

Supplemental Appendix

The Two Sides of Discretion: Assessing Efficiency and Quality in Government Purchases

Dimas Fazio

For Online Publication Only

In this online appendix, I present supplementary material and detailed information not included in the main manuscript titled ‘The Two Sides of Discretion: Assessing Efficiency and Quality in Government Purchases’. This appendix is organized as follows.

Section **A** details the systematic data cleaning process that includes standardizing unit measurements, harmonizing product descriptions, and unifying brand names. The methodology involves product classification based on CADMAT (*Cadastro dos Materiais*) descriptions and units of measure, price outlier treatment to address data entry errors, and handling of missing brand information.

Section **B** investigates whether the characteristics of winning firms differ between procurements below the small-value purchase (SVP) threshold (higher discretion) and those above the threshold (lower discretion). The findings suggest that procurements below the threshold are more likely to award contracts to politically connected and nearby firms, indicating potential favoritism. However, these firms also tend to be larger and more established, suggesting that experience and reliability are important factors in the decision-making process. When controlling for product quality by comparing procurements of the same brand and product, the differences in winning firm characteristics become less pronounced, implying that part of the reason for such preferences is to ensure higher-quality purchases.

Finally, Section **C** presents additional figures and tables that are referenced throughout the main manuscript. These figures and tables serve as robustness tests and provide further support and context for the paper’s findings, ensuring the validity and reliability of the results presented in the main text.

A Data Cleaning Process

The data cleaning process involved several systematic steps to ensure consistency and accuracy in the procurement dataset. First, I standardized unit measurements across product listings by developing a comprehensive set of cleaning functions that identified and normalized various unit formats (e.g., converting irregular expressions like "CAIX(A|AS)" to standardized "CAIXA", or "CJ(O|OS)" to "CONJUNTO"). This standardization included unit conversion for quantities, ensuring all measurements were expressed in comparable units (e.g., converting milliliters to liters, grams to kilograms). The process also extracted numeric quantities and textual unit descriptions separately, allowing for uniform comparisons across products that might be described differently but represent identical items.

For brand standardization, I implemented a multi-stage cleaning approach that removed extraneous characters, standardized formatting, and addressed common variations in brand names. Special attention was given to product-specific cleaning for items like printer cartridges, where terms like "ORIGINAL" or "GENUINO" were included across listings. To identify potential typos and variations in brand names, I calculated string distances between brand entries and clustered similar ones using both automated algorithms and manual verification. This process reduced the number of unique brand entries while maintaining meaningful distinctions between different manufacturers, ensuring that price comparisons across products accurately reflected genuine brand differences rather than data inconsistencies. Purchases awarded to suppliers registered as natural persons (11-digit CPF identifiers) are excluded, so the sample comprises firm (CNPJ) suppliers only.

Product Classification To facilitate meaningful analysis, products were classified based on the interaction between the product description in the *Cadastro dos Materiais* (CADMAT) and their respective units of measure. This approach allowed for more precise product identification compared to using CADMAT codes alone, as identical products might be listed under different measurement units. For instance, "MINERAL WATER" sold in gallons of 20 liters was treated as distinct from the same product sold in 1 liter bottles.

Removing Price Outliers To address potential data entry errors and extreme outliers, I calculate the median price of each product across all procurements in the same period and drop those observations with 10 times higher or lower prices than this median value. This approach corresponds approximately to removing observations below the 5th percentile and above the 95th percentile of the price

distribution for each product. Before this filtering, the data contained significant price variations that likely represented errors rather than genuine market differentials. For example, some identical products showed price variations of more than 1,000 times the median value, which is economically implausible for most standard goods.

Missing Brand Information The original dataset contained a substantial number of entries with missing brand information. After careful consideration, these observations were excluded from the main analysis to ensure that all comparisons between products could account for brand effects. To verify that this exclusion did not introduce selection bias, I conducted robustness checks using products with varying levels of brand information coverage (see Table C.4 in the Internet Appendix).

Pharmaceutical Quality Records ANVISA publishes its quality violations as free text in the Federal Official Gazette, with no structured fields identifying the manufacturer or the product concerned. To make these notices usable, I use a large language model to read each notice and extract the laboratory, the product and its active ingredient, the brand, the stated reason, and the type of action taken. I then keep the notices that suspend, interdict, or recall a product, and set aside the purely administrative ones (transfers of registration ownership, lapses, or the revocation of an earlier notice) which do not indicate a manufacturing problem. This extraction was performed once and its output is distributed with the replication package, so the analysis code itself makes no calls to any model and reproduces exactly as it stands.

Matching Purchases to Quality Violations Neither the procurement records nor the Gazette notices share a product identifier with the other, so the link between them has to be built from names. I do this in two steps. I first match each purchased medicine to ANVISA's product registry, which gives the active ingredient and indicates whether the product is sold as a generic or under a brand; I then match the registry entries to the violation notices. Both steps compare product and laboratory names, which are recorded inconsistently across the three sources, so I apply a graded sequence of rules that begins with exact agreement and moves through progressively weaker ones, allowing for small spelling differences or for one name to be contained within the other. Every match records the rule that produced it, and I keep only the more reliable ones, setting aside those that rest on the agreement of a single word of a name. Medicines that I match to the registry but to no notice are those without a recorded violation, and they form the comparison group.

B Winning Firm Characteristics

In addition to the effects on inefficiency and quality, discretion and auctions might differ on which firms are being awarded public contracts. On the one hand, awarding contracts to connected firms might direct public funds to possibly inefficient firms (Faccio, Masulis and McConnell, 2006; Schoenherr, 2019). This may not only translate into overpricing and inefficiencies but also represent a diversion of funds for personal gain. On the other hand, government agencies may choose specific firms because they know these firms can provide better-quality products (Butler et al., 2020). Ideally, after controlling for both product and quality, one would want to see these procurements picking firms that are similar to those that win via auctions.

To test this hypothesis, I investigate whether the characteristics of the winning firms are different across different procurement types. To measure whether firms and public agencies are connected, I first calculate a measure of political connection. I consider a firm to be politically connected if it has an owner who is also an elected politician of a party allied to the federal government. I take information on elected officials from the *Tribunal Superior Eleitoral* in Brazil. Data on firm owners comes from *Receita Federal*. An additional measure of connection comes from whether the winning firm is from the same municipality as the public agency. I also use three different measures of firm opacity. The first of them is firm size, a categorical variable equal to 1 for small firms, 2 for medium firms, and 3 for large firms. The second measure is the number of distinct firm owners, a measure that is also related to firm size. Finally, I calculate firm age as the year of procurement minus the year of the firm's creation. All of these measures are obtained from the Firm Registry dataset of *Receita Federal*.

In Panel A of Table B.1, I find that procurements below the threshold are more likely than procurements above the threshold to award contracts to connected and nearby firms. This suggests a waste of public resources, as public officials appear to be favoring connected firms. In Panel B of Table B.1, I show that these effects decrease when I compare the same product and brand across the threshold. The coefficient on $p(\text{connected})$ decreases slightly by about 10%, while the coefficient on $p(\text{same muni})$ decreases by 25% in magnitude.

Columns III to V of Table B.1 also show that firms awarded contracts in high-discretion procurements are larger in size (columns III and IV) and older (column V). These firms, thus, appear to be more established than the ones awarded contracts above the threshold. Larger and older firms are likely the ones that provide better-quality products to the government. Panel B confirms this hypothesis: once

I control for the same product and brand, the coefficients are smaller in magnitude, but they are still statistically significant.

These findings suggest that discretionary procurement enables agencies to select more established suppliers who can provide better-quality products, aligning with earlier evidence that about two-fifths of the price premium under discretion reflects the purchase of higher-quality brands. However, the persistent preference for connected firms, even when comparing identical products, indicates that not all firm selections under discretion can be explained by quality considerations.

Table B.1—Winning Firm Characteristics

Dep. Var.	p(connected) _{ipb}	p(same muni) _{ipb}	firm size _{ipb}	# owners _{ipb}	firm age _{ipb}
	I	II	III	IV	V
Panel A: Comparing Same Product					
below threshold _i	0.0020*** (0.0004)	0.208*** (0.009)	0.103*** (0.011)	0.136*** (0.011)	1.696*** (0.145)
Product*Quarter FE	yes	yes	yes	yes	yes
Obs	977,059	962,226	977,059	802,713	977,059
R ²	0.355	0.399	0.441	0.385	0.365
Panel B: Comparing Same Product & Brand					
below threshold _i	0.0018** (0.0007)	0.150*** (0.011)	0.048** (0.018)	0.104*** (0.015)	0.542** (0.174)
Brand*Product*Quarter FE	yes	yes	yes	yes	yes
Obs	977,059	962,226	977,059	802,713	977,059
R ²	0.819	0.859	0.867	0.858	0.852

This table compares the characteristics of firms that are awarded procurements above and below the small-value purchase threshold. On either side of the threshold, I fit a linear function of the distance to the threshold as in equation (1). The dependent variables are as follows: p(connected)_{ipb} is the probability that the firm that won the procurement *i* for product *p* and brand *b* is politically connected (column I); p(same muni)_{ipb} is the probability that the awarded firm is in the same municipality as the government agency (column II); firm size_{ipb} is a categorical variable of firm size equal to 1 for small, 2 for medium, and 3 for large firms (column III); # owners_{ipb} is the number of firm owners (column IV); and firm age_{ipb} is the firm age in years (column V). The explanatory variable in all columns, below threshold_i, is a dummy equal to one if procurement *i* at time *t* is conducted below the threshold, and zero otherwise. Panel A includes Product*Quarter fixed effects, effectively comparing outcomes in procurements of the same product and in the same quarter. Panel B includes Brand*Product*Quarter fixed effects, effectively comparing outcomes in procurements of the same brand, product, and in the same quarter. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors clustered at the product level are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

C Additional Figures and Tables

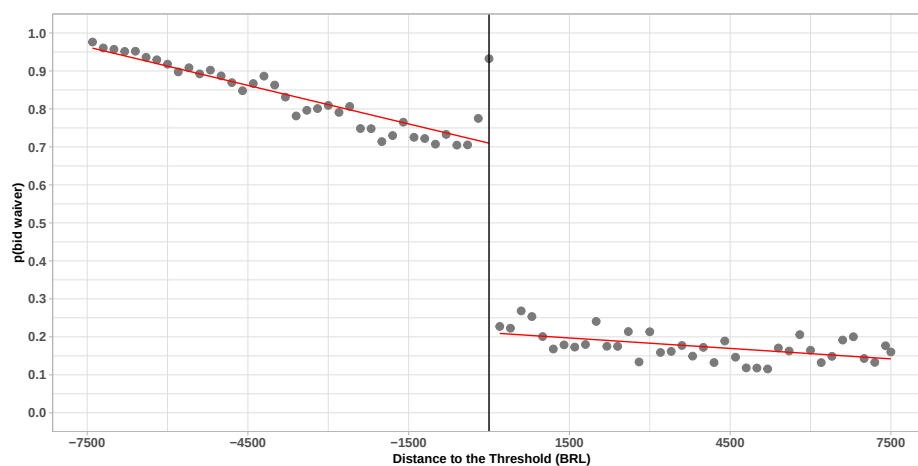
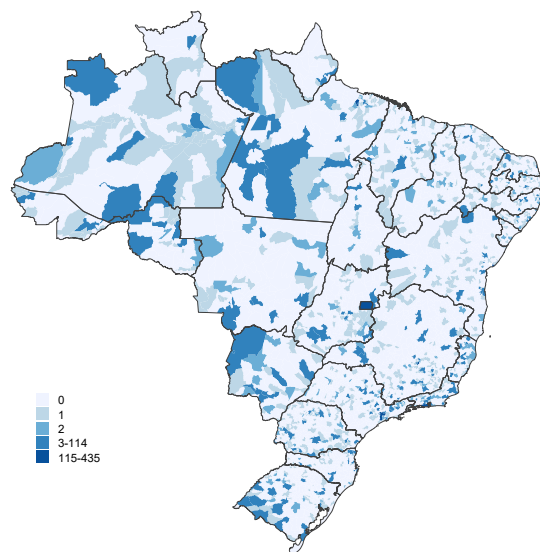
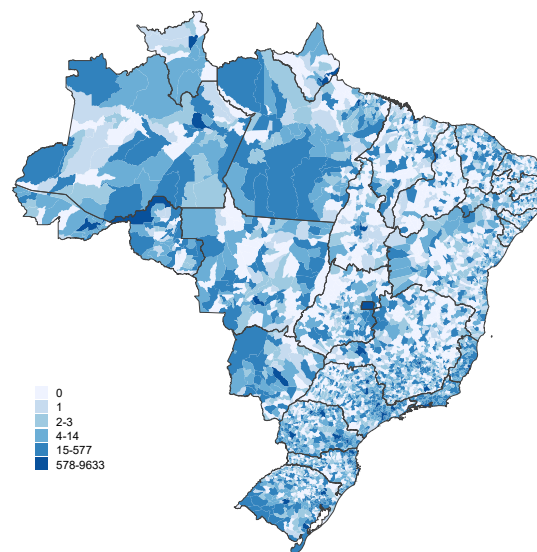


Figure C.1. *This figure illustrates the incidence of bid waivers around the small-value purchase threshold. Below the threshold, regulators permit products to be procured through bid waivers. Above the threshold, bid waivers are only allowed in special cases, such as emergency situations. In other cases, the main procurement procedure involves competitive auctions where the lowest price wins.*

8



Panel A: Number of Government Agencies



Panel B: Number of Government Suppliers

Figure C.2. This figure shows the geographic distribution of federal government procurement agencies (Panel A) and their suppliers (Panel B) across Brazilian municipalities. Data are from ComprasNet for the period 2013–2021.

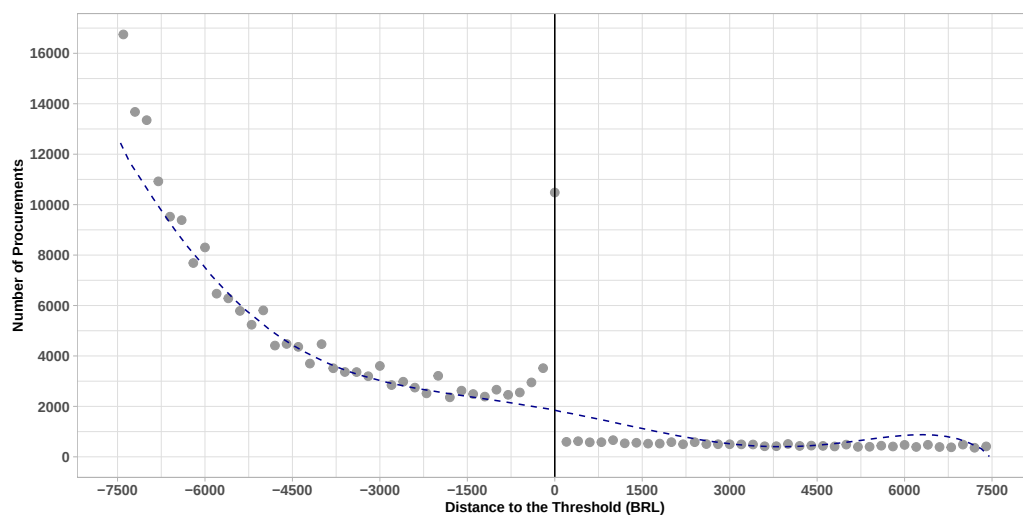
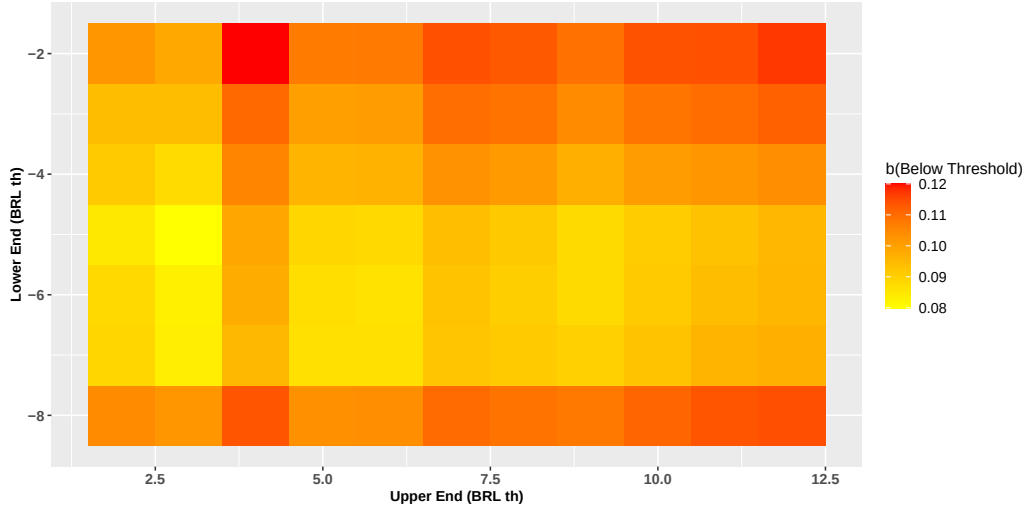
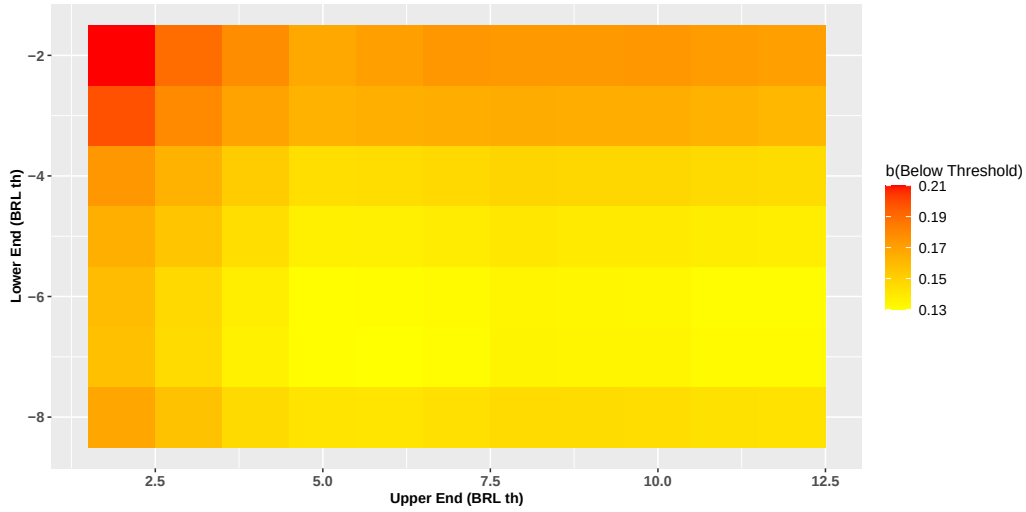


Figure C.3. This figure plots the number of procurements around the small-value purchase threshold. Below the threshold, regulators allow products to be procured by bid waivers. Competitive bidding is the norm above the threshold, and bid waivers are only allowed in special cases, such as emergency situations. The blue dashed line represents the counterfactual in the absence of bunching.

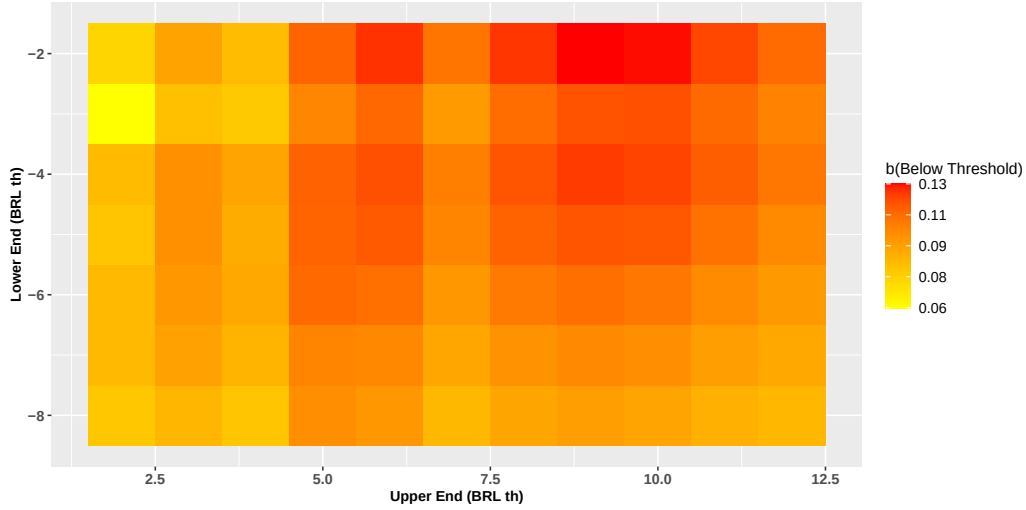


Panel A: Effect on log(price) for different bandwidths, 1st order polynomial

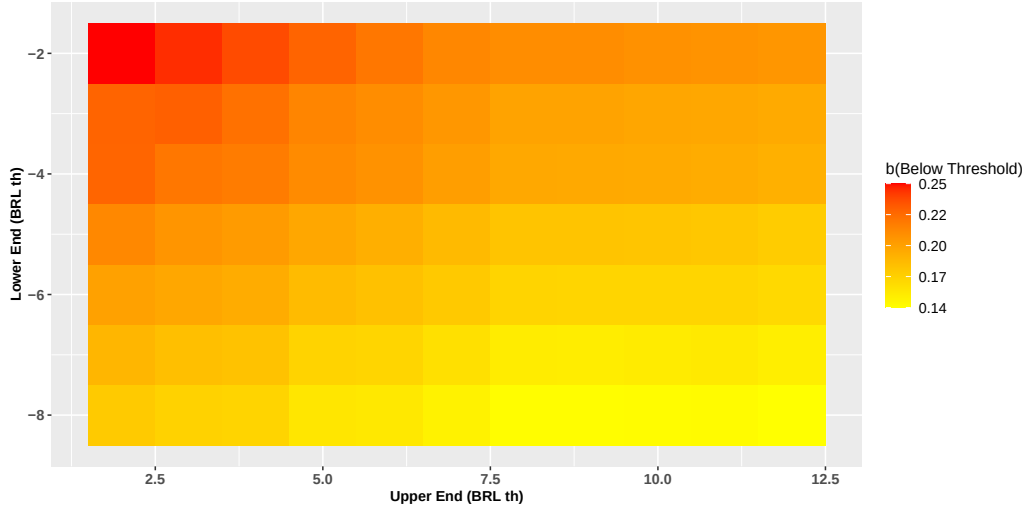


Panel B: Effect on log(brand price) for different bandwidths, 1st order polynomial

Figure C.4. This heatmap displays the estimated coefficients for estimating equation (1) at various bandwidths around the threshold. For instance, in the upper right corner, I use a bandwidth between BRL 2,000 below the threshold and BRL 12,000 above it to estimate equation (1). In Panel A, the dependent variable is $\log(\text{price})$, the natural logarithm of the unit price of product p in procurement i and product-brand-quarter fixed effects are included. In Panel B, the dependent variable is $\log(\text{brand price})$, and product-quarter fixed effects are included. In all estimations, I fit a first-order polynomial on either side of the threshold.

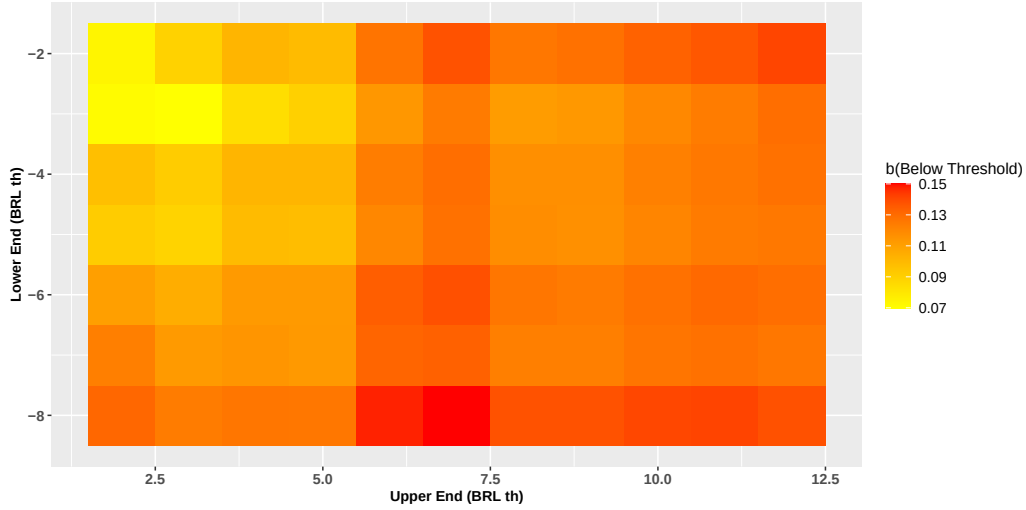


Panel A: Effect on log(price) for different bandwidths, 2nd order polynomial

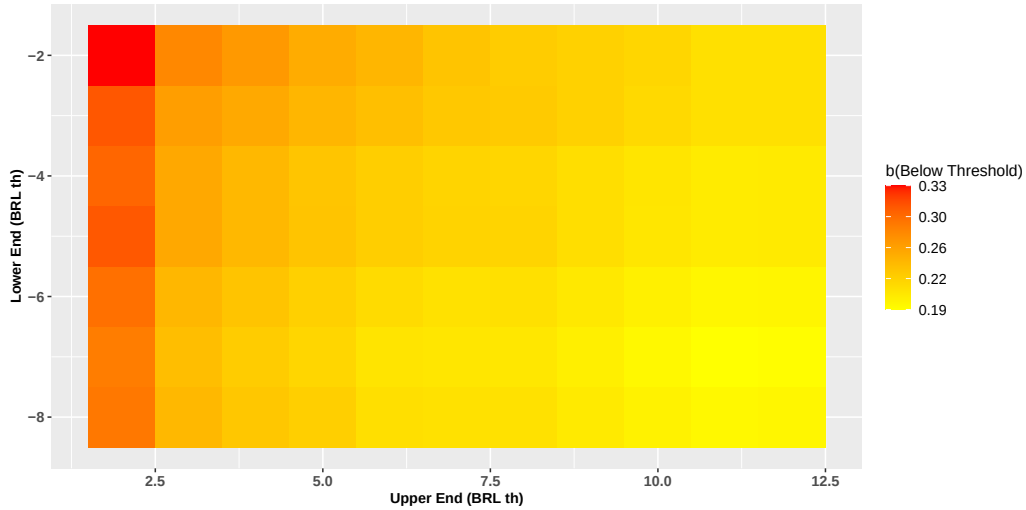


Panel B: Effect on log(brand price) for different bandwidths, 2nd order polynomial

Figure C.5. This heatmap displays the estimated coefficients for estimating equation (1) at various bandwidths around the threshold. For instance, in the upper right corner, I use a bandwidth between BRL 2,000 below the threshold and BRL 12,000 above it to estimate equation (1). In Panel A, the dependent variable is $\log(\text{price})$, the natural logarithm of the unit price of product p in procurement i and product-brand-quarter fixed effects are included. In Panel B, the dependent variable is $\log(\text{brand price})$, and product-quarter fixed effects are included. In all estimations, I fit a second-order polynomial on either side of the threshold.



Panel A: Effect on log(price) for different bandwidths, 3rd order polynomial



Panel B: Effect on log(brand price) for different bandwidths, 3rd order polynomial

Figure C.6. This heatmap displays the estimated coefficients for estimating equation (1) at various bandwidths around the threshold. For instance, in the upper right corner, I use a bandwidth between BRL 2,000 below the threshold and BRL 12,000 above it to estimate equation (1). In Panel A, the dependent variable is $\log(\text{price})$, the natural logarithm of the unit price of product p in procurement i and product-brand-quarter fixed effects are included. In Panel B, the dependent variable is $\log(\text{brand price})$, and product-quarter fixed effects are included. In all estimations, I fit a third-order polynomial on either side of the threshold.

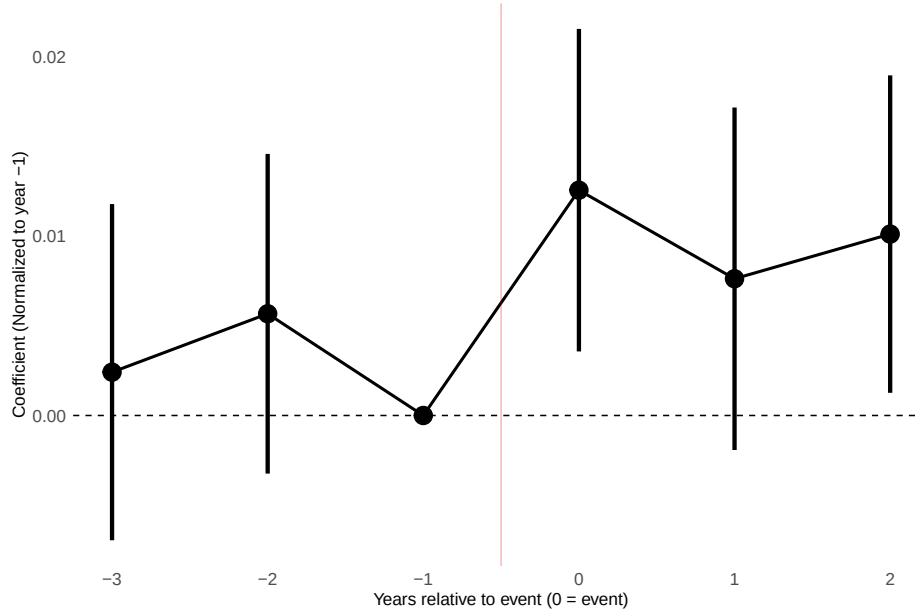


Figure C.7. This event study plots estimates of the dynamic relationship between medicine procurement from violating suppliers and hospital mortality at different time horizons. For each time period k relative to the event, I estimate: $Mortality_{hct+k} = \beta_k \cdot ShareViolations_{hct} + \alpha_{hc} + \gamma_{ct+k} + \varepsilon_{hct+k}$, where $Mortality_{hct+k}$ is the mortality rate k years after (or before) period t , and $ShareViolations_{hct}$ is the share of medicines purchased from manufacturers with ANVISA quality violations in the baseline period t . Each point represents the coefficient β_k , normalized so that the reference period ($k = -1$) equals zero. Vertical bars represent 95% confidence intervals with standard errors clustered at the hospital-disease level. Hospital-disease and disease-year fixed effects are included.

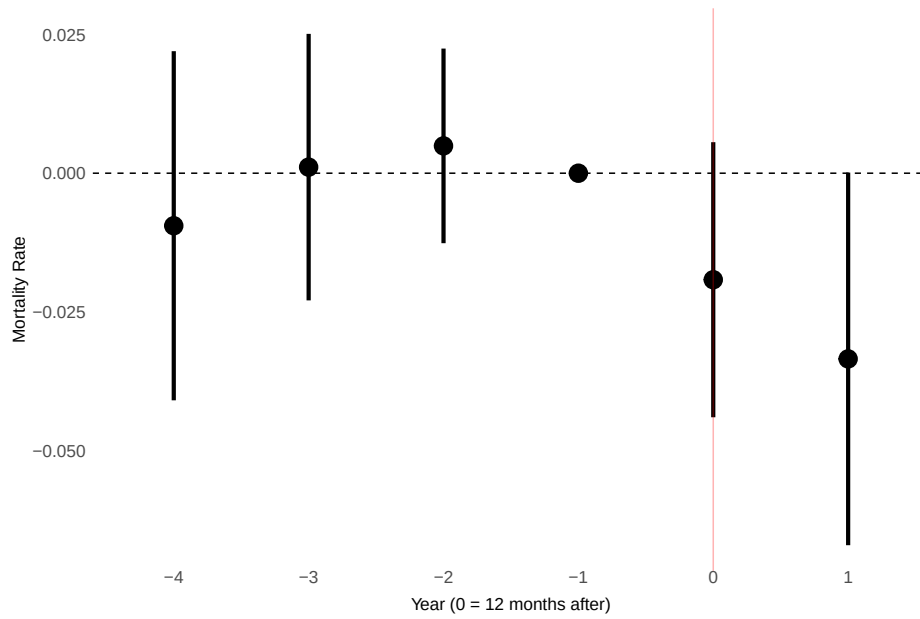


Figure C.8. *Event Study: Hospital Mortality and SVP Threshold Change.* This figure plots coefficients from an event study specification, where mortality in year k relative to the June 2018 reform is regressed on the interaction between year indicators and $treat_{hc}$ (the share of medicines purchased between BRL 8,000 and BRL 17,600 in the two years prior to the reform). Coefficients are normalized to year $k = -1$. Each point represents β_k , showing the differential mortality trend for hospital-disease pairs with higher pre-reform exposure to the BRL 8,000–17,600 range. Vertical bars represent 95% confidence intervals with standard errors clustered at the hospital level. Hospital-disease and disease-year fixed effects included.

Table C.1—List of Countries - Small-Value Purchase Thresholds and Direct Awards

Country	SVP Threshold?	Threshold Value	Law
Australia	Yes	AUD 200,000 for direct purchases from Small and Medium Enterprises	Commonwealth Procurement Rules
Austria	Yes	EUR 100,000 for products and services; EUR 200,000 for works	Federal Public Procurement Act 2018 (BVerG), the Federal Act on the Award of Concession Contracts 2018 (BVerGKonz) and the Federal Act on the Award of Contracts in the Fields of Defence and Security 2012 (BVerGVs)
Belgium	Yes	EUR 30,000	Act of 17 June 2016
Canada	Yes	CAD 25,000 for products; CAD 100,000 for works; CAD 40,000 for other contracts	Contracting Policy Notice 2007-4
Chile	Yes	USD 67,000	Law of Bases of Administrative Contracts for supply and services, No. 19.886
China	Yes	RMB 1 million for products and services; RMB 1.2 million for works	PRC Government Procurement Law

Continued on next page

C.1 – continued from previous page

Country	SVP Threshold?	Threshold Value	Law
Colombia	Yes	25 to 1,000 monthly minimum wages depending on contracting entity's budget (≈ USD 6,750 to USD 270,000)	Leyes 80 de 1993 y 1150 de 2007, y el decreto 1510 de 2013
Costa Rica	Yes	USD 58,550	Public Procurement Law
Czech Republic	Yes	CZK 2 million for products and services; CZK 6 million for public works	Act No. 134/2016
Denmark	Yes	EUR 40,000	Act 1410/2007
Estonia	Yes	EUR 40,000 for products and services; EUR 250,000 for works	Public Procurement Act
Finland	Yes	EUR 60,000 for products and services; EUR 500,000 for works	Section 25 of the Act on Public Contracts
France	Yes	EUR 40,000	Ordinance no. 2015-899
Germany	Yes	EUR 1,000 for products and services; EUR 3,000 for works	German Public Procurement Law

Continued on next page

C.1 – continued from previous page

Country	SVP Threshold?	Threshold Value	Law
Greece	Yes	EUR 20,000	Law 4412/2016
Hungary	Yes	HUF 15 million for products and services; HUF 25 million for works	Act CXLIII of 2015 on public procurements
Iceland	Yes	ISK 15,500,000 for products and services; ISK 49,000,000 for works	Act on Public Procurement
India	Yes	INR 25,000	General Financial Rules, 2017
Ireland	Yes	EUR 5,000 for products and services	National Irish Procurement Law
Israel	Yes	ILS 50,000	Mandatory Tenders Regulations
Italy	Yes	EUR 40,000 for products and services; EUR 150,000 for works	Legislative Decree no. 50/2016
Japan	Yes	Threshold is not disclosed in the law	Article 29-3 section 5 of the Accounting Act

Continued on next page

C.1 – continued from previous page

Country	SVP Threshold?	Threshold Value	Law
Korea	Yes	KRW 20 million for products and services; KRW 200 million for construction	Public Procurement Law
Latvia	Yes	EUR 4,000 for products and services; EUR 14,000 for works	2006 Law on Public Procurement
Lithuania	Yes	EUR 58,000 for products and services; EUR 145,000 for works	Law of Public Procurement (13/Aug/1996)
Luxembourg	Yes	EUR 8,000	Law of 8 April 2018
Mexico	Yes	Pre-specified and based on Authorized Budget for acquisitions and public works	2023 Federal Government Expenditure Budget
Netherlands	Yes	EUR 33,000 for Products and Services; EUR 150,000 for works	Public Procurement Act 2015
New Zealand	Yes	NZD 100,000 for products and services; NZD 9,000,000 for works	Government Procurement Rules
Norway	Yes	NOK 100,000	Public Procurement Act

Continued on next page

C.1 – continued from previous page

Country	SVP Threshold?	Threshold Value	Law
Poland	Yes	PLN 130,000	Public Procurement Law
Portugal	Yes	EUR 20,000 for products and services; EUR 30,000 for works	Decree-Law n.º 18/2008 of 29 January
Slovak Republic	Yes	Up to EUR 70,000 for products and services; Up to EUR 180,000 for works.	Act No 343/2015
Slovenia	Yes	EUR 40,000 for products and services; EUR 80,000 for public construction contracts	Public Procurement Act (ZJN-3)
Spain	Yes	EUR 15,000 for products and services; EUR 40,000 for works	Ley de Contratos del Sector Público 9/2017
Sweden	Yes	SEK 700,000	Sw. lag (2016:1145)
Switzerland	Yes	CHF 150,000 for products and services; CHF 300,000 for constructions	Federal Law on Public Procurement
Turkey	Yes	TRY 121,304	Public Procurement Law

Continued on next page

C.1 – continued from previous page

Country	SVP Threshold?	Threshold Value	Law
United Kingdom	Yes	GBP 70,778 for products and services; GBP 884,720 for works	Action PPN 10/21
United States	Yes	USD 10,000 (micro-purchases)	Federal Acquisition Regulation

Table C.2—Examples of Products and Brands

Product		Brand
Description	Unit	
Ballpoint Pen	1 unit	Bic
Flexible Electric Cable	1 meter	Corfio
Gloves for Non-Surgical Procedure	100 units	Descarpack
Battery	1 unit	Elgin
Ethyl Alcohol	1 liter	Itaja
TV	1 unit	LG
Coffee	500 grams	Odebrecht
Coffee	1 kilogram	Pilao
External HD	1 unit	Seagate
Sugar	1 kilogram	Uniao
Mineral Water	20 liters	Villa
Detergent	500 milliliters	Ype
HP Printer Toner Cartridge	1 unit	HP
White Board Pen	1 unit	Pilot
Insulin	3 milliliters	Lantus
Microscope	1 unit	Physis
Gas	1 liter	Petrobras

This table illustrates the product-brand structure of the procurement data. Each row shows a product (described by its name and unit of measurement) and one of the brands available for that product. The full sample contains 57,158 distinct product-unit combinations and 12.9 brands per product on average.

Table C.3—Government Agencies

Name of Government Agency	Classification
Universidade Federal do Rio Grande do Sul	Education
Universidade Federal do Pará	Education
Universidade Federal de Pernambuco	Education
Hospital Universitário UFSC	Hospitals
Hospital Universitário Antonio Pedro (UFF/RJ)	Hospitals
Hospital Universitário Gaffrée e Guinle (UNIRIO)	Hospitals
Grupamento de Apoio de São José dos Campos	Armed Forces
Grupamento de Apoio de Brasília	Armed Forces
14 Grupo de Artilharia de Campanha	Armed Forces
Comissão Nacional de Energia Nuclear	Other
Governo do Estado do Ceará	Other
Departamento de Logística em Saúde	Other

This table lists examples of federal government agencies in the procurement data, classified by type (Education, Hospital, Armed Forces, Other). The full sample contains 5,007 distinct procurement agencies, including purchasers of services and of products without brand information; 4,657 of them appear in the product analysis sample described in Section II.

Table C.4—Comparing Procurements Around the Small-Value Purchase Threshold: Sample with High Brand Information Availability

Dep. Var.	Comparing the Same Product			Comparing the Same Product & Brand		Procurement Level
	$\log(\text{price})_{ipb}$	$\log(\text{quant})_{ipb}$	$\log(\text{brand price})_{ipb}$	$\log(\text{price})_{ipb}$	$\log(\text{quant})_{ipb}$	# products _{it}
	I	II	III	IV	V	VI
below threshold _i	0.216*** (0.059)	0.076 (0.051)	0.142*** (0.042)	0.169*** (0.042)	0.094 ⁺ (0.055)	-2.400*** (0.466)
Product*Quarter FE	yes	yes	yes			
Brand*Product*Quarter FE				yes	yes	
Quarter FE						yes
Obs	247,961	247,961	247,961	247,961	247,961	92,191
R ²	0.926	0.836	0.949	0.977	0.940	0.063

This table compares procurement outcomes above and below the small-value purchase threshold for products in the upper quartile of brand information availability. In other words, I only keep those products whose information on brands is available in at least 83.4% of the observations. On either side of the threshold, I fit a linear function of the distance to the threshold as in equation (1). In columns I and IV, the dependent variable $\log(\text{price})_{ipb}$ is the logarithm of the price of product p from brand b procured in procurement i by agency $a(i)$ at time $t(i)$. In columns II and V, the dependent variable $\log(\text{quant})_{ipb}$ is the logarithm of the quantity procured. In column III, $\log(\text{brand price})_{ipb}$ is the logarithm of the average brand price of product p of brand b purchased in procurements at time t . In column VI, # products_i is the number of products in procurement i . The explanatory variable in all columns, below threshold_i, is a dummy equal to one if procurement i is conducted at or below the threshold, and zero otherwise, with this threshold status applying to all products and brands within that procurement. Columns I to III include Product*Quarter fixed effects, comparing outcomes for procurements of the same product and in the same quarter. Columns IV to V include Brand*Product*Quarter fixed effects, comparing outcomes for procurements of the same brand, product, and quarter. Column VI includes Quarter fixed effects and analyzes the number of products per procurement. Because $\log(\text{brand price})_{ipb}$ averages over all procurements in each product-brand-quarter cell, it is constant within each cell, and the coefficient on below threshold_i in column III therefore captures across-brand selection rather than within-brand price variation. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors clustered at the product level (columns I to V) and at the agency level (column VI) are presented in parentheses. ⁺, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.5—Brand quality

Product	Source	Description
Enamel Paint	INMETRO	Lead concentration in % (the lower, the better)
Toilet Paper	INMETRO	Score based on size, resistance, softness, and effectiveness
Ballpoint Pen	INMETRO	Pen writing capacity (in meters)
Washing Machine	INMETRO and PROTESTE	Washing efficiency (INMETRO); PROTESTE overall test score
Gas Stove	INMETRO and PROTESTE	Average yield of burners, in % (INMETRO); PROTESTE overall test score
Air Conditioner	INMETRO and PROTESTE	Energy efficiency score (INMETRO); PROTESTE overall test score
Centrifugal Pump	INMETRO	Pump yield (in %)
Fan	INMETRO	Energy efficiency score (in m ² /s/W)
Domestic Fridge	INMETRO	Energy efficiency score
Microwave	INMETRO and PROTESTE	Energy efficiency score (INMETRO); PROTESTE overall test score
Coconut water	PROTESTE	Score based on labeling, hygiene, chemical and sensorial analyses
Mineral Water	PROTESTE	Score based on labeling, hygiene, chemical and sensorial analyses
Cellphones	PROTESTE	Score based on display, sound, signal, portability, durability, SMS, camera, video, internet, and GPS
Rice	PROTESTE	Score based on acidity, labeling, cooking time, hygiene, chemical and sensorial analyses
Olive Oil	PROTESTE	Score based on acidity, labeling, conservation status, humidity levels, frauds, and sensorial analyses
Coffee	PROTESTE	Score based on labeling, hygiene, chemical and sensorial analyses
Beef	PROTESTE	Score based on labeling, hygiene, chemical and sensorial analyses
Beans	PROTESTE	Score based on labeling, hygiene, chemical and sensorial analyses
Iron (appliance)	PROTESTE	Score based on safety, performance, and instruction manual
Air Fryer	PROTESTE	Score based on noise, instructions manual, power cable, power efficiency, and safety
Yogurt	PROTESTE	Score based on labeling, hygiene, chemical and sensorial analyses
Milk	PROTESTE	Score based on labeling, hygiene, chemical and sensorial analyses
Pasta	PROTESTE	Score based on labeling, hygiene, chemical and sensorial analyses
Butter	PROTESTE	Score based on labeling, hygiene, chemical and sensorial analyses
Cream Cheese	PROTESTE	Score based on labeling, hygiene, chemical and sensorial analyses
Television	PROTESTE	Score based on image and sound quality, connectivity, smart features, and ease of use
Tablet	PROTESTE	Score based on connectivity, performance, touchscreen quality, battery life, and reliability
Blood Pressure Monitor	PROTESTE	Score based on measurement accuracy, safety, and regulatory conformity tests
Vacuum Cleaner	PROTESTE	Score based on suction performance, filtration, noise, and ease of use
Blender	PROTESTE	Score based on blending performance, noise, ease of use, and safety

This table lists the consumer products for which independent quality assessments are available, along with the testing organization (INMETRO or PROTESTE) and the quality criteria used. These assessments are used to construct the quality rank, upper-quartile rank, and highest rank measures in Tables 3 and 4. For product categories tested by both organizations (washing machines, gas stoves, air conditioners, and microwave ovens), a brand's quality rank is computed as the average of its ranks in the two sources; brands tested by only one of the two keep that source's rank.

Table C.6—Selected Critical Manufacturing Issues

Active Ingredient	Laboratory	Manufacturing Issue and Health Risk
Amoxicillin	Prati Donaduzzi	Substandard antibiotic concentration risking treatment failure and resistance
Benzylpenicillin	Teuto	Failed injection administration tests risking improper drug delivery
Ceftriaxone	Novafarma	Sterility concerns in broad-spectrum injectable antibiotic
Dexamethasone	Farmace	Cross-contamination with bronchodilator causing potential severe adverse reactions
Dobutamine	Novafarma	Quality issues in critical cardiac emergency medication
Dormec	IMEC	Failed dissolution test and incorrect labeling
Duzimicin	Prati Donaduzzi	Quality deviation in antibiotic suspension
Furosemide	Santisa	Critical defects in injectable diuretic affecting emergency treatment
Heparin	Eurofarma	Out-of-specification active ingredient risking anticoagulation failure
Ivermectin	Vitamedic	Manufacturing in non-authorized area affecting product quality
Levofloxacin	Halex	Unstable concentration in injectable antibiotic leading to treatment failure
Mesna	Novafarma	Quality failures in chemotherapy supportive medication
Morphine	Cristalia	Critical sterility breaches in controlled injectable opioid
Norepinephrine	Novafarma	Manufacturing deviations in vital vasopressor medication
Oxacillin sodium	Blau	Foreign particles in injectable medicine creating risk of embolism and infection
Vancomycin	Novafarma	Failed production controls in critical injectable antibiotic affecting safety

This table provides examples of critical manufacturing issues identified through ANVISA batch suspension notifications published in Brazil's Federal Official Gazette (*Diário Oficial da União*). These notifications form the basis of the quality violation measure used in Tables 3 and 4, column IV.

Table C.7—Generic Purchases and Quality Violations Around the SVP Threshold

Dep. Var.	generic _{ipb}	quality violation _{ipb}	
	I	II	III
below threshold _i	-0.001 (0.0132)	-0.115* (0.0514)	-0.000 (0.0002)
Product*Quarter FE	yes	yes	yes
Sample	Pharmaceuticals	Generic	Non-Generic
Obs	9,005	6,293	2,712
R ²	0.942	0.665	0.985

This table compares the likelihood of generic purchases and subsequent quality violations above and below the small-value purchase threshold. On either side of the threshold, I fit a linear function of the distance to the threshold as in equation (1). The dependent variable in column I is generic_{ipb}, a dummy equal to one for generic products. In columns II and III, quality violation_{ipb} is a dummy equal to one if the laboratory receives any ANVISA quality violation in the three years following procurement. Column II restricts the sample to generic products, while column III looks at non-generic products. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors clustered at the product level are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.8—Donut RD: Sensitivity of Results to Manipulation

Dep. Var.	$\log(\text{price})_{ipb}$	$\log(\text{brand price})_{ipb}$
	I	II
Panel A: Donut RD - BRL 2,500 Radius		
below threshold _{<i>i</i>}	0.122** (0.037)	0.121*** (0.020)
Product*Quarter FE		yes
Brand*Product*Quarter FE	yes	
Benchmark RD	0.101***	0.134***
Obs	686,598	686,598
R ²	0.971	0.924
Panel B: Donut RD - BRL 3,000 Radius		
below threshold _{<i>i</i>}	0.134** (0.045)	0.166*** (0.025)
Product*Quarter FE		yes
Brand*Product*Quarter FE	yes	
Benchmark RD	0.101***	0.134***
Obs	635,961	635,961
R ²	0.971	0.924

This table compares procurement outcomes above and below the small-value purchase threshold by removing observations where manipulation of the threshold is suspected. On either side of the threshold, I fit a linear function of the distance to the threshold as in equation (1). Panels A and B present the results when I drop observations whose procurement value is within BRL 2,500 and BRL 3,000 of the threshold, respectively. In column I, the dependent variable $\log(\text{price})_{ipb}$ is the logarithm of the price of product p from brand b procured in procurement i by agency $a(i)$ at time $t(i)$. In column II, $\log(\text{brand price})_{ipb}$ is the logarithm of the average brand price of product p from brand b purchased in procurements at time t . The explanatory variable, below threshold_{*i*}, is a dummy equal to one if procurement i is conducted at or below the threshold, and zero otherwise. In this specification, the estimated coefficient of below threshold_{*i*} still gives the estimates of outcomes at the threshold (as in Table 2), but it now allows for the possibility that observations that are close to the threshold are systematically different from observations farther away. Because $\log(\text{brand price})_{ipb}$ averages over all procurements in each product-brand-quarter cell, it is constant within each cell, and the corresponding coefficient on below threshold_{*i*} therefore captures across-brand selection rather than within-brand price variation. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors clustered at the product level are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.9—Comparing Auctions Around the Threshold: Finer Product Classification

Dep. Var.	log(price) _{ipb}			
	I	II	III	IV
below threshold _i	0.152*** (0.014)	0.093*** (0.013)		
below threshold _i · low description length _p			0.135*** (0.015)	0.085*** (0.018)
below threshold _i · high description length _p			0.190*** (0.024)	0.115*** (0.031)
Product*Quarter FE	yes		yes	
Brand*Product*Quarter FE		yes		yes
Obs	977,059	977,059	977,059	977,059
R ²	0.918	0.978	0.918	0.978

This table compares procurement outcomes above and below the small-value purchase threshold, using a finer classification of products than in the rest of the paper. On either side of the threshold, I fit a linear function of the distance to the threshold as in equation (1). The dependent variable $\log(\text{price})_{ipb}$ is the logarithm of the price of product p from brand b procured in procurement i by agency $a(i)$ at time $t(i)$. High Description Length_p and Low Description Length_p are defined as products above and below the median product description length, respectively. The explanatory variable in all columns, below threshold_i, is a dummy equal to one if procurement i is conducted at or below the threshold, and zero otherwise, with this threshold status applying to all products and brands within that procurement. Columns I and III include Product*Quarter fixed effects, effectively comparing outcomes in procurements of the same product and in the same quarter. Columns II and IV include Brand*Product*Quarter fixed effects, effectively comparing outcomes in procurements of the same brand, product, and in the same quarter. Standard errors, clustered at the product level in columns I and II and at the benchmark product-classification level in columns III and IV, are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.10—Calonico, Cattaneo and Titiunik (2014)’s Robust Nonparametric Estimator

Dep. Var.	Comparing the Same Product			Comparing the Same Product & Brand		Procurement Level
	$\log(\text{price})_{ipb}$	$\log(\text{quant})_{ipb}$	$\log(\text{brand price})_{ipb}$	$\log(\text{price})_{ipb}$	$\log(\text{quant})_{ipb}$	# products _{<i>i</i>}
	I	II	III	IV	V	VI
below threshold _{<i>i</i>}	0.198*** (0.008)	0.035*** (0.015)	0.184*** (0.007)	0.076*** (0.009)	0.041*** (0.021)	-2.920*** (0.377)
Product*Quarter FE	yes	yes	yes			
Brand*Product*Quarter FE				yes	yes	
Quarter FE						yes
Obs	235,787	153,371	197,657	123,032	47,046	51,128

This table compares procurement outcomes above and below the small-value purchase threshold using the robust nonparametric estimators proposed by Calonico, Cattaneo and Titiunik (2014). On either side of the threshold, I fit a linear function of the distance to the threshold as in equation (1). The symmetric bandwidths are estimated using the mean squared error (MSE) minimizing bandwidth of Calonico, Cattaneo and Titiunik (2014) with an Epanechnikov kernel. In columns I and IV, the dependent variable $\log(\text{price})_{ipb}$ is the logarithm of the price of product p from brand b procured in procurement i by agency $a(i)$ at time $t(i)$. In columns II and V, the dependent variable $\log(\text{quant})_{ipb}$ is the logarithm of the quantity procured. In column III, $\log(\text{brand price})_{ipb}$ is the logarithm of the average brand price of product p of brand b purchased in procurements at time t . In column VI, # products_{*i*} is the number of products in procurement i . The explanatory variable in all columns, below threshold_{*i*}, is a dummy equal to one if procurement i is conducted at or below the threshold, and zero otherwise, with this threshold status applying to all products and brands within that procurement. Columns I to III include Product*Quarter fixed effects, comparing outcomes for procurements of the same product and in the same quarter. Columns IV to V include Brand*Product*Quarter fixed effects, comparing outcomes for procurements of the same brand, product, and quarter. Column VI includes Quarter fixed effects and analyzes the number of products per procurement. Because $\log(\text{brand price})_{ipb}$ averages over all procurements in each product-brand-quarter cell, it is constant within each cell, and the coefficient on below threshold_{*i*} in column III therefore captures across-brand selection rather than within-brand price variation. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors clustered at the product level (columns I to V) and at the agency level (column VI) are presented in parentheses. ⁺, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.11—Running Variable Correction – Price and Quantity (Carril, Gonzalez-Lira and Walker, 2026)

Dep. Var.	Price and quantity outcomes (Table 2)		
	$\log(\text{price})_{ipb}$	$\log(\text{quant})_{ipb}$	$\log(\text{brand price})_{ipb}$
	I	II	III
Naive RDD	0.166*** (0.016)	0.135*** (0.019)	0.134*** (0.012)
Drop below-threshold auctions	0.211*** (0.015)	0.162*** (0.020)	0.166*** (0.012)
Corrected RDD (CGW)	0.253*** (0.010)	0.235*** (0.014)	0.211*** (0.008)

This table reports RDD estimates corrected for running variable contamination following Proposition 5 of Carril, Gonzalez-Lira and Walker (2026). The running variable (realized procurement value) is a potentially mismeasured version of the true assignment variable (estimated procurement value). Since competitive bidding lowers realized values below estimated values, auctions may appear below the threshold in the observed running variable, contaminating the treatment group and attenuating the naive RDD estimates. I model $\gamma < 0$ for auctions, as competition deflates their running variable ($\hat{\mu}_\gamma = -3,489$ BRL). Each row reports a different estimation approach: “Naive RDD” reports the benchmark uncorrected coefficients; “Drop below-threshold auctions” addresses the contamination directly by excluding the auctions whose realized values fall below the threshold (the below-threshold sample then contains only bid waivers, while the above-threshold sample is unchanged); and “Corrected RDD (CGW)” addresses the same contamination using the parametric correction from Proposition 5 of Carril, Gonzalez-Lira and Walker (2026). $\log(\text{price})_{ipb}$ is the logarithm of the unit price for product p of brand b in procurement i ; $\log(\text{quant})_{ipb}$ is the logarithm of the quantity procured; $\log(\text{brand price})_{ipb}$ is the logarithm of the average brand price of product p of brand b at time t . All specifications include Product*Quarter fixed effects. Because $\log(\text{brand price})_{ipb}$ averages over all procurements in each product-brand-quarter cell, it is constant within each cell, and the corresponding coefficient on below threshold _{i} therefore captures across-brand selection rather than within-brand price variation. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors clustered at the product-agency level are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.12—Running Variable Correction – Quality (Carril, Gonzalez-Lira and Walker, 2026)

Dep. Var.	Quality outcomes (Table 4)			
	Consumer (PROTESTE/INMETRO)			Pharmaceutical
	quality rank _{ipb}	upper-quartile rank _{ipb}	highest rank _{ipb}	quality violation _{ipb}
	I	II	III	IV
Naive RDD	0.875*** (0.250)	0.1011** (0.038)	0.105** (0.039)	−0.092* (0.042)
Drop below-threshold auctions	0.692 (0.535)	0.0929** (0.035)	0.081* (0.036)	−0.040 ⁺ (0.021)
Corrected RDD (CGW)	1.143 ⁺ (0.620)	0.2247*** (0.056)	0.277*** (0.059)	−0.256 ⁺ (0.137)

This table reports RDD estimates of quality outcomes corrected for running variable contamination following Proposition 5 of Carril, Gonzalez-Lira and Walker (2026). See notes to Table C.11 for details on the correction methodology. quality rank_{ipb} is the ordinal ranking of brand *b* for product *p* among all tested products in its category; upper-quartile rank_{ipb} is an indicator equal to one for brands in the upper-quartile of the rank distribution; highest rank_{ipb} is a dummy equal to one if brand *b* has the highest quality rank for product *p*; quality violation_{ipb} is an indicator equal to one if the manufacturer received any ANVISA quality violations within three years of procurement. All specifications include Product*Quarter fixed effects. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors clustered at the product level are presented in parentheses. ⁺, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.13—Comparing Procurements Around the Small-Value Purchase Threshold – Heterogeneous Effects by Product Differentiation

Dep. Var.	log(price) _{ipb}	log(brand price) _{ipb}
	I	II
below threshold _i · differentiated _p	0.103*** (0.019)	0.139*** (0.013)
below threshold _i · reference-priced _p	0.073* (0.031)	0.082*** (0.024)
below threshold _i · homogeneous _p	0.032 (0.070)	0.033 (0.043)
Brand*Product*Unit*Quarter FE	yes	
Product*Unit*Quarter FE		yes
Obs	977,059	977,059
R ²	0.969	0.920

This table compares procurement outcomes above and below the small-value purchase threshold, exploring heterogeneity by product differentiation following the classification in [Rauch \(1999\)](#). Products are classified as differentiated (prices depend on producer identity), reference-priced (prices listed in trade publications), or homogeneous (traded on organized exchanges). On either side of the threshold, I fit a linear function of the distance to the threshold as in equation (1). The dependent variable in column I is the log of the price of product p procured in procurement i at time t , with brand-product-unit-quarter fixed effects comparing procurements of the same brand, product, unit, and quarter. Column II uses the log of the average brand price of product p from brand b purchased in procurements at time t , with product-unit-quarter fixed effects. Because $\log(\text{brand price})_{ipb}$ averages over all procurements in each product-brand-quarter cell, it is constant within each cell, and the corresponding coefficient on below threshold_i therefore captures across-brand selection rather than within-brand price variation. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors clustered at the product-agency level are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.14—Agency Heterogeneity: Size and Discretion Intensity

Dep. Var.	log(price) _{ipb}				log(brand price) _{ipb}			
	I	II	III	IV	V	VI	VII	VIII
below threshold _i	0.0703 (0.0475)	0.0610 (0.0462)	0.0658** (0.0208)	0.0639** (0.0203)	0.0688* (0.0334)	0.0484 (0.0315)	0.0546*** (0.0134)	0.0548*** (0.0132)
below threshold _i · Agency Size (by Value) _{a,t-1}	0.0142 (0.0549)				0.0248 (0.0393)			
below threshold _i · Agency Size (by Purch Count) _{a,t-1}		0.0257 (0.0538)				0.0508 (0.0383)		
below threshold _i · Discretion Share (by Value) _{a,t-1}			0.0372 (0.0573)				0.1085** (0.0357)	
below threshold _i · Discretion Share (by Purch Count) _{a,t-1}				0.0440 (0.0546)				0.1184*** (0.0358)
Agency FE	yes	yes	yes	yes	yes	yes	yes	yes
Product*Quarter FE					yes	yes	yes	yes
Brand*Product*Quarter FE	yes	yes	yes	yes				
Obs	716,804	716,804	716,804	716,804	716,804	716,804	716,804	716,804
R ²	0.971	0.971	0.971	0.971	0.925	0.925	0.925	0.925

This table examines whether the price premium of below-threshold procurement varies with agency size and discretion intensity. On either side of the threshold, I fit a linear function of the distance to the threshold as in equation (1). In columns I–IV, the dependent variable $\log(\text{price})_{ipb}$ is the logarithm of the price of product p from brand b procured in procurement i at time t . In columns V–VIII, the dependent variable $\log(\text{brand price})_{ipb}$ is the logarithm of the average brand price of the product and brand procured. The explanatory variable below threshold _{i} is a dummy equal to one if procurement i is conducted below the threshold, and zero otherwise. This variable is interacted with four agency-level characteristics. Each characteristic is the agency's *decile rank*, computed within the year and rescaled to a 0–1 scale (0 = bottom decile, 1 = top decile), based on the agency's total procurement activity in the year prior to the procurement. Agency Size (by Value) and Agency Size (by Purch Count) are the decile ranks of the agency's total procurement value and total number of purchases; Discretion Share (by Value) and Discretion Share (by Purch Count) are the decile ranks of the share of the agency's procurement value and purchase count, respectively, conducted below the threshold. All specifications also include the un-interacted main effects of these four characteristics; their coefficients are omitted for brevity. Columns I–IV include Agency and Brand*Product*Quarter fixed effects. Columns V–VIII include Agency and Product*Quarter fixed effects. Because $\log(\text{brand price})_{ipb}$ averages over all procurements in each product-brand-quarter cell, it is constant within each cell, and the corresponding coefficient on below threshold _{i} therefore captures across-brand selection rather than within-brand price variation. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors clustered at the product level are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.15—DataSUS: International Classification of Diseases

Certain infectious and parasitic diseases
Neoplasms
Diseases of the blood and blood-forming organs and certain disorders involving the immune mechanism
Endocrine, nutritional and metabolic diseases
Mental and behavioural disorders
Diseases of the nervous system
Diseases of the eye and adnexa
Diseases of the ear and mastoid process
Diseases of the circulatory system
Diseases of the respiratory system
Diseases of the digestive system
Diseases of the skin and subcutaneous tissue
Diseases of the musculoskeletal system and connective tissue
Diseases of the genitourinary system
Pregnancy, childbirth and the puerperium
Certain conditions originating in the perinatal period
Congenital malformations, deformations and chromosomal abnormalities
Symptoms, signs and abnormal clinical and laboratory findings, not elsewhere classified
Injury, poisoning and certain other consequences of external causes
External causes of morbidity and mortality
Factors influencing health status and contact with health services
Codes for special purposes

This table lists different disease classifications from the World Health Organization's International Classification of Diseases. These categories are also employed by DataSUS in their hospital mortality dataset.

Table C.16—Real Effects of Discretion: Alternative Treatment Definitions

Dep. Var.	mortality rate _{hde_t}						
	all causes			cancer-related causes		non-cancer-related causes	
	I	II	III	IV	V	VI	VII
Panel A: purchases above 33% below the threshold							
below threshold _{hde} · post _{et}	-0.0044*** (0.0008)	-0.0049*** (0.0008)	-0.0595*** (0.0142)	0.0035 (0.0026)	0.0068** (0.0025)	-0.0048*** (0.0008)	-0.0055*** (0.0008)
Hospital*Disease*Event FE	yes	yes	yes	yes	yes	yes	yes
Disease*Event*Time FE	yes	yes	yes	yes	yes	yes	yes
Hospital*Event*Time FE			yes				
Controls		yes	yes		yes		yes
pre-treat avg(mortality rate)	0.058	0.058	0.058	0.083	0.083	0.055	0.055
Obs	1,067,087	1,049,143	1,049,143	67,500	67,180	999,587	981,963
R ²	0.881	0.886	0.903	0.925	0.930	0.874	0.879
Panel B: purchases above 66% below the threshold							
below threshold _{hde} · post _{et}	-0.0046*** (0.0008)	-0.0051*** (0.0008)	-0.0507*** (0.0081)	-0.0016 (0.0022)	0.0009 (0.0022)	-0.0048*** (0.0009)	-0.0054*** (0.0008)
Hospital*Disease*Event FE	yes	yes	yes	yes	yes	yes	yes
Disease*Event*Time FE	yes	yes	yes	yes	yes	yes	yes
Hospital*Event*Time FE			yes				
Controls		yes	yes		yes		yes
pre-treat avg(mortality rate)	0.058	0.058	0.058	0.083	0.083	0.055	0.055
Obs	1,076,792	1,059,462	1,059,462	96,612	96,335	980,180	963,127
R ²	0.880	0.884	0.904	0.913	0.918	0.873	0.879

This table compares hospital mortality rates between essential medicines purchased below and above the threshold. For each hospital-disease pair with a high proportion of emergency room medication purchases made below the SVP threshold, I select other hospital-disease pairs that make essential medicine purchases in the same quarter as controls. These events are then grouped into cohorts, and health outcomes around the date of purchase are compared using a “stacked” difference-in-differences approach. The dependent variable, mortality rate_{hde_t}, represents the ratio of deaths to hospitalizations in hospital *h* for disease *d* in event *e* at year *t*. In Panel A, the primary independent variable, below threshold_{hde}, is a dummy variable equal to one if at least 33% of the value of purchases of essential medicines for hospital *h* to treat disease *d* in event *e* was done via procurements below the threshold, and zero otherwise; in Panel B, this is adjusted to 66%. The variable Post_{et} is a dummy equal to one after the procurement and zero otherwise. Columns I to III present the results for all diseases, while columns IV to V and columns VI to VII present the results for cancer-related and non-cancer-related diseases, respectively. All specifications include hospital-disease-event fixed effects and disease-event-time fixed effects. Therefore, this strategy effectively compares purchases of medicines for the same disease below versus above the threshold. In column III, I further enhance the specification by adding hospital-event-time fixed effects to account for any time-varying changes in hospital characteristics that might explain the outcome. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors, clustered at the hospital-disease-event level, are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.17—Real Effects of Discretion: Excluding Repeat Purchases

Dep. Var.	mortality rate _{hdet}			
	all causes			
	I	II	III	IV
below threshold _{hde} · post _{et}	-0.0033 ⁺ (0.0017)	-0.0039* (0.0017)	-0.0039* (0.0017)	-0.0573*** (0.0097)
log(hospitalizations) _{hde,t=-1} · post _{et}		-0.0010*** (0.0001)	-0.0009*** (0.0001)	0.0016*** (0.0002)
\$ essential ER drugs per hospitalization _{hde} · post _{et}			0.0043*** (0.0005)	0.0084*** (0.0005)
Hospital*Disease*Event FE	yes	yes	yes	yes
Disease*Event*Time FE	yes	yes	yes	yes
Hospital*Event*Time FE				yes
pre-treat avg(mortality rate)	0.058	0.058	0.058	0.058
Obs	1,031,807	1,014,986	1,014,986	1,014,986
R ²	0.877	0.882	0.882	0.901

This table compares hospital mortality rates between essential medicines purchased predominantly below and above the small-value purchase (SVP) threshold. For each hospital-disease pair with a high proportion of emergency room medication purchases made below the SVP threshold, I select other hospital-disease pairs that make essential medicine purchases in the same quarter as controls. These events are then grouped into cohorts, and health outcomes around the date of purchase are compared using a “stacked” difference-in-differences approach. I exclude treated hospital-disease pairs that made additional purchases below the threshold in the following 3 years to address potential confounding effects from repeated below-threshold purchases. The dependent variable, mortality rate_{hdet}, represents the ratio of deaths to hospitalizations in hospital *h* for disease *d* in event *e* at year *t*. The main independent variable, below threshold_{hde}, is a dummy equal to one if the purchase of essential medicines for hospital *h* to treat disease *d* in event *e* was done via a procurement below the threshold and zero otherwise. Post_{et} is a dummy equal to one after the procurement and zero otherwise. All specifications include hospital-disease-event fixed effects and disease-event-time fixed effects. Thus, this strategy effectively compares purchases of medicines for the same disease below versus above the threshold. In column IV, I further enhance the specification by adding hospital-event-time fixed effects, addressing any time-varying changes in hospital characteristics that might explain the outcome. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors clustered at the hospital-disease-event level are presented in parentheses. ⁺, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.18—Medical Literature on Pharmaceutical Quality and Health Outcomes

Study	Setting	Key Finding
<i>Panel A: Quality Defects and Patient Harm — Developed Countries</i>		
Noh et al. (2025)	United States	India-manufactured generics associated with 54% more serious adverse events (hospitalization, death) than US-manufactured equivalents
Mansouri et al. (2022)	France	NDMA-contaminated generic valsartan increased liver cancer risk (aHR 1.12) and melanoma risk (aHR 1.10) among 1.4 million users
Blossom et al. (2008)	United States	Contaminated Chinese-sourced heparin caused 81 deaths and 785 serious injuries
Kishimoto et al. (2008)	United States	Identified over-sulfated chondroitin sulfate as the contaminant activating the contact system
Johnston and Holt (2014)	United Kingdom	UK MHRA issued 211 drug alerts (2005–2012), including 22 Class I (life-threatening) alerts
Kesselheim et al. (2008)	Meta-analysis	Properly manufactured generics are clinically equivalent to brand-name cardiovascular drugs
<i>Panel B: Quality Defects and Patient Harm — Developing Countries</i>		
Ordonez et al. (2019)	Colombia	21 percentage point higher ICU survival with brand-name vs. generic meropenem

Continued on next page

Table C.18 continued from previous page

Study	Setting	Key Finding
Renschler et al. (2015)	Sub-Saharan Africa	122,350 under-5 deaths per year attributed to poor-quality anti-malarials across 39 countries
World Health Organization (2017)	Global (LMICs)	72,000–169,000 child pneumonia deaths per year from substandard antibiotics; 116,000 additional malaria deaths
Laxminarayan et al. (2016)	Global	Substandard antibiotics with sub-therapeutic concentrations accelerate antimicrobial resistance
<i>Panel C: Prevalence of Substandard Medicines</i>		
Ozawa et al. (2018)	25 LMICs	13.6% of 67,839 sampled medicines are substandard or falsified (systematic review)
Bate, Jin and Mathur (2011)	17 countries	Drug quality significantly poorer among lowest-priced products; Indian-labeled drugs worse in Africa
Bate et al. (2008)	6 African countries	9–16% failure rates in field-based testing of antimalarials
Straka, Keohane and Liu (2017)	United States	Switching from brand to generic in narrow therapeutic index drugs associated with clinical deterioration
<i>Panel D: Mechanisms — Why Medication Quality Affects Mortality</i>		
Kumar et al. (2006)	United States	Each hour delay in therapeutic antibiotic levels increases sepsis mortality by 7.6%

Continued on next page

Table C.18 continued from previous page

Study	Setting	Key Finding
Rivers et al. (2001)	United States	Early goal-directed therapy reduced in-hospital mortality by 16 percentage points in severe sepsis
Amidon et al. (1995)	—	Biopharmaceutic classification: poor dissolution leads to inadequate bioavailability and therapeutic failure
ISIS-2 Collaborative Group (1988)	International	Aspirin and streptokinase each independently reduce vascular mortality in acute MI
The HOPE Investigators (2000)	International	ACE inhibitor ramipril reduces cardiovascular mortality by 26% in high-risk patients

This table summarizes published evidence on pharmaceutical manufacturing quality and health outcomes. Panel A reports evidence from developed countries linking quality defects to patient harm. Panel B reports analogous evidence from developing countries. Panel C documents the prevalence of substandard medicines. Panel D reports clinical evidence on the mechanisms through which medication quality affects patient outcomes — specifically, conditions where drug efficacy depends critically on bioavailability, timely therapeutic effect, and manufacturing consistency. “Serious adverse events” in Noh et al. (2025) include hospitalization, disability, and death as reported to the FDA Adverse Event Reporting System. aHR = adjusted hazard ratio. The cancer studies cited in the main text (Tannock et al., 2004; Hodi et al., 2010; Chapman et al., 2011) are omitted as they document conditions where even high-quality medications extend survival only modestly, consistent with the paper’s finding that mortality effects concentrate in non-cancer conditions.

Table C.19—Treatment Effects Depend on Quality Differentials

Dep. Var.	mortality rate _{hde_t}	
	Panel A:	Panel B: Below
	Both Zero Violations	Zero, Above Has Violations
	I	II
below threshold _{hde} · post _{et}	−0.0005 (0.0027)	−0.0076*** (0.0019)
Hospital*Disease*Event FE	yes	yes
Disease*Event*Time FE	yes	yes
pre-treat avg(mortality rate)	0.058	0.058
Obs	359,413	437,875
R ²	0.953	0.906

This table examines whether mortality effects depend on quality differentials between treated (below threshold) and control (above threshold) hospitals. Using the same stacked difference-in-differences methodology as Table 9, I partition the sample based on supplier quality. Panel A restricts the analysis to hospital-disease-event observations where *both* treated hospitals (below threshold) and control hospitals (above threshold) procured exclusively from manufacturers without documented ANVISA quality violations, thereby eliminating any quality differential. Panel B compares treated hospitals sourcing from manufacturers with zero violations to control hospitals sourcing from manufacturers with documented ANVISA violations (chemical composition deviations, contamination, dissolution failures, or stability problems), creating a quality differential. The dependent variable, mortality rate_{hde_t}, represents the ratio of deaths to hospitalizations in hospital *h* for disease *d* in event *e* at time *t*. The main independent variable, below threshold_{hde}, is a dummy equal to one if the purchase of essential medicines for hospital *h* to treat disease *d* in event *e* was predominantly done via procurements below the threshold. Post_{et} is a dummy equal to one after the procurement. All continuous dependent variables are winsorized at the 1st and 99th percentiles. All specifications include hospital-disease-event and disease-event-time fixed effects. Standard errors, clustered at the hospital-disease-event level, are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.20—Delivery Outcomes by Supplier Violations and Below-Threshold Procurement

Dep. Var.	delivered/budgeted _{hij}	log(days to delivery) _{hij}
	I	II
Panel A: Supplier Quality Violations		
quality violation _{hij}	−0.0234 (0.0154)	0.0709 (0.0561)
Hospital*Modality*Quarter FE	yes	yes
Obs	1,998	1,938
R ²	0.519	0.607
Panel B: Below-Threshold Procurement		
below threshold _{hij}	−0.0140 (0.0810)	−0.0936 (0.2266)
Hospital*Quarter FE	yes	yes
Obs	1,322	1,289
R ²	0.513	0.582

This table reports estimates of delivery outcomes on supplier quality violations (Panel A) and below-threshold procurement (Panel B) in the sample of essential medicines procured by hospitals. The dependent variable in column I is the fraction of the budgeted value actually delivered; in column II it is the log of the median number of days from purchase to delivery. Observations are at the procurement-firm level: subscripts h, i, and j index the procuring hospital, the procurement, and the winning firm, respectively. Panel A tests whether suppliers with documented ANVISA violations are slower to deliver: quality violation_{hij} equals one if the firm was cited by ANVISA for any quality violation (chemical composition deviations, contamination, dissolution failures, or stability problems). Both columns I and II include hospital-modality-quarter fixed effects. Panel B tests whether below-threshold procurement affects delivery: below threshold_{hij} is a dummy equal to one if the procurement value is below the SVP threshold. On either side of the threshold, I fit a linear function of the distance to the threshold as in equation (1), and restrict the sample in Panel B to procurements within BRL 7,500 of the threshold. Both columns I and II include hospital-quarter fixed effects. Standard errors, clustered at the hospital level, are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.21—Placebo Test: Effect of Below-Threshold Purchases of Unrelated Medicines on Hospital Mortality

Dep. Var.	mortality rate _{hde_t}		
	I	II	III
below threshold (related) _{hde} · post _{et}	-0.0086*** (0.0011)	-0.0088*** (0.0011)	-0.0088*** (0.0011)
below threshold (unrelated) _{hde} · post _{et}	0.0033*** (0.0006)	0.0031*** (0.0006)	0.0032*** (0.0006)
log(hospitalizations) _{hde,t=-1} · post _{et}		-0.0002 (0.0002)	-0.0001 (0.0002)
\$ essential ER drugs per hospitalization _{hde} · post _{et}			0.0054*** (0.0006)
Hospital*Disease*Event FE	yes	yes	yes
Disease*Event*Time FE	yes	yes	yes
Obs	894,648	884,442	884,442
R ²	0.881	0.887	0.887

This table tests whether purchasing unrelated medicines below the SVP threshold predicts mortality for disease d . The specification mirrors Table 9, but includes an additional variable: below threshold (unrelated)_{hde}, a dummy equal to one if hospital h predominantly purchases essential ER medicines for diseases *other than* d below the threshold in event e . If the mortality effects in Table 9 were driven by hospital-level confounders rather than medicine quality, this placebo treatment should also predict lower mortality. Instead, the coefficient on unrelated purchases is positive, indicating that the mortality reduction is specific to the procurement of disease-relevant medicines. The dependent variable is the mortality rate (deaths per hospitalization), winsorized at the 1st and 99th percentiles. Standard errors clustered at the hospital-disease-event level are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.22—Treated Hospitals Procure from Higher-Quality Suppliers

Dep. Var.	quality violation _{hde}	
	I	II
below threshold _{hde}	-0.3757*** (0.0141)	-0.3842*** (0.0175)
Event FE	yes	
Disease*Event FE		yes
Obs	118,247	118,247
R ²	0.530	0.676

This table examines whether hospitals procuring below the SVP threshold source medicines from higher-quality suppliers at the time of purchase. Using the same stacked panel as Table 9, the dependent variable quality violation_{hde} equals one if hospital *h* procuring medicines for disease *d* in event *e* sources from manufacturers cited by ANVISA for critical quality violations (chemical composition deviations, contamination, dissolution failures, or stability problems), and zero otherwise. The variable below threshold_{hde} is a dummy equal to one if the purchase of essential medicines for hospital *h* to treat disease *d* in event *e* was predominantly done via procurements below the threshold. Column I includes event fixed effects; column II adds disease-event fixed effects. Standard errors, clustered at the hospital-disease-event level, are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.23—Hospital Mortality and SVP Threshold Change

Dep. Var.	mortality rate _{hct}		ban share _{hct}	
	I	II	III	IV
treat _{hc} · post _t	−0.0153 ⁺ (0.0082)	−0.0233 ⁺ (0.0132)	−0.0862*** (0.0232)	−0.0706** (0.0246)
log(hospitalizations) _{hc,t−1} · post _t		−0.0051 (0.0042)		0.0094 (0.0065)
\$ essential ER drugs per hospitalization _{hc} · post _t		−4.33e-7 (4.91e-7)		2.62e-6 (1.89e-6)
Hospital*Disease FE	yes	yes	yes	yes
Disease*Year FE	yes	yes	yes	yes
Obs	720	715	767	731
R ²	0.803	0.805	0.361	0.373

This table estimates the effect of the June 2018 SVP threshold increase on hospital mortality and medicine quality. The variable treat_{hc} is defined as the share of life-saving medicine purchases for disease *c* by hospital *h* with values between BRL 8,000 and BRL 17,600 in the two years prior to the reform. Post_t is a dummy equal to one after June 2018 and zero before. The dependent variable in columns I and II is the mortality rate (winsorized deaths per hospitalization) and in columns III and IV is the share of procurement value from manufacturers with ANVISA quality violations. All specifications include hospital-disease and disease-year fixed effects. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors clustered at the hospital-disease level are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

Table C.24—External Validity: Discretion Above the Threshold and Purchases of Services

Dep. Var.	log(price) _{ipb}		log(price) _{ipf}	
	Above the SVP Threshold		Services	
	I	II	III	IV
bid waiver _i	0.167*** (0.010)	0.113*** (0.012)		
below threshold _i			0.116* (0.059)	-0.008 (0.078)
Item*Quarter FE	yes		yes	
Brand*Item*Quarter FE		yes		
Firm*Item*Quarter FE				yes
Obs	1,820,385	1,820,385	73,494	73,494
R ²	0.90	0.95	0.89	0.97

This table provides tests of external validity. In columns I and II, the dependent variable $\log(\text{price})_{ipb}$ is the logarithm of the price of product p from brand b procured in procurement i by agency $a(i)$ at time $t(i)$. In columns III and IV, the dependent variable $\log(\text{price})_{ipf}$ is the logarithm of the price of service p from firm f procured in procurement i by agency $a(i)$ at time $t(i)$. In columns I and II, I analyze the effects of discretion in product purchases via bid waivers above the SVP threshold. The main independent variable is bid waiver_{*i*} which is a dummy equal to one if procurement i at time t was conducted with discretion and zero if it was conducted via a competitive auction. In columns III and IV, I study the effects of discretion on the procurement of services around the SVP threshold. On either side of the threshold, I also fit a linear function of the distance to the threshold as in equation (1). The main independent variable, below threshold_{*i*}, is a dummy equal to one if procurement i at time t is conducted below the threshold, and zero otherwise. Columns I and III add Item (product or service)*Quarter fixed effects. Column II adds Brand*Item*Quarter fixed effects and column IV adds Firm*Item*Quarter fixed effects to control for firm-specific characteristics, as services do not have brands. All continuous dependent variables are winsorized at the 1st and 99th percentiles. Standard errors clustered at the item (product or service) level are presented in parentheses. +, *, **, and *** denote significance levels of 10%, 5%, 1%, and 0.1%, respectively.

References

- Amidon, Gordon L., Hans Lennernäs, Vinod P. Shah, and James R. Crison.** 1995. “A Theoretical Basis for a Biopharmaceutic Drug Classification: The Correlation of in Vitro Drug Product Dissolution and in Vivo Bioavailability.” *Pharmaceutical Research*, 12(3): 413–420.
- Bate, Roger, Ginger Zhe Jin, and Aparna Mathur.** 2011. “Does Price Reveal Poor-quality Drugs? Evidence from 17 Countries.” *Journal of Health Economics*, 30(6): 1150–1163.
- Bate, Roger, Paola Coticelli, Richard Tren, and Amir Attaran.** 2008. “Antimalarial Drug Quality in the Most Severely Malarious Parts of Africa – A Six Country Study.” *PLoS ONE*, 3(5): e2132.
- Blossom, D. B., A. J. Kallen, P. R. Patel, et al.** 2008. “Outbreak of Adverse Reactions Associated with Contaminated Heparin.” *New England Journal of Medicine*, 359(25): 2674–2684.
- Butler, J. V., E. Carbone, P. Conzo, and G. Spagnolo.** 2020. “Past Performance and Entry in Procurement: An Experimental Investigation.” *Journal of Economic Behavior & Organization*, 173: 179–195.
- Calónico, S., M. D. Cattaneo, and R. Titiunik.** 2014. “Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs.” *Econometrica*, 82(6): 2295–2326.
- Carril, R., A. Gonzalez-Lira, and M. S. Walker.** 2026. “Competition under Incomplete Contracts and the Design of Procurement Policies.” *American Economic Review*, 116(2): 535–581.
- Chapman, Paul B., Axel Hauschild, Caroline Robert, John B. Haanen, Paolo Ascierto, James Larkin, Reinhard Dummer, Claus Garbe, Alessandro Testori, Michele Maio, Jeffrey Sosman, John M. Kirkwood, Alexander M. Eggermont, Brigitte Dreno, Keith Nolop, Jenny Li, Barry Nelson, James Hou, Richard J. Lee, Keith T. Flaherty, and Grant A. McArthur.** 2011. “Improved Survival with Vemurafenib in Melanoma with BRAF V600E Mutation.” *New England Journal of Medicine*, 364(26): 2507–2516.
- Faccio, M., R. W. Masulis, and J. J. McConnell.** 2006. “Political Connections and Corporate Bailouts.” *Journal of Finance*, 61: 2597–2635.
- Hodi, F. Stephen, Steven J. O’Day, David F. McDermott, Jeffrey S. Weber, Jeffrey A. Sosman, John B. Haanen, Rene Gonzalez, Caroline Robert, Dirk Schadendorf, Jessica C. Hassel, Wallace Akerley, Alfons J. M. Van den Eertwegh, Jose Lutzky, Paul Lorigan, Jay M. Vaubel, Gerald P. Linette, David Hogg, Christian Ottensmeier, Celeste Lebbe, Christian Peschel, Ian Quirt, Joseph I. Clark, Jedd D. Wolchok, Jeffrey Weber, Junlin Tian, M. Joanna Yellin, Gary M. Nichol, Axel Hoos, and Walter J. Urba.** 2010. “Improved Survival with Ipilimumab in Patients

- with Metastatic Melanoma.” *New England Journal of Medicine*, 363(8): 711–723.
- ISIS-2 Collaborative Group.** 1988. “Randomised Trial of Intravenous Streptokinase, Oral Aspirin, Both, or Neither Among 17,187 Cases of Suspected Acute Myocardial Infarction: ISIS-2.” *Lancet*, 332(8607): 349–360.
- Johnston, Andrew, and David W. Holt.** 2014. “Substandard Drugs: A Potential Crisis for Public Health.” *British Journal of Clinical Pharmacology*, 78(2): 218–243.
- Kesselheim, Aaron S., Alexander S. Misono, Joy L. Lee, Margaret R. Stedman, M. Alan Brookhart, Niteesh K. Choudhry, and William H. Shrank.** 2008. “Clinical Equivalence of Generic and Brand-Name Drugs Used in Cardiovascular Disease: A Systematic Review and Meta-analysis.” *JAMA*, 300(21): 2514–2526.
- Kishimoto, T. K., K. Viswanathan, T. Ganguly, et al.** 2008. “Contaminated Heparin associated with Adverse Clinical Events and Activation of the Contact System.” *New England Journal of Medicine*, 358(23): 2457–2467.
- Kumar, Anand, Daren Roberts, K E Wood, et al.** 2006. “Duration of Hypotension Before Initiation of Effective Antimicrobial Therapy is the Critical Determinant of Survival in Human Septic Shock.” *Critical Care Medicine*, 34(6): 1589–1596.
- Laxminarayan, Ramanan, Devi Sridhar, Martin Blaser, Min Wang, and Mark Woolhouse.** 2016. “Achieving Global Targets for Antimicrobial Resistance.” *Science*, 353(6302): 874–875.
- Mansouri, Fatima, Jérémie Botton, Laura Semenzato, Nadia Haddy, and Mahmoud Zureik.** 2022. “N-nitrosodimethylamine-Contaminated Valsartan and Risk of Cancer: A Nationwide Study of 1.4 Million Valsartan Users.” *Journal of the American Heart Association*, 11(24): e026739.
- Noh, In Joon, John Gray, George Ball, Zachary Wright, and Hyunwoo Park.** 2025. “Are All Generic Drugs Created Equal? An Empirical Analysis of Generic Drug Manufacturing Location and Serious Drug Adverse Events.” *Production and Operations Management*, 34(9): 2601–2617.
- Ordonez, Karen, Max M. Feinstein, Sergio Reyes, Cristhian Hernandez-Gomez, Christian Pallares, and Maria V. Villegas.** 2019. “Clinical and Economic Impact of Generic Versus Brand Name Meropenem Use in an Intensive Care Unit in Colombia.” *The Brazilian Journal of Infectious Diseases*, 23(4): 237–245.
- Ozawa, Sachiko, David R. Evans, Sophia Bessias, Deson G. Haynie, Tatenda T. Yemeke, Sandra K. Laing, and James E. Herrington.** 2018. “Prevalence and Estimated Economic Burden of Substandard and Falsified Medicines in Low- and Middle-Income Countries: A Systematic Review and Meta-analysis.” *JAMA Network Open*, 1(4).
- Rauch, James E.** 1999. “Networks versus Markets in International Trade.” *Journal of International Economics*, 48(1): 7–35.
- Renschler, Joshua P., Kirsten M. Walters, Paul N. Newton, and Ramanan Laxminarayan.** 2015. “Estimated Under-Five Deaths Associated with Poor-Quality Anti-

- malarials in Sub-Saharan Africa.” *American Journal of Tropical Medicine and Hygiene*, 92(6 Suppl): 119–126.
- Rivers, Emanuel, Bryant Nguyen, Scott Havstad, Jeff Ressler, Andrew Muzzin, Brian Knoblich, Eric Peterson, and Michael Tomlanovich.** 2001. “Early Goal-Directed Therapy in the Treatment of Severe Sepsis and Septic Shock.” *New England Journal of Medicine*, 345(19): 1368–1377.
- Schoenherr, D.** 2019. “Political Connections and Allocative Distortions.” *Journal of Finance*, 74(2): 543–584.
- Straka, Robert J., Daniel J. Keohane, and Lawrence Z. Liu.** 2017. “Potential Clinical and Economic Impact of Switching Branded Medications to Generics.” *American Journal of Therapeutics*, 24(3): 278–289.
- Tannock, Ian F., Ronald de Wit, William R. Berry, John Horti, Agata Pluzanska, Kim N. Chi, Stephane Oudard, Charles Theodore, Nicholas D. James, Inga Tureson, Marcus Roessner, Mario A. Eisenberger, and Patrick Powell.** 2004. “Docetaxel Plus Prednisone or Mitoxantrone Plus Prednisone for Advanced Prostate Cancer.” *New England Journal of Medicine*, 351(15): 1502–1512.
- The HOPE Investigators.** 2000. “Effects of an Angiotensin-Converting-Enzyme Inhibitor, Ramipril, on Cardiovascular Events in High-Risk Patients.” *New England Journal of Medicine*, 342(3): 145–153.
- World Health Organization.** 2017. *A Study on the Public Health and Socioeconomic Impact of Substandard and Falsified Medical Products*. Geneva, Switzerland: World Health Organization.