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Master's Dissertation

Jump Bidding in Public Procurement Descending Auctions

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Pontifícia Universidade Católica do Rio de Janeiro
Centro de Ciências Sociais
Departamento de Economia

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Abstract

Mata Quispe, Zenon David; Gimenes, Nathalie (Advisor); Lima, Lucas (Co-advisor). **Jump Bidding in Public Procurement Descending Auctions**. Rio de Janeiro, 2026. 65p. Master's Dissertation – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

I study why bidders place jump bids—price cuts larger than necessary to take the lead—in descending procurement auctions and how these cuts affect contracted prices. Using 2,961,454 Brazilian federal procurement auctions from 2015 to 2018, I document that jump bidding is widespread among bidders but used selectively: 91.7% of usual bidders jump at least once, yet jumps account for only 11.1% of bids. I evaluate alternative explanations by considering auction rules, within-auction variation across phases and price states, and responses to jumps. The evidence is most consistent with a response to the risk that the auction ends before a bidder can bid again. Monitoring costs may also play a role. Rival reactions are inconsistent with deterrence, and bidder anonymity and standardized goods reduce the plausibility of reputation and common-value signaling as general explanations. Finally, I estimate the price effect by instrumenting jump bidding with random-phase duration. Under exact exclusion, each additional duration-induced jump is associated with a 4.25 percentage point reduction in the contracted-price-to-reference-value ratio, a 6.3% reduction from the mean of 0.68. Allowing for a direct effect of the instrument to construct sensitivity ranges places the reduction between 1.59 and 2.11 percentage points (2.3–3.1% relative to the mean). In a sample where non-credible standing bids obscure jump size, the estimate falls to a statistically significant but economically negligible 0.15 percentage points. This pattern is consistent with the effect operating through the information that a jump conveys rather than through the price cut itself.

Keywords

Jump bidding; descending auctions; procurement auctions; government procurement; random ending.

Resumo

Mata Quispe, Zenon David; Gimenes, Nathalie (Orientadora); Lima, Lucas (Co-orientador). **Jump Bidding em Leilões Descendentes de Compras Públicas**. Rio de Janeiro, 2026. 65p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Estudo por que licitantes fazem *jump bids*—reduções de preço maiores do que o necessário para assumir a liderança—em leilões descendentes de compras públicas e como essas reduções afetam os preços contratados. Utilizando 2.961.454 leilões de compras públicas federais brasileiras de 2015 a 2018, documento que *jump bidding* é generalizado entre licitantes mas utilizado seletivamente: 91,7% dos licitantes habituais fazem ao menos um *jump bid*, ainda que *jumps* representem apenas 11,1% dos lances. Avalio hipóteses alternativas considerando as regras do leilão, variação dentro do leilão entre fases e estados de preço, e respostas aos *jumps*. A evidência é mais consistente com uma resposta ao risco de o leilão terminar antes de um licitante poder fazer outro lance. Custos de monitoramento também podem desempenhar um papel. As reações dos rivais são inconsistentes com dissuasão, e o anonimato dos licitantes e produtos padronizados reduzem a plausibilidade de reputação e sinalização de valor comum como explicações gerais. Finalmente, estimo o efeito sobre o preço instrumentalizando *jump bidding* com a duração da fase aleatória. Sob exclusão exata, cada *jump* adicional induzido pela duração está associado a uma redução de 4,25 pontos percentuais na razão preço-contratado-para-valor-referência, uma redução de 6,3% da média de 0,68. Permitindo um efeito direto do instrumento para construir intervalos de sensibilidade, a redução fica entre 1,59 e 2,11 pontos percentuais (2,3–3,1% relativamente à média). Em uma amostra onde os lances líderes não-críveis obscurecem o tamanho do *jump*, a estimativa cai para 0,15 pontos percentuais, estatisticamente significativa mas economicamente negligenciável. Este padrão é consistente com o efeito operando por meio da informação que um *jump* transmite, em vez de por meio da redução de preço em si.

Palavras-chave

Jump bidding; leilões descendentes; leilões de compras públicas; compras governamentais; término aleatório.

Contents

1 Introduction

In a descending-price auction, jump bidding occurs when a bidder lowers the standing price by substantially more than is necessary to become the leader. A random ending makes prompt bidding valuable because the auction may close before a bidder gets another opportunity to bid, but it does not by itself explain the size of the cut. If the auction ends before a rival responds, an incremental bid secures the same position as a jump, but at a higher profit. Why, then, do bidders jump?

The effect of jump bids is far from trivial. Aggressive cuts reduce the standing price and pull the final price lower, yet they may simultaneously deter rivals from continuing to bid, eroding the subsequent price competition. Determining which effect dominates is particularly important in Brazilian public procurement, which represents 12.5% of GDP (OECD, 2023; Ribeiro & Inácio, 2019). Even modest changes in auction outcomes can have substantial fiscal consequences.

Brazilian federal procurement provides a functional setting for studying why bidders jump and how jump bidding affects prices. The purchases are conducted through the *Pregão Eletrônico* platform, where jump bidding is common among regular bidders. Using data from this platform for 2015–2018, I first document the prevalence and correlates of jump bidding. I then assess which candidate mechanisms are theoretically plausible in this environment and whether their predictions are consistent with observed bidding patterns and rivals' responses. Finally, I estimate how jump bidding affects the prices paid by the government.

The first challenge is measurement because the idea of a large price cut requires stipulating what large is. I propose several definitions, evaluate their properties, and use the measure that is most comparable across auctions and can better detect meaningul cuts. The alternatives do not differ substantially in the incidence of jump bidding.

Under the preferred measure, jump bidding is widespread across bidders but used selectively: 92% of bidders with at least five auction participations jump at least once, yet jumps represent only 11% of bids. Auctions pass through initial and alert phases, during which they cannot close, before entering a random phase that can end at any instant over the next 30 minutes. The random phase contains 75% of all bids and 77% of eventual winning bids.

The share of jumps falls from 16% in the initial phase to 10% in the random phase. This decline partly reflects the evolution of the standing bid. By the random phase, it is usually below the reference value, leaving less room for a large cut. The same constraint explains why decrements in the initial phase are roughly two to three times as large at higher percentiles. Holding the standing bid's distance from the reference value fixed reverses the comparison: decrements are larger during the random phase.

Although the analysis cannot establish why bidders jump, it narrows the set of plausible explanations. First, I assess whether the auction environment satisfies the conditions required for the main families of mechanisms proposed in the literature, as well as for a response to ending risk tailored to this setting. Second, I test the clearest prediction of blanket deterrence by examining whether rivals respond more slowly, submit fewer subsequent bids, or exit more often after jumps.

Most mechanisms proposed in the literature have limited scope as general explanations. Private, bidder-specific costs and a public reference value weaken mechanisms that rely on common-value uncertainty; anonymous bidding weakens those that require targeted or attributable actions; and the short monitoring window limits explanations based on attention or participation costs. Behavioral hypotheses remain possible as a residual. The systematic relationship between jumping, auction conditions, and bidder experience weighs against a purely random account, but it does not distinguish strategic responses from state-dependent heuristics or learning. Rival responses provide complementary evidence against blanket deterrence: rivals respond faster and bid more after jumps, although a modest increase in exit leaves selective deterrence among high-cost rivals open.

Ending risk fits the institutional setting and the observed bidding patterns better than the alternatives considered. Once the random phase begins, the auction can close at any instant, creating an incentive for an immediate deep cut rather than a sequence of smaller bids that could not be completed. Within auctions, jumps become more likely when the standing bid is higher and, conditional on that level, during the random phase. These findings, together with the limited plausibility of the alternative mechanisms considered, favor ending risk, but they are not conclusive. Further research is needed to distinguish ending risk from mechanisms that may generate similar bidding behavior.

The evidence consistently suggests a negative effect of jump bidding on contracted prices. Within product-group × quarter cells, each additional jump is associated with a contracted price 1.1 percentage points lower relative to the reference value. The relationship is negative across all subgroup splits, and the same pattern holds when jump intensity is measured by total jump depth. Instrumenting jump intensity with random-phase duration produces a marginal-response estimate of a 4.25-percentage-point reduction per additional jump under monotonicity and exact exclusion. Because longer phases also permit additional non-jump bids, exact exclusion is unlikely. A sensitivity range calibrated from zero-jump auctions places the jump-count effect between -0.0211 and -0.0159 and remains below zero for total jump depth over the stated direct-effect support. In a selected sample where a non-credible standing bid obscures jump size, the jump-count estimate falls to -0.0015. This attenuation suggests visibility as a channel but selection or heterogeneous effects are also plausible.

Prior work offers two main explanations for jump bidding. In informational models, jumps communicate strength and can discourage rivals under affiliated values (Avery, 1998). A second family attributes jumps to bidding frictions, including the costs of submitting or revising bids, impatience, and uncertainty about future bidding opportunities (Daniel & Hirshleifer, 2018; Easley & Tenorio, 2004; Isaac et al., 2007). Barkley et al. (2021) provide a timing-based rationale: in fixed-duration auctions, bidders jump to reduce the risk of being displaced before another opportunity to bid arises. Extending this logic to auctions with random closure, I propose ending risk as an explanation. A bidder may sacrifice margin through a deeper cut to reduce the chance of losing before it can bid again. The auction rules and the phase- and state-dependent patterns provide indirect support for this interpretation.

This work also expands the research on Brazilian federal procurement. Szerman (2012) provides the institutional analysis of the ComprasNet mechanism on which this paper builds. The closest evidence on strategic conduct is Fazio and Zaldokas (2024), who study post-auction withdrawal intended to benefit a connected runner-up. This paper instead studies bidding during the auction, documenting the timing and intensity of jumps and estimating their effect on contracted prices. More broadly, it adds within-auction bidding dynamics to the applied procurement literature (Asker, 2010).

The closest work is Borges de Oliveira et al. (2019), who estimate the effect of random-phase duration on procurement prices and find that longer phases generate 2.8% savings. Here I focus to the contracted-price effect of jump bidding and present a battery of exercises that favor the robustness of the results.

The remainder of the document presents the institutional setting, data and definition of jump bidding, descriptive evidence, candidate mechanisms and rival responses, contracted-price analysis, and conclusions in Sections 2 to 7, respectively.

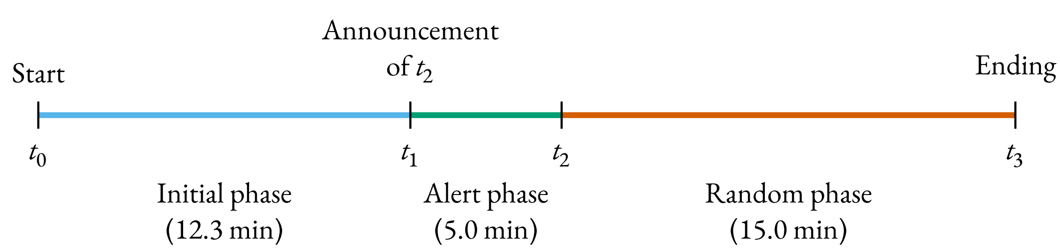
2 Institutional Setting

2.1 Brazilian Federal Procurement

The Brazilian federal government procures common goods and services—objects whose performance and quality can be specified using standard market criteria—through *Pregão Eletrônico*, a dynamic descending auction administered via the federal portal Compras.gov.br (previously known as ComprasNet).[1] This modality accounts for the large majority of federal procurement transactions by volume.[2] Any supplier—firm or individual—may participate after registering in the federal supplier registry (SICAF) and the procurement portal. To participate in a given auction, a supplier must submit a proposal before the session. After the auction, the procuring agency verifies the provisional winner's qualification (Brazil, 2005; Brazil, Ministry of Planning, Budget and Management, 2005).

2.2 Auction Timeline

Figure 1: Auction timeline



Note: Segment widths are proportional to each phase's median duration; the median (in minutes) appears in parentheses below each phase.

Each auction proceeds in three phases. Before the session opens at t_0, the government posts a public reference value— its ex-ante price estimate, formally defined in Section 3— and interested suppliers submit sealed price proposals. A bidder can win with an initial proposal if the price is never beaten by an open-phase bid.

At t_0, the bidding phase begins; its first segment is the *initial phase* $[t_0, t_1)$. Its duration is not fixed by any rule but is typically short and it carries no time pressure, because every

[1] The rules that governed the 2015–2018 sample are set out in Decree No. 5,450/2005 (Brazil, 2005). For institutional analyses of Brazil's procurement framework, see Fiuza (2009) and Fiuza and Medeiros (2014). Szerman (2012) provides the first systematic empirical study of this auction platform.

[2] The OECD reports that around 98% of federal competitive bidding is conducted through reverse auctions (OECD, 2021).

bidder knows the auction cannot end yet. The standing bid— the current lowest offer— starts at the lowest initial proposal and is then updated as bids arrive.

Two rules govern bidding: each bidder's new offer must be strictly lower than its previous offer, and at least 20 seconds must elapse between consecutive bids by the same bidder (Brazil, 2005; Brazil, Ministry of Planning, Budget and Management, 2013). Bids need not undercut the current standing bid, so a bidder may submit an offer above it.

At t_1, the auctioneer publicly announces that the random phase will begin at a predetermined time t_2, typically about five minutes later. This announcement defines the *alert phase* $[t_1, t_2)$, during which bidders face elevated urgency relative to the initial phase, though less than in the subsequent random phase.

At t_2, the auction enters the random phase $[t_2, t_3]$. In this phase, the system determines the session end t_3 drawing it uniformly from $[t_2,\ t_2 + 30\,\text{min}]$ (Brazil, 2005). The auction can end immediately after t_2, so delaying an offer risks losing the chance to bid again.

Once the session closes at t_3, the lowest bidder is only the provisional winner. The procuring agency then verifies whether the offer is genuine and whether the bidder satisfies the tender's qualification requirements. If either condition fails, the agency examines the next offer in rank order (Brazil, 2005).

The above implies that the displayed minimum need not be the offer that ultimately receives the award nor an offer that is credible to rivals. I therefore introduce an ex-post rule to identify bids *non-credible* bids, bids unlikely to be accepted. This helps refine the detection of jump bids and examine the specific set of suspicious bids.

The auction's information structure is transparent in prices but anonymous in bidders. During the public session, the system reports the lowest registered bid in real time without identifying its bidder (Brazil, 2005; Brazil, Ministry of Planning, Budget and Management, 2005). The interface also allows bidders to see the five lowest current offers after completing a CAPTCHA (Brazil, Ministry of Planning, Budget and Management, 2005). Identities become public only after the session closes.

3 Data

3.1 Data Sources and Sample Construction

The data comprise publicly available records of auctions conducted on Compras.gov.br between 2015 and 2018. Although auctions are organized into lots, each item within a lot is procured through a separate descending auction with its own reference value, bidding history, and outcome. For simplicity, I use the term "auction" to refer to an item-auction unless otherwise noted.

For each auction, the records include the description, quantity, unit of supply, reference value, awarded firm, final contracted price, and procurement status (e.g., accepted, under analysis, or cancelled). The data also identify all suppliers submitting an initial proposal and record second-by-second timestamps for every bid during the bidding phase, as well as the timing of key auction events such as bidder disqualifications and winner approval.

The raw data are filtered using two sets of restrictions: validity restrictions to remove unreliable records and scope restrictions to define the auctions included in the analysis.

The validity restrictions remove records that cannot be trusted as faithful accounts of a completed auction. I drop auctions that did not reach a completed award—those not marked accepted, with or without a pending appeal notice—and auctions missing the phase-boundary timestamps or a recorded winning bid. I also drop auctions with internal inconsistencies: the lowest observed bid exceeding the recorded winning price, or a winning price that does not match the winner's own lowest offer. Finally, I remove timing anomalies—bids timestamped after the recorded close of the random phase, a first bid placed on a different calendar day from that close, or a random phase exceeding its thirty-minute rule cap—and collapse duplicate timestamps, retaining the lowest bid recorded for a firm at a given instant.

The scope tier imposes three further restrictions. First, I retain only auctions awarded under an item-level lowest-price rule.[3] I exclude auctions awarded on the basis of the largest percentage discount from the reference value, as well as auctions in which multiple items are bundled into a single award determined by the lowest combined total. Both formats imply bidding incentives that differ from those of standard item-level price auctions and account for only a small fraction of observations in the raw data. Second, although the reference value is not a formal constraint, final contracted prices almost never exceed it. Exceptions reflect data-entry errors on the reference value, emergency procedures, or post-auction adjustments outside the standard mechanism. I therefore keep auctions whose final contracted price is weakly below the reference value. Third, I retain auctions with at least two registered partic-

[3]Bids may be quoted either as unit prices or total values.

ipants, defined as firms with an initial proposal.

After all validity and scope restrictions, the sample contains 2,961,454 auctions and 125,110,016 submitted offers, including both initial proposals and open-phase bids.

The descriptive, mechanism, and reduced-form analyses further restrict attention to auctions with at least one open-phase bid, since only these auctions can feature jump bidding. This excludes 149,778 auctions, or 5.06% of the universe before imposing the open-bid requirement. At least two firms submitted initial proposals in these auctions, but no bidder placed a bid during the open phase. Their prices are determined by sealed proposals rather than dynamic bidding.

The analysis sample spans a broad range of standardized goods and services. Nearly every procured item maps to one of the federal government's two procurement catalogs: CATMAT (*Catálogo de Materiais*) for goods and CATSER (*Catálogo de Serviços*) for services. I define broad product groups using the two-digit CATMAT code and the three-digit CATSER code. Appendix Table A.1 reports the distribution across the top 20 groups.

Throughout, I use the term *bid* to refer to any offer placed during the open bidding phase, as distinct from the initial proposals. These cannot be classified as jump bids because there is no standing bid when suppliers submit them.

3.2 Summary Statistics

Table 1 reports summary statistics at the auction and bid levels for the sample of auctions with at least one bid, the basis for the descriptive, mechanism, and reduced-form exercises.[4] The excluded no-bid auctions have nearly identical auction-level moments.

[4]The raw data contain 125,110,016 offer records, including initial proposals; 103,239,646 are open-phase bids in the analysis sample. With this sample size, I emphasize economic magnitude and report statistical significance selectively.

Table 1: Summary statistics

Variable	N	Mean	SD	P10	P25	Median	P75	P90
Panel A: Auction level								
Participants	2,811,676	7.63	5.40	3.00	4.00	6.00	10.00	14.00
Active bidders	2,811,676	5.10	3.84	2.00	2.00	4.00	7.00	10.00
Total reference value (R$ 000s)	2,811,676	30.64	96.90	0.21	0.75	3.33	15.64	61.53
Contracted price / ref. value	2,811,676	0.68	0.26	0.30	0.48	0.71	0.92	1.00
Bids	2,811,676	36.72	49.39	2.00	6.00	18.00	48.00	96.00
Bids per active bidder	2,811,676	7.33	9.79	1.00	1.50	3.67	9.00	18.25
Pre-random duration (min)	2,811,676	44.24	233.28	5.12	10.52	20.90	40.33	75.67
Random phase duration (min)	2,811,676	15.13	8.62	3.15	7.70	15.15	22.60	27.05
Winner–runner-up spread (p.p.)	2,572,430	11.25	31.04	0.01	0.10	0.84	6.67	27.91
Panel B: Bid level								
Time between bids (sec)	100,427,970	51.24	335.63	3.00	4.00	10.00	20.00	63.00
Decrease (R$, > 0)	84,478,291	10.30	58.25	0.01	0.01	0.03	0.49	4.90
Decrease / standing bid (%, > 0)	84,478,291	1.00	2.67	0.00	0.02	0.13	0.60	2.37
Decrease / ref. value (%, > 0)	84,478,291	0.69	1.91	0.00	0.02	0.09	0.40	1.56
Decrease / ref. value, capped (%, > 0)	80,729,184	0.73	2.08	0.00	0.02	0.09	0.41	1.62

Note: Panel A reports auction-level moments; Panel B reports bid-level moments. Contracted price equals the negotiated value when renegotiation occurs, otherwise the winning price. Means and standard deviations of total reference value, the winner–runner-up spread, and the bid-level decrement variables are winsorized at the 1st and 99th percentiles to limit the influence of extreme outliers; reported percentiles are unaffected. The winner–runner-up spread and the relative decrements are expressed in percentage points.

At the auction level, the median auction attracts 6 participants (mean 7.63), of whom 4 submit at least one bid (mean 5.10), so roughly one-third of registrants only submit initial proposals. The median auction receives 18 bids, though the count is highly right-skewed (mean 36.72, $P_{90} = 96$). Bids per active bidder are also right-skewed, with a median of 3.67 (mean 7.33, $P_{90} = 18.25$).

The typical auction is small in value. The median total reference value[5] is R$3,330 (mean R$30,640), with a right skew that spans R$210 at P_{10} to R$61,530 at P_{90}. The contracted price equals 71% of the reference value at the median (mean 68%), implying government savings of about 29% relative to the reference value. The median winner–runner-up spread is 0.84 percentage points, indicating intense competition.

The pre-random duration, which includes the initial and alert phases, has a median of 20.90 minutes and is highly right-skewed (mean 44.24, $P_{90} = 75.67$). The random phase duration has a median of 15.15 minutes (mean 15.13), close to the theoretical mean of 15 minutes under the Uniform$[0, 30]$ distribution.

At the bid level, the median interval between bids is 10 seconds, suggesting that bidders actively monitor the auction. Bid decreases are highly right-skewed: the median decrease is just R$0.03, compared with a winsorized mean of R$10.30 (R$157.86 unwinsorized).

[5] It is computed as the per-unit reference price multiplied by the quantity.

Normalizing bid decreases by auction-specific scales leaves the distribution largely unchanged. Relative to the standing bid, the median decrease is 0.13% (mean 1.00%); relative to the reference value, 0.09% (mean 0.69%); and using the capped reference-value measure yields nearly identical values (median 0.09%, mean 0.73%).[6]

3.3 Defining Jump Bids

In the ascending-auction literature, a jump bid is conventionally defined as a bid that exceeds the standing price by more than the minimum required increment (Avery, 1998). This definition is standard in empirical studies of spectrum, internet, and automobile auctions (Easley & Tenorio, 2004; Grether et al., 2015; Isaac et al., 2007; Raviv, 2008).

That definition is not well suited to the present setting. Although the platform allows bidders to undercut the standing price by as little as R$0.0001, such decrements are rare.[7] Price cuts instead occur predominantly in decrements of R$0.01.

The relevant decrement also varies with the scale of the auction. A R$0.01 reduction is negligible when the standing price is R$10,000 but substantial when it is R$10. A fixed nominal threshold would therefore treat bids with very different economic significance as equivalent and would not provide a consistent measure of jump bidding across auctions.

An alternative is to define jump bids by comparing decrements with an auction-level benchmark. Following Raviv (2008), who expresses the bid increment relative to the item's presale estimate to define jumps, I consider several possible benchmarks.

One possibility is to normalize each bid by a decrement observed within the same auction. A natural candidate is the minimum positive decrement, which equals R$0.01 in most auctions. Its main drawback is that it is determined by the realized bidding path. The same absolute reduction may be classified differently in otherwise similar auctions simply because one auction contains a smaller undercut. Using the median decrement reduces sensitivity to any single bid, but it does not solve the underlying problem: the benchmark remains endogenous to the auction's sequence of bids. Under either measure, the classification of an earlier bid may change due to decrements submitted later in the auction.

The reference value is fixed before bidding and common to every bidder. The standing bid instead evolves with the bidding history but is predetermined relative to each focal bid. A raw standing-bid benchmark classifies large decreases from above the reference value as jumps, even though those decreases are mechanically required to reach the binding reference

[6] The capped measure computes each decrement from the lower of the credible standing bid and the reference value, so it counts only the part of a decrease that pushes the price below the reference value.

[7] Among positive decrements, only 0.31% are exactly R$0.0001, and they appear in just 2.06% of auctions with at least one positive decrement. By contrast, 97.90% of positive decrements are multiples of R$0.01, and R$0.01 is the smallest positive decrement observed within the auction in 72.10% of auctions.

value. The reference value therefore provides the relevant benchmark until the standing bid falls below it; after that the standing bid is a more appropriate benchmark.

The preferred measure also corrects the value of standing bid by discarding bids unlikely to result in a contract. Let p_a be the negotiated price where available and the winning bid otherwise. A non-winning supplier is flagged when its lowest competitive bid is at least 25% below p_a. For a flagged supplier, the first bid, including proposals, that meets this condition and all later bids by that supplier are excluded from the credible standing path.

Definition 1 (Capped reference-normalized decrement and jump bids)**.** For bid i in auction a made at timestamp t, let the credible standing bid be

$$s_t^* = \min\{b_{ja} : j \text{ is retained and placed strictly before } t\}.$$

Initial proposals enter s_t^*, and bids sharing timestamp t do not enter one another's standing history. Let v_a be the auction's reference value. The *capped standing bid* is $s_t^{\text{cap}} = \min\{s_t^*, v_a\}$ and the *capped reference-normalized decrement* is

$$d_{ia} = \frac{s_t^{\text{cap}} - b_{ia}}{v_a}.$$

Bid i is a *jump bid* if $d_{ia} > 0.01$.

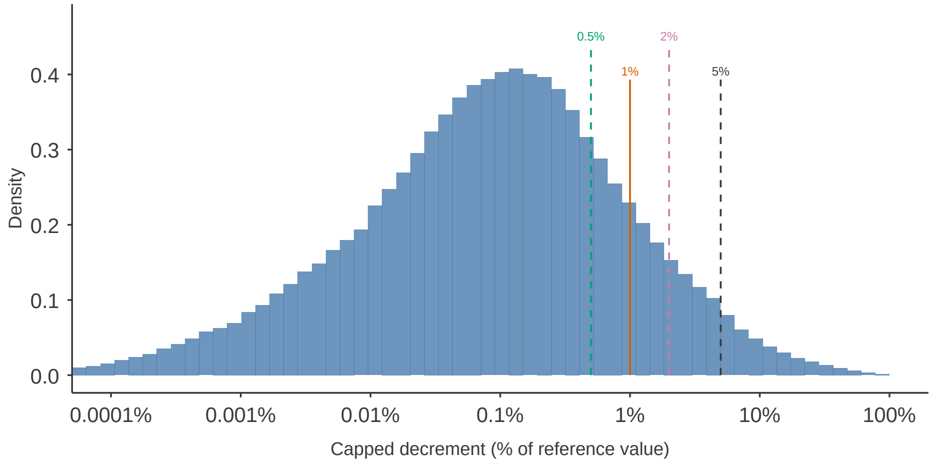
For transparency, I also report the same measure using the platform's nominal running minimum s_t in place of s_t^*.

Figure 2 plots positive values of the capped reference-normalized decrement on a logarithmic axis. The distribution is smooth over several orders of magnitude, with a mass of near-zero, rounding-scale moves and a long right tail. It has no natural boundary between ordinary and aggressive bids, so identifying jump bids requires choosing a threshold on economic grounds. The vertical lines show candidate thresholds of 0.5%, 1%, 2%, and 5%.

No cutoff within the grid is strictly preferred on statistical grounds. Prevalence varies smoothly across the grid, so the measured prevalence and phase ranking do not hinge on the primary 1% threshold.

Table 2 compares the threshold grid, two alternative capped measures (the capped discount and capped auction-median ratio), and two uncapped measures. Each definition is reported for both the nominal and credible standing paths, with jump prevalence further broken down by auction phase. The credibility adjustment has only a modest effect on overall prevalence. The prevalence ranking across phases is also similar across definitions except at the most extreme thresholds.

Figure 2: Distribution of positive capped reference-normalized decrements



Note: The histogram uses positive capped reference-normalized decrements on the credible standing path. The horizontal axis reports decrements as a percentage of the reference value on a logarithmic scale. Vertical lines mark the 0.5%, 1%, 2%, and 5% thresholds.

Table 2: Prevalence of jump bid across definitions and phases

	Overall share			Share by phase		
Definition	Nominal	Credible	Δ	Initial	Alert	Random
Capped: decrement from min(standing bid, reference value)						
Decrease / reference value > 1%	10.53	11.14	+0.61	16.37	14.89	9.69
Decrease / reference value > 0.5%	16.78	17.43	+0.64	22.54	21.47	15.94
Decrease / reference value > 2%	6.10	6.64	+0.55	11.13	9.65	5.44
Decrease / reference value > 5%	2.38	2.79	+0.41	5.53	4.41	2.09
Decrease / standing bid > 1%	14.44	15.05	+0.61	19.14	18.11	13.89
Decrease / standing bid > 5%	4.09	4.63	+0.54	7.63	6.53	3.85
Decrease / median decrease > 5	12.18	12.68	+0.50	12.68	13.33	12.56
Uncapped: decrement from the raw standing bid						
Decrease / reference value > 1%	11.41	11.41	+0.00	17.51	15.71	9.73
Decrease / minimum decrement > 5	35.44	35.44	+0.00	35.71	35.93	35.31

Note: "Decrease" is the reduction from the standing bid. *Nominal* uses the platform's running-minimum standing history; *Credible* uses the credible standing history s_t^*, which excludes active non-credible bids; Δ is Credible – Nominal in percentage points.

4 The Landscape of Jump Bidding

This section establishes six stylized facts about jump bidding in Brazilian procurement auctions. Jump bids are widespread across bidder careers but remain a minority of bids: 91.7% of bidders observed in at least five auctions jump at least once, while 11.1% of bids are jumps. Its incidence also varies across auction phases. The share of jumps is lower in the random phase than before it, but the number of jumps per minute is higher because overall bidding accelerates.

4.1 Auction Dynamics: When and Where

Fact 1. *The random phase is the auction: 75.4% of bids and 77.1% of eventual winning bids are placed during this phase.*

Table 3 summarizes bidding activity and outcomes by auction phase.

Table 3: Auction Dynamics by Phase

Panel A: Bidding activity

Phase	Bids	Share (%)	Med. bids/min	Mean bids/min
Initial phase	11,719,190	11.35	0.18	0.43
Alert phase	13,694,768	13.27	0.67	1.30
Random phase	77,825,688	75.38	1.29	2.37

Panel B: When are auctions decided

	Final offer		Winning bid	
Phase	N	Share (%)	N	Share (%)
Initial phase	2,579,623	18.00	216,641	7.71
Alert phase	2,217,933	15.47	247,520	8.80
Random phase	9,536,384	66.53	2,166,736	77.06

Note: Panel A reports bid-level statistics. Panel B reports terminal-event statistics by auction phase. *Final offer* refers to bidder–auction pairs classified according to the phase in which the bidder places its final bid. *Winning bid* refers to auctions classified according to the phase in which the winning bid is placed. Final-offer shares sum to 100%. Winning-bid shares sum to 93.6% because 180,779 auctions (6.4%) are decided before the bidding phase begins.

Panel A shows that bidding intensity rises across phases. The median bidding rate increases from 0.18 bids per minute in the initial phase to 0.67 in the alert phase, coinciding with the announcement of the imminent random ending, and to 1.29 in the random phase. These rates are 3.7 and 7.2 times the initial-phase rate. The phase comparisons are descriptive and combine changes in timing, auction state, and bidder composition. The random phase accounts for 75.4% of all bids despite having a shorter mean and median duration than the previous phases combined.

Panel B turns to the auction's terminal events. The left block reports the phase in which each firm places its final, lowest offer: two-thirds (66.5%) wait for the random phase, while the remaining third commit earlier—18.0% in the initial phase and 15.5% in the alert phase. The right block reports where auctions are actually decided: 77.1% of winning bids are placed during the random phase, against 7.7% in the initial and 8.8% in the alert phase, with the remaining 6.4% decided at the proposal stage. The random phase is thus the dominant stage of the auction in terms of both bidder commitment and auction outcomes: the majority of final offers and decisive bids fall within it.

4.2 Prevalence and Phase Dependence

Fact 2. *The share of bids that are jumps declines across phases yet jump bids per minute still rise, because overall bidding intensity accelerates faster than the jump share falls.*

Table 4 reports the share of bids classified as jump bids under four alternative thresholds based on the principal jump-bid measure introduced in Section 3.3, along with the median and mean jump-bid rate per minute.[8]

Table 4: Jump Bid Prevalence and Rate by Auction Phase

		Jump share at threshold				Jumps per min	
Phase	Bids	> 0.005	> 0.01	> 0.02	> 0.05	Median	Mean
Initial phase	11,719,190	22.54	16.37	11.13	5.53	0.00	0.08
Alert phase	13,694,768	21.47	14.89	9.65	4.41	0.00	0.20
Random phase	77,825,688	15.94	9.69	5.44	2.09	0.09	0.25

Note: The first four numeric columns report the share (%) of bids classified as jumps under different cutoffs of the prefered capped reference definition.

The decline in jump share as the auction approaches and enters the random phase is robust across the entire reference grid. Under the primary threshold (0.01), the share falls

[8] A small fraction of bids (0.91%) are self-outbids—bids placed by the current standing-bid holder. These are concentrated among less experienced bidders (median experience 282 auctions vs. 1,332 for regular bidders), involve tiny adjustments (median discount 0.26%), and occur almost immediately after the 20-second cooldown expires (median 27 seconds). The pattern is consistent with re-optimization under the increasing ending hazard. Self-outbids are excluded from the mechanism analysis in Section 5.

monotonically from 16.4% in the initial phase to 14.9% in the alert phase and 9.7% in the random phase. The same pattern holds across alternative thresholds, ranging from 22.5% to 15.9% at the loosest cutoff (0.005) and from 5.5% to 2.1% at the strictest (0.05). Across phases, overall prevalence falls from 17.4% to 11.1%, 6.6%, and 2.8% as the cutoff tightens from 0.5% to 1%, 2%, and 5% (Table 2). Thus, the monotone decline in the share of jumps as the auction progresses does not hinge on any specific threshold.

A mechanical force can account for much of this decline. The standing bid crosses below the reference value early: in 60.4% of auctions it does so during the initial phase and in a further 20.2% during the alert phase, so for roughly four in five auctions bidders are already competing below the reference before the random phase begins (Table 5). From that point onward, the standing bid continues to fall, steadily shrinking the feasible range for additional undercutting. Under the main definition, a jump bid is identified by the proportional reduction relative to the smaller of the standing bid and the reference value. Once the standing bid falls below the reference value, it becomes the relevant benchmark. As this benchmark declines, a fixed jump threshold becomes harder to exceed within the narrowing space of feasible bids, mechanically reducing the observed jump-bid share.

Table 5: When does the standing bid first reach at or below the reference value?

Phase	Auctions	%
Initial phase	1,696,941	60.35
Alert phase	567,575	20.19
Random phase	347,508	12.36
Post-auction	199,652	7.10

Note: "Post-auction" auctions never cross during the bidding phase but are negotiated at or below the reference in the qualification stage.

The rate columns show the countervailing force. Although the jump share falls, overall bidding intensity accelerates sharply across phases (Fact 1). This volume effect outweighs the declining share, so the mean number of jump bids per minute still rises—from 0.08 in the initial phase to 0.20 in the alert phase and 0.25 in the random phase. The median is starker: a typical initial- or alert-phase minute contains no jump at all (median 0.00), whereas the median random phase carries a positive jump rate (0.09).

Jumps concentrate in the random phase because total bid volume is higher there, not because the probability of a jump conditional on bidding is higher. Two-thirds of bidders place their final, lowest offer during this phase (Table 3). These phase totals do not distinguish within-bidder timing from changes in the composition of active bidders.

Fact 3. *Early phases show larger decrements because the standing bid sits closer to the reference value, leaving more room below it. Conditional on the standing bid's distance from the reference within auction, the pattern reverses: decrements are higher in the random phase.*

Table 6: Distribution of decrement size (capped reference-normalized decrement) by auction phase

Group	N	P10	P25	P50	P75	P90	P95	P99
All phases	80,729,184	0.003	0.018	0.094	0.410	1.622	3.650	14.926
Initial phase	8,614,434	0.004	0.023	0.137	0.787	3.640	7.691	28.437
Alert phase	10,546,584	0.003	0.022	0.122	0.620	2.727	5.701	21.587
Random phase	61,568,166	0.003	0.017	0.086	0.356	1.286	2.807	11.205

Note: Percentiles of the capped reference-normalized decrement, expressed as a percentage of the reference value. Computed over bids with positive decrements.

Table 6 shows that decrement size generally declines monotonically across phases at nearly every reported quantile. The differences are substantial in the upper tail: the 90th percentile falls from 3.64% of the reference value in the initial phase to 2.73% in the alert phase and 1.29% in the random phase, while the 99th percentile falls from 28.44% to 21.59% and 11.21%, respectively. The same ordering holds at the median, where decrements decline from 0.14% to 0.12% and 0.09%.

Although capping the reference-normalized decrement prevents an above-reference standing bid from inflating the measure, it does not account for the genuine decline in the standing bid as the auction progresses. As the standing bid falls, the scope for further price reductions narrows, mechanically compressing the decrement distribution in later phases.

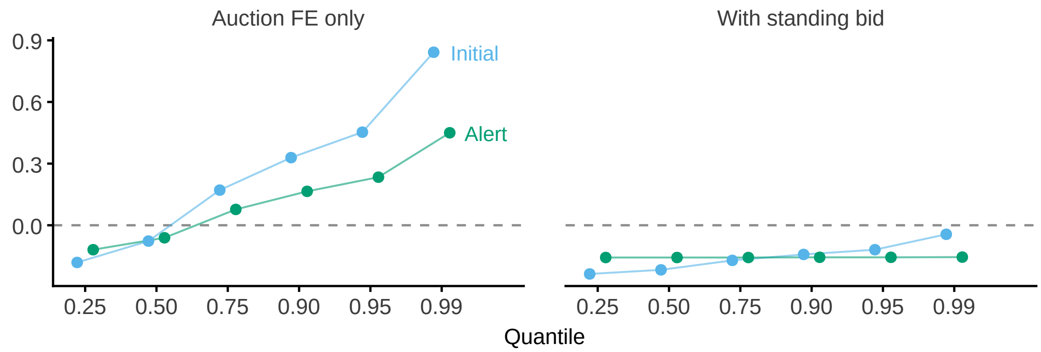
The early-phase advantage reported in Table 6 not only disappears but reverses when the standing bid is held constant. Figure 3 plots the estimated early-phase coefficients[9] (random phase reference) from Machado–Santos Silva (Machado & Santos Silva, 2019) quantile regressions[10] of the log capped decrement on phase dummies, at quantiles $\tau \in \{0.25, 0.50, 0.75, 0.90, 0.95, 0.99\}$. Appendix Table B.1 reports these coefficients for three specifications, with controls added sequentially.

Auction fixed effects alone (left panel of Figure 3) absorb a sizable share of the initial-phase decrement advantage across much of the distribution, though they do little to close the gap in the extreme tail. The initial–random gap is negative at the lower quartile (−0.181 log

[9]Coefficients are log points (proportional effects $e^{\beta} - 1$), not the level percentages of Table 6.

[10]The Machado–Santos Silva estimator absorbs the auction fixed effects that classical Koenker and Bassett (1978) quantile regression cannot handle at this scale, but it imposes a location–scale structure.

Figure 3: Conditional quantile effects of initial phases on decrement size



Note: The panels reproduce columns (1) and (2) of Appendix Table B.1. The sample contains open-phase bids with a positive capped reference-normalized decrement on the credible standing path and at least one active competitor. The left panel includes auction fixed effects only; the right panel adds the standing bid normalized by the reference value. Coefficients are Machado–Santos Silva (MM-QR) log-point differences for the Initial- and Alert-phase indicators relative to the random phase at $\tau \in \{0.25, 0.50, 0.75, 0.90, 0.95, 0.99\}$. Vertical bars are 95% confidence intervals based on standard errors clustered by auction.

units for the initial phase, −0.119 for the alert phase at $\tau = 0.25$), still negative at the median (−0.077), and positive only in the upper half, where it climbs steeply (+0.171 at $\tau = 0.75$, +0.329 at $\tau = 0.90$, +0.842 at $\tau = 0.99$). The decrement excess that Table 6 shows at every quantile across auctions is therefore concentrated in the within-auction upper tail: below the median, the conditional early–random difference is already negative before adding the standing-bid control.

The standing bid accounts for the rest. The right panel adds it, and the sign flips at every τ: the initial–random gap is −0.237 at $\tau = 0.25$, −0.217 at the median, and attenuates toward zero in the extreme tail (−0.044 at $\tau = 0.99$) while remaining negative at every quantile. Adding the full mechanism-regression control vector—time since the last bid by any bidder (winsorized at p99), bid order, and cumulative distinct active bidders, alongside the standing bid normalized by the reference value (winsorized at p1/p99)—preserves the reversal at every quantile and, if anything, deepens it slightly into the tail (−0.195 at $\tau = 0.25$ to −0.219 at $\tau = 0.99$; specification 3 of Appendix Table B.1). Holding the standing bid and the remaining controls fixed, random-phase decrements are larger across the reported conditional distribution.

The reversal after conditioning on the standing bid is consistent with differences in the distance left for prices to fall. At the start of each auction the standing bid often sits at or above the reference; as it falls—below the reference before the random phase in four in five auctions (Table 5)—the feasible range for further reductions narrows.

Appendix Table B.2 repeats the within-auction comparison under two alternative normalizations of the capped decrement. Under the capped discount, the initial-phase coefficient is −0.348 with auction fixed effects and −0.166 with the full control vector. Under the capped auction-median ratio, the corresponding coefficient is 0.005 before adding the standing-bid and within-auction state controls and −0.199 with the full control vector. The conditional phase reversal therefore does not depend on the preferred reference-value normalization.

Appendix Table B.3 instead estimates the probability that a decrement exceeds fixed pooled thresholds without imposing the Machado–Santos Silva location–scale structure. The full-control coefficients are nonpositive for the initial phase and negative for the alert phase at every reported threshold, although the initial-phase estimates at the two highest thresholds are close to zero.

4.3 Auction-Level Patterns

Fact 4. *The share of auctions containing jump bids rises with registered participation, from 43.7% with two registered participants to 88.4% with 20 or more. Jumps per active bidder peak at 0.99 in the 3–4-participant bin and decline to 0.39 in the 20-or-more bin.*

Table 7: Jump Bid Prevalence by Number of Participants

Participants	Active bidders	Auctions	% with jumps	Jumps per auction	Jumps per active bidder
2	1.64	244,450	43.74	1.60	0.83
3–4	2.48	667,427	60.34	2.73	0.99
5–9	4.44	1,164,065	76.55	4.34	0.95
10–19	8.48	626,650	86.27	5.69	0.69
20+	16.49	109,084	88.44	6.15	0.39

Note: Auction-level statistics by number of participants. Active bidders: suppliers with ≥ 1 bid during the bidding phase.

Table 7 shows a monotonic relationship between registered participation and the presence of a jump bid. Among auctions with two registered participants, 43.7% contain at least one jump bid. The share rises to 60.3% for 3–4 participants, 76.6% for 5–9, 86.3% for 10–19, and 88.4% for 20 or more.

The intensive margin differs. Total jump bids per auction rise from 1.60 with two registered participants to 5.69 with 10–19 participants. Part of this increase reflects that auctions with more registered participants also contain more bidding. Normalizing by the number of active bidders produces a non-monotonic pattern. Jumps per active bidder are 0.83 in auctions with two registered participants, peak at 0.99 for 3–4 participants, and then decline to 0.95 for 5–9, 0.69 for 10–19, and 0.39 for 20 or more.

4.4 Jump Bidding Frequency and Win Rates

> **Fact 5.** *Jump bidding is widespread across bidders: only 8.3% of bidders with ≥ 5 participations never jump. Sorting bidders into equally sized quartiles by jump-bid share, the top quartile has win rates 9 to 15 percentage points above the bottom quartile within broad bids-per-auction quintiles.*

Table 8: Bidder Quartiles by Jump Bidding Frequency

	Bidders		Jump share (%)	Auctions	Bids	Win rate (%)	
Quartile	N	Share	Range	Median	Median	Median	Mean
Q4 (highest)	9,891	25.00	23.6–100.0	40	208	19.83	25.79
Q3	9,892	25.00	10.9–23.6	49	331	15.94	21.12
Q2	9,892	25.00	3.7–10.9	41	314	13.89	18.71
Q1 (lowest)	9,892	25.00	0.0–3.7	20	151	9.44	15.43

Note: Sample restricted to bidders with ≥ 5 auction participations. Bidders are split into four quartiles by their jump-bid share. "Range" reports the minimum and maximum jump share (%) within each quartile.

Table 8 sorts bidders with at least five auction participations into quartiles by the share of their bids that are jump bids.[11] Jumping is widespread across careers: only 3,285 bidders (8.3%) never place a jump bid. Despite this, jumps account for 11.1% of bids. The distribution of bidder-level jump shares is heavily right-skewed, so the equal-count quartiles span unequal ranges: the bottom quartile jumps on at most 3.7% of its bids, whereas the top quartile spans 23.6% to 100%.

The bottom quartile is also the least active, with a median of 20 auctions and 151 bids against 40 to 49 auctions and 208 to 331 bids in the upper three quartiles. Win rates rise monotonically with jump-bid share: from a 9.4% median (15.4% mean) in the bottom quartile to 19.8% (25.8% mean) in the top. The most frequent jumpers are thus neither inexperienced nor marginal participants: they compete more actively and win more often.

[11] The ≥ 5 auction filter is essential. Without it, the bottom quartile is dominated by one-time participants who placed too few bids for jumping behavior to be meaningful.

Table 9: Win Rates by Bidding Intensity and Jump Frequency

	Mean win rate (%) by jump-share quartile			
Bids/auction quintile	Q1 (lowest)	Q2	Q3	Q4 (highest)
Q1 (lowest)	6.90	8.76	11.86	19.38
Q2	9.49	12.53	15.58	24.70
Q3	13.24	16.79	20.49	27.78
Q4	17.89	20.57	25.42	32.30
Q5 (highest)	24.60	28.39	31.73	33.68

Note: Sample restricted to bidders with ≥ 5 auction participations. Rows are quintiles of mean bids per auction; columns are quartiles of jump-bid share.

Table 9 decomposes win rates by bidding intensity (mean bids per auction, in quintiles) and jump-share quartile. The top jump-share quartile holds the highest win rate within every intensity quintile, 9 to 15 percentage points above the bottom quartile. The positive association between jump frequency and winning therefore remains within each broad intensity quintile. These bins do not hold bidding intensity constant because bidders remain heterogeneous within quintiles. The ordering is monotonic in both margins—rising with jump share within every intensity quintile, and with bidding intensity within every quartile.

4.5 Credibility of Large Jump Bids

Fact 6. *Most large jump bids are credible: 83.6% pass the credibility screen. Among the 16.4% non-credible, most are consistent with bidder entry errors during submission.*

This subsection introduces *large jumps*: jump bids that clear the strictest cutoff of the reference grid, $d_{ia} > 0.05$—a capped decrement exceeding five percent of the reference value. I classify them using the canonical bid-level credibility indicator that constructs s_t^*.

Table 10 reports the results. Panel A shows that 83.6% of large jump bids are credible and 16.4% are non-credible.

Panel B classifies the non-credible bids using a hierarchical taxonomy detailed in Appendix A.2. The dominant category is a "wrong leading digit" (66.0%): the bid replaces its leading digit with another, as when R$7,169 is entered as R$1,169. Follow-on bids account for 13.4% and arise after a prior bid corrupts the nominal standing price. The remaining bids divide among decimal errors, intentional withdrawals, unit/total confusion, dropped digits, and an unexplained group.

Table 10: Credibility and Classification of Large Jump Bids

Panel A: Credibility of large jump bids

Category	N	Share (%)
Credible	2,409,223	83.63
Non-credible	471,710	16.37

Panel B: Classification of non-credible bids

Category	N	Share (%)
Leading digit substitution	311,098	65.95
Follow-on response	63,156	13.39
Decimal place error	5,990	1.27
Withdrawal	2,509	0.53
Unit/total price confusion	2,062	0.44
Omitted leading digit	612	0.13
Unexplained	86,283	18.29

Note: Panel A classifies all large jump bids (capped reference-normalized decrement $d_{ia} > 0.05$) using the credible standing history s_t^*. Panel B classifies the 471,710 non-credible bids.

Non-credible large jumps are concentrated in the random phase, which contains 84.7% of them. The screen therefore does not rule out time pressure as a source of submission errors.

The credibility classification above is an *ex post* concept: a bid is labeled non-credible when it lies implausibly far below the contracted price. During the auction itself, competitors face real-time uncertainty and cannot see competitors' identities because the auction is anonymous (Section 2); reputation, compliance history, and past disqualifications are all unobserved while bidding is live. Credibility must therefore be inferred from the bid amount alone. For most jump bids, the price is only weakly informative: an aggressive cut may reflect either a genuinely low-cost bidder or an error. Only at the extreme tail does non-credibility become obvious from magnitude alone, such as a bid of R\$0.0001 on a contract worth thousands. Real-time credibility is therefore continuous and imperfectly observed.

4.6 Determinants of Jump Bidding

I examine which variables predict jumping at three observation levels. Column 1 of Table 11 uses bid-level variation within auctions and bidders; column 2 compares auction-level jump shares; and Table 12 compares firms. Separating these levels prevents a within-auction association from being conflated with differences across auctions or firms.

Table 11: Determinants of jump bidding

	Within-auction	Between-auction
	(1)	(2)
	Jump bid	*Jump rate*
Standing bid / ref. value	0.1640***	-0.1508***
	(0.0075)	(0.0066)
Initial phase	-0.0369***	
	(0.0018)	
Alert phase	-0.0207***	
	(0.0009)	
Time in random phase	-0.0001	
	(0.0001)	
Participants (reference: 2 bidders):		
3–4		-0.0082
		(0.0071)
5–9		-0.0400***
		(0.0143)
10–19		-0.0906***
		(0.0219)
20+		-0.1430***
		(0.0263)
Log total reference value		-0.0105***
		(0.0022)
Random phase duration		-0.0009***
		(0.0001)
Fixed effects	Auction + bidder	Quarter
Clustering	Auction, bidder	Purchasing unit, sector
Observations	103,239,646	2,811,676

Note: Column (1) is a within-auction linear probability model of the jump indicator at the bid level (random phase omitted). Column (2) is a between-auction regression of the auction jump rate on auction-level characteristics. Standing bid / ref. value winsorized at the 1st and 99th percentiles. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column 1 of Table 11 estimates a linear probability model of jump placement with auction and bidder fixed effects. A clear pattern is that jumps are concentrated in the random phase. Relative to the random phase, the probability of jumping is 3.7 percentage points lower in the initial phase and 2.1 points lower in the alert phase.

The standing bid relative to the reference value enters positively (+0.164). Once the standing bid falls below the reference value, higher standing bids leave more room to jump, so I interpret this coefficient primarily as capturing feasibility rather than a behavioral response to price levels. Conditional on the standing bid, each additional elapsed minute since the random phase began has an estimated coefficient of −0.0001 and is not statistically significant. The specification therefore shows no detectable within-random-phase time gradient after conditioning on the included auction state.

Column 2 takes the auction as the unit and regresses each auction's jump share on auction-level characteristics, with quarter fixed effects and standard errors two-way clustered by purchasing unit and product sector. The standing-bid coefficient flips sign: the auction-mean standing bid relative to the reference value enters at −0.1508, against +0.1640 in column 1. This contrast suggests that environments with systematically higher standing bids tend to exhibit less jump activity overall.

The auction jump rate also falls with registered participation. Relative to auctions with two registered participants, the difference is statistically flat at three or four participants and then reaches −4.00, −9.06, and −14.30 percentage points in the five-to-nine, ten-to-nineteen, and twenty-or-more bins. This intensive-margin association complements Fact 4: auctions with more registered participants are more likely to contain a jump, but jumps account for a smaller share of their bids. The regressions do not identify the effect of adding a participant or the type of bid that an additional participant would place. Higher-value auctions and those with longer random phases also have slightly lower jump shares (−1.05 percentage points per log unit of total reference value; −0.09 points per minute).

The third level is the firm. Column 1 of Table 12 regresses the firm's jump rate on auction experience[12] and finds no relationship (+0.003). This unconditional estimate confounds experience with how a firm bids. More experienced firms place more bids (log-correlation = 0.87), and a firm's jump rate depends mechanically on its bidding: a firm that submits many small bids per auction inflates its bid count without adding jumps, lowering its measured jump rate. The remaining columns therefore compare firms with similar *bidding volume*—total number of bids—and *bidding intensity*—bids per auction.

Conditioning on volume and intensity turns the experience gradient negative. Adding both as linear controls (column 2), or as fixed effects for each volume×intensity quintile cell (columns 3–4), yields a negative slope. Within these controls, a one-log-unit increase in experience is associated with a jump rate about 1.3 percentage points lower. The estimate stays negative whether each firm counts equally (column 3) or is weighted by its bid count (column 4), and the within-cell experience slope is negative in 22 of the 25 cells. This pattern is consistent with learning through repeated participation, but the cross-firm comparison is not enough to identify learning.

[12]Bidder experience is the total number of distinct auctions in which the supplier participated over 2015–2018; it enters in logs.

Table 12: Bidder experience and jump bidding

	(1)	(2)	(3)	(4)
Log bidder experience	0.0033***	-0.0341***	-0.0132***	-0.0088***
	(0.0004)	(0.0018)	(0.0010)	(0.0024)
Volume & intensity	None	Linear	Strata FE	Strata FE
Bid-weighted	No	No	No	Yes
Observations	43,971	43,971	43,971	43,971

Note: Sample: bidders with ≥ 5 auction participations. Outcome: supplier jump rate (share of bids that are jumps). Regressor of interest: log cumulative auction participations. Column (1) is unconditional; (2) adds log total bids (volume) and log bids per auction (intensity) as controls; (3)–(4) replace them with volume×intensity quintile fixed effects (25 cells). Column (4) weights observations by supplier bid count. Heteroskedasticity-robust standard errors in parentheses. *, $p < 0.10$, **, $p < 0.05$, ***, $p < 0.01$.

Taken together, these facts show that jump bidding is widespread across bidder careers (Fact 5), declines as a share of bids across phases (Fact 2), rises in auction incidence with registered participation (Fact 4), and is largely credible even among the largest jumps (Fact 6). The unconditional early-phase advantage in jump intensity largely reflects the standing-price state: conditional on that state, random-phase decrements are larger at every reported quantile (Fact 3). The next section examines which auction conditions are associated with jumping and how rivals respond. Section 6 then estimates the association between jumps and the price paid by the government and presents the IV design.

5 Candidate Mechanisms for Jump Bidding

Section 4 established what jump bidding looks like in Brazilian procurement: it is pervasive and concentrated in the random phase, and the apparent higher early-phase jump intensity (Fact 3) disappears and reverses, once the state of the auction is held fixed within the same auction. This section asks which mechanisms could generate those patterns and which could plausibly operate in this setting.

The candidate explanations are not mutually exclusive. Some share the same underlying conditions but explain jumps through different channels. Private-cost signaling is rival-directed: a bidder sacrifices margin because the jump may induce rivals to withdraw, trading a lower profit conditional on winning for less competition. Direct monitoring or bid-revision costs are self-directed: a bidder sacrifices margin to reduce its own future attention and revisions. Rival exit can reflect belief-based deterrence or simply a response to ordinary competition. An uncertain ending creates urgency to secure the lead, but its implication for jump size depends on strategic motives.

The analysis first examines the institutional suitability of the possible explanations. It then reports exploratory rival-response evidence on blanket and selective deterrence and examines whether the phase and state patterns are consistent with ending risk. These exercises narrow the set of plausible explanations but do not favor a single mechanism and cannot explain each individual jump.

5.1 Institutional Scope of Candidate Mechanisms

Jump bidding has been studied almost entirely in ascending auctions, where the main explanations involve preemptive signaling, the winner's curse, and deterrence of weaker rivals (Avery, 1998; Ettinger & Michelucci, 2016b; Horner & Sahuguet, 2007). An aggressive raise in that setting corresponds to a deep cut in a procurement auction. Whether the same mechanisms have broad scope depends on the information and bidding environment. Private costs are a maintained benchmark for the *Pregão*. The auction procures common goods and services with standard market specifications, publishes a reference value, uses a random closing rule, displays the price state, and conceals bidder identities during bidding.

The explanations operate at different levels. Common-cost uncertainty, costly bidding, anonymity, and the random ending are features of the environment. Signaling and economizing on future bids are channels through which a jump can affect payoffs. Deterrence and rival exit are possible outcomes. The same condition does not make the channels identical. Costly monitoring can support private-cost signaling or incetivize bidders to sacrifice margin to reduce later bid revision. Table 13 keeps these channels separate and compares their scope. Its notes point to the literature related to each mechanism family.

The standing price is inexpensive to observe, and bidders can react to it in real time. However, the price displayed as the standing bid is not always a price firms can rely on. The displayed price may reflect an entry error or an offer a bidder cannot honor. Sometimes these bids are removed, but not always (Section 4.5). When they remain visible, they obscure the credible competitive frontier. Firms can also access the five best offers, but the 10-second CAPTCHA is costly in the random phase, when the auction can end at any moment.

Nor are the bids a binding commitment to supply. The provisional winner can decline to formalize the award or fail the later qualification stage (Section 2), so the lowest offer is often not the one that ultimately wins. A deep cut is therefore neither a guaranteed win nor a credible promise to deliver at that price.

A common treatment views jump bidding as a device for signaling strength and deterring weaker rivals (Avery, 1998; Horner & Sahuguet, 2007). One branch relies on uncertainty about a common component: a jump changes rivals' beliefs about the value of winning or their exposure to the winner's curse (Ettinger & Michelucci, 2016a, 2016b). Standardized goods and a public reference value limit this channel, although common cost shocks can remain. The institution therefore gives common-component signaling limited scope.

Private-cost signaling does not require common-value uncertainty. A sufficiently deep cut can credibly signal a low cost and thus a willingness to bid aggressively going forward. This may induce some rivals to withdraw, reducing the need for further price cuts. Thus, a jump is worthwhile when the expected gain from this deterrence exceeds the margin sacrificed. Costly bid revision supports this channel: a high-cost type gains less from imitating a jump meant to end the contest, so a sufficiently large cut remains informative of low cost (Daniel & Hirshleifer, 2018). Anonymity does not prevent rivals from observing the price path, so they can still infer that some rival has a low cost.

Monitoring and bid-revision costs provide a separate motive. A bidder can save monitoring and revision costs by substituting a sequence of bids across time with one deep offer (Easley & Tenorio, 2004; Grether et al., 2015; Isaac et al., 2007). A participant jumps when the costs avoided exceed the margin sacrificed. Greater impatience or higher continuation costs can therefore produce a deeper cut. The median monitoring window is short, but attending to the auction is not costless. Non-credible bids can obscure the competitive frontier, observing the five best offers requires a CAPTCHA workaround, and firms may monitor several auctions at once. This channel may therefore matter for a subset of firms or auctions.

Another possibility is that jumps are used as communication within a bidding ring. Code bidding and phantom-bid tactics have been documented in spectrum and procurement settings (Asker, 2010; Cramton & Schwartz, 2000). Fazio and Zaldokas (2024) study post-

Table 13: Candidate mechanisms for jump bidding

Channel	Key precondition	Scope in this setting	Assessment
Information hypotheses			
Common-component signaling	Uncertainty about a shared cost component	Offerings with standard specifications and the public reference value reduce uncertainty	Unlikely as a general account
Private-cost signaling	Bidder expects a jump to induce some rivals to withdraw; the expected gain from weaker competition exceeds the margin sacrificed	Bids cannot be observed when a non-credible standing bid is present	Possible for a subset: selective deterrence open
Friction hypotheses			
Direct monitoring / bid-revision cost	Costly future attention or revisions; one deep bid reduces the need to monitor or bid again	The window is short, but CAPTCHA access, and simultaneous auctions generate costs	Possible for a subset
Response to uncertain ending	A positive termination hazard; depth reduces the risk of losing before another opportunity to bid	Random phase creates the ending risk	Possible for most auctions
Structural and strategic hypotheses			
Reputation in repeated play	Observable persistent identity	Bidders are anonymous during the auction	Very unlikely
Collusive signaling	A cartel and an attributable in-auction signal	Anonymity limits attribution and verification	Unlikely as a general account
Behavioral hypotheses			
Behavioral bidding	Heuristic or non-optimizing behavior	Experience and auction-state patterns are inconsistent with a purely random account	Unlikely as a general account

Notes: In private-cost signaling, the return to jumping comes from a change in rivals' continuation decisions; costly bidding or continuation can make the signal credible (Daniel & Hirshleifer, 2018). Under direct monitoring or bid-revision costs, the return comes from reducing the bidder's own future participation, without requiring belief updating (Easley & Tenorio, 2004; Grether et al., 2015; Isaac et al., 2007). Common-component signaling includes preemption, information hiding, and winner's-curse creation (Avery, 1998; Ettinger & Michelucci, 2016b; Horner & Sahuguet, 2007). Ending-response accounts build on sudden-termination and candle-auction logic (Füllbrunn & Sadrieh, 2012; Milgrom, 2004). Reputation requires persistent identity (Bikhchandani, 1988); collusive signaling includes code bidding and phantom or kamikaze bids (Asker, 2010; Cramton & Schwartz, 2000; Fazio & Zaldokas, 2024). Behavioral bidding is a residual category here rather than a mechanism attributed to a specific cited model.

auction withdrawal intended to benefit a connected runner-up in Brazilian procurement. Widespread jump use across bidders weighs against a blanket collusive interpretation but cannot exclude targeted signals in particular markets. Real-time anonymity makes any signal harder to attribute, although identities disclosed after the auction can support repeated relationships. Chassang et al. (2022) develop screens based on isolated winning bids and missing close losing bids in Japanese procurement. Figure C.1 adapts their relative-margin diagnostic to this setting. Margins concentrate near zero, which is consistent with close competition but does not exclude coordination. Most large jumps are credible under the canonical screen, and two-thirds of the non-credible remainder have a wrong-leading-digit pattern (Table 10). Together, these facts speak against collusion as a general account.

The uncertain-ending response has broad institutional scope because every bidder faces the random closing rule. The hazard makes prompt leadership valuable, but it does not explain why a larger cut may be better than a minimal undercut to take the lead. Large cuts can be preferable to reduce the risk of losing before having a chance to bid, avoid future costly revisions, or deter rivals. Ending risk can therefore interact with direct monitoring costs or private-cost signaling. Section 5.3 develops this interpretation.

Heuristic or non-optimizing bidding can be a residual explanation. Section 4.6 shows that jumping varies systematically with the price state and bidder experience. These results are inconsistent with a purely random account, but cannot rule out a heuristic explanation.

5.2 Exploratory Rival-Response Evidence

Rival responses are informative about the rival-directed signaling mechanism, but not directly about the self-directed monitoring-cost mechanism. Blanket deterrence through signaling predicts less rival participation and more exit after a jump. Selective signaling need not produce the same pattern: high-cost rivals may exit while low-cost survivors continue bidding more intensively. I estimate the associations separately by phase because the random phase adds urgency from the closing risk.

Table 14 reports the results across three outcomes: the seconds until the next competitor bid, the number of competitor bids within 60 seconds, and an indicator for whether any competitor exits within 60 seconds.[13]

Panel A compares jump with non-jumps. Conditional on controls, jumps are followed by more rival bids within the next minute: 0.12 more in the initial phase, 0.28 in the alert phase, and 0.14 in the random phase. They are also associated with increases of 4.0, 5.4, and

[13] The response-time outcome is defined only when a rival responds; the bid-count and exit outcomes are defined for all bids. The specifications exclude self-outbids and non-credible bids, include auction fixed effects, and cluster standard errors by auction and supplier.

6.4 percentage points in the probability that at least one rival exits. Conditional on a rival responding, response times are 39.9, 11.9, and 4.6 seconds shorter, respectively.

Panel B compares larger jumps with smaller ones. The former have no consistent association with response times and coincide with more rival exit in every phase, by 3.7, 5.5, and 7.2 percentage points. Only in the random phase are they also followed by fewer rival bids, by 0.26 bids.

Table 14: Competitor response to jump bids, extensive margin

	Time to next		Compet. bids 60s		Any exit 60s	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Jump vs. non-jump (all bids)						
Initial	-58.25***	-39.91***	0.1573***	0.1179***	0.0363***	0.0400***
	(2.30)	(2.11)	(0.0041)	(0.0042)	(0.0008)	(0.0008)
Alert	-13.85***	-11.94***	0.2321***	0.2779***	0.0378***	0.0541***
	(0.53)	(0.49)	(0.0108)	(0.0110)	(0.0011)	(0.0009)
Random	-5.19***	-4.57***	0.3321***	0.1412***	0.0548***	0.0636***
	(0.12)	(0.12)	(0.0077)	(0.0108)	(0.0008)	(0.0007)
Observations						
Initial	10,674,394	10,674,394	10,778,599	10,778,599	10,778,599	10,778,599
Alert	12,750,687	12,750,687	12,889,923	12,889,923	12,889,923	12,889,923
Random	73,710,507	73,710,507	76,018,345	76,018,345	76,018,345	76,018,345
Panel B: Large vs. smaller jump (jumps only)						
Initial	-29.74***	3.41	0.0689***	0.0047	0.0210***	0.0372***
	(2.63)	(2.71)	(0.0033)	(0.0035)	(0.0013)	(0.0013)
Alert	-4.75***	-1.75***	0.0453***	0.0719***	0.0209***	0.0545***
	(0.51)	(0.52)	(0.0051)	(0.0069)	(0.0013)	(0.0014)
Random	-1.04***	0.96***	0.1263***	-0.2569***	0.0468***	0.0720***
	(0.11)	(0.10)	(0.0107)	(0.0057)	(0.0013)	(0.0010)
Observations						
Initial	1,408,760	1,408,760	1,426,218	1,426,218	1,426,218	1,426,218
Alert	1,536,803	1,536,803	1,561,767	1,561,767	1,561,767	1,561,767
Random	6,343,407	6,343,407	6,673,024	6,673,024	6,673,024	6,673,024
Controls		✓		✓		✓

Note: Each cell is a separate regression, estimated within the stated phase. Panel A contrasts jump bids against non-jump bids over all bids; Panel B contrasts large jumps against smaller jumps. Controls: standing bid/ref. value and time since last bid. All specifications include auction fixed effects. Standard errors are two-way clustered by auction and supplier. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 15 reports the intensive margin, regressing rival reactions on the log capped decrement among jumps. The results mirror Panel B. Larger decrements are associated with increases in rival exit of 2.7, 4.0, and 5.0 percentage points across the three phases. In the random phase they are also followed by 0.16 fewer rival bids, while the bid-count association is flat in the initial phase and positive in the alert phase.

Table 15: Competitor response to jump bids, intensive margin

	Time to next		Compet. bids 60s		Any exit 60s	
	(1)	(2)	(3)	(4)	(5)	(6)
Initial	-18.77***	4.00**	0.0442***	0.0003	0.0152***	0.0270***
	(1.44)	(1.58)	(0.0020)	(0.0024)	(0.0007)	(0.0008)
Alert	-3.28***	-1.26***	0.0364***	0.0565***	0.0152***	0.0397***
	(0.30)	(0.32)	(0.0029)	(0.0044)	(0.0008)	(0.0008)
Random	-0.69***	0.65***	0.0993***	-0.1602***	0.0321***	0.0497***
	(0.06)	(0.06)	(0.0069)	(0.0039)	(0.0008)	(0.0006)
Observations						
Initial	1,408,760	1,408,760	1,426,218	1,426,218	1,426,218	1,426,218
Alert	1,536,803	1,536,803	1,561,767	1,561,767	1,561,767	1,561,767
Random	6,343,407	6,343,407	6,673,024	6,673,024	6,673,024	6,673,024
Controls		✓		✓		✓

Note: Each cell is a separate regression, estimated within the stated phase. The regressor is the log capped reference-normalized decrement, a within-jump dose-response (slope of rival reaction in the size of the jump, among jumps). Controls: standing bid/ref. value and time since last bid. All specifications include auction fixed effects. Standard errors are two-way clustered by auction and supplier. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

The increase in rival exit is consistent with deterrence. In most cases, however, it coincides with more intensive engagement by surviving rivals, contrary to blanket deterrence's prediction. Larger random-phase jumps are the exception: they coincide with more exit and fewer subsequent bids. This pattern is compatible with selective deterrence or private-cost signaling. The results are inconsistent with a general shutdown of competition, but they do not distinguish belief-mediated deterrence from the direct effect of the lower price.

Appendix Table C.1 conditions the pre-random response regressions on the standing price immediately after the focal bid. The coefficients remain inconsistent with deterrence.

5.3 The Ending-Response Mechanism

The random ending is a modern *candle auction*: the sale closes at an unpredictable moment within a publicly specified range (Brazil, 2005; Milgrom, 2004). The stopping time is $t_3 \sim \text{Uniform}[t_2, t_2 + 30]$. The termination hazard rises as the window closes. A stochastic close makes delay risky and pulls competition earlier, where a hard deadline would invite last-second sniping (Füllbrunn & Sadrieh, 2012; Roth & Ockenfels, 2002). In a descending auction, ending risk favors securing the lead promptly during the random phase.

The determinants regression in Section 4.6 shows a pattern consistent with this mechanism. After absorbing additive auction and bidder effects, jumps concentrate in the random phase. Within that phase, elapsed time adds no explanatory power once the price level is controlled (Table 11, column 1). Ending risk therefore has broad institutional scope and is consistent with the phase and state dependence of jumping. The evidence does not isolate it from monitoring costs, bid-revision costs, displacement risk, or strategic responses that also become more important in the random phase.

5.4 Summary

Table 16 summarizes the findings. Common-component signaling, reputation, and collusion are unlikely to explain jump bidding generally in this setting. Private-cost signaling and monitoring or bid-revision costs share costly continuation as a condition, but the return to jumping differs. Signaling is rival-directed: the bidder sacrifices margin to induce withdrawal and reduce future competition. Direct monitoring costs are self-directed: the bidder sacrifices margin to reduce the need to monitor the auction. Observed rival responses to jumps are inconsistent with deterrence while leaving selective signaling open. Ending risk has broad institutional scope and is consistent with the phase and state patterns. Stronger conclusions require a model of the strategic environment and assumptions that link the empirical evidence to specific mechanisms.

Table 16: Summary of main mechanisms

Mechanism	Test that bears on it	Assessment
Common-component signaling	Institutional screen: standardized goods and a public reference value reduce common uncertainty	Unlikely as a general account
Private-cost signaling	Rival-response comparisons test whether jumps reduce rival continuation; belief updating is not observed	Possible for a subset: selective deterrence open; not separately identified
Direct monitoring / bid-revision cost	The bidder's own monitoring and revision costs are unobserved; the short window limits average savings, but attention frictions remain	Possible for a subset; not separately identified
Response to uncertain ending	Section 4.6 phase and state dependence; timing cannot separate ending risk from other random-phase channels	Possible for most auctions; not separately identified
Reputation in repeated play	Institutional screen: bidders are anonymous during the auction	Very unlikely
Collusive signaling	Institutional screen: anonymity limits attribution and verification	Unlikely as a general account

6 The Effect of Jump Bidding on Prices

This section estimates the effect of jump bidding on the contracted price that the government ultimately pays. The baseline sample comprises 2,445,301 auctions with at least one realized random-phase bid and enough within-product × quarter variation to identify the fixed effects specification.[14] This requirement excludes 366,172 auctions (13.0%) and keeps the OLS and IV samples aligned. Appendix Table D.1 describes the excluded auctions, and Appendix Table D.2 reports OLS without the restriction. The IV interpretation remains conditional on the selected sample.

The central empirical challenge is endogeneity: bidders choose when and how aggressively to jump in response to the same unobservables that shape the final price. I therefore combine three complementary pieces of evidence: within-product comparisons that hold fixed product–quarter heterogeneity and observed auction characteristics; an instrumental variables strategy that exploits the independently randomized duration of the random phase; and a set of robustness exercises that explicitly allow the instrument to have a direct effect on price and ask whether the qualitative conclusion survives. Every piece of evidence points the same way: jump bidding lowers the contracted price.

Appendix Figure C.1 reports relative margins around the winning-bid threshold. Their concentration near zero is consistent with close competition, but it does not rule out coordination.

6.1 Within-Product Comparison

I begin with the auction-level specification

$$\frac{P_a}{v_a} = \alpha_{pq} + \beta J_a + X_a'\gamma + \varepsilon_a,$$

where P_a/v_a is the contracted price normalized by the reference value, α_{pq} is a fixed effect for the product group × quarter cell containing auction a, and J_a is one of two intensive-margin jump measures: the jump count (the number of jump bids in the auction, $d_{ia} > 0.01$) and total jump depth (the sum of d_{ia} over the auction's jump bids, the cumulative reference-normalized price reduction contributed by those jumps). Controls X_a comprise log(participants), log(total reference value), mean bidder experience, and random phase duration. Standard errors are two-way clustered by product group and winning firm. The contracted price equals the negotiated value when post-auction renegotiation occurred and the

[14] 203 such auctions fall into singleton cells and are removed in the fixed effects specification.

winning bid otherwise[15]. Normalizing by the reference value makes magnitudes comparable across heterogeneous products.[16]

Table 17 reports the estimates with and without controls for the jump count and total jump depth. All four specifications agree: more jump bidding is associated with a lower contracted price, at the 1% level in every column. With controls, each additional jump bid lowers the contracted price by 1.08 percentage points of the reference value (column 2), and each unit of total jump depth lowers it by 3.06 percentage points (column 4). Adding controls reduces the count coefficient by 24% (from −0.0142 to −0.0108) and the depth coefficient by 31% (from −0.0446 to −0.0306), indicating that a meaningful share of the correlation reflects observable auction characteristics.

Table 17: Effect of Jump Bidding on Contracted Price

	Jump count		Total jump depth	
	(1)	(2)	(3)	(4)
Coefficient	-0.0142***	-0.0108***	-0.0446***	-0.0306***
	(0.0008)	(0.0007)	(0.0074)	(0.0057)
Controls		✓		✓
Observations	2,445,301	2,445,301	2,445,301	2,445,301
R^2	0.160	0.302	0.061	0.248

Note: Dep. variable: contracted price / reference value. All specifications include product group × quarter fixed effects. Standard errors are two-way clustered by product group and winning firm. "Jump count": number of jump bids in the auction. "Total jump depth": sum of the capped reference-normalized decrements over all jump bids in the auction. Controls: log(participants), log(total reference value), mean bidder experience, and random phase duration. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

The interpretation of β is descriptive. Within a product–quarter, auctions in which bidders jump more may differ from those in which they do not along dimensions of sup-

[15]Post-auction renegotiation occurs in 11.6% of auctions and almost always reduces the price further (97.8% of cases, median reduction 1.3% of the winning bid). Using the winning bid directly as the outcome produces nearly identical OLS estimates, slightly larger in magnitude, consistent with jump-bid auctions renegotiating marginally less on average.

[16]Reference values are not fixed primitives: the procuring unit sets each one from price research that may incorporate the outcomes of earlier auctions for similar items, so a sequence of low contracted prices can feed back into lower future reference values (government learning). Two features limit the concern for the present design. First, the product group × quarter fixed effect absorbs any common drift in reference values within a cell, so identification rests on within-cell, within-quarter variation rather than on the slow-moving level that learning would shift. Second, because the outcome is normalized by the reference value, a proportional downward revision of v_a rescales numerator and denominator together and leaves P_a/v_a first-order unchanged.

ply, demand, or bidder composition that X_a does not capture. The sign of the correlation is nonetheless informative: it runs opposite to what deterrence would predict.

A first concern is mechanical. The negative relationship in Table 17 could arise by construction, because auctions with more or larger jumps end at a lower standing price, which the contracted price tends to track. The link is not deterministic: the contracted price is not necessarily the lowest bid, since lowest bids are frequently disqualified and the award instead goes to a surviving bid in 16.6% of auctions. To formally address the endogeneity concern, I present further evidence in Section 6.4.

6.2 Heterogeneity

Figure 4 and Figure 5 summarize the within-product association of total jump depth and the jump count across five subgroup splits: market competitiveness, total reference value, product frequency, bidder experience, and bidding intensity.

The association is negative in every subsample. It is larger in markets with fewer bidders (−0.0499 vs. −0.0108 for total jump depth) and in lower-value auctions (−0.0644 vs. −0.0144). In both settings, each jump bid moves the standing bid by a larger share of the auction value, consistent with jump bidding revealing otherwise uncertain competitive intensity. The correlation is also larger in lower-bid-rate auctions than in higher-bid-rate auctions (−0.1584 vs. −0.0123 for total jump depth). These descriptive differences vary with the competitive environment and the remaining bidding.

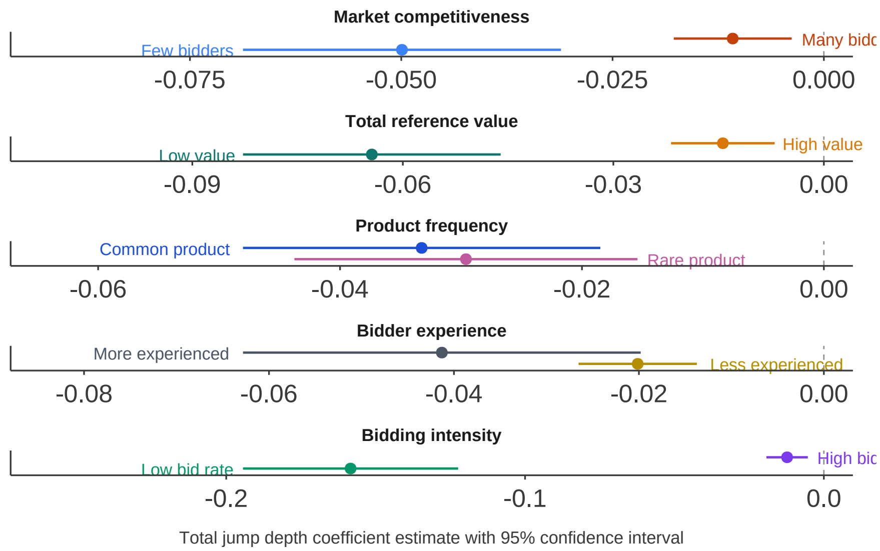
6.3 Instrumental Variables and Calibrated Sensitivity

I use random-phase duration as an instrument for jump-bidding intensity, exploiting the same institutional feature studied by Borges de Oliveira et al. (2019). The sample-period rule required the platform to select a random closing interval of no more than 30 minutes after the closing warning (Brazil, 2005). This rule is valid as an instrument because the randomization is independent of bidder types and the auction state at t_2.

Longer random phases admit more opportunities to bid, including opportunities to jump. The causal interpretation also maintains monotonicity: extending the latent closing time must weakly increase cumulative jump count or depth for each auction. The platform rules motivate this assumption but do not establish it, because bidder responses can change when the realized duration changes.[17]. The first-stage F-statistics in Table 18 are 54,800 for the jump count and 8,405 for total jump depth.

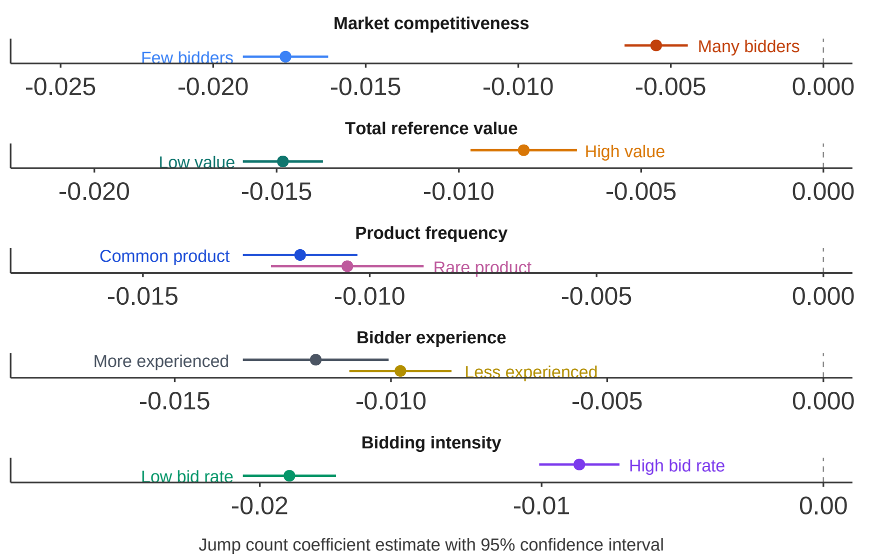
[17] Under monotonicity, 2SLS is a non-negatively weighted average of marginal treatment responses to duration rather than a binary-complier LATE (Angrist & Imbens, 1995; Imbens & Angrist, 1994)

Figure 4: Heterogeneous associations of total jump depth with the contracted price



Note: Markers are OLS coefficients on total jump depth within each labeled subsample; horizontal bars are 95% confidence intervals. The outcome is the contracted price divided by the reference value. Specifications include the controls listed in Section 6.1 and product group × quarter fixed effects; standard errors are two-way clustered by product group and winning firm.

Figure 5: Heterogeneous associations of the jump count with the contracted price



Note: Markers are OLS coefficients on the jump count within each labeled subsample; horizontal bars are 95% confidence intervals. Specifications include the controls listed in Section 6.1 and product group × quarter fixed effects; standard errors are two-way clustered by product group and winning firm.

All IV specifications condition on predetermined auction-state controls measured at t_2 (standing bid normalized by reference value, number of active bidders, bids placed before t_2) together with the baseline covariates and product group × quarter fixed effects.[18] Standard errors are two-way clustered by product group and winning firm.

The 2SLS estimate is interpreted as a weighted average of marginal price responses among auctions whose jump intensity changes with random-phase duration, conditional on monotonicity and exact exclusion.

Because random-phase duration is unlikely to affect price only through jump bidding (longer phases allow more bidding of any kind), I do not treat the 2SLS point estimate as definitive. Instead, I report a calibrated sensitivity range (Conley et al., 2012). The direct-effect is centered at the zero-jump placebo estimate $\hat{\gamma} = -0.0025$ per minute and extends three placebo standard errors in each direction. Interpreting this range for jump-active auctions requires the direct effect measured in zero-jump auctions to be informative about the direct effect in jump-active auctions.

[18]For auctions with no bids before the random phase, the standing bid at t_2 is the lowest initial proposal and the number of active bidders is zero.

Table 18: IV Estimates: Effect of Jump Bidding on Contracted Price

	(1) OLS	(2) 2SLS	(3) CHR sensitivity range
Panel A			
Jump count	-0.0100***	-0.0425***	[-0.0211, -0.0159]
	(0.0007)	(0.0010)	
Observations	2,445,301	2,445,301	
R^2	0.516	0.484	
First-stage F	—	54800.2	—
Panel B			
Total jump depth	-0.0194***	-0.8820***	[-0.4376, -0.3295]
	(0.0049)	(0.0400)	
Observations	2,445,301	2,445,301	
R^2	0.466	0.484	
First-stage F	—	8405.0	—

Note: Dep. variable: contracted price / ref. value. Instrument: random phase duration (minutes). All specifications use the auction-level IV sample and include product group × quarter fixed effects plus pre-determined controls (standing bid at t_2/reference value, active bidders at t_2, bids before t_2, log(participants), log(total reference value), mean bidder experience). Column (1): OLS. Column (2): 2SLS. Column (3): calibrated Conley–Hansen–Rossi sensitivity range over direct effects from $\hat{\gamma}-3\,\mathrm{SE}(\hat{\gamma})$ to $\hat{\gamma}+3\,\mathrm{SE}(\hat{\gamma})$, centered at $\hat{\gamma} = -0.0025$, estimated in zero-jump auctions. Interpreting the range for jump-active auctions requires the direct-effect calibration to transport across samples. Standard errors are two-way clustered by product group and winning firm. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table 18 reports, for each measure, the OLS estimate on the IV sample, the 2SLS estimate, and the Conley–Hansen–Rossi (CHR) sensitivity range over the stated direct-effect support. The 2SLS point estimates are larger in absolute value than the corresponding OLS estimates: -0.0425 for the jump count and -0.882 for total jump depth, compared with -0.0100 and -0.0194. Several factors may contribute to the gap. First, the weighted marginal-response estimand can differ from the average within-product association in OLS. Second, the subgroup estimates in Section 6.2 show heterogeneity in the within-product association across auction competitiveness groups, so different weighting across groups can matter. Third, unobservables that raise prices and jumping would compress the OLS coefficient toward zero.

For the jump count, the calibrated sensitivity range is $[-0.0211, -0.0159]$; for total jump depth, it is $[-0.4376, -0.3295]$. Both ranges lie below zero over the stated direct-effect support and under the transport assumption from zero-jump to jump-active auctions. Direct effects outside that support can change this conclusion.

Restricting to auctions whose winning bid was placed during the random phase yields moderately larger 2SLS estimates (−0.0459 for the jump count, −1.114 for total jump depth; the RP-decided column of Table 19). This shows that the estimates are not smaller among random-phase-decided auctions, but it does not completely eliminate selection concerns.

The headline specifications require at least one random-phase bid. Auctions excluded by this restriction have fewer participants and a lower median reference value (Appendix Table D.1). Removing the restriction leaves OLS coefficients of −0.0114 for the jump count and −0.0354 for total jump depth (Appendix Table D.2). The negative within-product association is therefore not specific to the sample of auctions with random-phase bids.

6.4 Exclusion Restriction and the Role of Observability

Random-phase duration can affect price through the volume of bidding and through the composition of bids. Under the *volume channel*, a longer random phase lowers prices by admitting more bids of any kind. Under the *composition channel*, visible and credible single-step moves in the standing bid convey information that incremental bids reveal more slowly. This subsection reports a selected-sample visibility diagnostic and a calibration exercise.

The "Hidden J." column of Table 19 is a selected-sample visibility diagnostic. It contains 15,845 auctions with at least one realized random-phase jump and a standing bid at t_2 classified ex post as non-credible. These restrictions condition on post-duration outcomes and can select auctions with different treatment effects or direct duration effects. I argue that this sample is informative because the auctions part of it evolve as any other auction, except for the friction created by the non-credible standing bid.

The jump-count estimate falls from −0.0425 to −0.0015 and total jump depth from −0.8820 to −0.0105, attenuations of roughly 28-fold and 84-fold. Both remain statistically significant but are economically small relative to the baseline. The attenuation pattern is consistent with visibility contributing to the baseline estimate. Selection and heterogeneous direct effects of duration provide alternative explanations. Appendix Table D.4 repeats the comparison at 10%, 25%, and 50% non-credibility gap thresholds, and the estimates are attenuated at all three.

Table 19: IV robustness and a selected information-friction comparison

	(1)	(2)	(3)	(4)
Panel A: Placebo reduced form				
Specification	Placebo			
RP duration	-0.0025***			
	(0.0001)			
Observations	573,071			
Panel B: Jump count IV robustness				
Specification		Baseline	RP-decided	Selected hidden J.
Jump count (IV)		-0.0425***	-0.0459***	-0.0015***
		(0.0010)	(0.0008)	(0.0003)
Observations		2,445,301	2,166,533	15,845
First-stage F		54800.2	55629.8	865.7
Panel C: Total jump depth IV robustness				
Specification		Baseline	RP-decided	Selected hidden J.
Total jump depth (IV)		-0.8820***	-1.1137***	-0.0105***
		(0.0400)	(0.0286)	(0.0024)
Observations		2,445,301	2,166,533	15,845
First-stage F		8405.0	16175.7	248.8

Note: Panel A reports the placebo reduced-form effect of random-phase duration on contracted price in zero-jump auctions. Panel B reports alternative IV specifications for the jump count; Panel C reports the same for total jump depth. All IV columns include baseline pre-determined controls and product group × quarter fixed effects. "Baseline": baseline 2SLS. "RP-decided": restricts to auctions whose auction-stage winning bid was placed during the random phase. "Selected hidden J.": restricts to auctions with at least one realized random-phase jump and a standing bid at t_2 classified as non-credible using ex-post information. This selected-sample comparison is descriptive and does not create an exogenous information friction. Standard errors are two-way clustered by product group and winning firm. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

The CHR exercise asks whether the negative sign survives over the calibrated direct-effect support. Both sensitivity ranges in Table 18 lie below zero (Section 6.3). The calibration comes from zero-jump auctions, whereas the effect of interest concerns jump-active auctions. Its interpretation therefore depends on transport across these samples.

As a further check, Appendix Table D.5 re-computes the sensitivity ranges under stratum-specific placebo calibrations based on pre-random-phase competition (active bidders $\leq$ 2, 3–4, $\geq$ 5) and the pre-random-phase standing-bid tercile. The most conservative calibration is $\hat{\gamma} = -0.0033$, from zero-jump auctions with three to four active bidders before the random phase. Under this calibration, the ranges remain below zero: $[-0.0167, -0.0058]$ for the jump count and $[-0.3476, -0.1214]$ for total jump depth.

Together, the exercises help reduce the exclusion concern. The sign remains negative over the calibrated direct-effect support, conditional on transport from zero-jump auctions. The selected-sample attenuation is consistent with visibility as the key channel.

6.5 The Choice of Intensive-Margin Measure

Table 20 reports the full IV chain (reduced form, first stage, 2SLS with and without controls, and the CHR sensitivity range) for the two headline measures, the jump count and total jump depth. The reduced form is identical across columns: a one-minute increase in the random phase reduces P_a/v_a by 0.44 percentage points. The implied IV estimate is obtained by scaling this common reduced form by each measure's first stage. Both measures have a strong positive first stage (a longer random phase admits more bids and more jumps), so the 2SLS estimates are -0.0425 for the count and -0.882 for total depth.

Table 20: IV Estimates for the Intensive-Margin Measures

	Jump count	Total jump depth
Shared reduced form		
RP duration	-0.0044***	-0.0044***
→ contracted price	(0.0003)	(0.0003)
First stage		
RP duration	0.1048***	0.0050***
→ treatment	(0.0068)	(0.0003)
First-stage F	54800.2	8405.0
Second stage		
2SLS (with controls)	-0.0425***	-0.8820***
	(0.0010)	(0.0400)
2SLS (FE only)	-0.0393***	-0.8239***
	(0.0011)	(0.0405)
Calibrated sensitivity		
CHR sensitivity range	[-0.0211, -0.0159]	[-0.4376, -0.3295]
Observations	2,445,301	2,445,301

Note: All 2SLS specifications with controls include standing bid at t_2/reference value, active bidders at t_2, bids before t_2, log(participants), log(total reference value), mean bidder experience, and product group × quarter fixed effects. "FE only" omits the covariates and keeps only fixed effects. Standard errors are two-way clustered by product group and winning firm. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Appendix Table D.3 reports IV diagnostics for the two share-based measures (the fraction of competitive bids that are jumps and the fraction that are large jumps), which produce positive 2SLS estimates. A longer random phase admits both jump and non-jump bids. Because jumps are less frequent than non-jump bids, the count of jumps rises while their share of all bids falls, producing a negative first stage for both share measures. Dividing a negative reduced form by a negative first stage reverses the sign of the 2SLS ratio. A valid treatment measure should respond to the random-phase instrument only through jump incidence: the jump count and total jump depth satisfy this condition, and the share measures do not, which is why the main analysis uses the count and depth measures.

6.6 Summary

Random-phase, duration-induced jump bidding is associated with lower contracted prices across treatment definitions, specifications, and subgroup splits. The calibrated sensitivity ranges remain below zero over the stated direct-effect support, conditional on transport from zero-jump auctions. Estimates are much smaller in the selected Hidden J. sample, a pattern consistent with visibility as a channel. To interpret this as a causal effect, however, requires addressing further selection and heterogeneous direct duration effects concerns. Within-product OLS, the weighted marginal-response 2SLS estimate, and the calibrated ranges span a wide range, so the design is more informative about the sign than about a particular magnitude.

7 Conclusion

Jump bidding is common in Brazilian federal procurement descending auctions. Nearly every bidder jumps at least once, although jumps remain a minority of bids, and even the deepest cuts are generally credible offers rather than entry errors.

Why bidders jump is harder to establish. Signaling and reputation have limited scope under the assumed private-cost benchmark and anonymous bidding. Blanket deterrence also fits the evidence poorly: jumps are followed by sooner and more frequent rival bids, even though some rivals exit. Only the deepest cuts are associated with both more exit and fewer subsequent bids, a pattern compatible with selective deterrence. The concentration of jumps in the random phase is also consistent with an uncertain-ending response, but the evidence cannot isolate that mechanism as the main account.

Price estimates are consistently negative across specifications and calibrations, but become economically negligible when the standing bid is classified as non-credible. This attenuation suggests visibility drives the baseline result, though selection and heterogeneous effects remain alternative explanations that deserve further study. Causal interpretation of the IV estimates relies on the standard assumptions (independence, monotonicity, exclusion, and sample-transport) detailed in Sections 6.3 and 6.4."

The findings suggest two broader lessons. First, the platform should ensure that the displayed standing bid accurately reflects the current competitive price. Second, it is not necessarily true that jumps reduce price competition: rivals remain active after most jumps, and the price estimates for duration-induced jumps are negative.

Three limitations remain. First, the explanation for why bidders jump rests on theoretical screening and correlations rather than direct identification. Second, the price result applies to jumps induced by auction duration; it does not reveal what would happen if jumps were banned or the auction format changed. Third, the data cover auctions held under the 2015–2018 random-close regime, so the findings may not extend to the post-reform period.[19]

These limitations suggest three directions for future research. Exogenous changes in bidding rules or information disclosure could separate the effects of jumps from those of incremental bidding. A structural model that incorporates the random close, heterogeneous costs, and uncertainty about bid credibility could distinguish among mechanisms and evaluate alternative auction rules. Finally, data from the post-reform period could show whether the results hold under a different ending procedure.

[19] After the sample period, Decree 10.024/2019 replaced the 30-minute random-close protocol with open and open–closed bidding modes, based respectively on automatic extensions and a shorter random period followed by a final sealed bid (Brazil, 2019).

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A Data and Measurement

This appendix exhibits supporting material for the sample and measurement choices of Section 3: the sectoral composition of the analysis sample and the classification of non-credible large jump bids.

A.1 Product Composition of the Analysis Sample

Table A.1 reports how the analysis sample distributes across the top product groups of the federal procurement catalogs introduced in Section 3.1.

Table A.1: Top 20 Most Frequent Product Groups

Product group	Auctions	Bids per auction	Mean participants	Median total ref. value (R$)	Jump %
Medical, dental, and veterinary equipment	380,589	21.7	6.0	3,952	17.7
Subsistence	292,189	39.1	6.9	9,245	10.6
Office supplies and stationery	176,928	29.5	8.8	1,409	14.0
Laboratory instruments and equipment	112,602	33.1	6.4	1,393	10.9
Electrical and electronic equipment components	101,019	37.3	7.9	1,449	12.5
IT equipment, parts, and ICT supplies	89,987	47.1	11.6	6,500	10.2
Vehicle components	89,740	42.3	7.6	2,560	11.1
Pipes, tubes, hoses, and fittings	79,048	30.3	6.7	753	13.1
Hand tools	75,398	48.2	7.2	801	8.5
Paints, sealants, and adhesives	70,850	43.2	9.1	2,449	10.5
Food preparation and serving equipment	68,573	48.9	8.9	3,380	8.2
Hardware and abrasives	67,409	33.4	7.2	975	13.9
Books, maps, and other publications	62,598	21.6	5.8	520	11.3
Chemical substances and products	54,941	29.8	5.9	1,280	12.5
Electrical conductors and power distribution equipment	51,490	45.5	10.6	3,477	9.2
Containers and packaging	49,977	34.6	7.6	3,500	11.6
Firefighting, rescue, and safety equipment	47,224	33.8	7.4	3,024	12.0
Cleaning equipment and materials	46,812	36.0	9.2	3,790	12.1
Maintenance and repair of metal products, machinery, and equipment	44,603	40.1	7.2	13,658	12.0
Construction materials	43,085	38.1	6.7	9,247	9.1
Other	806,611	42.6	8.1	4,932	9.6
Total	2,811,673	36.7	7.6	3,333	11.1

Note: The 20 most frequent product groups, defined by official CATMAT (goods) and CATSER (services) codes; 3 auctions with no official code are excluded. Bids per auction and mean participants are auction-level means. Jump % is the share of open-phase bids classified as jumps under the headline definition.

A.2 Credibility Screen and Classification of Non-Credible Large Jumps

This subsection applies the canonical classifier in Definition 1 to large jump bids and then classifies the flagged bids by likely source.

Step 1 (credibility). A large jump satisfies $d_{ia} > 0.05$ on the credible standing path.

Step 2 (classification). Let p_a denote the contracted price, m_a the median across bidders of each bidder's best competitive bid, and q_a the procured item quantity. Let b_{ia}^{-} be the bidder's previous competitive bid, using their initial proposal for the first competitive bid and the nominal standing bid s_t if no proposal is available. A transformed amount x is *close* when $x < b_{ia}^{-}$ and it is at least half of b_{ia}^{-}, within 25% of s_t or p_a, or within 75% of m_a. Let w_a and n_a denote the recorded winning bid and negotiated value. The rules in Table A.2 are applied in ascending priority order; each bid receives the first category it satisfies.

Table A.2: Classification of non-credible large jump bids

Category	Transformation or condition	Interpretation
1. Unit/total price confusion	First competitive bid with $q_a > 1$: $b_{ia}q_a$ is close for lot-total pricing, or b_{ia}/q_a is close for per-unit pricing.	Unit price and lot total interchanged.
2. Withdrawal	$100b_{ia} \leq \min\{s_t, b_{ia}^{-}, m_a, w_a, n_a\}$, omitting n_a when unavailable.	Even a 100-fold correction remains below every benchmark; withdrawal.
3. Decimal-place error	$b_{ia}10^k$ is close for some $k \in \{1, \ldots, 5\}$; also $b_{ia} = w_a < n_a$ when n_a is observed.	Misplaced decimal or winning amount corrected upward by auctioneer.
4. Leading digit substitution	For $b_{ia} \geq 1$, replacing its leading digit with a different $d \in \{1, \ldots, 9\}$ produces a close value.	First digit mistyped.
5. Omitted leading digit	For $b_{ia} \geq 1$, prepending $d \in \{1, \ldots, 9\}$ produces a close value.	First digit omitted.
6. Follow-on response	$s_t < 0.75p_a$, $s_t < 0.75m_a$, and $b_{ia} \geq 0.50s_t$.	Rational response to a corrupted standing price.
7. Unexplained	None of the preceding rules is satisfied.	No tested transformation or condition fits.

Note: Symbols and the definition of "close" are given in the text above.

B The Landscape of Jump Bidding

This appendix reports three exercises for Fact 3 in Section 4.2. Table B.1 reports the full Machado–Santos Silva coefficients across six quantiles and three specifications. Table B.2 compares within-auction phase differences under alternative normalizations of the capped decrement. Finally, Table B.3 estimates phase differences in the probability that a decrement exceeds five fixed pooled thresholds without imposing the MM-QR location–scale structure.

Table B.1: Conditional phase differences across the distribution of decrement size

	(1) Auction FE only		(2) + Standing bid		(3) + Full controls	
	Initial	Alert	Initial	Alert	Initial	Alert
τ = 0.25	-0.181***	-0.119***	-0.237***	-0.157***	-0.195***	-0.128***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
τ = 0.50	-0.077***	-0.061***	-0.217***	-0.157***	-0.197***	-0.142***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
τ = 0.75	0.171***	0.077***	-0.171***	-0.157***	-0.203***	-0.172***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
τ = 0.90	0.329***	0.165***	-0.142***	-0.156***	-0.207***	-0.191***
	(0.004)	(0.002)	(0.004)	(0.002)	(0.004)	(0.003)
τ = 0.95	0.453***	0.234***	-0.119***	-0.156***	-0.209***	-0.207***
	(0.004)	(0.003)	(0.004)	(0.003)	(0.005)	(0.003)
τ = 0.99	0.842***	0.450***	-0.044***	-0.155***	-0.219***	-0.257***
	(0.007)	(0.004)	(0.007)	(0.004)	(0.007)	(0.005)

Note: Dep. variable: log capped reference-normalized decrement on the credible standing path. Coefficients are log-point differences from the random phase, estimated by Machado–Santos Silva method-of-moments quantile regression. Column (1): phase only; (2) adds standing bid/reference value; (3) adds active bidders, bid order, and time since last bid. All columns include auction fixed effects. Quantiles within a column share a common location–scale fit, so rows are not independent and $\tau = 0.99$ is an extrapolation. Standard errors are one-way clustered by auction. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

The alternative-normalization exercise uses the capped decrement $s_{ia}^{\text{cap}} - b_{ia}$ on the credible standing path, where $s_{ia}^{\text{cap}} = \min\{s_t^*, v_a\}$. The capped discount is $(s_{ia}^{\text{cap}} - b_{ia})/s_{ia}^{\text{cap}}$. The capped auction-median ratio is $(s_{ia}^{\text{cap}} - b_{ia})/\widetilde{\Delta}_a^{\text{cap}}$, where $\widetilde{\Delta}_a^{\text{cap}}$ is the auction-level median positive capped decrement. The regressions use the logarithm of each measure and include bids for which both measures are positive. These are measures of decrement size rather than alternative definitions of a jump bid.

Table B.2: Phase differences in decrement size under alternative normalizations

	Panel A: Log capped discount			Panel B: Log capped median ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
Initial phase	-0.348***	-0.185***	-0.166***	0.005	-0.202***	-0.199***
	(0.022)	(0.025)	(0.025)	(0.022)	(0.025)	(0.025)
Alert phase	-0.256***	-0.145***	-0.131***	-0.015	-0.156***	-0.150***
	(0.018)	(0.017)	(0.015)	(0.018)	(0.017)	(0.015)
Standing bid / ref.		✓	✓		✓	✓
Full controls			✓			✓
Observations	80,261,889	80,261,889	80,261,889	80,261,889	80,261,889	80,261,889
R^2	0.503	0.504	0.504	0.162	0.165	0.166

Note: Dep. variable: log capped discount (Panel A) and log capped auction-median ratio (Panel B), both defined in the text above. Columns (1) and (4) include phase dummies only; (2) and (5) add standing bid/reference value; (3) and (6) add active bidders, bid order, and time since last bid. All columns include auction fixed effects and use the random phase as the reference. Standard errors are two-way clustered by auction and supplier. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table B.3: Phase differences in the probability of exceeding decrement thresholds

	(1)	(2)	(3)
$\tau = 0.25$ *(threshold* $q_{25} = -8.634$*)*			
Initial phase	-2.06***	-2.43***	-2.28***
	(0.25)	(0.29)	(0.30)
Alert phase	-1.46***	-1.71***	-1.60***
	(0.23)	(0.24)	(0.20)
$\tau = 0.75$ *(threshold* $q_{75} = -5.502$*)*			
Initial phase	1.33***	-2.92***	-3.49***
	(0.40)	(0.43)	(0.45)
Alert phase	0.81***	-2.09***	-2.42***
	(0.26)	(0.24)	(0.24)
$\tau = 0.90$ *(threshold* $q_{90} = -4.132$*)*			
Initial phase	3.41***	-1.03***	-1.02***
	(0.30)	(0.33)	(0.32)
Alert phase	2.02***	-1.01***	-0.92***
	(0.19)	(0.16)	(0.15)
$\tau = 0.95$ *(threshold* $q_{95} = -3.324$*)*			
Initial phase	3.15***	-0.57**	-0.17
	(0.23)	(0.24)	(0.23)
Alert phase	1.73***	-0.81***	-0.47***
	(0.14)	(0.10)	(0.10)
$\tau = 0.99$ *(threshold* $q_{99} = -1.926$*)*			
Initial phase	1.09***	-0.35***	-0.05
	(0.10)	(0.09)	(0.08)
Alert phase	0.47***	-0.51***	-0.29***
	(0.05)	(0.04)	(0.03)
Standing bid / ref.		✓	✓
Full controls			✓
Observations	80,487,725	80,487,725	80,487,725

Note: The outcome is $\mathbf{1}\{\log d_{ia} > q_\tau\}$, where q_τ is the pooled sample quantile of the log capped decrement at the stated τ. Coefficients are percentage-point differences from the random phase. Column (1): phase only; (2) adds standing bid/reference value; (3) adds active bidders, bid order, and time since last bid. All columns include auction fixed effects. Standard errors are two-way clustered by auction and supplier. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

C Candidate Mechanisms

This appendix reports two supporting exercises for the mechanism analysis: competitor responses conditional on the post-bid auction state and relative bid margins around the winning-bid threshold.

Table C.1 conditions the pre-random response regressions on the standing price immediately after the focal bid. This price is mechanically affected by the focal bid. The estimates are therefore conditional descriptive comparisons.

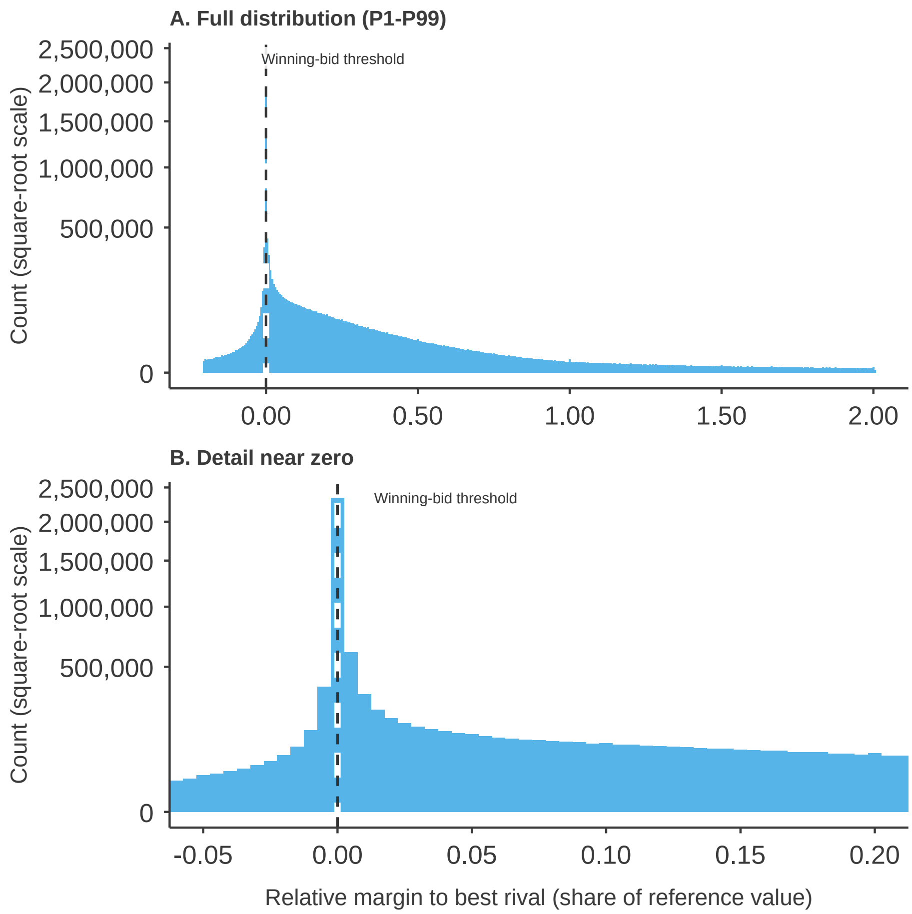
Table C.1: Pre-random competitor responses conditional on the post-bid state

	Time to next competitor bid (s)		Competitor bids within 60 s		Any competitor exit within 60 s	
	FE only (1)	+ controls (2)	FE only (3)	+ controls (4)	FE only (5)	+ controls (6)
Panel A. Large-jump indicator						
Large jump	-11.17***	-13.89***	0.0006	0.0798***	0.0198***	0.0554***
	(1.58)	(1.71)	(0.0050)	(0.0048)	(0.0012)	(0.0010)
Observations	3,282,300	3,282,300	3,334,732	3,334,732	3,334,732	3,334,732
R^2	0.371	0.372	0.647	0.651	0.367	0.389
Panel B. Continuous jump size						
Log capped decrement	-8.06***	-10.16***	0.0055*	0.0609***	0.0145***	0.0396***
	(0.93)	(1.04)	(0.0030)	(0.0031)	(0.0007)	(0.0006)
Observations	3,282,300	3,282,300	3,334,732	3,334,732	3,334,732	3,334,732
R^2	0.371	0.372	0.647	0.651	0.368	0.390

Note: The sample contains Initial- and Alert-phase jump bids with at least one active competitor, excluding bids by the standing-bid holder. Panel A compares large jumps ($d_{ia} > 0.05$) with other jumps; Panel B uses the log capped reference-normalized decrement. Odd columns include auction fixed effects only; even columns add standing bid/reference value, time since the previous bid, and the post-bid standing price over the reference value. Standard errors are two-way clustered by auction and supplier. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Figure C.1 reports margins around the winning-bid threshold. The relative-margin diagnostic is adapted from Chassang et al. (2022), who study Japanese procurement auctions. For the winner (negative values), the margin is the winning bid minus the runner-up bid, normalized by the reference value. For each non-winner (positive values), it is the bidder's best bid minus the winning bid. Their concentration near zero is consistent with close competition but does not rule out coordination.

Figure C.1: Relative bid margins around the winning-bid threshold



Note: Each observation is a bidder–auction pair, in auctions with at least two active bidders. The distribution is trimmed at P_1 and P_{99}.

D The Effect of Jump Bidding on Prices

This appendix reports additional checks and diagnostics that bear directly on the price analysis: sample composition and OLS sensitivity to the random-phase-bid restriction, IV diagnostics for share-based treatments, the selected hidden-jump comparison across non-credibility thresholds, and CHR sensitivity ranges under different direct-effect calibrations.

Table D.1 compares the auctions included by the requirement of at least one random-phase bid with those excluded by it.

Table D.1: Auction characteristics by Section 6 sample inclusion

Variable	Excluded No RP bid	Included At least one RP bid	Standardized difference
N auctions	366,172	2,445,504	
Reference value (R$)	18,391 (31)	47,972 (44)	-0.003
Participants	4.80 (4.00)	8.06 (7.00)	-0.717
Negotiated ratio	0.7901 (0.9055)	0.6589 (0.6860)	0.517
Winning ratio (P1–P99 winsorized mean)	0.8227 (0.9151)	0.6745 (0.6877)	0.506
Jump share	0.2394 (0.0000)	0.1877 (0.1111)	0.184
Number of jump bids	1.25 (0.00)	4.51 (3.00)	-0.690

Note: Cells report means, with medians in parentheses. Included auctions have at least one random-phase (RP) bid; excluded auctions have none. The negotiated ratio is the contracted price over the reference value; the winning ratio uses the pre-negotiation winning bid and may exceed one. Only the winning ratio is winsorized (pooled P1–P99), and only for its mean and standardized difference. The standardized difference is $(\bar{x}_E - \bar{x}_I)/\sqrt{(s_E^2 + s_I^2)/2}$. Inclusion depends on realized bidding, so the table describes the sample rather than testing balance.

Table D.2 removes the random-phase-bid requirement. The negative OLS association remains close to the headline estimate.

Table D.2: OLS robustness to including auctions without random-phase bids

	Jump bid measure	
	Jump count	Total jump depth
Coefficient	-0.0114***	-0.0354***
	(0.0007)	(0.0062)
Controls	✓	✓
Observations	2,811,488	2,811,488
R^2	0.311	0.259

Note: Dep. variable: contracted price / reference value. The sample drops the requirement of at least one random-phase bid, adding the 366,172 (13.0%) auctions that Table 17 excludes; 188 auctions fall out for lacking an official product-group code or forming singleton fixed-effect cells. Treatments, controls, and fixed effects match Table 17. Standard errors are two-way clustered by product group and winning firm. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table D.3 reports first stages and IV estimates for the share-based jump measures. Because duration changes both the numerator and denominator, the estimates are diagnostics rather than causal effects of a greater propensity to jump.

Table D.3: IV diagnostics for share-based jump measures

	Jump share	Large-jump share
Shared reduced form		
RP duration	-0.0044***	-0.0044***
→ contracted price	(0.0003)	(0.0003)
First stage		
RP duration	-0.0005***	-0.0003***
→ treatment	(0.0000)	(0.0000)
First-stage F	1228.0	954.7
Second stage		
2SLS (with controls)	8.2701***	15.6128***
	(0.7180)	(1.2592)
2SLS (FE only)	11.5267***	17.9078***
	(1.1631)	(1.5653)
Calibrated sensitivity		
CHR sensitivity range	[3.0892, 4.1029]	[5.8320, 7.7457]
Observations	2,445,301	2,445,301

Note: Dep. variable: contracted price / reference value. Instrument: random-phase duration. The treatments are the share of competitive bids that are jumps and the share that are large jumps. Duration moves both the numerator and denominator of each share, so the first stages are negative and the 2SLS ratios are diagnostics rather than causal effects. Controls and fixed effects match Table 18; "FE only" keeps only fixed effects. Standard errors are two-way clustered by product group and winning firm. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table D.4 repeats the selected hidden-jump exercise of Section 6.4 at 10%, 25%, and 50% non-credibility gap thresholds.

Table D.4: Selected hidden-jump comparison across non-credibility thresholds

Gap threshold	10%	25%	50%
Panel A: Jump count			
Jump count (IV)	-0.0017***	-0.0015***	-0.0014***
	(0.0002)	(0.0003)	(0.0005)
Observations	25,569	15,845	5,938
Panel B: Total jump depth			
Total jump depth (IV)	-0.0132***	-0.0105***	-0.0096**
	(0.0022)	(0.0024)	(0.0041)
Observations	25,569	15,845	5,938

Note: Dep. variable: contracted price / reference value. Instrument: random-phase duration. Treatment: jump count (Panel A) and total jump depth (Panel B). At threshold $g \in \{0.10, 0.25, 0.50\}$, the pre-random standing bid s_{a,t_2} is non-credible when its bidder is not the awarded winner, $s_{a,t_2} < w_a$, and $(w_a - s_{a,t_2})/w_a > g$, where w_a is the recorded winning bid. Each column also requires at least one random-phase jump; the samples are nested in g. Controls and fixed effects match Table 18, where the baseline estimates are -0.0425 and -0.8820. Standard errors are two-way clustered by product group and winning firm. $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$.

Table D.5 reports CHR sensitivity ranges under direct-effect calibrations estimated within strata of the pre-random auction state.

Table D.5: CHR sensitivity ranges under state-dependent direct-effect calibrations

Panel A: Stratum-specific placebo estimates			
Stratum	N	$\hat{\gamma}$	SE
Active ≤ 2 (low)	411,337	-0.0021	0.0001
Active 3–4 (mid)	103,719	-0.0033	0.0002
Active ≥ 5 (high)	58,305	-0.0022	0.0002
Standing bid tercile 1 (low)	191,120	-0.0018	0.0001
Standing bid tercile 2 (mid)	187,986	-0.0020	0.0001
Standing bid tercile 3 (high)	194,255	-0.0005	0.0000

Panel B: Baseline vs. state-dependent CHR sensitivity ranges			
Treatment	Baseline CHR	State-dependent CHR	Sign stable?
Jump count	[-0.0211, -0.0159]	[-0.0167, -0.0058]	Yes
Total jump depth	[-0.4376, -0.3295]	[-0.3476, -0.1214]	Yes

Note: Panel A reports the reduced-form effect $\hat{\gamma}$ of random-phase duration on contracted price / reference value, estimated within zero-jump auctions by stratum. Competition strata use active bidders at t_2 (at most 2, 3–4, at least 5); standing-bid strata are global terciles of the standing bid at t_2 over the reference value within zero-jump auctions. Panel B compares the headline CHR ranges with ranges centered on the most negative stratum estimate (active bidders 3–4) and extending three standard errors each way. Controls, fixed effects, and clustering match Table 18. Applying these ranges to jump-active auctions requires the calibration to transport across strata.