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Efficiency gains from anti-corruption in pharmaceuticals procurement: Analysis of 9 countries across 3 continents

Working Paper series: GTI-WP/2023:04

02 June 2023, Budapest, Hungary

1 - Central European University
2 - Government Transparency Institute

Summary

Public procurement of pharmaceutical products represents a large share of countries' health care spending. The crucial importance of pharmaceutical products has been further exposed by the COVID-19 pandemic. Inefficiencies and corruption risks in public spending on the procurement of pharmaceuticals increase medical costs and place a heavy burden on national budgets and patients.

To support policymakers in identifying strategies for improving value for money in the procurement of pharmaceutical products, this report assesses the impact of corruption risks on unit prices using pharmaceutical procurement data and identifies effective scenarios for cost savings. Specifically, the report aims to:

- Map the variation in unit prices of pharmaceutical procurement within and across countries.
- Explain the price differences for standardized pharmaceutical products with the help of corruption risk factors.
- Estimate potential savings due to lowering corruption risks.

The study has an exceptionally wide scope and range. It analyzes pharmaceutical procurement data from 9 countries (Armenia, Brazil, Chile, Dominican Republic, Kazakhstan, Mexico, Russia, Ukraine, and Uruguay) across 3 continents. Contract and purchase level public procurement data were directly collected from official government sources (e.g., public procurement advertisement websites). In order to allow for a cross-country analysis, national product codes and descriptions were matched to a widely-used global, standard product classification - Anatomical Therapeutic Chemical Classification System (ATC). The analysis investigates the unit price impacts of 7 corruption risk indicators (e.g., non-advertisement of tender opportunities) and their composite score, the Corruption Risk Indicator (CRI henceforth). Indicators take a value between 0 and 1, where 0 indicates the least risky behavior, while 1 indicates the riskiest behavior.

Drawing on regression models, the study finds that corruption risks – CRI – have a substantial and significant effect on the unit price of pharmaceutical products across the 9 countries studied. For instance, one red flag change or about 0.14-point CRI decrease is associated with 16% lower unit prices. Moreover, individual corruption risk indicators also substantially influence unit prices, for example, single bid tenders tend to be 59% more expensive than multiple-bids tenders. Based on these findings, the study also reviews the price impact of 3 alternative corruption risk reduction scenarios. For the more conservative scenario, a 1/3rd decrease in CRI across the board is estimated to lead to a 14% decrease in total prices paid for pharmaceuticals. For the more ambitious scenario, a 2/3rd decrease in CRI is estimated to decrease total spending by 25%. Lastly, a complete reduction of CRI, i.e., when CRI equals 0 (no corruption risk), is estimated to decrease total spending by 33.5%. Nevertheless, the price impacts of corruption risks and the corresponding efficiency gains vary considerably across countries. For example, in the 1/3rd CRI decrease scenario, we find potential efficiency gains vary from 6% in Armenia to 19% in Kazakhstan with the rest of the countries falling in between.

Acknowledgements

We are grateful to Olena Nikulina and Nóra Regös for their assistance in preparing the underlying dataset for this analysis. We are also thankful for the funding, guidance and support of Transparency International - Global Health.

1. Introduction

The COVID-19 pandemic challenged the already heavily burdened healthcare sectors all around the world. Governments poured extensive public resources into health responses to the pandemic, for example by increasing the purchasing of specific drugs. What such emergency spending exposed has already been a problematic phenomenon for decades: overpricing of pharmaceuticals due to corruption and favoritism. For instance, Kohler et al. (2015) find that between 10 and 25 percent of global spending on public procurement is lost due to corruption. Zooming in on the LAC region, Savedoff (2007, 1) projects a conservative estimate of $28 billion diverted from health services, with a large share of this portion to Mexico and Brazil. To tackle exploding healthcare costs and ensure value for money, a targeted approach is needed which addresses the underlying corruption risks most extensively impacting pharmaceutical prices and value for money more broadly. Such a targeted anti-corruption approach requires the collection and analysis of detailed and high-quality data on pharmaceutical prices and their determinants.

However, so far there has been a paucity of studies looking at the problems of corruption in pharmaceutical procurement systematically in sufficient scale and detail. Most studies rely on interviews and/or focus groups with managers or high-ranking officials (David-Barrett et al. 2017) or re-interpret findings from the earlier literature (Martin et al. 2007). Instead, our approach relies on the collection of large-scale public procurement data that can be standardized to allow for comparison across as well as within countries. To address these gaps, the objectives of this analysis are as follows:

- *Map the variation in unit prices of pharmaceuticals within and across countries.*
- *Explain the price differences for standardized pharmaceutical products with the help of corruption risk factors.*
- *Estimate potential savings due to lower corruption risks.*

This paper represents a major shift from existing studies, whose data limitations prevented the exploration of variation across as well as within countries. Hence, this analysis uses large-scale, micro-level administrative data, rather than broad, perception-based indicators as is often the case in the literature (Bate and Mathur 2018). Our dataset includes 9 countries: Armenia, Brazil, Chile, Dominican Republic, Kazakhstan, Mexico, Russia, Ukraine, and Uruguay, from 3 continents: the Americas, Europe, and Asia. The country selection was constrained by the availability of sufficiently high quality and wide scope of publicly available pharmaceutical procurement data. In the country selection, we, nevertheless, aimed to draw on a balanced global sample of countries with different levels of development and corruption control institutions.

Our main indicator of corruption risk is the Corruption Risk Index (CRI). CRI is a composite index that is calculated as a simple average of available individual red flags single bidding, the length of advertisement period, length of the decision period, publication of call for tender, the type of procedure, buyer's concentration, tax havens (whether or not bidders are registered in tax havens) and s Benford's law (investigate for potential manipulation of contract values through the law of anomalous numbers). The composite CRI is a more robust indicator for detecting risks of corruption compared to its individual components, considering that across time and regions, corruption can thrive using different strategies. Therefore, using only individual 'red flags' across such a variety of contexts runs the risk of underestimating the effect. CRI is defined based on existing corruption theories, and it is a data-driven index (we define risky categories by running a series of validity regressions). For details see Fazekas and Kocsis (2020). These risk factors are associated with deviations from rules and principles governing public procurement processes, as well as the manipulation of outcomes (denoting possible complicity between buyers and suppliers). By scoring each contract using the CRI methodology we are able to compare contracts on a global scale and identify potential policy and behavior changes that lower the likelihood of corruption. In addition, by linking CRI to unit prices, the analysis of red flags points to impactful, yet feasible policy interventions within the existing institutional and legal frameworks.

To investigate the effect of CRI (and individual red flags) on unit prices we employ fixed-effects ordinary least squares regressions (for a comparison of alternative methods see Fazekas et al (2021)). OLS regression models allow for price prediction and simulation of hypothetical scenarios. Furthermore, OLS regression models are suitable for the relatively easy interpretation of coefficients, i.e., how input (CRI) contributes to the output (log unit price). The method helps us handle large amounts of data while accounting for the heterogeneity of countries and markets. We use three fixed effects variables: country, year, and product. The fixed-effects approach allows us to make comparisons within these groups while accounting for any variation across the groups.

We identify 3 main sets of findings. First, we observe a surprising variation across countries in terms of unit prices even for some of the more generic pharmaceutical products, such as paracetamol, and ibuprofen. Second, the models predicting unit prices using red flags of corruption identify substantial price effects across countries, years, and products. For example, individual red flags such as single bidding or the use of non-open procedure types, are associated with 58 and 56 percent higher prices, respectively. The effect of CRI, combining all 7 red flags, is likewise large. For example, 1 additional red flag, that is about 0.14-point CRI increase is associated with 16% higher prices. Third, we outline two policy scenarios to identify efficiency gains to be made from better control of corruption. For the more conservative scenario, a 1/3rd decrease in CRI across the board is estimated to lead to a 13.6% decrease in prices paid for pharmaceuticals. For the more ambitious scenario, a 2/3rd decrease in CRI is estimated to decrease prices by 24.6%. Nevertheless, the price impacts of corruption risks and the corresponding efficiency gains vary considerably across countries. For the 1/3rd CRI decrease scenario, we find potential efficiency gains vary from 6% in Armenia to 19% in Kazakhstan with the rest of the countries falling in between.

2. Market and Institutional Context

Given the great diversity of national pharmaceutical procurement systems, the following section aims to provide a selected review of different market conditions and institutional reforms across countries and regions. Such a review, even though it cannot be comprehensive due to space constraints, helps better contextualize and interpret subsequent results on pharmaceutical prices and corruption risks. Although our cases are in different regions in the world (Latin America and the Caribbean - LAC; as well as Eastern Europe and Central Asia - EECA) some similarities concerning procurement of pharmaceutical products emerge between them.

2.1 Market Conditions

The wide variety of pharmaceutical market conditions is well exemplified by the presence of low-cost and generic products (e.g., ibuprofen) as well as highly complex and expensive therapeutic pharmaceutical products (e.g., cancer therapeutics). We can also observe significant variation in the size of purchases, i.e., products that are purchased in large quantities and procured regularly, and products that are purchased intermittently and in smaller quantities. The dataset used for this analysis reflects this diversity. It includes at least 400 products with an average unit price ranging from less than USD 1 to products costing more than several thousand USD. Such a range of conditions underpins the importance of diverse procurement strategies that can maximize value for money and stimulate savings in such complex markets (Fazekas et al, 2021).

The market structure of the pharmaceutical industry globally and in selected countries represents a key constraint for governments to achieve value for money. Some countries are highly specialized in selected pharmaceutical products and produce and export large volumes, while at the same time, they may also import many other drugs (Vargas et al. 2022, 11-22). Such specialization affects market concentration and the relationship between domestic buyers/suppliers and potential foreign bidders in public procurement. Considering the complexity of products, synthetic or biological drugs, and originator or generic products, there is a variation among the case study countries in terms of production and consumption. For instance, countries such as Mexico and Uruguay satisfy around 45 percent of their demand with domestic production, while Chile's domestic production amounts to only 15 percent (Vargas et al. 2022, 10). Like Mexico, domestic producers dominate the Ukrainian market, due to the lower prices offered (Golubtsova et al. 2019). Such broad market conditions are imposing fewer possibilities for maneuvering of public officials.

Nevertheless, not all aspects of market concentration are defined by market actors. Instead, government officials dispose of considerable discretion over procurement strategies impacting market structure in both short and long terms. Such actions may be driven by the capacity and incentives of the public authorities and also likely reflect existing institutional and regulatory frameworks.

2.2 Institutional Choices and Reforms

Regulatory and institutional frameworks for pharmaceutical procurement are quite different in each of the countries analyzed. Such frameworks influence procurement activities and outcomes. Regulations influence the availability of procedure types and the expectations for which types to use by purchasing bodies, such as the use of competitive or non-competitive procedure types. Regulations of different countries set different monetary thresholds for the mandatory use of different procedures setting standards of transparency (e.g., advertisement of tender opportunities), openness of competition (open competition, invitation only, etc.), or procedural constraints (e.g., minimum number of days for advertising tender opportunities).

Within these regulatory constraints, government officials face a range of discretionary choices such as: the time allowed for bidders to submit their bids (most often minimum threshold is set), the time allocated to evaluate bids and decide, selection of the different competitive or non-competitive procedure types, or the size of the purchase (quantity and value). Such discretionary choices are not only influenced by regulations but also by broader institutional constraints. For instance, the purchased quantity has to comply with budgetary restrictions or planning procedures. Some pharmaceuticals could be mandated to have priority due to their clinical status, whether they are produced by a domestic company, or even certain suppliers (domestic or international) could have a preferential status.

A handful of these market constraints have been addressed by public authorities through major reforms of national public procurement systems. To illustrate, Mexico has introduced a series of reforms since 2000 with the primary aim of reducing the proportion of direct awards (type of procedure), which has resulted in some savings (Gómez-Dantés et al. 2022, 3-4). However, since the COVID-19 pandemic increased attention has been placed on emergency procurement, a category that is also considered a special risk factor (Kühn and Sherman, 2014; Transparency International report 2006, 21). Furthermore, Fazekas et al. (2021), in their analysis of strategic sourcing analysis of LAC countries, find that product bundling contributes to price savings in procurement. However, leveraging joint procurement is constrained by the spending and budgetary powers of different purchasing authorities. For instance, Brazil's procurement takes place at federal as well as state levels, which lends greater autonomy to different organizational levels, but also complicates joint purchasing and hence leveraging scale to achieve savings (Fazekas et al. 2021, 5). Moreover, different jurisdictions have different needs for pharmaceutical products that also affect the size of purchases and bundling of purchases (Nemzoff et al. 2019; Huff, Rousselle 2012).

While addressing major market and institutional constraints could generate considerable savings and are important for the macro-level analysis, the subsequent analysis is more selective. It considers factors that reflect decisions made by purchasing bodies, and to some degree also bidding firms, within the existing institutional framework. In other words, we focus on red flags for corruption which reflect procurement choices over which government officials have discretion. These directly or indirectly influenceable procurement choices do not require major institutional reforms, instead, they could be achieved at different stages of the procurement process through improvements to the organizational quality. In line with the above discussion, the factors considered in the following analysis include: the length of advertisement period, time spent on selecting a winning bid, share of single bidders, publishing a call for tender publications among others.

3. Research Design

3.1 Data

The starting point of this research is to draw on detailed, new data to be able to address our research objectives in a novel light. To this end, we screened a large sample of contract-level public procurement datasets collected by the Government Transparency Institute[1] to identify those datasets which are publicly available, contain unit price information, have sufficiently detailed product codes, and the data scope is sufficiently wide. All these datasets are directly collected from official government sources such as public procurement publication portals or open data repositories. The resulting dataset for the analysis includes pharmaceutical contracts and purchases from 9 countries: Armenia, Brazil, Chile, Dominican Republic, Kazakhstan, Mexico, Russia, Ukraine, and Uruguay. For each country, we selected all pharmaceutical product contracts and purchases. Our dataset contains public procurement contracts for the period 2000-2021, with some variation across countries. For instance, Brazil and Uruguay's data go back to 2000 and 2004, respectively.

Of crucial importance for our analysis of unit prices is having at disposal detailed and standardized product categories that can be compared across 9 countries. We identified and selected pharmaceutical products by filtering for relevant product codes in the national classification system and keywords in the product descriptions. After selecting the relevant product codes, we proceeded with matching national product codes to an international standard classification: Anatomical Therapeutic Chemical Classification System (ATC)[2] - as the most comprehensive drugs and active ingredients classification. For contracts that could not be matched using the national product code (e.g., the national code was missing), we assigned ATC codes to contracts based on an elaborate keyword search for active ingredients in the product descriptions (a detailed explanation is available in Appendix 2). Throughout the whole process, we also conducted manual crosschecks.

The total number of contracts related to pharmaceutical products collected for the purposes of our analysis is 417,799. However, missing or incorrect data on the official government publication portals prevented us from analyzing the complete dataset. Particularly affected are countries[3] that do not offer sufficient information to provide standardization of product codes (as a tool for cross-country comparison); or the ones that do not publish complete information related to the financial aspects of the tender, such as tender price, bid price, quantity, necessary for calculating unit prices. The data harmonization process, especially the standardization of product codes, resulted in a loss of 2⁄3 of observations, unfortunately. Furthermore, in some years the number of observations was insufficient for quantitative analysis. We are still left with a large dataset of 131,434 observations across 9 countries that offer sufficient cross-country and cross-

[1] See: https://www.govtransparency.eu/gtis-global-government-contracts-database/
[2] https://www.whocc.no/atc/structure_and_principles/ (accessed 03/10/2022)
[3] Most affected by this is Mexico.

product heterogeneity to allow us to compare. Table 1 provides an overview of the size of our data with all available pharmaceutical contracts in the first row and the number of standardized observations we have used for our analysis. There are still significant differences across countries, with Russia representing the fewest observations and Chile representing the highest number of observations.

Table 1: Overview of data used by country

country	Armenia	Brazil	Chile	Dominican Republic	Kazakhstan	Mexico	Russia	Ukraine	Uruguay
Number of pharma contracts	17744	49834	75411	38993	11736	136636	5020	52326	39685
Number of standardized pharma contracts	17663	1257	41548	29148	4704	5684	1508	16151	13771

For a more intelligible overview of our data and red flags, in Table 2 we systematize the size of each country sample, the temporal scope for our data as well as the applicable red flags per country.

Government Transparency Institute

Table 2: Available red flags by country

	Number of observations	***Years***	***Total spending (Million $)***	***Procedure type***	***Decision period***	***Submission period***	***Single bid***	***Call for tender***	***Buyer concentration***	***Benford's law***	***CRI***
Armenia	17744	2016 - 2021	40.84	✓	✓	✓	✓	✓	✓	✓	✓
Brazil	40059	2004-2021	116.35		✓	✓	✓	✓			✓
Chile	75541	2014 - 2021	7206.51	✓	✓	✓	✓	✓	✓		✓
Dominican Republic	38983	2018 - 2021	3233.26	✓	✓	✓		✓	✓		✓
Kazakhstan	11593	2016 - 2021	21.79	✓		✓			✓	✓	✓
Mexico	136526	2012 - 2021	367.84	✓	✓	✓	✓	✓	✓		✓
Russia	5020	2017-2021	96.87	✓	✓	✓					✓
Ukraine	52649	2016 - 2021	592.60	✓	✓	✓	✓		✓	✓	✓
Uruguay	39684	2004 - 2021	49.88	✓	✓	✓	✓	✓	✓		✓

3.2 Indicators

To research our research objectives, first, we calculated and quality-checked unit prices of pharmaceutical products; second, we identified and validity-tested a range of corruption risk indicators, finally, we also defined a small set of control variables to account for market, country and period-specific factors which would confound our estimates (Table 3).

First, the analysis aims to explain the variation of unit prices of pharmaceutical products within and across countries, i.e., what can explain the price differences for standardized pharmaceutical products with the help of corruption risk factors. In this context, we define unit prices as

$$unit\ price\ at\ contract\ award = \frac{total\ value\ of\ items\ contracted}{standardized\ quantity\ of\ items\ contracted} \qquad \text{(Equation 1)}$$

This formulation of unit prices implies that different units are taken as a basis within different product groups (i.e., ml, mg, kg, etc.). This means that prices are only directly comparable within product groups, while changes in prices, such as % price savings, can be compared also across products. Unit prices are defined at the point of contract award, so cannot take into account any eventual cost overruns or underruns which certainly introduce a downward bias in the subsequent analysis. This means that corruption is likely to lead to cost overruns on top of increasing contract award prices, but we only observe the latter. As observed unit prices within markets turned out to be highly skewed, with a considerable number of high-value outliers, we calculated the natural logarithm of unit prices to be used in the regression analysis.

Table 3: Summary of variables used in the analysis

Type	Variable name	Variable Type
Price	(log) unit price	Continuous
Control variables	atc_code (reflects product code)	Categorical
	Country	Categorical
	Year (of contract)	Categorical
Individual red flags	Call for tender	Binary
	Procedure type	Categorical
	Submission period	Categorical
	Decision period	Categorical
	Benford's law	Categorical
	Single bidding	Binary
	Buyer market concentration	Continuous
Composite risk indicator	CRI	Continuous

Second, the analysis identified corruption risk factors or red flags which are used as explanatory factors for unit prices in the analysis. For measuring corruption risks, we rely on a well-established proxy indicator approach: the Corruption Risk Index (CRI) (Fazekas and Kocsis, 2020). The CRI is based on typologies of corrupt situations that are specific to public procurement and detectable with open public procurement data. Calculating the CRI starts by identifying a range of individual risk factors. Then these red flags are validity tested individually. Finally, the valid indicators are combined into a composite indicator.

A range of individual factors has been identified in the literature (Fazekas et al, 2018), however, only a subset of these could be calculated across the 9 countries under study:

- **Non-publication of call for tenders.** The lack of announcement of a call for tender in an official journal leads to limited competition as fewer potential bidders are informed about a new tender. Limiting the opportunities for potential bidders to participate in tenders runs the risk that suppliers will be selected based on favoritism. Such tenders are not conducive to the principles of open and fair public procurement.
- **Non-open procedure types.** Non-open procedure types are less transparent and create opportunities to limit the received range of bids or to exclude certain bids. It allows public officials to extract illegal rent during the procurement process (Auriol et al, 2011). An illustrative example of this is contracts awarded to bidders without prior competition or request for quotation, particularly in the context of contracts that are of higher value.
- **Length of submission period.** This indicator captures the difference between the first contract notice publication date and the deadline by which suppliers can submit their bids

(bid deadline). Two types of risks can arise regarding this factor. The first one relates to short submission periods. This can be associated with unfair competition considering the lack of time at the bidder's disposal to prepare adequate documentation for the tender. The second risk relates to extensive submission periods, as it can indicate potential tinkering with the tender specifications, such as modifying the terms in order to favor specific bidders, or potential legal obstacles due to the conditions set in the tender.

- **Length of decision period.** The decision period red flag is focused on the time difference between the submission period and the announcement of the contract award. In a similar vein to the previous red flag, short periods can indicate unfair competition, due to the lack of time spent on the evaluation of bids. Conversely, an extensive decision period might suggest potential challenges by certain bidders and playing favoritism.
- **Benford's law**. The logic behind using Benford's Law, or first digit law, as a red flag is to find if there is any manipulation with the numbers of submitted prices. The law assumes a natural distribution of the first digits in numbers which is observed in a large number of digit distributions. This red flag compares the digit distribution of contract values in the public procurement data to test its conformity with Benford's law.
- **Single bidder contract.** This indicator focuses on the number of participants in a tender. It indicates whether only one bidder took part in the tender or not. Submitting only one bid in an otherwise competitive product market directly indicates restricted competition. Given that corruption is easier to organize and achieve with restricted competition, single bidding can point to likely corrupt tendering practices (Klasnja, 2016).
- **Buyer spending concentration.** High buyer spending concentration indicates corruption risks because dominant market positions can be misused by bidders to extract rents, and, on the other hand, corruption can lead to a higher concentration of spending for specific bidders. It is calculated as the share of contract value that is awarded to the same supplier by the same buyer in a year.

We conduct validity tests of each of the individual indicators in the full public procurement data, using regression analysis. The validity test for each red flag examines how well its use in public procurement tenders fits with corruption logic. Single bidding in a competitive market is the simplest sign of limited competition because it suggests competitors who could have bid did not show up for the tender. Therefore, to assess the validity of each red flag we run regressions to verify whether they are associated with single bidding. In addition, these regressions also allow for identifying thresholds (e.g., how many days exactly a risky submission period is) or categories (e.g., which exact national procedure types are non-open) that are most strongly associated with restricted competition. Such associations indicate potential corrupt strategies, for example avoiding the publication of the call for tenders so that only the favored bidder can put in a bid. Once individual red flags are validated and the risk thresholds and categories are identified, we calculate the CRI score as a simple arithmetic average of all validated, available red flags. When one or more red flags are missing for a particular tender, we adjust the weights of the observed red flags in the CRI to reflect equal weights for the observed values. The full details of red flag definitions for each country can be found in Appendix 1.

It is important to note that the individual red flags and the composite CRI do not intend to identify corruption per se, but rather measure the risk thereof, in an objective manner. The advantage of our approach to studying corruption risks is the comprehensive and consistent way of using these indicators across and within countries. One key advantage of the composite score over the use of individual indicators is that dominant corruption techniques may vary across countries so pooling a range of red flags makes for a more robust estimation.

3.3 Methods

The institutional and market context section above briefly highlighted the diversity of contexts within which pharmaceutical procurement takes place. Moreover, the data and indicators sections outlined the differences in corrupt behaviors and the different data points available to track them. Considering these 2 sets of challenges to reliably estimate the impact of corruption risks on unit prices, we opted for a methodology that controls for a large part of this variation across countries, markets, and time.

The biggest source of variation in prices is arguably coming from the country's institutional context. Given that we have at least a few thousand contracts in each country, we can consider country-level differences in the analysis. Furthermore, our dataset includes standardized product codes which capture key market-level features such as market structure. Finally, a large portion of the standardized observations (131,434) is within the period 2015-2021, allowing us to control for influences that are prone to year-to-year changes.

Hence, the explanatory analyses incorporate the list of indicators listed in Table 3 and employ a traditional regression method (Ordinary Least Squares). Our dependent variable (log unit price) is first regressed on each individual red flag, controlling for countries, years, and product codes (atc_code). In this model presented in equation 2, Log (Pr_i) is the natural logarithm of unit price for the *i*th item purchased, X_{1i} stands for the individual red flags or CRI, and X_{2i} refers to the set of controls (country, year, product code) that are used as a fixed effect. Lastly, ε_i refers to the error term of the regression model. Our regression model can be presented as:

$$Log(P_{ri}) = \alpha_i + \beta 1 * X_{1i} + \beta 2 * X2_i + \varepsilon_i \qquad \text{(Equation 2)}$$

Ordinary least square regression is a computationally efficient methodology that helps design models with hundreds of thousands of observations and hundreds of predictors and control variables while at the same time yielding high explanatory power. It is also designed to identify the independent effects of each predictor while holding all other factors constant, so we can zoom in on average effects across a wide variety of markets and institutional contexts.

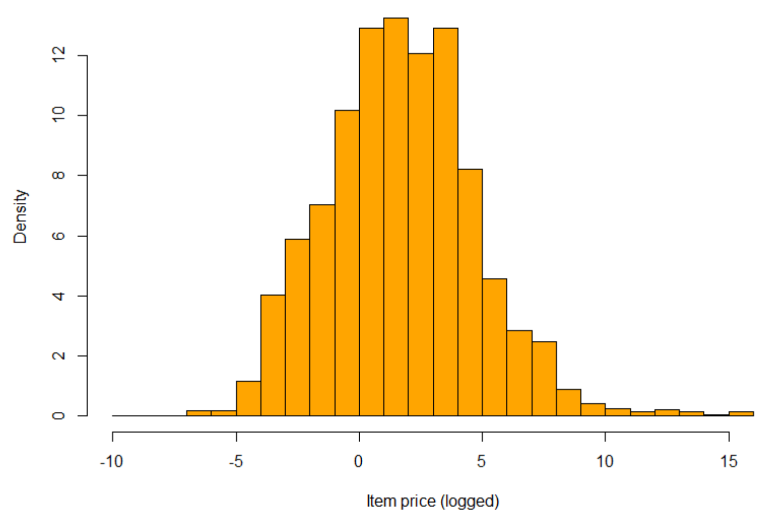
Once a high-quality regression model is estimated, we explore policy scenarios that point to total efficiency gains from different degrees of corruption risk reductions, considering the different institutional and market contexts. We estimate two scenarios, a more conservative scenario, One-third Cut, where we reduce the CRI scores by ⅓, and a more ambitious scenario, Two-third Cut, where we reduce the CRI scores by ⅔.

4. Results

4.1 Overview of unit prices

This section illustrates the variation of prices across different countries and products which contributes to our first research goal while it also serves as a useful background for the regression analysis. We first visualize the distribution of prices across all countries, product groups, and years (Figure 1). Unit prices are logged in most subsequent analyses. This is necessary because the distribution of unit prices is highly skewed and does not follow a normal distribution, that is it has some very high-values (i.e., expensive drugs) with the bulk of contracts falling in the low-value range. Transforming unit prices into logs also normalizes the distribution. Linear regression assumes normality or symmetrical distribution; hence the normalization of distribution renders the linear regression results "valid".

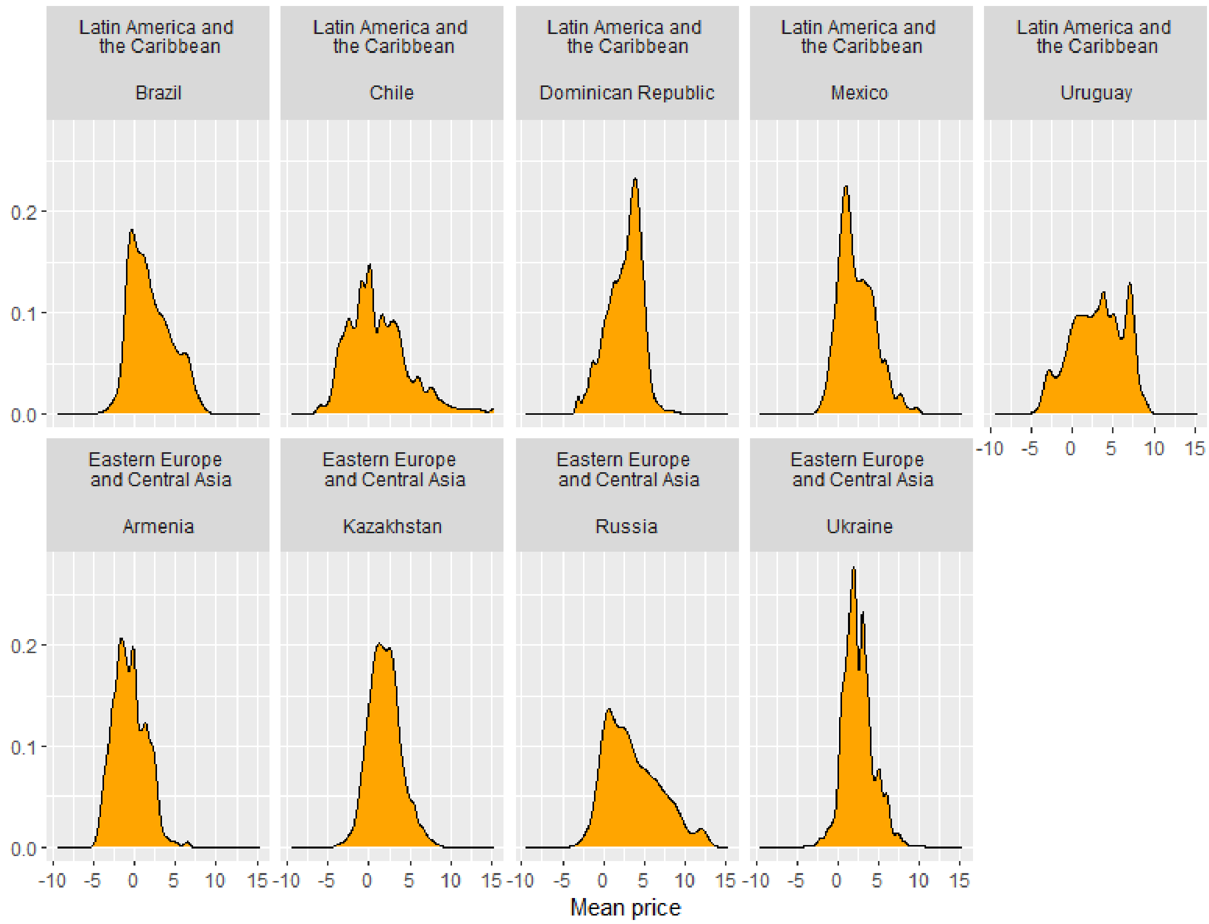
Figure 1: Histogram of logged unit price



To better illustrate the differences in unit prices across countries, we have also split the data by country (Figure 2)[4]. Overall, the log unit price distributions are close to normal with minor variations, such as Uruguay where it is flatter, indicating greater variation of prices, and countries such as Ukraine that have high peaks around the mean.

[4] In order to have a better comparative picture of how cases compare between them, we use proportions instead of total count on the y scale.

Figure 2: Plot of mean logged unit price, by country



Our dataset contains a wide variety of products, ranging from generic (everyday) products to complex medications used for the treatment of specific illnesses. While the classification system is highly standardized, we may expect that the former would be more comparable across countries than the latter. To gain greater insight into the price variation across products and countries we have extracted a sample of 5 pharmaceutical products, which are generic enough, i.e., products that are sold under the general name for a type of product rather than its brand name, and are standardized enough: ibuprofen, paracetamol, diclofenac, dexamethasone, and acetylsalicylic acid. Figure 3 below shows the mean price for each of these products by country and the regional average. We see that countries such as Chile have cheaper products, whilst countries such as the Dominican Republic are on the more expensive end of the scale. Some products show much smaller variation across countries, such as paracetamol. On the lower end of the scale, in countries such as Uruguay, the average price is slightly below 1 USD, while in the Dominican Republic, it is almost 10 times more expensive. Even more apparent differences are noticed for Ibuprofen or Acetylsalicylic acid.

Figure 3: Mean unit price for selected products, (standardized) USD (constant, etc.), by country

However, looking at national average prices only tells part of the story around price differences. The diversity of prices within each county can tell us a great deal about the potential for savings within existing institutional frameworks and market constraints. Simply put, if some buyers can achieve significantly lower prices than the national average, there are efficiency gains to be made most likely. Surprisingly, when looking at price variations around the mean, we see that even in the most expensive markets, such as Mexico or the Dominican Republic, it is possible to find the product at a price below the average price of the cheapest country among the 9 studied countries (Figure 10 in Appendix 4).

4.2 Overview of corruption risks

This section offers a brief overview of corruption risks across countries, highlighting both individual red flags and the composite CRI score. It is a key step for building an explanatory model and understanding the costs of corruption in pharmaceutical procurement.

Table 4 presents average scores for each red flag and the composite CRI. Recall, each contract is scored on the available red flags on a scale of 0 (lowest risk) to 1 (highest risk). The country average values are not fully comparable as the composition of contracts differs across countries, for example having more or less generic drugs. In addition, the availability of individual red flags also varies across countries, as reporting requirements are different and there are considerable missing rates for some variables. This underscores our analytical approach to measuring the price impact of corruption risks within countries, rather than across.

Table 4: Average score for each red flag (0-1. 0 - lowest risk, 1 - highest risk)

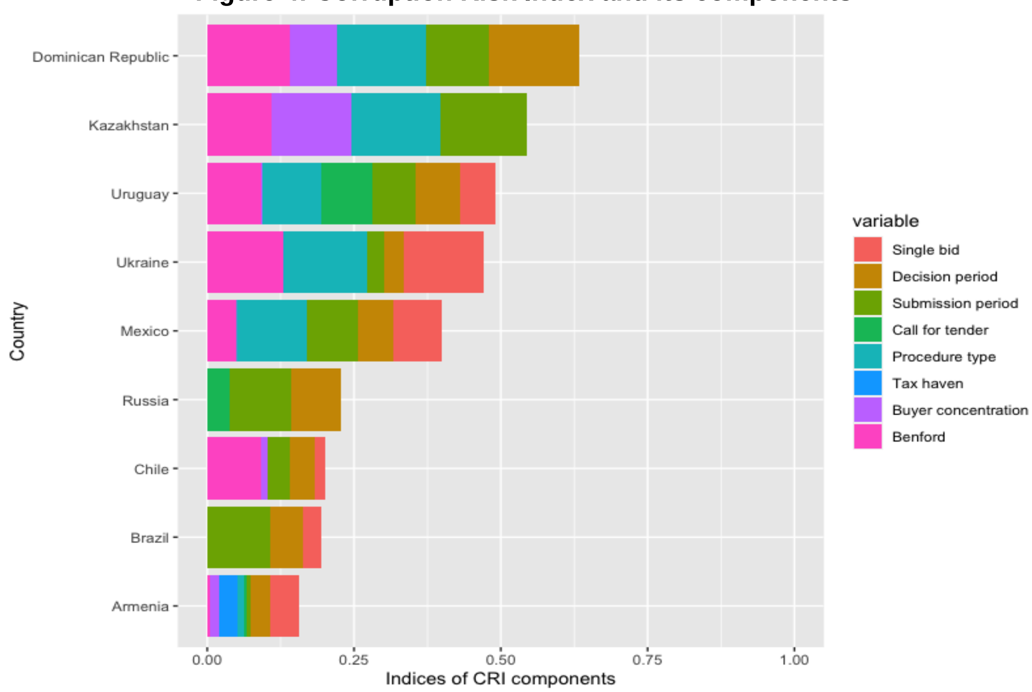
Red Flag / Country	Single bid	Decision period	Submission period	Call for Tender	Procedure Type	Buyer Concentration	Benford's law	CRI
Dominican Republic	...	0.92	0.65	0.00	0.91	0.48	0.84	0.61
Kazakhstan	...	...	0.59	...	0.61	0.54	0.44	0.60
Uruguay	0.59	0.76	0.73	0.88	0.99	0.03	0.92	0.51
Ukraine	0.73	0.14	0.14	0.00	0.75	...	0.61	0.50
Mexico	0.65	0.49	0.69	0.00	0.95	0.01	0.40	0.41
Russia	...	0.25	0.31	0.12	0.00	...	...	0.24
Chile	0.11	0.31	0.26	0.00	...	0.08	0.64	0.22
Brazil	0.12	0.23	0.43	0.00	...	...	...	0.19
Armenia	0.39	0.27	0.05	0.04	0.09	0.12	0.04	0.14
Average[5]	0.25	0.47	0.45	0.02	0.8	0.24	0.5	0.38

[5] The scores indicate averages for the full dataset.

Considering that we take the average of individual red flags in the composition of the CRI, it is also useful to show the extent to which each red flag contributes to the CRI (Figure 4).[6] This also amply demonstrates that corruption tends to manifest itself in different techniques in different contexts. Figure 4 helps us emphasize and grasp which corruption techniques are more prevalent in which countries. We group by country and stack the share of each red flag in the composition of CRI. Each red flag is illustrated with a different color. The final length of the bar shows the total CRI for the said country.

In some cases, the CRI could be composed of all individual red flags, while in other cases only 4 or 5 red flags contribute to its composition. Although this could represent a certain limitation for countries where fewer red flags are present, overall, the approach presents more robust information for investigating the risk of corruption vis-a-vis using individual red flags. Importantly, because we calculate the average of only the available red flags, this should not distort the results. For instance, if for country A there are four individually validated red flags, we calculate the CRI as the average of these four. In country B, there could be six individually validated red flags, and, therefore, we divide their average by six.

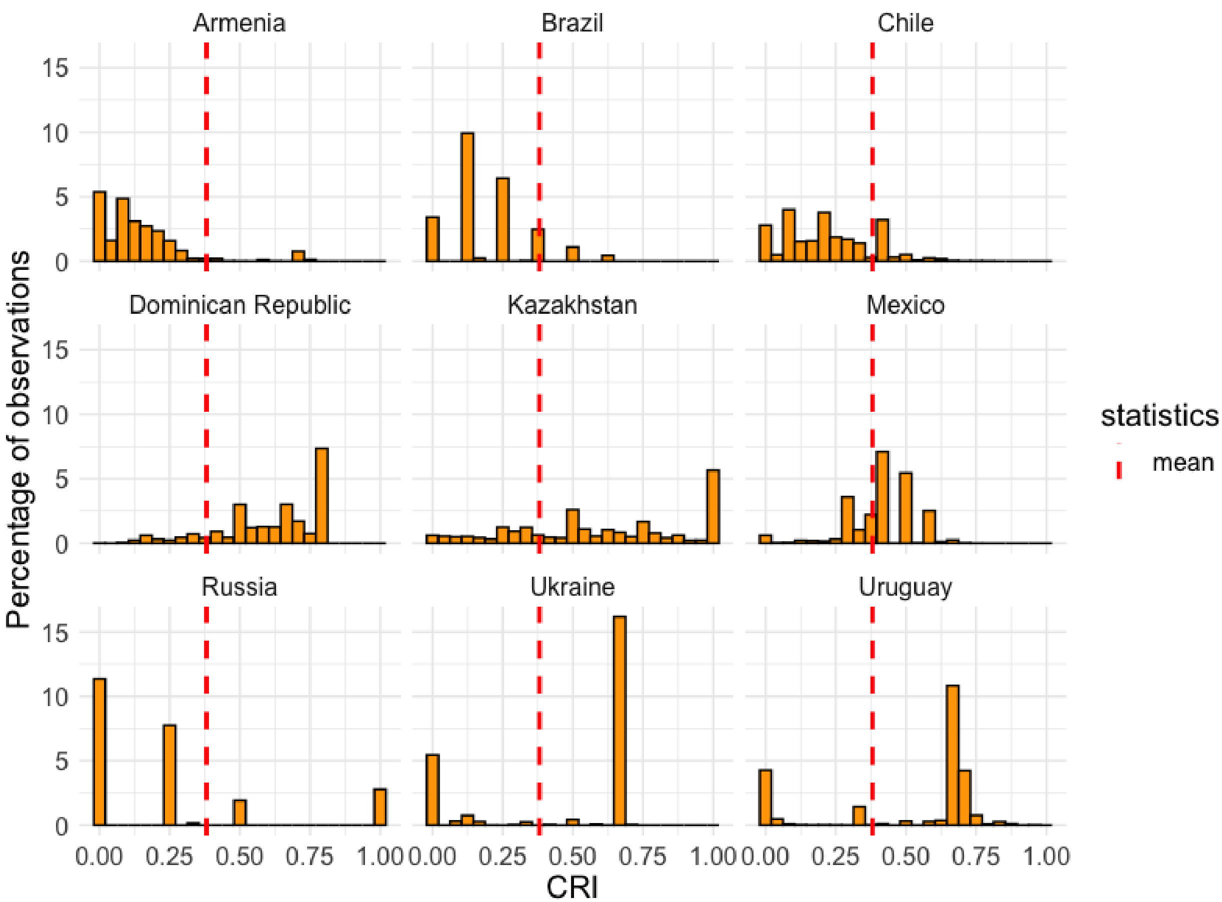
Figure 4: Corruption Risk Index and its components



[6] The length of each bar indicates the mean CRI score for each country on a 0-1 scale, and each bar is filled by the proportion of individual red flags in composing the CRI. The full bar length indicates the CRI on a scale of 0 to 1, where closer to 1 indicates higher risk for corruption. Each individual indicator that contributes to the CRI creation of each country is also included with different colors to the relative extent that they are represented within the total CRI.

Given that the bulk of the analysis exploits variation within countries and markets, we also showcase the variation of corruption risks within each country. Figure 5 illustrates how contracts are distributed according to their CRI scores in each country (note the y-axis represents percentages of observations within each country to make the scales comparable). We split each country into 25 bins and count how many observations are within each bin. The vertical red dashed line indicates the mean CRI score for the full dataset, considering all countries. The histograms amply demonstrate that risk distributions are quite varied within each country, with some having distributions skewed to the right (e.g., Armenia) while others skewed to the left (e.g., Dominican Republic).

Figure 5: Average scores of CRI for each country



4.3 Effect of corruption risks on pharmaceutical unit prices

This section builds explanatory models for the variation of pharmaceutical unit prices across countries, years, and markets. We develop different models for each "red flag" and one model for the composite indicator. Considering the variety of countries and products that are encompassed with our analysis as well as the long time period we have in our data, we use fixed-effects for country, year, and product groups. These fixed-effects take into consideration the unobserved heterogeneity for each of these categories. In other words, we explain variation in unit prices with the help of corruption red flags within countries, years, and product groups. We also assume that there might be a correlation within different group products, and for this purpose, we cluster our standard errors. Overall, not all predictors display substantial and significant relationships nor explain the equal size of the variation in unit prices. Furthermore, not all red flags had an equal number of observations, as some countries were missing some of the red flags, hence the different number of observations per "red flag". Nevertheless, using the composite index, the CRI can overcome these limitations.

All red flags, except for decision period (and submission period only at 0.1 level) show a substantial and significant effect on the (log) unit prices (Table 5). Looking at the results in Table 5 we can see that if a tender received only one bid it is associated with a 59 percent higher unit price compared to receiving multiple bids (column 6). The effect of a call for tenders is even more substantial. We relate this finding to our consideration in the first part of the study where we have discussed that having a call for tenders increases competition. Bidders have a greater chance to prepare and submit bids if they are aware of the tender in the first place. Our results suggest that if there was a call for tenders, as opposed to no, it is associated with 85 percent higher unit prices (column 1) after we control for country, year, and product groups. The procedure type follows a similar rationale. But here the base category is having an open procedure/tender or negotiated procedure with prior announcement. Compared to these, restricted procedures, urgent or outright awards (associated with risky tenders) show an increase of 55 percent in the unit price (column 2). The submission period also shows a significant relationship in line with our expectations. Non-risky submission periods (coded as 0) are also significant, although the significance level is lower (significant at 0.1 level, column 3). However, for the interpretation of this category (the exact periods as opposed to groups) we must also take into consideration which periods are considered risky, non-risky, and medium-risky in which country (refer to the tables in section - Overview of Indicators). Using acceptable or close conformity (Benford's law) as a base category, we find that tenders that have non-conform prices see 83 percent higher unit prices (column 5). One red flag, decision period, is not significant (column 4).

Table 5: Main results individual red flags

Dependent Variable:	Log Unit Price is the Dependent Variable						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Call for Tender	0.8597***						
	(0.1553)						
Procedure Type		0.5579***					
		(0.1285)					
Submission Period			0.2216*				
			(0.1271)				
Decision Period				0.2391			
				(0.1473)			
Benfords Law					0.8371***		
					(0.1578)		
Single Bid						0.5896***	
						(0.0946)	
Buyer Concentration							0.5854***
							(0.1389)
Fixed-effects							
country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
atc_code	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	126,600	75,278	80,593	99,379	85,131	77,215	108,386
R^2	0.45400	0.54186	0.47552	0.41344	0.55213	0.44700	0.47218
Within R^2	0.00210	0.00882	0.00156	0.00112	0.01539	0.00810	0.00302

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

Moving beyond the individual effects of the red flags on our composite index, CRI, the results are also large and significant (Table 6). As we have discussed earlier, the benefit of using the CRI is its ability to capture different techniques related to corruption. The effect of the CRI is even more substantial compared to the individual red flags. Namely, higher CRI scores relate to higher prices per unit. Going from the lowest risk (CRI=0) to the highest risk observed (CRI=1) is associated with a 110 percent increase in unit prices. Considering one red flag change, which is about 0.14-point CRI increase, is associated with 16% higher unit prices, we expect to see 110 percent lower prices for the product in question, by holding our controls constant across time, country, and product groups. Our models explain approximately 45 percent of the total variation in unit prices, with the exception of the procedure type which performs slightly better (explaining 54% of the variation). The first column of Table 6 represents a model with all red flags in one model. We see that red flags such as a call for tender or single bidding continue to stay substantial and significant. Lastly, in Figure 6 we illustrate the effect of all red flags and the CRI with their confidence intervals. Further, robustness tests can be found in Appendix 3, Table 27 and 28, where we run the same model specifications but control for contract value. The results remain substantially the same.

Figure 6: Main results with confidence intervals (all models)

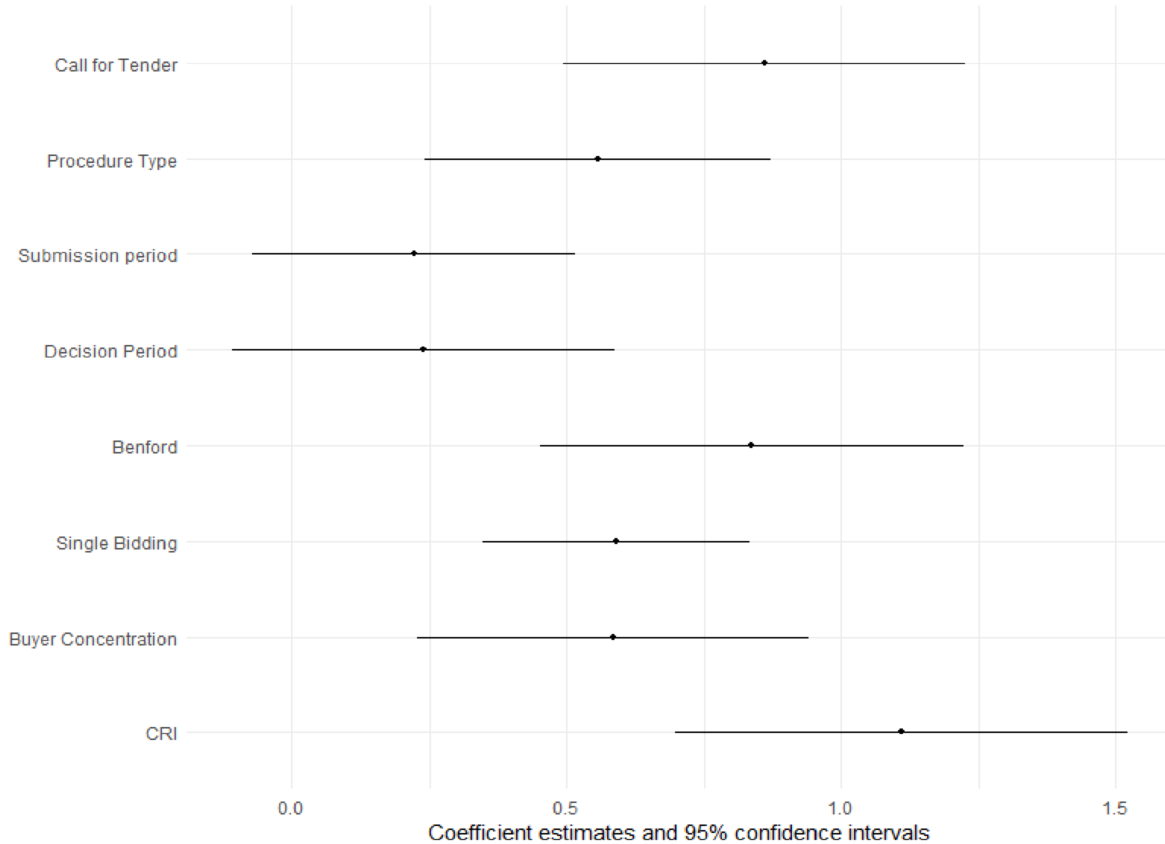


Table 6: Main results – CRI & all red flags

Dependent Variable:	Log Unit Price is the Dependent Variable	
Model:	(1)	(2)
Variables		
Call for Tender (1)	0.7655*	
	(0.3025)	
Procedure Type (0.5)	0.1141	
	(0.3009)	
Procedure Type (1)	0.3105	
	(0.2647)	
corr_proc99	0.1288	
	(0.4720)	
Submission Period (0.5)	-0.2409	
	(0.2467)	
Submission Period (1)	0.0494	
	(0.2556)	
corr_subm99	-0.5656**	
	(0.1764)	
Decision Period (0.5)	0.0630	
	(0.0428)	
Decision Period (1)	0.1020	
	(0.1164)	
corr_decp99	0.1562	
	(0.1138)	
Benfords law (0.5)	0.4008	
	(0.2840)	
Benfords law (1)	0.8046	
	(0.4858)	
corr_ben99	0.9754*	
	(0.4810)	
Single Bidding (1)	0.6335**	
	(0.2251)	
corr_singleb99	0.8667**	
	(0.2879)	
Buyer Concentration	0.3194	
	(0.1974)	
CRI		1.109***
		(0.2620)
Fixed-effects		
country	Yes	Yes
year	Yes	Yes
atc_code	Yes	Yes
Fit statistics		
Observations	108,385	131,303
R^2	0.48363	0.45246
Within R^2	0.02465	0.00853

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

4.4 Large Markets and Specific Products

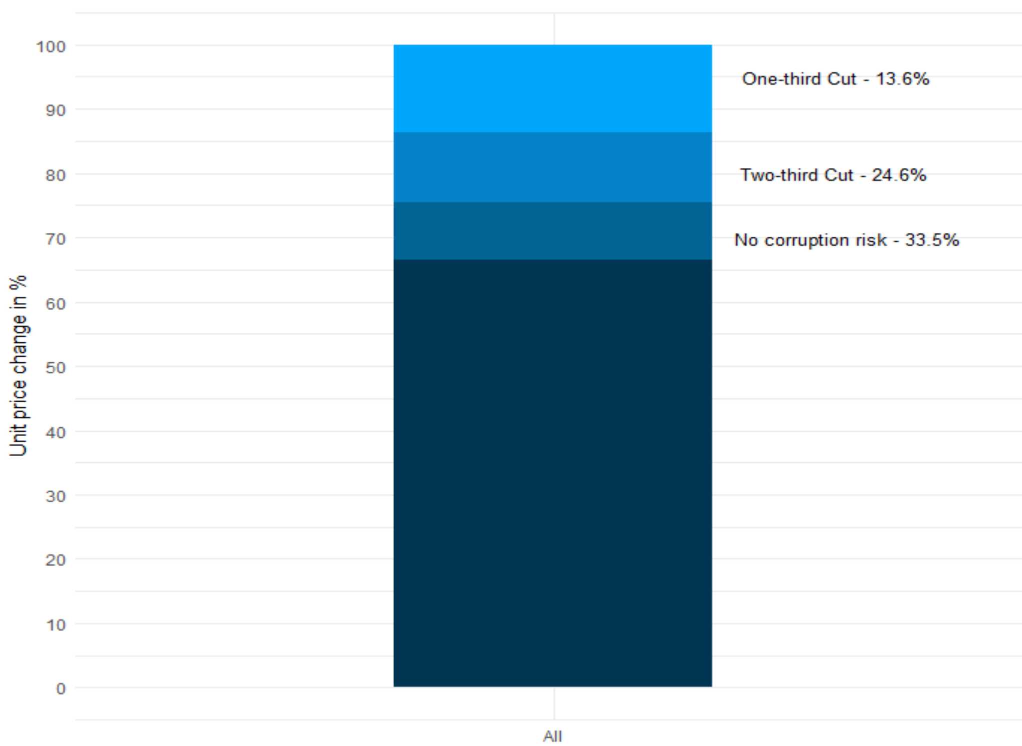
We supplement our analysis by focusing on large markets of widely purchased products and also on the specificities of selected products. First, within each country, we identify large markets. Large markets are characterized by a few products contributing to a larger share of observations and a larger share of the money spent. For instance, 28 percent of the markets account for 57 percent of the contracts and 87 percent of total spending (Table 21 in Appendix 3). Overall, large markets do not behave differently from our main analysis when it comes to the size and direction of effects. The regression models account for a similar share of the total variation in unit prices (See appendix 3-Large Markets subsection). As for the CRI's price impact, we also find large and significant impacts: one unit change of CRI (from 0 to 1) is associated with a 113 percent increase in prices. When we look at individual red flags we see similar effects, however, some red flags are no longer significantly associated with unit price.

Second, we look at selected products already highlighted in Figure 3 above, which are very standardized and hence highly comparable across countries, time, and regions. Figure 3 explored the distribution of a few selected pharmaceutical products which to a large extent are standardized across countries and continents. The products also represent a large share of the total procurement dataset, accounting for over 13 percent of it. With more than 17000 observations, we have a sufficient sample size to run the same regression models as before (See Appendix 3-Selected Products subsection). The frequent procurement of these products with very high degrees of substitutability makes them less vulnerable to corruption, as many suppliers could offer them, increasing competition and hence making it harder to organize and maintain corrupt relationships. The results of the regression contradict these expectations. The impact of corruption risks on unit prices is double compared to our base model. The regression also explains 44 percent of the variation. In terms of CRI impact, if a tender is considered most risky - (CRI=1), compared to non-risky (CRI=0), the model predicts a 257 percent increase in unit prices (Table 23 in Appendix 3). These results indicate that greater attention should be placed on the procurement of the most standardized and widely purchased pharmaceuticals. Particularly because a large share of these products (or their variants) is domestically produced.

4.5 Efficiency gains from reducing corruption risks

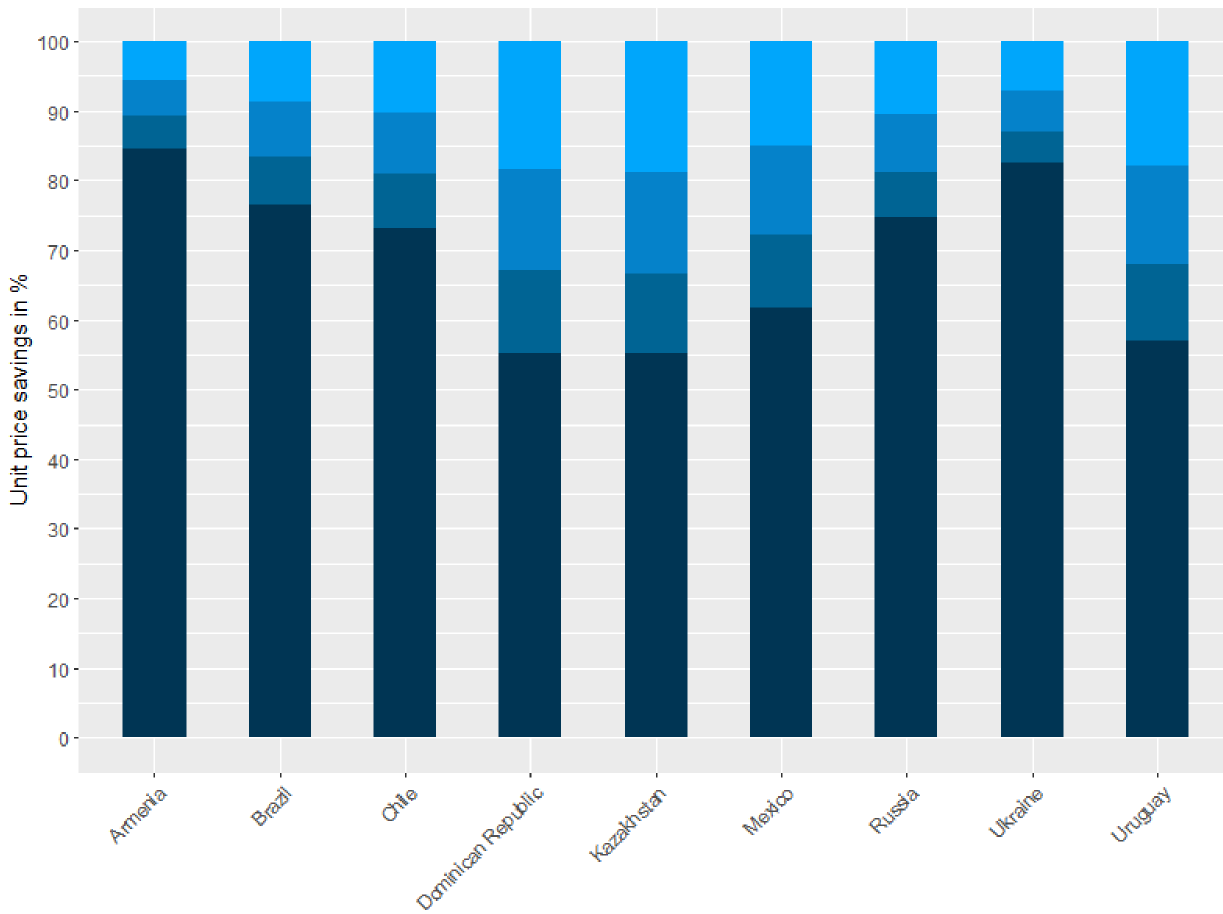
In our previous section we have identified several individual red flags (call for tender, procedure type, Benford's law, single bidding, and buyer spending concentration) as significant predictors of unit prices. More importantly, our main predictor of interest, CRI, is a substantial and significant predictor of unit prices too. We define potential reforms that can lower CRI across all contracts, then we use our best model to predict the impact of lower CRI on average as well as total prices paid for pharmaceuticals. Based on this, we calculate potential savings from different reform packages, reflecting different degrees of corruption risk reductions: One-third Cut, Two-third Cut and No Corruption Risk scenarios. In the first scenario, One-third Cut, we reduce the CRI score by ⅓ across the board (i.e., the absolute risk reduction is lower when the starting risk level is low and high when the status quo is high risks). In the second scenario, Two-third Cut, we reduce the CRI score by ⅔ for all contracts. In the last scenario we consider, no corruption risk, the CRI score equals zero.

Figure 7: Summary of total savings (%), all countries



For both scenarios, we reduced the CRI scores for the entire dataset and used our best regression model to predict counterfactual unit prices. Based on this model and the newly hypothesized lower CRI we have obtained alternative prices paid, for all countries together and also individually. In the case of the more conservative scenario, One-third Cut, we estimate total savings, for all countries, of 13.6%, while for the Two-third Cut scenario, the estimated total savings rise to 24.6%. Last, when the CRI equals zero (no corruption risk), the estimated savings rise to 33.5% (Figure 7). Moving beyond aggregate calculations, we also estimate potential savings for the 3 scenarios for individual countries (Figure 8). For individual countries, when the CRI equals 0 (no corruption risk), we can estimate savings up to 15% in Armenia and 17% in Ukraine, on the lower end of the savings scale, and approximately 45% in Dominican Republic and Kazakhstan, on the higher end of the scale.

Figure 8: Total savings associated with the 3 scenarios, % unit price decrease



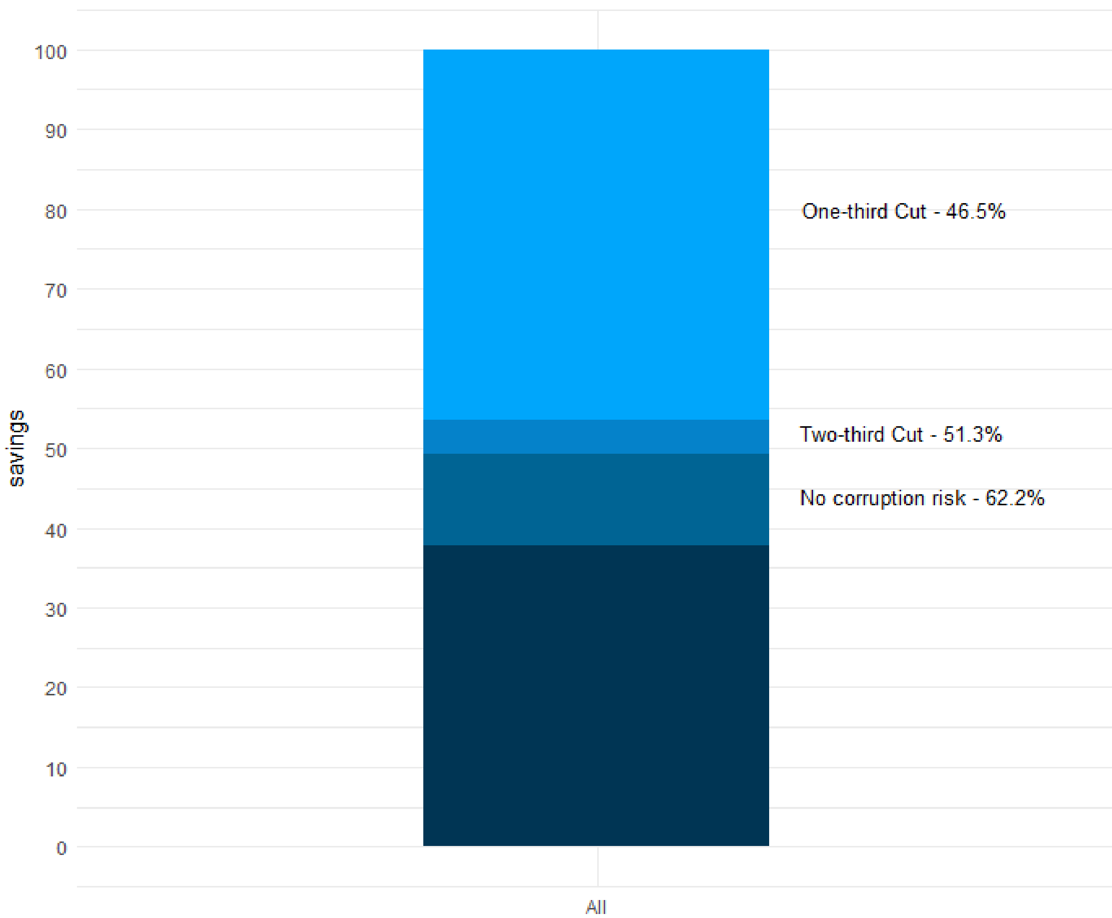
In Table 7, for each country, we present the reduction of CRI score, based on our two scenario models, the percentage of saving as well as the total amount of savings in million dollars. In the case of the One-third Cut scenario, savings range from 6% in Armenia to much larger potential savings in Kazakhstan (19%) and Dominican Republic (18%). For the Two-third Cut scenario, we also see large variation among countries. Dominican Republic and Kazakhstan (both 33%) and Uruguay (32%) show greater potential for savings. In order to identify the total savings in million $, we first calculate the total value of all contracts awarded within a country, based on the contract-level data (Figure 10). On the basis of this, we estimate total savings. The total savings amount depends on the total value of the contracts that are represented in our dataset which reflects the country size, public procurement rule differences (e.g., some countries require more transparent publication than others), and also the differences in the rate of product codes standardized (i.e., some countries' national product codes could be better matched to ATC than others). For countries, such as the Dominican Republic and Chile, our dataset contains more observations, which results in total spending and savings that is significantly higher compared to other countries.

Table 7: Price savings summary, all countries

Country	CRI	CRI - One-third Cut	CRI - Two-third Cut	Total Spending (in Million $)	Total Savings - One-third Cut (in Million $)	Total Savings - Two-third Cut (in Million $)	Total Savings - No corruption risk (in Million $)	Average unit price decrease One-third cut (%)	Average unit price decrease Two-third cut (%)	Average unit price decrease No corruption risk (%)
Armenia	0.142	0.095	0.047	40.84	2.29	4.39	6.32	5.6	10.8	15.48
Brazil	0.193	0.129	0.064	116.35	10.26	19.30	27.3	8.8	16.6	23.46
Chile	0.218	0.146	0.073	7206.51	734.54	1373.46	1930.62	10.2	19.1	26.78
Dominican Republic	0.614	0.410	0.205	3233.26	589.87	1064.04	1446.46	18.2	32.9	44.73
Kazakhstan	0.604	0.403	0.201	21.79	4.09	7.27	9.76	18.8	33.3	44.81
Mexico	0.410	0.274	0.137	367.84	55.54	101.94	140.75	15.1	27.7	38.26
Russia	0.243	0.162	0.081	96.87	10.24	18.22	24.52	10.6	18.8	25.32
Ukraine	0.476	0.317	0.159	592.60	42.79	76.67	103.54	7.2	12.9	17.47
Uruguay	0.519	0.346	0.173	49.88	8.98	15.99	21.46	18.0	32.1	43.03

We also explore savings potential for the 5 selected generic products discussed above. We already established that these products are associated with higher prices and greater attention should be paid to their procurement. The savings potential is also higher for these selected products than for the full sample of pharmaceuticals (Figure 9). In the case of the One-third Cut, we estimate total savings, for all countries, of 46.5%. In the case of the Two-third Cut scenario, the effect slightly reduces, however, we can still estimate total savings of 51.3%. Last, when CRI equals 0 (no corruption risk), the total estimated savings for all countries rise to substantial 62.2%.

Figure 9: Summary of total savings (%), all countries - for generic products



5. Conclusions and further research

The analysis looked at an unprecedentedly large and standardized dataset of pharmaceutical products across 9 countries from 3 continents. It revealed a surprising variation in unit prices even for the same product within each country. While average prices vary across countries and over time to a great degree, this within-country variation shows that low-price purchases are possible even in countries with otherwise high average price levels. The analysis also identified key corruption risks impacting pharmaceutical prices. Our results indicate that all red flags (except the decision period) are significantly and substantially associated with lower unit prices. To reinforce this point, even small changes in procurement practices such as avoiding publishing a call for tender are associated with 85 percent higher unit prices. Similar results are also obtained for improving the submission period given to bidders. Riskier periods, such as extremely short or too long (precise definitions are in Appendix 1), are associated with 22 percent higher prices. Giving more time to bidders could go some way to yield lower unit prices. Single bidding on otherwise competitive markets by default indicates restriction of competition, as only one bidder is present when others could have bid. Such tenders are associated with 58 percent higher unit prices. Through all our analyses, whether we look at the entire dataset, only large markets or specific generic pharmaceutical products, some red flags such as single bidding, no publication of a call for tenders, or the type of procedure are consistently associated with higher unit prices. The CRI, which represents the mean of all (available) red flags, is even more substantial across all our regression models.

With reference to our price prediction models, we have devised two feasible policy scenarios, which are based on CRI modifications, as well as a scenario representing the upper limit to policy improvements, when corruption risks equal 0. In the more conservative scenario, we reduce the CRI scores by ⅓, or about 2 out of 7 red flags, and accordingly estimate potential savings (total savings in millions of dollars and average % unit price decrease). On account of this scenario, we have estimated potential savings of 13.6% for all countries. Nonetheless, when we inspect the variation for individual countries, savings range from 6% in Armenia and 7% in Ukraine to countries with markedly bigger potential savings, such as the Dominican Republic (18%) and Kazakhstan (19%). Our other scenario, the Two-third Cut scenario, is more ambitious, it entails a ⅔ reduction in corruption risks (CRI) across the board. The estimated savings for all countries amounted to a 24.6% lower average unit price. We can once again observe noticeable variations across countries. The Dominican Republic and Kazakhstan (at 33%) show much more sizable potential for savings contrasted with Armenia (11%) and Ukraine (13%). In the last scenario, when the CRI equals 0 (no corruption risk), the estimated savings for all countries amount to 33.5% lower average unit price. We can continue to observe significant variations across countries. The Dominican Republic and Kazakhstan's potential for savings reaches approximately 45%, while Armenia (15.5%) and Ukraine (17.5%) are still on the lower end of the savings scale. By presenting counterfactual scenarios that estimate potential savings, both scenarios aim to demonstrate useful guidance for policymakers in devising effective policy reforms that could lead to substantial savings in the public procurement of pharmaceutical products.

Furthermore, our analysis has shown the benefits of using detailed data on identifying potential corruption risk, whereby our models explain a little under 50% of the variation of unit prices. The sheer volume of our standardized dataset covering many countries underlines the feasibility and potential of large-scale, micro-level pharmaceutical price analysis. The methodology and results of our models show the potential to assist policymakers with identifying and tackling corruption risks in pharmaceutical procurement. Although our savings scenarios are achievable and can directly relate to policy decisions made by the relevant authorities, their successful implementation, such as overcoming institutional resistance can be challenging. Future studies could focus on regular monitoring of prices and their determinants as well as extending the approach to further corruption risk factors. Such further research can also be used to explore and verify the feasibility and results of the outlined saving scenarios.

Nonetheless, our analysis is not without limitations, some of which could be addressed with more complete data, a reform that could be implemented by national procurement agencies. One such reform would concern reducing the amount of inconsistent reporting of procured quantities (e.g., in Ukraine), that has led to unrealistically high prices for certain products (this meant we had to remove such outlier observations from the analysis). Another example is the lack of product information in some countries such as Mexico which has prevented us from analyzing a large share of collected contracts (this is because, in the absence of product codes, it is not possible to calculate average unit prices for products, as we have no suitable benchmark prices). One final possible limitation refers to the aggregation of the CRI and it is directly connected with data availability. Although the CRI is designed to capture a range of different corrupt behaviors and the associated risks, it is naturally limited by the lack of complete data. Missing data can affect the CRI scores compared to other more transparent countries that publish more complete data. Such lack of completeness in certain cases could drive the CRI down. One instance from our dataset could be the case of Russia. Due to lack of data on the number of bidders, the rate of single bidding is not part of the Russian CRI, which leads to a lower CRI compared to other countries where bidder number information is published. Despite these limitations, methodologically speaking, our model has identified significant and substantial effects across all its iterations and has moderate explanatory power. Our counterfactual scenarios are one step closer to explaining a potential causal relationship between our explanatory factors and unit price, however, we cannot claim that it is precisely so. The rationale of our alternative scenarios speaks directly to the literature, and their translation into relevant policies for reforms could lead to strategies for generating savings.

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Appendix 1 - Red flag definitions

Table 8: Overview of indicators - Armenia

ARMENIA	
Indicator name	**Indicator definition**
Single bidder contract	0 = more than one bid received 1 = only one bid received
Call for tenders publication	0 = publication of call for tenders 1 = no publication of call for tenders
Procedure type	0 = framework agreement, open procedure, open tender, urgent open tender, negotiated procedure with preliminary announcement 0.5 = electronic auction, request for quotation, simplified procedure 1 = bipartite contest, non-procurement expense, negotiated procedure with no preliminary announcement, single source, urgent single source
Length of submission period	Number of days between publication of call for tenders and submission deadline 0 = 10-365 days 0.5 = 4-9 days 1 = 0-3 days
Length of decision period	Number of calendar days between submission deadline and announcing of contract award 0 = 8 - 365 days 1 = 0 - 7 days
Benford's law	distribution of first digits 0 = acceptable conformity and close conformity 0.5 = marginally acceptable conformity 1 = nonconformity

Table 9: Overview of indicators - Brazil

BRAZIL	
Indicator name	**Indicator definition**
Single bidder contract	0 = more than one bid received 1 = only one bid received
Call for tenders publication	0 = publication of call for tenders 1 = no publication of call for tenders
Length of submission period	Number of days between publication of call for tenders and submission deadline 0 = 15-22 days 0.5 = 0-14 days 1 = 23-365 days

Length of decision period	Number of calendar days between submission deadline and announcing of contract award 0 = 21-729 days 0.5 = 5-20 days 1 = 0 - 4 days

Table 10: Overview of indicators - Chile

CHILE	
Indicator name	**Indicator definition**
Single bidder	0 = more than one bid received 1 = only one bid received
Call for tenders publication	0 = publication of call for tenders 1 = no publication of call for tenders
Procedure type	0 = open 1 = restricted, outright award
Length of submission period	0 = 9-157 days 0.5 = 7-8 days 1 = 0-6 days
Length of decision period	Number of calendar days between submission deadline and announcing of contract award 0 = 19-183 days 0.5 = 9-18 days 1 = 0 - 8 days

Table 11: Overview of indicators - Dominican Republic

DOMINICAN REPUBLIC	
Indicator name	**Indicator definition**
Call for tenders publication	0 = publication of call for tenders 1 = no publication of call for tenders
Procedure type	0 = approaching bidders, open, other 0.5 = restricted 1 = minitender, sole source

Length of submission period	Number of days between publication of call for tenders and submission deadline 0 = 4-200 days 1 = 0-3 days
Length of decision period	Number of calendar days between submission deadline and announcing of contract award 0 = 11-362 days 1 = 0 - 10 days

Table 12: Overview of indicators - Kazakhstan

KAZAKHSTAN	
Indicator name	**Indicator definition**
Single bidder contract	0 = more than one bid received 1 = only one bid received
Call for tenders publication	0 = publication of call for tenders 1 = no publication of call for tenders
Procedure type	0 = auction, open 1 = from one source, special procedure competition
Length of submission period	Number of days between publication of call for tenders and submission deadline 0 = 7 - 13 days 1 = 0 - 7 and 13+ days
Benford's law	distribution of first digits 0 = acceptable conformity and close conformity 0.5 = marginally acceptable conformity 1 = nonconformity

Table 13: Overview of indicators - Mexico

MEXICO	
Indicator name	**Indicator definition**
Single bidder contract	0 = more than one bid received 1 = only one bid received
Call for tenders publication	0 = publication of call for tenders 1 = no publication of call for tenders
Procedure type	0 = open, other 0.5 = approaching bidders, restricted 1 = outright award

Length of submission period	Number of days between publication of call for tenders and submission deadline 0 = 15-365 days 0.5 = 4-14 days 1 = 0-3 days
Length of decision period	Number of calendar days between submission deadline and announcing of contract award 0 = 9-365 days 0.5 = 2-8 days 1 = 0 - 1 days
Benford's law	distribution of first digits 0 = acceptable conformity and close conformity 0.5 = marginally acceptable conformity 1 = nonconformity

Table 14: Overview of indicators - Ukraine

UKRAINE	
Indicator name	**Indicator definition**
Single bidder contract	0 = more than one bid received 1 = only one bid received
Procedure type	0 = open, competitive dialog 0.5 = simplified procurement procedure, subthreshold purchase 1 = concluded contracts, negotiated procedure, negotiated procedure for urgent need,
Length of submission period	Number of days between publication of call for tenders and submission deadline 0 = 7+ days 1 = 0-6 days
Length of decision period	Number of calendar days between submission deadline and announcing of contract award 0 = 14+ days 1 = 0-14 days
Benford's law	distribution of first digits 0 = acceptable conformity and close conformity 0.5 = marginally acceptable conformity 1 = nonconformity

Table 15: Overview of indicators - Russia

RUSSIA	
Indicator name	**Indicator definition**
Procedure type	0 = open, dps_purchase, approaching bidders 1 = restricted, outright award

Length of submission period	Number of days between publication of call for tenders and submission deadline 0 = 9-365 days 1 = 0-8 days
Length of decision period	Number of calendar days between submission deadline and announcing of contract award 0 = 5-365 days 1 = 0-4 days

Table 16: Overview of indicators - Uruguay

URUGUAY	
Indicator name	**Indicator definition**
Single bidder contract	0 = more than one bid received 1 = only one bid received
Call for tenders publication	0 = publication of call for tenders 1 = no publication of call for tenders
Procedure type	0 = open, other 0.5 = restricted 1 = outright award
Length of submission period	Number of days between publication of call for tenders and submission deadline 0 = 6-162 days 0.5 = 4-5 days 1 = 0-3 days
Length of decision period	Number of calendar days between submission deadline and announcing of contract award 0 = 29-183 days 0.5 = 7-28 days 1 = 0-6 days

Appendix 2 - Data preparation details

Medicine Procurement Pricing Data Retrieval, Standardisation, and Publication:

Data sources and preparation overview

Our sample for the analysis includes pharmaceutical contracts from 9 countries: Chile, Mexico, Brazil, Uruguay, Dominican Republic, Armenia, Kazakhstan, Russia, and Ukraine. These national public procurement datasets were collected by GTI from official procurement sources (such as procurement notices, or structured data publications upon availability). They contain the most relevant tender information such as product codes, procedure types, dates, buyer and supplier details, prices, and item-level information (unit price, quantity).

For each country, we selected all pharmaceutical product purchases. For this, we filtered the data for the relevant product codes in the national classification systems. For example, in the Armenian procurement data, we filtered for the tenders with product codes starting with 336. This approach has a limitation - the national procurement datasets have a certain amount of missing values in the product classification variable (the missing rate across countries varied from 0% to 53%). Therefore, this approach does not allow to perfectly identify all of the pharmaceutical tenders. We tried to partly overcome this limitation by including tenders with the relevant keywords (e.g., the word “pharmaceutical” in the national languages) in the tender title. This method has partially allowed us to improve our matching problem to a certain extent, however, not all titles could be matched as they do not always contain relevant terms.

After selecting all pharmaceutical product tenders in the 9 national datasets, we narrowed down the selected tenders to those that were matched to the standard classification - Anatomical Therapeutic Chemical Classification System (ATC). The years covered are largely in the period between 2016 and 2021, with differences across countries.

Table 17: Overview of the data by country

Country	National classification system	Number of pharma contracts	Number of standardized pharma contracts
Chile	United Nations Standard Products and Services Code	75541	42138

Mexico	Clasificador Único de las Contrataciones Públicas	156906	6648
Brazil	Catálogo de Materiais e Servicos	49833	5061
Uruguay	SICE - Sistema de Información de Compras y Contrataciones del Estado	44699	14564
Dominican Republic	United Nations Standard Products and Services Code	38983	29377
Armenia	Armenian United Procurement Classifier	39188	17571
Kazakhstan	Unified Nomenclature Directory of Goods, Works, and Services	22675	11593
Russia	Russian Classifier of Products by Type of Economic Activity	116956	4626
Ukraine	Common Procurement Vocabulary	153011	52649

Product code standardization

The selected global standard is Anatomical Therapeutic Chemical Classification System (ATC). ATC was identified to be the most comprehensive drugs and active ingredients classifier.

In order to standardize the national pharma samples, we had to merge them with the ATC. Since the official comprehensive correspondence tables between the national classification systems and the ATC are not available, the merge included multiple iterations and exploited different merging methods: 1) exact merge, 2) approximate merge based on string similarity metrics.

Overall, the process of merging can be divided into 2 steps: 1) merging national classification systems with the ATC based on the drugs/active ingredients names, 2) merging contracts with ATC based on searching for the drugs/active ingredients names in the tender or/and lot title.

Box 1. Example of merging contracts with ATC based on searching for the drugs/active ingredients names in the tender or/and lot title

In the example below, the tender from the Ukrainian procurement data is merged to the relevant ATC code with the search for the relevant drug name in the tender title. As the Ukrainian tenders for pharmaceuticals often list the name of the drug/active ingredient in

English in the tender title, the merge can be achieved with a simple keyword search and exact merge by the keyword.

tender_id	ATC.Name	ATC.code
Фармацевтична продукція дексаметазон (Dexamethasone)	dexamethasone	A01AC02

The implementation of both steps often required translation of the drug/active ingredient name in the national classification system or/and tender title from the local language to English. The translation was done using Google Translate API.

Box 2. Example of merging national classification systems with the ATC based on the drugs/active ingredient names.

In the example below, the item from the national classification system of Kazakhstan (ЕНС ТРУ) is merged with the relevant record in the ATC. The product name was translated from Russian (the national classification system of Kazakhstan is published in both Russian and Kazakh languages), and then merged to the ATC using the product name as a key column.

Код ЕНС ТРУ (eng. - national classification code)	**Наименование ЕНС ТРУ на русском** (eng. - product name)	**Product name translated**	**ATC.Name**	**ATC.code**
212012.900.000003	Дексаметазон	Dexamethasone	dexamethasone	A01AC02

To account for the risk of errors or slight differences in the names of drugs and active ingredients in the national samples, we also applied approximate merging methods - the algorithm searched for strings that are the most likely to be similar in the national and the ATC datasets. While approximate merging is a powerful method to match string columns, it should be applied with caution to avoid false matches. To minimize the risk of getting false matches, we allowed a small string distance (e.g., we searched for strings that were different by 1 or 2 letters). In order to verify the results, we did multiple rounds of manual checks on random samples of matched records.

Box 3. Example of the approximate merging.

In this example, the tender from the Ukrainian procurement data is merged with the relevant ATC code with the search for the relevant drug name in the tender title. However, the name of the drug in the tender title is slightly different from the name of this drug in the ATC dataset - eno**ks**aparin and eno**x**aparin. Therefore, we were able to merge these records using fuzzy matching.

tender_id	ATC.Name	ATC.code
Еноксапарин (Enoksaparin)	enoxaparin	B01AB05

Standardized sample

The files are exported to the CSV format. We used OCDS variable names for the variables in the datasets. For the current data export, we selected the set of relevant variables, mainly price variables (Table 2).

Table 18: Overview of the available variables

Name	Description
tender_id	An identifier for this tender process.
lot_id	An identifier for this lot within tender.
tender_title	A title for this tender. This will often be used by applications as a headline to attract interest, and to help analysts understand the nature of this procurement.
tender_value_amount	The total estimated value of the procurement.
lot_value_amount	The estimated value of the lot.
tender_value_currency	The currency of the amount.
unit_price	The price for a single unit of measure of a product sold.
quantity	The number of units to be provided.
tender_publications_firstcallfortender date	Publication date of the first call for tender announcement.
tender_awarddecisiondate	The award decision date.
contractsignaturedate	The date of signing the tender.

tender_biddeadline	The final deadline until when companies can submit a bid. It is based on the latest call for a tender document published.
tender_year	Year of the tender.
country	The country name.
ATC.code	Code of the product according to the Anatomical Therapeutic Chemical Classification System

While the above-outlined variables (table 18) list outlines key variables for the analysis - price information, standardized product code, key dates of the tendering process, the dataset can be updated with more variables if needed, such as:

- procedure type
- the number of bids
- bid price
- bidder and buyer information (e.g., address, name)
- national product classification
- final tender and lot values.

Appendix 3 – Additional regression analyses

Armenia

Table 19: Main results for Armenia - individual red flags

Dependent Variable:	Log Unit Price is the Dependent Variable						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Call for Tender	1.514***						
	(0.0460)						
Procedure Type		0.9653***					
		(0.0374)					
Submission Period			1.277***				
			(0.0422)				
Decision Period				0.3628***			
				(0.0265)			
Benfords Law					0.0030		
					(0.0458)		
Single Bid						0.4532***	
						(0.0190)	
Buyer Concentration							-0.2465***
							(0.0604)
Fixed-effects							
country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
atc_code	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	17,663	17,663	17,663	17,663	17,638	17,663	17,662
R^2	0.67368	0.66619	0.67070	0.65705	0.65340	0.66433	0.65361
Within R^2	0.05870	0.03707	0.05008	0.01071	2.56×10^{-7}	0.03173	0.00096

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 20: CRI results for Armenia

Dependent Variable: Log Unit Price is the Dependent Variable	
Model:	(1)
Variables	
CRI	1.960***
	(0.0592)
Fixed-effects	
country	Yes
year	Yes
atc_code	Yes
Fit statistics	
Observations	17,663
R^2	0.67395
Within R^2	0.05946

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Dominican Republic

Table 21: Main results for the Dominican Republic - individual red flags

Dependent Variable:	Log Unit Price is the Dependent Variable				
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
Procedure Type	1.364***				
	(0.0562)				
Submission Period		0.5229***			
		(0.0257)			
Decision Period			0.9486***		
			(0.0444)		
Benfords Law				-0.3738***	
				(0.0517)	
Buyer Concentration					0.5245***
					(0.0365)
Fixed-effects					
country	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes
atc_code	Yes	Yes	Yes	Yes	Yes
Fit statistics					
Observations	29,148	29,148	29,148	14,725	28,931
R^2	0.24727	0.24271	0.24384	0.34158	0.24045
Within R^2	0.02018	0.01425	0.01572	0.00365	0.00723

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 22: CRI results for the Dominican Republic

Dependent Variable:	
Log Unit Price is the Dependent Variable	
Model:	(1)
Variables	
CRI	1.716***
	(0.0740)
Fixed-effects	
country	Yes
year	Yes
atc_code	Yes
Fit statistics	
Observations	29,148
R^2	0.24595
Within R^2	0.01846

IID standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Large markets

Table 23: Main results for individual red flags - large markets

Dependent Variable:	Log Unit Price is the Dependent Variable						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Single Bid	0.5838***						
	(0.0834)						
Call for Tender		0.9376					
		(0.5142)					
Decision Period			0.2184				
			(0.2646)				
Benfords Law				1.095			
				(0.6712)			
Procedure Type					0.6521*		
					(0.2931)		
Buyer Concentration						0.5232***	
						(0.1079)	
Submission Period							0.2803
							(0.2758)
Fixed-effects							
country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
atc_code	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	49,701	86,667	68,586	58,257	51,169	75,069	56,985
R^2	0.39912	0.41822	0.35962	0.53073	0.43774	0.43441	0.41041
Within R^2	0.00584	0.00177	0.00075	0.01967	0.01091	0.00227	0.00235

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

Table 24: CRI results for large markets

Dependent Variable:	Log Unit Price is the Dependent Variable
Model:	(1)
Variables	
CRI	1.135***
	(0.2657)
Fixed-effects	
country	Yes
year	Yes
atc_code	Yes
Fit statistics	
Observations	89,525
R^2	0.41761
Within R^2	0.00783

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

Selected Products

Table 25: Main results for individual red flags - selected products

Dependent Variable:	Log Unit Price is the Dependent Variable						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Single Bid	1.546***						
	(0.2232)						
Call for Tender		2.097***					
		(0.2845)					
Decision Period			0.6251*				
			(0.2837)				
Benfords Law				1.532**			
				(0.4635)			
Procedure Type					1.154**		
					(0.2970)		
Buyer Concentration						0.6800**	
						(0.2391)	
Submission Period							0.5755
							(0.3014)
Fixed-effects							
country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
atc_code	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	9,742	16,844	15,110	12,897	10,446	15,001	13,262
R^2	0.29697	0.43660	0.43516	0.55642	0.42049	0.45195	0.53299
Within R^2	0.03601	0.00877	0.00522	0.02227	0.01713	0.00414	0.00956

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

Table 26: CRI results for a selection of generic products

Dependent Variable:	Log Unit Price is the Dependent Variable
Model:	(1)
Variables	
CRI	2.574***
	(0.3974)
Fixed-effects	
country	Yes
year	Yes
atc_code	Yes
Fit statistics	
Observations	17,162
R^2	0.44477
Within R^2	0.02681

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

Robustness tests

Table 27: Results for individual red flags (controlling for contract value)

Dependent Variable:	Log Unit Price is the Dependent Variable						
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables							
Call for Tender	0.8249***						
	(0.1564)						
Procedure Type		0.9359***					
		(0.1247)					
Submission Period			0.2786**				
			(0.1329)				
Decision Period				0.2638*			
				(0.1444)			
Benfords Law					0.8190***		
					(0.1590)		
Single Bid						0.6041***	
						(0.0969)	
Buyer Concentration							0.5683***
							(0.1410)
Fixed-effects							
country	Yes	Yes	Yes	Yes	Yes	Yes	Yes
year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
atc_code	Yes	Yes	Yes	Yes	Yes	Yes	Yes
ca_contract_value10	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics							
Observations	125,239	71,320	75,374	98,125	81,585	75,943	103,594
R^2	0.45948	0.56882	0.48939	0.42171	0.56150	0.45253	0.48318
Within R^2	0.00194	0.01902	0.00200	0.00126	0.01329	0.00849	0.00247

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

Table 28: CRI results (control for contract value)

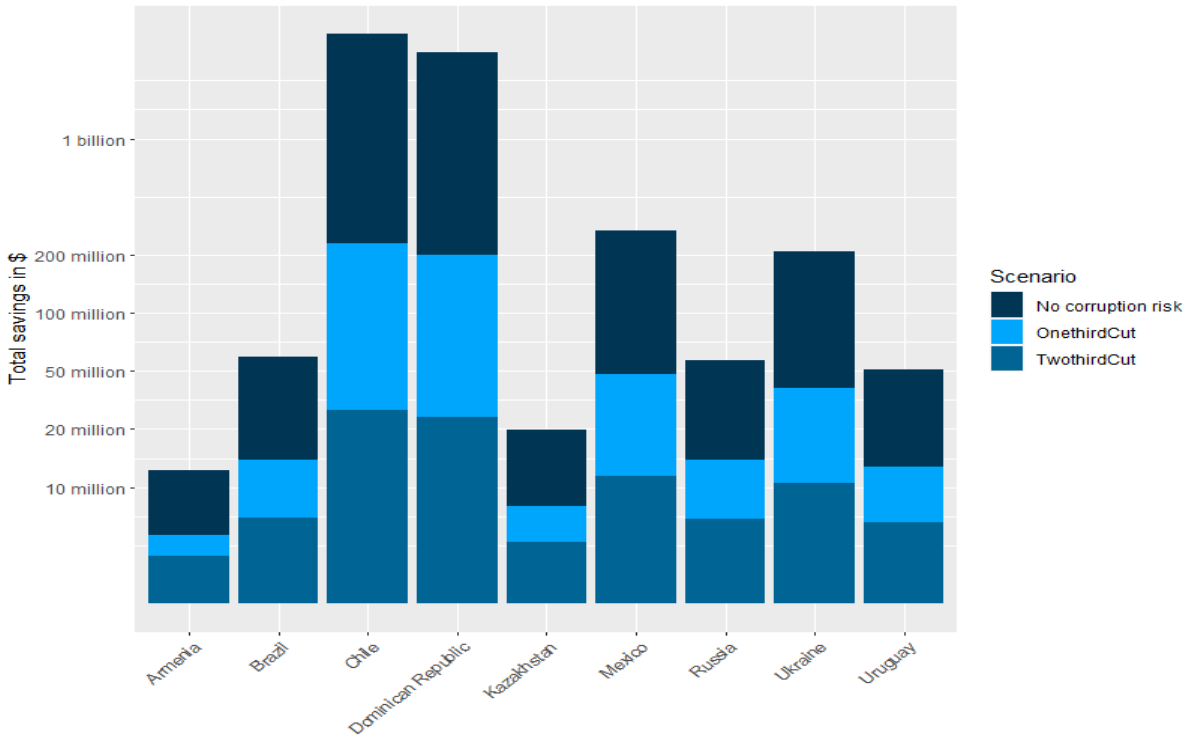
Dependent Variable:	Log Unit Price is the Dependent Variable
Model:	(1)
Variables	
CRI	1.271***
	(0.2811)
Fixed-effects	
country	Yes
year	Yes
atc_code	Yes
ca_contract_value10	Yes
Fit statistics	
Observations	125,238
R^2	0.46374
Within R^2	0.00981

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

Appendix 4 - Further graphs

Figure 10 illustrates the total amount of savings per country associated with the three different scenarios, One-third Cut, Two-third Cut, and CRI = 0. Each shade of color represents the total savings within each scenario.

Figure 10: Summary of total savings, in Million $[7]



To illustrate the 1 standard deviation from the mean product price in each country (Figure 11), we have transformed the unit price variable into logarithm. The logarithm helps us to normalize the distribution of prices so that products with very high prices will not distort the figure. The negative values in the graph indicate that these prices have only a fraction, or a product price less than one. We also see a huge deviation in the Chilean market for a relatively standardized product. This could also be an indication that even tenders with such products tend to be overpriced.

[7] We use a log scale for better illustration. For illustration, the 100000-reference point on the y-axis indicates 1 Billion

Figure 11: Unit price (log) with 1 standard deviation for selected products, by country