to imperfect product classification.

Moreover, we correct our estimates of buyer fixed effects using empirical Bayes shrinkage methods since estimation noise mechanically leads to overdispersion in these coefficients. By considering estimates with and without this shrinkage correction, we assess the extent to which the dispersion of buyer effects is magnified by estimation noise. This correction is potentially relevant, and most previous work has not accounted for it. We explain in detail the shrinkage method we employ in Appendix A.

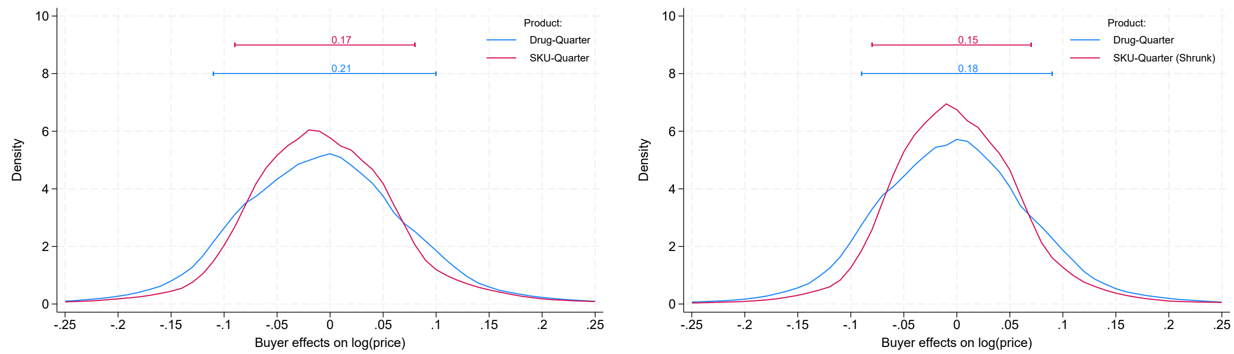
Buyers pay vastly different procurement prices for the *same* products in our setting. Figure 1 shows the estimated distributions of buyer fixed effects $\hat{\eta}_i$, and the 10*th* and 90*th* percentiles of each distribution for both product definitions. Panel (a) displays the raw estimates, while Panel (b) displays the shrunk estimates. We highlight three patterns in these results. First, there is substantial dispersion in the prices different buyers pay for the same products. Regardless of the specification, the estimated distributions of buyer effects display a large dispersion. Our preferred specification uses product-quarter fixed effects and shrinkage, which is the red density in Figure 1-(b). For this specification, the agency at the 90*th* percentile of the distribution of buyer effects pays 16.2 percent more than the agency at the 10*th* percentile ($\exp(\log p_{90th} - \log p_{10th}) = 1.162$). Second, by comparing distributions within each panel, it is clear that the distribution of buyer effects is compressed when the product definition is more granular, as expected. Third, by comparing across panels, we see that shrinking buyer effects indeed reduces the dispersion of estimates. In particular, the estimated difference between the 90*th* and 10*th* percentiles would be 18.5 percent without the shrinkage correction. Moreover, using a coarser product definition would further increase the estimated difference to 23.4 percent. Overall, accounting for more accurate product definitions and estimation noise reduced the dispersion of buyer effects by 44.4 percent.

Taken together, these results support one of the main stylized facts in this literature, namely that there is substantial dispersion in prices paid by different agencies for the same product. However, our results also call for caution on the exact magnitude of the previously documented dispersion in procurement prices across public agencies. We now explore the characteristics of the buyers that systematically predict these differences.

3.2 Correlates of Buyer Effects

We now take the estimates of buyer fixed effects from equation (1) and project them on a set of buyer observables to shed light on the demand-side drivers of procurement prices. We follow Bandiera, Prat and Valletti (2009) and group these variables into institutional, geographic, and size-related drivers. Additionally, we use hospital characteristics in a specification that restricts attention to the healthcare sector.

Figure 1: Distribution of buyer effects on log(price)



(a) Raw estimates

(b) Shrunk estimates

Notes: This figure displays the density of buyer effects in log drug prices, estimates at the drug (blue) and product level (red). Panel (a) displays raw estimates, whereas Panel (b) displays results after shrinkage using empirical Bayes methods. The brackets on top of the densities indicate the 10*th* and 90*th* percentiles of each distribution.

Table 2 presents the results. The first four columns use the full sample of buyers across all sectors. In columns (1), (2), and (3), we consider institutional, geographic, and size-related covariates in isolation, respectively, while column (4) includes them jointly. In column (5), we restrict the sample to buyers in the healthcare sector, for which we have additional characteristics that we include in the regression on top of the geographic and size-related covariates.

When considered jointly, all three sets of variables matter to explain buyer effects. Buyers in the healthcare and municipal sectors pay 19 percent and 12 percent less than those in other sectors, respectively.[10] Buyer size (as measured by procurement volume) and the number of distinct drugs purchased by a buyer also correlate with buyer effects: larger agencies tend to pay more—after controlling for purchase size when estimating equation (1). This pattern may be due to the organization's competence in managing procurement efficiently (Bucciol, Camboni and Valbonesi, 2020). Finally, geography matters, although relatively less than institutional and size-related covariates, as its correlation with buyer effects is limited after controlling for the other drivers in column (4).

In addition to explaining buyer effects using fixed observable characteristics, we study whether the product types that buyers purchase explain buyer effects. A buyer designs a procurement auction according to their preferences. For example, a very price-sensitive buyer places a high weight on the price component of seller bids, which leads to a low-price seller winning the auction. In our context, low-price sellers are often unbranded generics, whereas innovator and branded

[10]We complement these regression results with Appendix Figure A.2, which reports the distributions of buyer effects by agency type. Consistent with the regression results, this figure shows that the distributions of buyer effects for agencies from the central government and the army are shifted to the right of those for healthcare and municipality agencies.

Table 2: Correlates of buyer effects

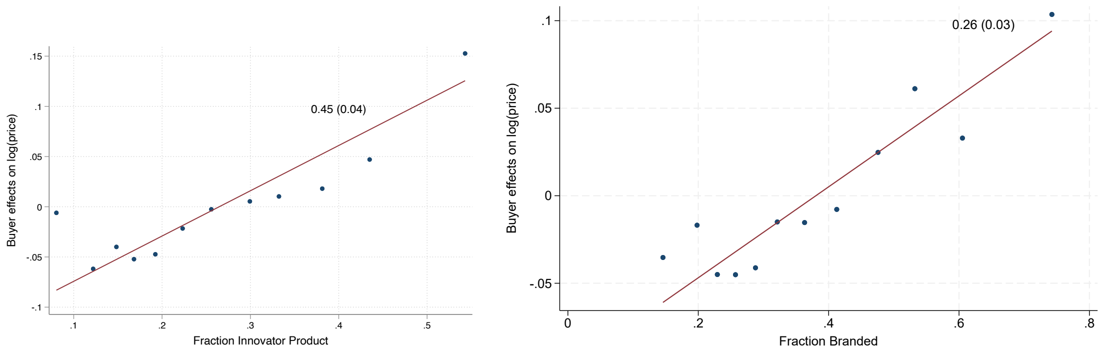
	(1)	(2)	(3)	(4)	(5)
	All				Healthcare
Healthcare	-0.179***			-0.189***	
	(0.023)			(0.021)	
Municipality	-0.160***			-0.115***	
	(0.023)			(0.021)	
In North		-0.020		-0.035*	-0.049*
		(0.024)		(0.021)	(0.026)
In Center-North		-0.021		-0.035**	-0.028
		(0.019)		(0.016)	(0.021)
In Metropolitan		0.069***		0.005	-0.004
		(0.018)		(0.017)	(0.019)
In Center-South		-0.017		-0.030**	-0.036**
		(0.015)		(0.013)	(0.017)
Log spending			0.036***	0.045***	0.056***
			(0.005)	(0.005)	(0.011)
Log number of different drugs purchased			-0.071***	-0.087***	-0.050**
			(0.014)	(0.013)	(0.022)
Log number of beds					-0.021*
					(0.012)
High complexity hospital					-0.031
					(0.026)
Medium complexity hospital					-0.022
					(0.020)
R-squared	0.125	0.070	0.123	0.311	0.424
Adj. R-squared	0.121	0.063	0.119	0.299	0.394
Observations	436	436	436	436	165

Notes: This table displays results from regressions of estimates of buyer effects from equation (1) on buyer characteristics. All controls are reported in the table. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

generic drugs often charge substantially higher prices (Atal, Cuesta and Sæthre, 2022). To provide evidence for whether this is a relevant driver of buyer effects, we compute the share of auctions won by an innovator and by a branded generic for each buyer and correlate those variables with our estimates of buyer effects estimated at the drug level. Figure 2 shows that buyer effects correlate strongly with how often a buyer awards contracts to innovators and branded generics. These patterns suggest that the degree to which buyers pay different prices is partly driven by heterogeneous buyer preferences over differentiated products available on the market—in addition to the institutional, geographical, and size drivers discussed above.

These results are related to previous work in this literature. Consistent with the findings in Table 2, Bandiera, Prat and Valletti (2009) find that the institutional characteristics of buyers are more relevant than their location in explaining the differences in the prices they pay, and

Figure 2: Buyer effects on log(price) and buyer preferences



(a) Fraction of Innovator Purchases

(b) Fraction of Branded Purchases

Notes: This figure displays binned scatter plots of estimates of buyer effects at the drug level from equation (1) and the share of purchases in which the buyer ends up purchasing an innovator or a branded generic drug, in panels (a) and (b) respectively. The coefficient for the slope is reported, along with its standard error in parentheses.

the dispersion we estimate between buyers from different government segments is similar to theirs. Moreover, Decarolis *et al.* (2020) find that employee cooperation is the main driver of buyer efficiency in their setting. Although we cannot measure this variable—they collect their data through surveys—we document that larger and more complex agencies among healthcare sector buyers are relatively more efficient. Our results also relate to existing work studying how buyer preferences shape procurement outcomes (e.g., Kang and Miller, 2021; Szucs, 2023; Carril, Gonzalez-Lira and Walker, 2022). In particular, the patterns we document in Figure 2 are similar to the results by Fazio (2022), who finds that procurement offices in Brazil pay higher prices for branded drugs when equipped with more discretion. Finally, Best, Hjort and Szakonyi (2023) build a broad set of potential drivers of buyer efficiency and find that some of the most predictive ones are related to the ability of buyers to attract competition to the auction, which we discuss in Section 4 below.

4 Supply-side Drivers of Procurement Prices

Having provided evidence for the demand-side drivers of procurement prices, we now study their supply-side drivers. Our goal is to quantify the contribution of market characteristics relative to the roles of buyers in explaining procurement prices. This exercise is relevant to provide policy recommendations, as the policy tools to improve buyer behavior (e.g., vary the degree of buyer discretion) differ from the mechanisms that affect the structure of the markets they buy from.

Our main focus is on how procurement prices vary across buyers exposed to different market structures when purchasing a particular drug. We study this through two complementary approaches. First, we develop a comprehensive descriptive regression analysis and a variance decomposition to document the extent to which market structure explains the variation in procurement prices and compare that with the explanatory power of buyer effects. However, while we include a rich set of fixed effects to control for unobserved factors that could explain price differences, we cannot fully rule out the potential endogeneity of market structure.[11] To address this issue, we complement the regression analysis with a case study that exploits changes in market structure associated with drug patent expirations, to which we give a more causal interpretation.

4.1 Market Structure as a Driver of Procurement Prices

We estimate various regressions to disentangle the influence of market structure and buyer effects on procurement prices. These regressions roughly follow a specification of the form:

$$\log p_{ijt} = \gamma M_{ijt} + X'_{ijt}\beta + \eta_i + \mathrm{FE}_{ijt} + \varepsilon_{ijt} \tag{2}$$

where the dependent variable is the log of the price of the winner in an auction by buyer i for product j in quarter t; M_{ijt} is a variable measuring market structure; X_{ijt} is a set of auction observables; dummies for within-drug deciles of purchased quantity, and dummies for the type of auction that originated the contract. η_i is a set of buyer fixed effects, and FE_{ijt} is a set of fixed effects that becomes increasingly richer across specifications and ranges from quarter fixed effects to interacted region-drug-quarter fixed effects.

We consider three variables to measure market structure M_{ijt}. The first two variables are the number of potential drug sellers in the national and regional markets in a year-long window.[12] More precisely, the set of potential sellers for an auction in a given drug and national (regional) market in quarter t correspond to the set of sellers that are considered active in the public procurement market in that period t. A seller is considered active if it submits at least one bid in auctions by any buyer in the country (region) within one year since its last bid. This definition assumes that a seller is active in a market if it bids in a procurement auction at least once a year. The third

[11] One particular form of endogeneity that might affect the interpretation of our decomposition exercise is the existence of feedback effects between demand-side and supply-side factors. This may occur in procurement contexts whenever actions undertaken by the buyer (i.e., demand) affect market entry (i.e., supply). Previous work has documented these types of effects, including Marion (2007) and Krasnokutskaya and Seim (2011) on the effect of bid preferences, and Kang and Miller (2021) and Carril, Gonzalez-Lira and Walker (2022) on buyer efforts to promote competition. We believe that this is less of a concern in our context for two reasons. First, regulation heavily restricts individual buyers and leaves little discretion to make decisions about auction design or contract design in ways that could significantly influence bidders' decisions to enter the market. Second, in our preferred specifications we use broad definitions of market structure that are unlikely to be affected by individual buyers. We further discuss the possibility of endogenous market structure when describing our empirical specification.

[12] We consider both national and regional measures of market structure since, by adding the geographic dimension, we capture that market conditions may differ depending on where the buyer is located, e.g., that some buyers are located in the country's extremes where fewer sellers operate. The regions are large enough to include several buyers of different sectors and characteristics.

variable that measures market structure zooms more directly into each auction and consists of simply computing the number of bidders in a particular auction.

Although market structure can be an endogenous outcome, we argue that this is less of a concern for the first two variables, since several other buyers from different sectors, sizes, and characteristics purchase the same drug. It suffices that a seller bids once in a market-year to be part of the market. Hence, it is unlikely for a specific buyer to shape these measures of market structure, and it is instead likely that changes in the market conditions are given to the buyer—to the extent that market-level unobservables drive these changes in market structure, drug-quarter fixed effects in our rich specifications may control for them. This is important as we aim to separately identify the influence of market conditions on prices from that of buyer characteristics. For the third variable, entry into auctions is likely endogenous and jointly determined by demand- and supply-side characteristics. We report the results for this measure to provide further evidence of how market structure correlates with procurement prices and to study how this correlation changes when accounting for buyer effects.

Table 3 shows the results of this analysis. Panels A, B, and C display the results for market structure measured at the national, regional, and auction levels, respectively. The specification of fixed effects becomes more granular as we move to the right of the table—to the point that the fixed effects fully absorb the variation in market structure in columns (7) and (8). Finally, odd columns display results without buyer effects, while even columns include buyer effects. A few things are worth highlighting from these results. First, in all specifications, we find that a higher number of potential drug sellers is associated with lower prices, consistent with standard competitive effects. This holds regardless of whether we measure national, regional, or auction-level market structure. Second, by comparing across the first four columns in each panel, it is easy to note that a measure of market structure has a stronger impact on R-squared than buyer fixed effects. This pattern suggests that market conditions may indeed be an important driver of dispersion in procurement prices. Third, the results in Panel C are of particular interest in light of recent work by Best, Hjort and Szakonyi (2023), who find that one of the main drivers of buyer effects is the ability of procurement officers to get bidders to compete in their auctions. The results in Panel C show that market structure remains a significant driver of buyer effects even after including buyer fixed effects in columns (4) and (6), suggesting that market structure plays a relevant role in explaining dispersion in procurement prices independent of the ability or behavior of the procurement officer.[13]

We complement this regression analysis with a formal analysis-of-variance (ANOVA) to decompose how much of the variation in log prices is explained by buyer effects, market structure, and other characteristics. Appendix Table A.1 reports the results for the same specification of equation (2) as column (4) of Table 3-B. The model has an R-squared of 11 percent. Half of the

[13] Appendix Table A.2 shows that we obtain similar results if we measure market structure as the number of products in the national and regional market instead of the number of sellers.

Table 3: Procurement prices and market structure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A - Country-level market structure								
Number of sellers in the market			-0.013*	-0.012				
			(0.007)	(0.008)				
R-squared	0.047	0.071	0.107	0.120	0.532	0.555	0.583	0.602
Adj. R-squared	0.047	0.071	0.107	0.120	0.512	0.535	0.538	0.559
N	807,461	807,461	807,461	807,461	807,461	807,461	788,855	788,855
B - Region-level market structure								
Number of sellers in the market			-0.019**	-0.019*	-0.003***	-0.001		
			(0.010)	(0.011)	(0.001)	(0.001)		
R-squared	0.047	0.071	0.102	0.115	0.533	0.556	0.583	0.602
Adj. R-squared	0.047	0.071	0.102	0.115	0.513	0.537	0.539	0.559
N	799,732	799,732	799,732	799,732	799,732	799,732	782,642	782,642
C - Auction-level market structure								
Number of bidders in auction			-0.048***	-0.046***	-0.040***	-0.041***		
			(0.007)	(0.005)	(0.005)	(0.004)		
R-squared	0.041	0.063	0.081	0.093	0.656	0.667	0.697	0.707
Adj. R-squared	0.041	0.062	0.080	0.092	0.633	0.644	0.650	0.661
N	386,695	386,695	386,695	386,695	386,695	386,695	369,014	369,014
Number of bidders in auction			-0.048***	-0.046***	-0.040***	-0.041***		
			(0.007)	(0.005)	(0.005)	(0.004)		
R-squared	0.041	0.063	0.081	0.093	0.656	0.667	0.697	0.707
Adj. R-squared	0.041	0.062	0.080	0.092	0.633	0.644	0.650	0.661
N	386,695	386,695	386,695	386,695	386,695	386,695	369,014	369,014
Auction controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Buyer FE	No	Yes	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	Yes	Yes	Yes	No	No	No	No
Drug-quarter FE	No	No	No	No	Yes	Yes	No	No
Region-drug-quarter FE	No	No	No	No	No	No	Yes	Yes

Notes: This table displays results from regressions of procurement prices on market structure characteristics and fixed effects in from equation (2) on buyer characteristics. Panel A displays estimates for the full sample for the number of sellers in the national market. Panel B displays estimates for the full sample for the number of sellers in the regional market. Panel C displays estimates for a subsample of auctions matched to bid data, for the number of bidders in the auction. Standard errors clustered at the drug level in parentheses. *** p<0.01, ** p<0.05, * p<0.1

model's explanatory power can be attributed to the number of potential sellers in the market. For comparison, buyer fixed effects are jointly statistically significant but explain less than one-third of the variation in prices than the number of potential sellers in the market and roughly half of what auction-level controls (drug quantity and auction type) do.

These results, taken together, help to put into perspective the role of buyer effects in explaining dispersion in procurement across buyers. Buyer effects are relevant, but they explain a relatively small fraction of the price variation. Moreover, this evidence suggests that even rough proxies of market structure may have more explanatory power than buyer effects.

4.2 A Case Study on Changes to Market Structure due to Patent Expiration

In the previous section, we documented a strong correlation between market structure and procurement prices. However, while changes in market structure at the national or regional level are unlikely to be explained by buyer attributes or behavior, they may be driven by market-level unobservables. To provide a more causal interpretation of the relationship between market structure and procurement prices, we leverage the expiration of drug patents as a natural experiment that induces changes in market structure. A patent grants an innovator an exclusive right to sell products based on the patented molecule. Hence, this gives innovators a monopoly in upstream markets, curtailing product diversity and limiting the number of sellers. Once the patent has expired, generic manufacturers can enter the market and sell the drug, which is the source of variation that we use in this analysis.[14]

To develop this analysis, we match our data to patent expiration dates. Using data from the NBER Orange Book Patent Expiration dataset and IQVIA, we find expiration dates for 728 active ingredients.[15] From this set of matched active ingredients, 545 (74.9 percent) had their patent expire before 2011, 121 (16.6 percent) had their patent expire within our time window between 2011 and 2020, and 62 (8.5 percent) had their patent still unexpired by the fourth quarter of 2020.[16] We leverage this variation for our analysis.

We use an event-study design to estimate how patent expiration affects the entry of generic products in government procurement and procurement prices. We estimate the following specification:

$$y_{jt} = \sum_{k=-8}^{18} \beta_k \cdot \mathbb{1}[t - E_j = k] + \mu_j + \lambda_t + \varepsilon_{jt} \tag{3}$$

where y_{jt} is an outcome for drug j in period t; E_j is the period in which the patent for drug j expires; and μ_j and λ_t are drug and time fixed effects, respectively. The coefficients of interest are β_k, which capture the dynamic effects of patent expiration on y_{jt}.

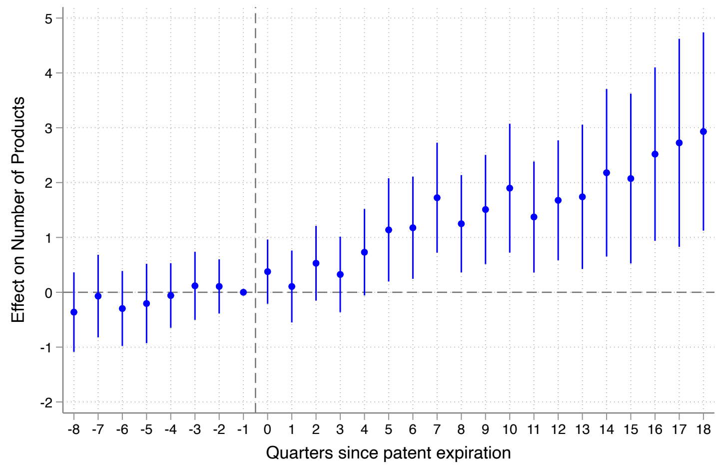
Patent expiration induces the entry of new products, as shown by Figure 3-(a). Product entry occurs gradually and grows steadily for up to four years after the patent expiration. The number of different products on the market increases by almost three on average across drugs in our sample,

[14] This source of variation has already been used in previous research studying the impacts of generic entry, although generally using much smaller sample sizes (e.g., Frank and Salkever 1997; Caves *et al.* 1991; Grabowski and Vernon 1992; Griliches and Cockburn 1994). Vondeling *et al.* (2018) provide a recent review of the literature.

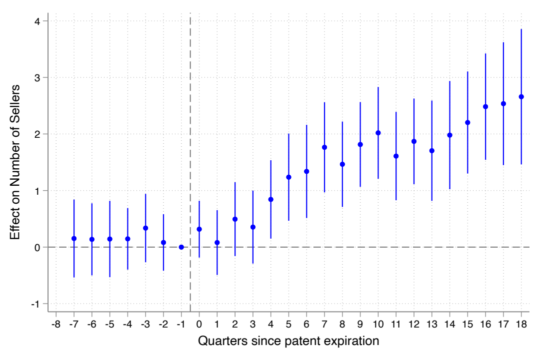
[15] We directly obtain expiration dates for 481 active ingredients to the NBER Orange Book Dataset. For the other 248, we inferred their expiration date from the first appearance of generics in the IQVIA data on retail sales in our setting. The unmatched active ingredients mostly had their expiration dates before the first issue of the Orange Books in 1985 or are products subject to FDA approval, e.g., dietary supplements.

[16] Appendix Figure A.3 displays the timing of patent expiration dates. The blue line shows the share of expired patents by each quarter among all matched active ingredients, and the red line shows the share of expired patents among those that experienced an expiration between 2010 and 2020 (switchers). As the figure shows, the distribution of expiration dates was relatively uniform over time in our sample.

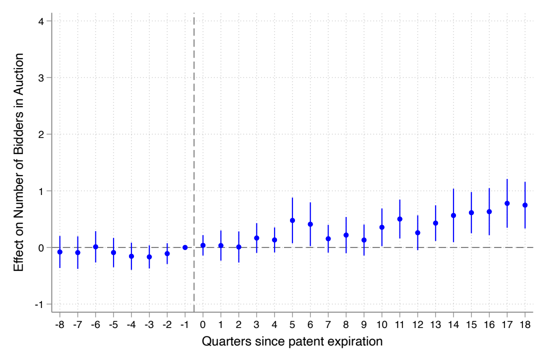
Figure 3: The effect of patent expiration on market structure



(a) Number of products in the market



(b) Number of sellers in the market



(c) Number of bidders in the auction

Notes: This figure plots the point estimates and confidence intervals of β_k in equation (3). Panel (a) displays results from a drug-quarter-level regression for the number of products in the market. Panel (b) displays results from a drug-quarter-level regression for the number of sellers in the national market. Panel (c) displays results from an auction-level regression for the number of bidders in each auction. Standard errors are clustered at the drug level.

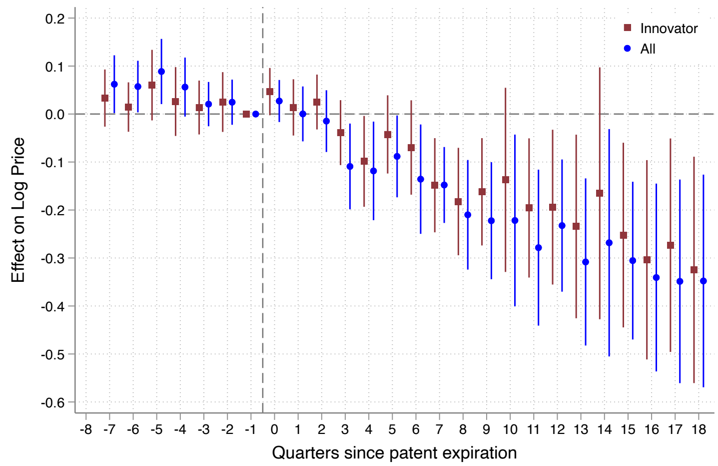
which is economically significant considering that the average drug in the data has four products available and a median of two before patent expiration.[17][18]

Consistent with the increase in the number of products in the market, Figure 3-(b) shows that the number of sellers in the national market also increases after patent expiration. Our estimates imply that four years after patent expiration, the number of sellers of a particular drug increases

[17] Drugs under patent often have more than one product since innovators often offer multiple varieties of a drug.

[18] Appendix Figure A.4 compares the entry of products into the procurement market with that into the retail market using IQVIA data. This comparison serves as a check that product proliferation occurs simultaneously in both markets. Note that the Chilean version of IQVIA does not distinguish between unbranded generic products but rather groups them into one unbranded generic category. This likely explains why we estimate slightly larger impacts in the procurement market than in the retail market.

Figure 4: The effect of patent expiration on prices: Innovator vs. All products



Notes: This figure plots the point estimates and confidence intervals of β_k in equation (3). An observation is a drug-quarter. The outcome variable is the log average procurement price of all products (blue) and the innovator only (red). Standard errors are clustered at the drug level.

by 2.4, from a baseline of 4.5 and a median of three.[19] Moreover, having more sellers in the market translates into an increase in the number of bidders in procurement auctions. Figure 3-(c) shows results for this outcome, implying that the average auction had 0.6 more bidders four years after patent expiration. The results for these three outcomes suggest that patent expirations induce sizable changes in market structure, translating into a larger number of bidders in procurement auctions.

The increase in the number of products and sellers in procurement markets strongly affects auction prices. Figure 4 displays the impact of patent expiration on procurement prices.[20] Average procurement prices decrease steadily after patent expiration, with the total decrease reaching almost 30 percent four years after patent expiration. This decrease in average paid prices is not driven solely by lower-priced entrants: we estimate a slightly smaller price decrease on innovator prices. These results suggest that the increased numbers of products and sellers in the market have strong competitive effects.

[19] Even though drugs under patent are only manufactured by a single laboratory, they could have multiple sellers if the innovator also sells to wholesalers that then source the procurement market.

[20] While pre-trends are to a large extent mechanically parallel for market structure outcomes, the fact that pre-trends in prices are parallel is reassuring, as it suggests that preemptive behaviors by the incumbent innovator before patent expiration were not particularly strong in this setting (e.g., Ellison and Ellison 2011).

4.3 Discussion

These two sets of results highlight the relevance of market structure as a driver of procurement prices. The first set of results from the regression analysis in Section 4.1 implies that adding a marginal seller to the market is associated with a price decrease of approximately 1.5 percent. Even though we attempt to control for unobservables using rich fixed effects, these estimates are harder to interpret causally due to the potential endogeneity issues discussed above. The second set of results from the patent expiration analysis in Section 4.2 implies that adding an additional seller to the market leads to a price decrease of around 11.7 percent four years after patent expiration.[21] This result is not directly comparable to those from the first analysis: the estimates are local to a restricted sample of active ingredients for which their patent expires within our sample period and, perhaps more importantly, the estimates are local to the entry of the first firms starting from a monopoly market structure, which most likely have stronger competitive effects on prices than subsequent entry (Bresnahan and Reiss, 1991). With those caveats in mind, this estimate suggests that the impact of adding a seller to the procurement market could be as high as 72 percent of the gap between the 10*th* and 90*th* percentiles of buyer effects from our preferred specification in Section 3.1.

It is also informative to compare our estimates to those obtained by Atella, Ceschin and Decarolis (2021), who estimate the procurement price effects of a merger between two prosthesis manufacturers. They find that the merger led to an increase in prices of around 7 percent, which is 40 percent lower than our estimate of 11.7 percent. There are at least two reasons that could justify this difference. First, while a merger between two suppliers implies a mechanical reduction in the number of potential sellers, it may also entail efficiency gains that would attenuate the price effect. Second, the market they study features a relatively low initial concentration, implying that expected price effects should be lower than in our case with an initial monopoly (Bresnahan and Reiss, 1991).

5 Conclusion

This paper documents the main drivers of price dispersion in pharmaceutical drug public procurement in Chile. Using detailed data from hundreds of thousands of procurement auctions, we separately estimate the extent to which buyer effects and market structure explain procurement prices in this setting.

Our estimates of buyer effects imply substantial differences in prices paid by different public agencies for the same product, consistent with the previous literature. Our granular data allows

[21] This estimate comes from combining our results for the impacts of patent expiration on the number of sellers in the market and on prices, namely $(\exp(-.33) - 1)/2.4 = -0.117$.

us to show that these estimates of buyer effects would be substantially larger had we not properly controlled for all product characteristics—which we do by defining products at the barcode level—and accounted for estimation noise using shrinkage methods. However, perhaps the more important result of the paper is that we show that supply-side drivers of procurement prices explain more of the variation in prices than demand-side drivers, even though the latter have received more attention from the literature. This result calls for the attention of policymakers to the determinants of the competitive environment in procurement.

While our analysis highlights the role that the supply side of public procurement plays in the market, discussing specific policies and regulations that could affect market structure and participation in procurement auctions is beyond the scope of this paper. Delivering more accurate policy implications for improving overall efficiency in public procurement by targeting the supply side of the market is a productive avenue for future research.

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Appendix

A Empirical Bayes Shrinkage

We are interested in features of the distribution of η_i across buyers, which are overdispersed due to noise. We follow a hierarchical approach to correct estimates from measurement error (Morris, 1983; Abdulkadiroğlu *et al.*, 2020), assuming the following structure:

$$\begin{aligned} \hat{\eta}_i|\eta_i, s_i &\sim N(\eta_i, s_i^2) \\ \eta_i|s_i &\sim N(\mu_\eta, \sigma_\eta^2) \end{aligned}$$

The first step involves estimating parameters for each unit $\{\hat{\eta}_i, s_i\}_{i=1}^I$. A second (deconvolution) step requires estimating $(\mu_\eta, \sigma_\eta^2)$, which, given our previous assumptions can be estimated from $\{\hat{\eta}_i, s_i\}_{i=1}^I$:

$$\begin{aligned} \hat{\mu}_\eta &= \frac{1}{I}\sum_{i=1}^{I} \hat{\eta}_i \\ \hat{\sigma}_\eta^2 &= \frac{1}{I}\sum_{i=1}^{I} \left[(\hat{\eta}_i - \hat{\mu}_\eta)^2 - s_i^2\right] \end{aligned}$$

from where by treating $(\hat{\mu}_\eta, \hat{\sigma}_\eta^2)$ as priors, we can update $(\hat{\eta}_i, s_i)$ to form individual posterior estimates $\{\hat{\eta}_i^*\}_{i=1}^I$:

$$\hat{\eta}_i^* \equiv \mathbb{E}[\eta_i|\hat{\eta}_i, s_i] = \left(\frac{\sigma_\eta^2}{\sigma_\eta^2 + s_i^2}\right) \cdot \hat{\eta}_i + \left(\frac{s_i^2}{\sigma_\eta^2 + s_i^2}\right) \cdot \hat{\mu}_\eta \tag{4}$$

such that the posterior mean $\hat{\eta}_i^*$ shrinks the noisy estimate $\hat{\eta}_i$ toward prior mean $\hat{\mu}_\eta$ based on signal-to-noise ratio. The latter is also known as the *attenuation factor*. Appendix Figure A.1 shows the distribution of attenuation factors. The median factor is 0.08.

B Data Description

B.1 NBER Orange Books

In 1984, the Drug Price Competition and Patent Term Restoration Act was passed, creating a more expedited way for generics to enter the market. Since then, generics could get approved by showing bioequivalence to a certified branded drug instead of going through clinical trials. From 1985 onwards, all patents and regulatory exclusivities were registered by the FDA in "The Orange Book" as a way to inform potential generic producers about patents that could impede their entry into the market (Durvasula *et al.*, 2023).

Exclusivities are granted by the FDA and hence reported directly into the book by them. Patents are self-reported by their holders, who have strong incentives to do so given the advantages it provides in the case of a challenge by an aspiring generic competitor (Durvasula *et al.*, 2023).

We are using two data files from the /4_clean_exclusivity_tables_stata/ folder of The Orange Book patent and exclusivity data:

- **FDA_drug_patents.dta** contains information on patents associated with specific products. It includes edition, patent number, active ingredient, product name, patent expiration date, use code, and substance and product claims indicators. It also includes the application type and number, which refer to the New Drug Application (NDA) submitted to the U.S. Food and Drug Administration (FDA) for the approval of the patented product.

- **FDA_drug_exclusivity.dta** contains information on regulatory exclusivities granted by the FDA. It includes edition, active ingredient, product name, exclusivity expiration, exclusivity code, application type, and application number.

Patents and exclusivity periods can affect the entry of generics into the market. We use both data files for that reason. Multiple aspects of a drug (active ingredient, formulation, or use method) can be protected by a patent or exclusivity, leading to various patents (and expiration dates) associated with each product and active ingredient. Overall, these data files contain 1486 active ingredients. The median number of expiration dates per active ingredient is three.

For each active ingredient in our data set, we kept all of the patents in the Orange Book related to it by product name or active ingredient (giving priority to the former). To identify which expiration date is the one that governs each active ingredient in practice, we used IQVIA data on retail purchases and the following criteria:

1. We only used patents that indicated protection of drug substances.

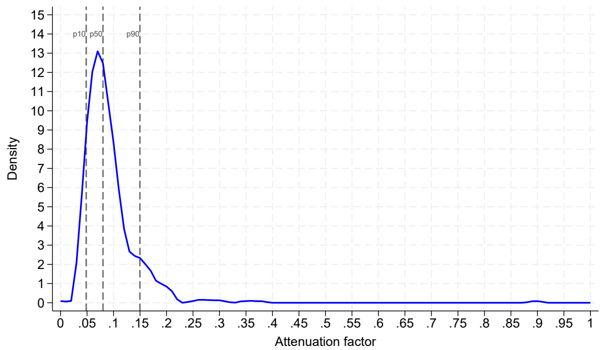
2. We only used exclusivities that were categorized as "generic-blocking exclusivity" by Durvasula *et al.* (2023) .

3. All expiration dates after the first appearance of generic or branded products with that active ingredient in IQVIA were eliminated.

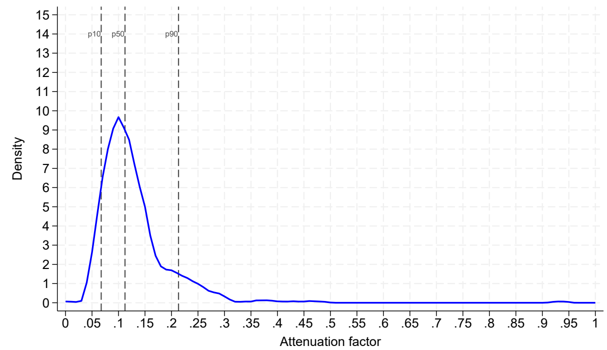
4. Out of the remaining expiration dates, we picked the latest one.

C Additional Figures

Figure A.1: Attenuation factor



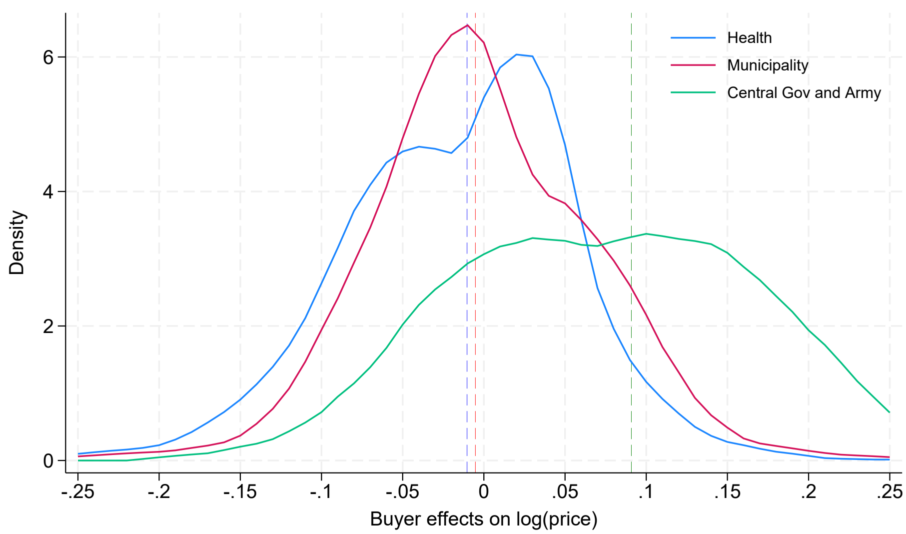
(a) Drug FE



(b) Product FE

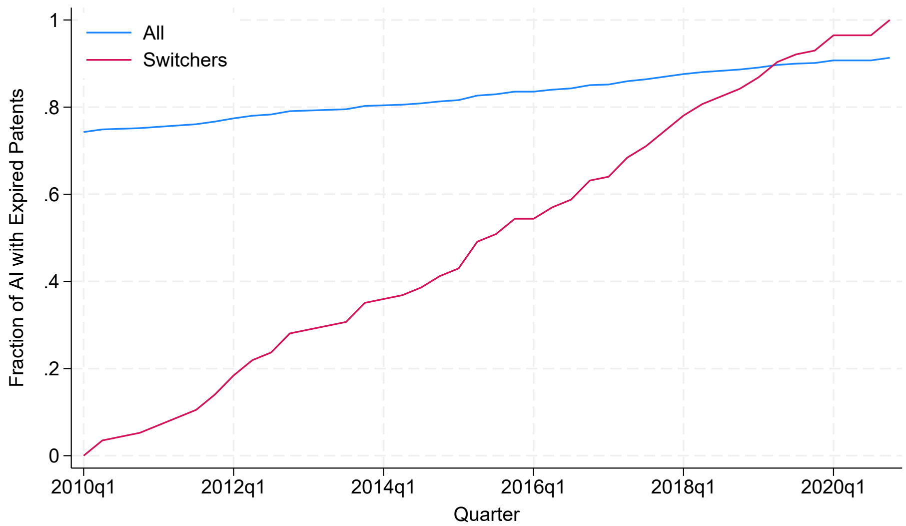
Notes: This figure displays the distribution of the attenuation factor associated with the empirical Bayes shrinkage procedure we implement on buyer effects. Panel (a) displays results for buyer effects estimated at the drug level. Panel (b) displays results for buyer effects estimated at the product level.

Figure A.2: Buyer effects on log(price) by buyer sector



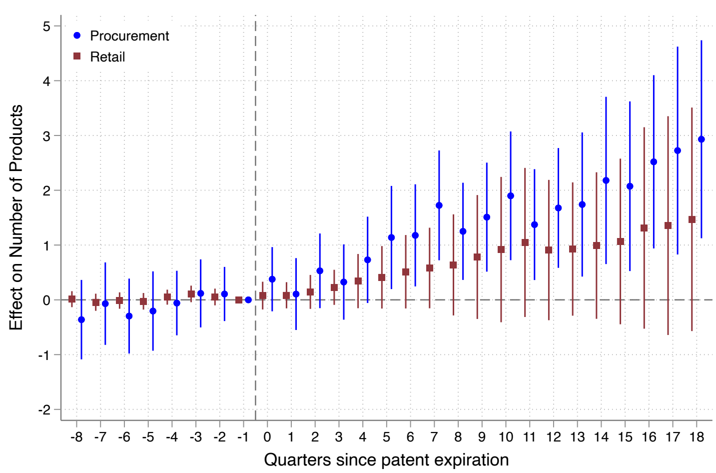
Notes: This figure displays the density of buyer effects in log drug prices, for agencies from the healthcare sector (blue), municipality sector (red), and central government and army (green). The dashed lines display the mean buyer effect for each group of buyers.

Figure A.3: Fraction of active ingredients with expired patents



Notes: This figure shows the share of active ingredients matched to patent expiration for which the patent has already expired by the quarter indicated in the x-axis. The figure reports the unconditional share (blue), and the share within our sample period (red).

Figure A.4: The effect of patent expiration on product availability: Procurement vs. Retail



Notes: This figure plots the point estimates and confidence intervals of β_k in equation (3). An observation is a drug-quarter. The outcome variable is the number of different products available in the procurement market (blue) and retail market (red). Standard errors are clustered at the drug level.

D Additional Tables

Table A.1: Analysis of variance (ANOVA)

Source	Partial SS	df	F-stat
Model	35,669.8	487	214.0
Number of sellers in the market	13670.3	1	39,947.5
Buyer FE	4,005.8	431	27.2
Quarter FE	914.3	39	68.5
Auction type FE	200.7	7	83.8
Auction quantity decile FE	8,021.0	9	2604.4
Residual	273,506.6		
N	799,732		

Notes: This table presents an analysis of variance ANOVA. The sum of square errors is calculated using partial (or marginal) sums of squares. This method is convenient as it is agnostic about the order of inclusion as in sequential approaches; however, it has the disadvantage that the sum of squares does not match the model sum of squares; we present the model sum of squares as well.

Table A.2: Procurement prices and market structure (measured as the number of products)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A - Country-level market structure								
Number of products in the market			-0.012*	-0.011*				
			(0.006)	(0.007)				
R-squared	0.047	0.071	0.118	0.131	0.532	0.555	0.583	0.602
Adj. R-squared	0.047	0.071	0.117	0.131	0.512	0.535	0.538	0.559
N	807,461	807,461	807,461	807,461	807,461	807,461	788,855	788,855
B - Region-level market structure								
Number of products in the market			-0.020*	-0.020*	-0.002*	-0.000		
			(0.011)	(0.011)	(0.001)	(0.001)		
R-squared	0.047	0.071	0.107	0.122	0.532	0.555	0.583	0.602
Adj. R-squared	0.047	0.071	0.107	0.121	0.512	0.536	0.538	0.559
N	806,438	806,438	806,438	806,438	806,438	806,438	788,085	788,085
Auction controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Buyer FE	No	Yes	No	Yes	No	Yes	No	Yes
Quarter FE	Yes	Yes	Yes	Yes	No	No	No	No
Drug-quarter FE	No	No	No	No	Yes	Yes	No	No
Region-drug-quarter FE	No	No	No	No	No	No	Yes	Yes

Notes: This table displays results from regressions of procurement prices on market structure characteristics and fixed effects in from equation (2) on buyer characteristics. Panel A displays estimates for the full sample, for the number of products in the national market. Panel B displays estimates for the full sample, for the number of products in the regional market. Standard errors clustered at the drug level in parentheses. *** p<0.01, ** p<0.05, * p<0.1