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Internal Economies of Scale in Small Firms: Evidence from Set-Aside Programs in Random-Ending Public Procurement Auctions[1]

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Abstract

This study investigates the presence of internal economies of scale among small firms participating in Brazilian government procurement auctions. The analysis focuses on paired set-aside auctions with random ending times, which allocate procurement volumes between a non-exclusive auction and an exclusive auction for small firms. Using multiple Regression Discontinuity Designs (RDDs), the study examines how firms' bidding behavior in the second auction to end is influenced by their outcome in the first auction. The methodology takes advantage of the randomized nature of auction endings to isolate causal effects and compare changes in normalized bids between winning and losing firms. The results reveal that firms bid more aggressively after winning the first auction, indicating a decrease in average costs associated with larger expected production volumes. These findings demonstrate the existence of internal economies of scale in small firms, providing insights for the design of more efficient auction mechanisms. By considering internal economies of scale, policymakers can improve procurement strategies, potentially achieving significant government cost savings.

Keywords

Procurement Auctions, Set-Asides, Economies of Scale, Regression Discontinuity Design.

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1 Introduction

Public procurement auctions are a common tool used by governments throughout the world to acquire goods and services from private firms. Some countries' laws mandate that all government procurements should be done through competitive methods, such as auctions, and in many cases, on-line platforms are opted to conduct procurement operations.

This thesis analyzes evidence from 4496 Brazilian government procurement auctions conducted through a system called ComprasNet, from 2015 to 2018. ComprasNet[1] was a public system of procurement auctions used by federal agencies on the buyers' side and by a variety of firms on the sellers' side. Szerman (2012) says procurement operations made with ComprasNet amounted to R$27 billion in 2010, which represents 0.7% of Brazillian GDP and 46% of all procurement volume on that year, showing ComprasNet operations' relevance on government spending. According to the official website[2], the first three quarters of 2024 saw R$153 billion in approved purchases — of which R$41 billion were sold by small firms —, indicating this system is still very much relevant.

(BRASIL, 2014) mandates that, if a public procurement consists of divisible goods valued at more than R$80,000.00, then 25% of the total product volume procured must be obtained via a dedicated auc-

[1] The system is now called *Compras.gov.br* and its website can be found in ⟨https://www.gov.br/compras/pt-br⟩.

[2] Acessed on the 18th of Nov. 2024: ⟨https://www.gov.br/compras/pt-br⟩.

tion for small firms, with the remaining 75% procured through an auction encompassing both large and small firms.[3] Therefore, during the analyzed period, ComprasNet implemented a set-aside policy for divisible products, which included both an exclusive auction and a non-exclusive auction. A pair of exclusive and non-exclusive auctions begin simultaneously but do not necessarily end at the same time. The ending time of each auction follows a uniform distribution, where the random variable T representing the ending time is uniformly distributed as $T \sim U[0, 1800]$. Thus, each pair consists of a first auction, defined as the one with the smallest T value, and a second auction, defined as the one with the largest T value.

This study explores the same-starting-time set-aside feature and the random ending time feature to evaluate whether small firms experience internal economies of scale. Using multiple Regression Discontinuity Designs, it examines bidding behaviors across different scenarios. In particular, the study explores how small firms' bidding behavior changes in second auctions depending on whether they won or lost the first auction. By analyzing firm behavior when bidding for the entire procurement volume compared to a fraction of it, this study highlights the presence of internal economies of scale among small firms participating in Brazilian government procurement auctions. The findings suggest a promising path for further investigation, with the potential to achieve relevant government budget savings through the adoption of more efficient auction designs.

The remainder of this thesis is organized as follows: Chapter 2

[3] The first federal law to make set-asides mandatory was passed in 2007.

reviews the relevant literature, including topics such as bid subsidy programs, set-aside programs, and internal economies of scale. Chapter 3 introduces the dataset, providing key descriptive statistics for various sample aggregations. The methodology is detailed in Chapter 4, which explains the application of the Regression Discontinuity Design (RDD) to address the research questions. Chapter 5 presents the main findings alongside robustness checks to ensure the internal validity of the results. Chapter 6 concludes the thesis by summarizing the findings, discussing their significance for the literature and auction design, and addressing limitations and opportunities for future research. Lastly, Appendix A examines sector-specific data but finds the results unreliable due to limited observations.

2 Literature Review

Bid preference programs typically take one of two formats: either a separate auction is held exclusively for favored firms, or favored firms compete with non-favored firms in the same auction but receive a 'discount' on their bids. In the latter case, if a favored firm bids X, its bid is considered as $(1-t)X$ in the bidding pool — where $t \in (0,1)$ — and, if the favored firm wins the auction, it still receives X as payment. The first format is referred as a set-aside program and the second as a bid subsidy program. Section 2.1 and Section 2.2 offer a brief overview of literature on both types.

Given this thesis' focus on investigating economies of scale in small firms' cost structures, Section 2.3 delves into literature examining economies of scale and firm cost structures using auction data.

2.1 Set-Aside Programs

There is an extensive literature on set-aside programs and whether they raise or decrease procurement costs, with evidence showing both effects. Denes (1997) shows that, as long as the pool of bidders is not reduced, set-aside policies in dredging contract auctions don't increase contract prices, and could even decrease prices. Tkachenko et al. (2023) finds similar results with more recent data on Russian granulated sugar e-auctions. Lastly, with a broader dataset on Russian set-aside policies, Kashin et al. (2019) also finds positive results concerning the reduction of contract prices, but highlights that contracting authorities preferred non-set-aside auctions, suggesting the existence of risks not included on the final price, such as performance uncertainty and other problems of information asymmetry that arise when procuring small firms.

On the other hand, Athey et al. (2013) shows, with U.S. Timber Auction data, that restricting entrance of bigger firms through set-aside Programs leads to an increase in participation of small firms, but result in higher contract prices. The study develops a model that suggests, through counterfactual estimations, that subsidizing small firms' bids could lead to an increase in competition without as much efficiency loss as in set-aside Programs.

Besides giving an extensive overview on ComprasNet characteristics and nuances, two key findings should be highlighted from Szerman (2012) that are relevant to this thesis. First, the study rationalizes the late-bidding behavior observed in random-ending auctions, demonstrating that sniping is not prevented by random endings and suggesting that final prices could be lower with a more efficient auction mechanism. Second, using a fuzzy Regression Discontinuity Design (RDD) approach, it reveals that the set-aside program increased the number of bidders but did not affect the final contract prices, among other outcomes.

2.2 Bid Subsidy Programs

Bid subsidy programs are also very popular within auction literature. As stated above, Athey et al. (2013) suggest that bid subsidy programs can be more beneficial in terms of revenue and efficiency than set-aside programs. This section analyzes what other studies have said about these programs.

McAfee & McMillan (1989) model bidding in procurement auctions under imperfect information and find, through simulations, that governments can reduce contract prices through an increase in competitiveness when implementing such bid preference programs. Moreover, the study finds that preferences should be given to firms that have a cost disadvantage and that the optimal preference program must take into account the number of advantageous and disadvantageous bidders. It's interesting to note that the study models interactions between the government and foreign and domestic firms, but the model can be easily translated to small and large firms and produce the same results.

Reis & Cabral (2015) analyze the impact of the September 2007 Brazilian federal law, which mandated that 25% of the total amount in auctions of divisible goods be set aside for small firms. Using a dataset of auctions from 2003 to 2012, the study finds that while there was no effect on prices, there was an increase in contract terminations. This increase is attributed to small firms, which tend to have contracts terminated due to poor performance more often than larger firms, according to the paper.

On the other hand, evidence presented by Marion (2007), suggests that bid subsidies increased procurement costs in California Highway projects. Krasnokutskaya et al. (2011) also examine California Highway procurements, focusing on the differences in optimal bid subsidy levels when participation is considered endogenous rather than exogenous.

2.3 Economies of Scale

Studies such as Gaver and Zimmerman (1977) and Luton and McAfee (1986) demonstrate early interest in analyzing economies of scale within auction settings and their relationship with bidding behaviors.

Gentry et al. (2022) study the cost synergy effects in simultaneous auctions. The paper develops a model and estimates its results using data from highway transportation procurement auctions. It finds relevant synergy effects, highlighting the importance of considering cost synergies when designing auctions for similar goods.

Kong (2021) uses data on adjacent oil and gas leases to disentangle the effects of synergy and affiliation in the sector. By separating these effects, the paper investigates the scale gains from winning neighboring leases. An RDD is employed to detect a discontinuity in the probability of winning a second auction based on the margin of victory in the first auction, indicating the presence of synergy between adjacent leases. Kong's main question is similar to this thesis' aim of evaluating whether small firms' marginal costs decrease with an increase in scales of production. Some similarities are also present on the estimation method; in both this thesis and Kong's study, firms that lost the first auction serve as a control group for firms that won the first auction.

The main differences between this thesis and Kong (2021) are that ComprasNet paired auctions are simultaneous, feature a random-ending mechanism, encompass several sectors, and have a set-aside policy. Due to the random-ending mechanism, identification is possible without using firms that bid similarly as a control group. Additionally, information about firms from more than just one sector can be inferred, although the synergy effects on costs can only be identified for small firms.

3 Data

This chapter provides a detailed description of the data. Section 3.1 outlines the data's origin and structure, offering insight into its key components. Section 3.2 presents relevant descriptive statistics through tables and figures, aiding in the understanding of auction mechanisms and supporting the assumptions discussed in later chapters.

3.1 Overview

Data was given to the author by his advisors and was previously obtained through the webscrapping of ComprasNet auction reports by the advisors and their research assistants. It encompasses a set of procurement auctions that had a random phase and were part of the set-aside policy implemented by ComprasNet. The first auction from the data had its random phase start on the 23rd of January of 2015 and the last auction had its random phase closing on the 29th of March of 2018.

This study uses five datasets: the first includes, for each auction, a description of the good, the quantity being auctioned, the final price, the winner firm, whether it's an exclusive auction or a non-exclusive auction and the reference value (the lowest initial firm proposal, which is believed by government agency to be the lowest market price); the second includes all bids from each auction, when it was done, by which firm; the third includes initial proposals made before the start of the auction, in each auction and by each participating firm; and the fourth includes all random-phase events, such as the random phase start and the random phase end; the fifth includes a description of each item and to which group of material it can be classified — for example, whether it's a chemical product or a construction tool.

A soft-match of the goods' description in the first dataset with the goods' description in the fifth dataset is made, attributing material categories to each auction. Then, auction sectors are proxied by aggregating the 63 material categories into 7 sectors, with few adjustments for misleading soft-matches. Finally, whether the sectors — proxied to control for firm similarities such as size, cost structure, business models and more — effectively fulfill their role is assessed by analyzing whether firms competing within the same categories are grouped in the same sectors. The analysis leads to the conclusion that proxied sectors sufficiently capture firm similarities.

To ensure the validity of the study, a series of restrictions were applied to the sample. Section 4.2 provides a detailed description of the final sample and the reasons behind each of these restrictions.

3.2 Descriptive Statistics

A series of tables and figures describe the data and validate methodological decisions, including sample restrictions and the use of RDDs to estimate treatment effects.

Table 3.1 presents descriptive statistics for the full sample — it includes all observations, without time window filtering. The first section of the table provides statistics across all sectors, while the second and third sections display statistics specifically for the Civil Construction Machinery and Equipment (MCC) sector and the IT, Electrical, and Office Materials (MIE) sector, respectively.

The median of normalized bids exceed the mean across all sample groups, except for one, indicating a negatively skewed distribution of normalized bids, in which smaller normalized bids are more frequent. An interesting feature is that for sample aggregations of winning firms, the number of firms per auction is always one, as each auction has only a single winner. In the All Sectors data, winning firms (W | Agg) show higher median and mean normalized bids than winning firms (L | Agg), suggesting that winning firms generally bid more aggressively.

In non-exclusive auctions, winning firms (W | NE) have higher median and mean bids (16.93 and 12.38, respectively) than in exclusive auctions (W | E), where the median and mean bids are 16.37 and 10.35. This suggests that winning firms generally bid more aggressively in non-exclusive second auctions, with a notably lower standard deviation in non-exclusive auctions (28.32) compared to exclusive auctions (33.71). A similar bidding pattern is observed among losing firms. In non-exclusive auctions (L | NE), losing firms have a higher median bid (16.82) and mean bid (11.87) compared to exclusive auctions (L | E), with median and mean bids of 15.08 and 8.64, respectively.

Sector-specific data reveals mean and median bid patterns across auction types and firm situations that differ from those observed in sector-aggregate data, with losing firms (L — Agg) generally exhibiting higher mean and median bids than winning firms (W — Agg). Mean and median bids are particularly higher in the MIE sector compared to the MCC sector, suggesting more intense competition in MIE. However, this interpretation is challenged by the average number of firms per auction, which is higher in MCC (2.22) than in MIE (1.98).[1]

Table 3.2 provides descriptive statistics for the 12-second window sample used in RDD estimations in the following chapter. Its layout mirrors that of Table 3.1. Initially, the data included seven sectors, but filtering for the 12-second window significantly reduced observations, leaving sample sizes too small for meaningful statistical inference in most sectors. Consequently, only the MCC and MIE sectors were used. However, as shown in Appendix A, even these sectors can't yield conclusive analyses due to the limited number of observations. The table highlights the scarcity of bids, specially among winning firms.

For sector-aggregate data, winning firms (W | Agg) have higher median and mean normalized bids (20.11 and 16.09, respectively) than losing firms (L | Agg), with a median of 16.45 and a mean of 10.72. This indicates that winning firms tend to bid more aggressively than losing firms within the 12-second window, following the pattern observed in the complete sample. The standard deviation is comparable between the two groups, with winning firms at 25.93 and losing firms at 25.11, suggesting similar variability in normalized bids across both

[1] Any conclusions about sector competition levels based on descriptive statistics should be approached with caution, as these figures do not capture the complex dynamics of competition. However, they may offer some preliminary insights.

groups.

Table 3.1 – Descriptive statistics — Complete sample

Sample Group	Normalized Bids				Firms		Auctions
	Mean	Median	Std. Dev.	Total	per Auction	Total	Total
			All Sectors				
Agg | Agg	11.14	16.30	29.49	16505	1.94	317	321
W | Agg	12.19	16.67	30.98	7358	1.00	177	292
L | Agg	10.65	16.00	28.24	9147	1.41	193	236
W | E	10.35	16.37	33.71	3483	1.00	97	144
W | NE	12.38	16.93	28.32	3875	1.00	107	148
L | E	8.64	15.08	30.50	4302	1.39	103	115
L | NE	11.87	16.82	26.03	4845	1.42	111	121
			Civil Construction Machinery and Equipment				
Agg | Agg	2.29	7.33	25.29	7386	2.22	49	97
W | Agg	2.02	6.72	27.73	2922	1.00	32	92
L | Agg	2.42	7.73	23.56	4464	1.50	34	82
W | E	2.43	5.24	34.84	1588	1.00	24	52
W | NE	1.32	8.49	15.28	1334	1.00	19	40
L | E	2.31	4.56	29.13	2212	1.41	23	44
L | NE	4.04	10.86	15.74	2252	1.61	22	38
			IT, Electrical, and Office Materials				
Agg | Agg	12.97	15.79	28.68	3629	1.98	114	84
W | Agg	12.38	14.92	29.84	1627	1.00	53	71
L | Agg	13.32	16.50	27.69	2002	1.34	75	71
W | E	18.85	14.83	27.20	809	1.00	28	36
W | NE	8.36	15.01	32.26	818	1.00	32	35
L | E	17.39	12.85	23.49	838	1.24	40	37
L | NE	9.75	19.13	30.09	1164	1.44	44	34

Note: The first column indicates the sample grouping by firm situation: W (Winners), L (Losers), or Agg (both); and auction type: E (Exclusive), NE (Non-Exclusive), or Agg (both).

Table 3.2 – Descriptive statistics — 12-second window sample

Sample Group	Normalized Bids				Firms		Auctions
	Mean	Median	Std. Dev.	Total	per Auction	Total	Total
			All Sectors				
Agg | Agg	11.71	18.07	25.51	394	1.73	179	208
W | Agg	16.09	20.11	25.93	174	1.00	104	165
L | Agg	10.72	16.45	25.11	220	1.28	108	151
W | E	16.09	21.64	24.15	84	1.00	59	80
W | NE	14.53	18.68	27.54	90	1.00	59	85
L | E	9.29	15.66	21.45	107	1.24	58	75
L | NE	11.71	17.20	28.22	113	1.33	64	76
			Civil Construction Machinery and Equipment				
Agg | Agg	2.20	8.88	16.01	163	2.04	33	71
W | Agg	1.80	9.45	17.36	63	1.00	22	61
L | Agg	2.60	8.52	15.19	100	1.38	22	61
W | E	5.92	12.07	16.89	35	1.00	17	34
W | NE	0.71	6.18	17.67	28	1.00	11	27
L | E	2.96	8.94	15.21	52	1.27	16	33
L | NE	0.77	8.07	15.31	48	1.50	16	28
			IT, Electrical, and Office Materials				
Agg | Agg	12.40	15.26	24.60	86	1.58	55	50
W | Agg	16.70	17.53	22.78	36	1.00	26	33
L | Agg	11.71	13.62	25.93	50	1.24	37	37
W | E	20.90	24.27	22.32	19	1.00	15	17
W | NE	9.43	10.00	21.46	17	1.00	14	16
L | E	18.21	15.11	22.85	22	1.05	18	20
L | NE	10.80	12.44	28.48	28	1.47	22	17

Note: The first column indicates the sample grouping by firm situation: W (Winners), L (Losers), or Agg (both); and auction type: E (Exclusive), NE (Non-Exclusive), or Agg (both).

In sector-aggregate data, winning firms bid slightly more aggressively in exclusive auctions (W | E) — with mean and median normalized bids of 16.09 and 21.64, respectively — than in non-exclusive auctions (W | NE), where mean and median normalized bids are 14.53

and 18.68, respectively. This contrasts with the pattern observed in the complete sample. For losing firms, the trend shows higher mean and median bids in non-exclusive auctions (11.71 and 17.20) than in exclusive auctions (9.29 and 15.66). Thus, the pattern for losing firms remains consistent with that in the complete sample.

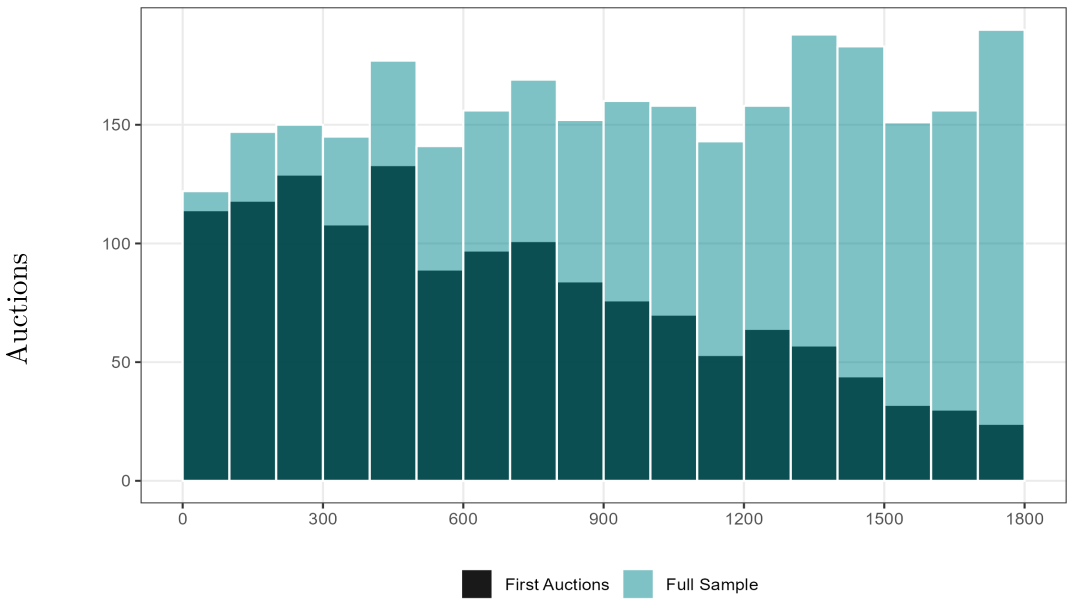
Finally, sector-specific data for the 12-second window sample follows the pattern observed for the complete sample in terms of mean, median, and firm participation. A notable exception is the cohort of losing firms in exclusive second auctions within the MIE sector, where the mean normalized bid exceeds the median, indicating a positively skewed distribution.

Figure 3.1 displays a histogram of auction ending times across the sample. The downward trend in the ending times of first auctions is expected by design, as first auctions are the shortest in a pair of auctions, while second auctions are the longest of the pair. An unexpected feature is the slightly smaller number of auctions ending within the first 100 seconds — the first bin. Since the sample consists only of auctions with bids placed during the random phase, it is possible that auctions with a short duration were removed due to a lack of bids in the random phase. While this cannot be precisely asserted, it is a possible reason for the lower frequency of auctions. Moreover, the continuity of the first auction ending times' distribution is addressed in Section 4.1, as this is a necessary assumption for the validity of the RDD. For now, it suffices to observe that the Full Sample's ending times follows a uniform distribution —— as expected by design ——

while the First Auctions' ending times follow a downward-sloping, continuous distribution.

Figure 3.2 shows the histogram of firm victories. As shown in the plot, most firms win a small amount of auctions — which corresponds to the first bin — or no auctions at all. Out of the 1132 firms in the sample, a small amount of firms wins a big amount of auctions: only 28 firms win more than 20 auctions and 8 firms win more than 50 auctions.

Figure 3.1 – Ending Time of Auctions



Ending Time (Seconds)

Figure 3.3 presents the histogram of reaction time, measured in seconds. We define reaction time as the time between one bid and the following bid in each auction, for each of the bids, except for the first one. The biggest reaction time is of 1480 seconds, but we exclude reaction times longer than 200 seconds from the graph for visual purposes, as they are rare occurrences. The average reaction time of 16 seconds[2] is portrayed in the graph. This number is important to justify a sample restriction made in Section 4.2.

Figure 3.4 displays the distribution of volume ratios between non-exclusive and exclusive auctions, defined as the ratio of goods auctioned in the non-exclusive auction (Q_{NE}) to those in the exclusive auction (Q_E). As mandated by (*Lei complementar nº 147, 2014*), this ratio should be 3, meaning the non-exclusive auction volume should be three times that of the exclusive auction. Yet, when government agencies set a total auction volume that is not divisible by four, this precise ratio cannot be achieved. Therefore, most paired auctions exhibit a volume ratio close to 3. Still, a small portion of auction pairs shows a volume ratio of around 9 (indicating that 90% of the total volume is allocated to the non-exclusive auction), and an even larger portion has a ratio of around 19, representing a 95% to 5% split.

[2] The average calculation includes reaction times bigger than 200 seconds

Figure 3.2 – Firm Victories

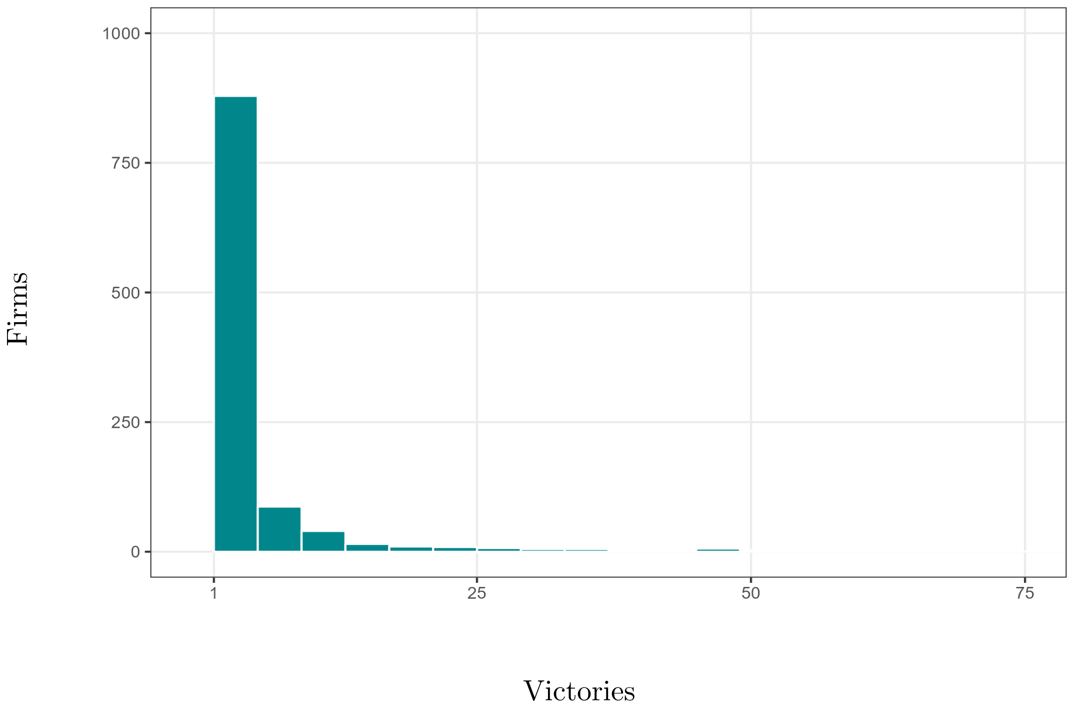
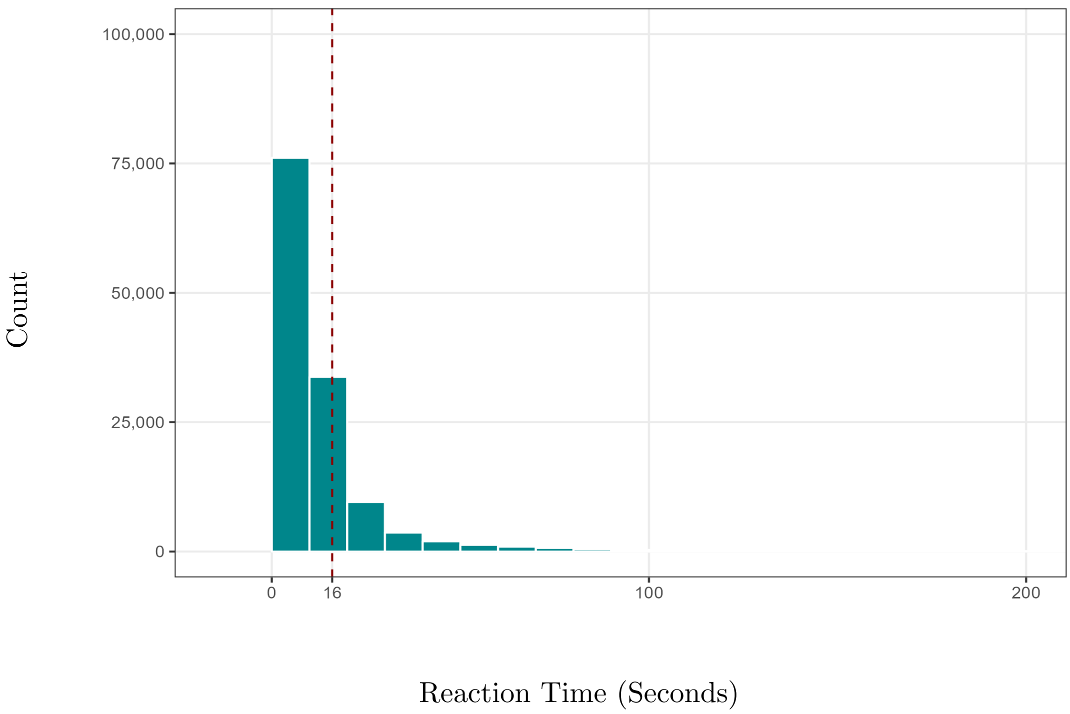


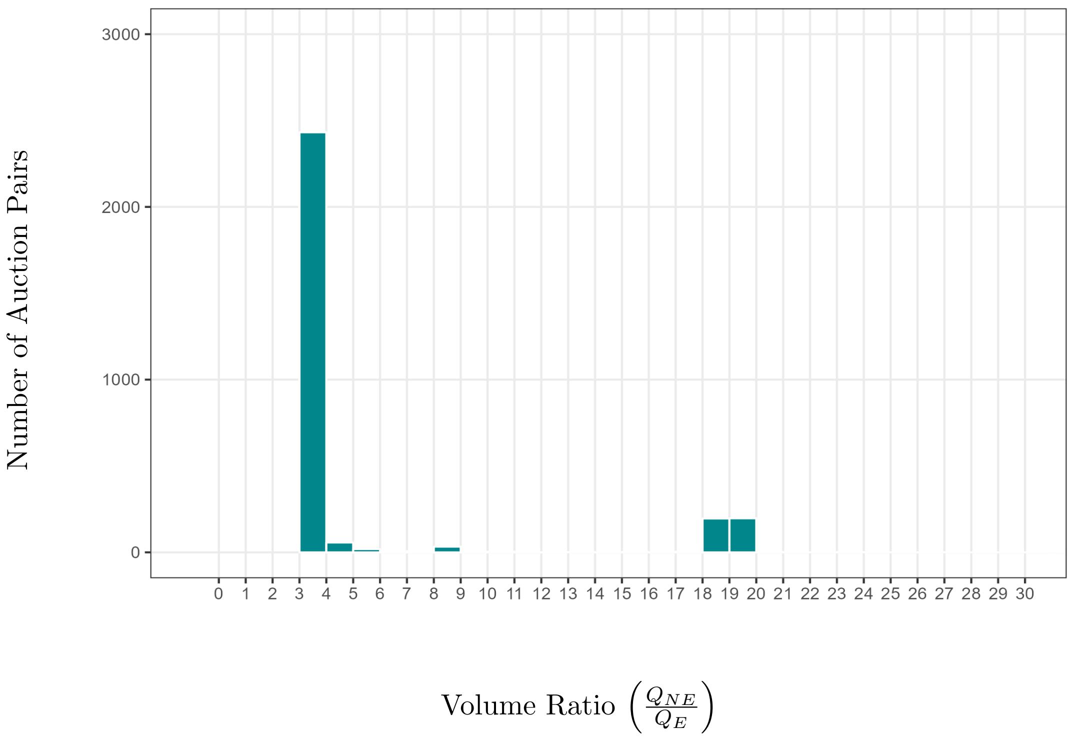
Figure 3.3 – Reaction Time Histogram



Although these deviations suggest non-compliance with auction guidelines, they do not compromise the identification of synergy effects. When a firm wins the first auction, its anticipated production volume increases. This change in expected volume allows the firm to adjust its belief, factoring in potential internal economies of scale.

Even so, this non-compliance does complicate a precise analysis of the impact of each additional percentage of volume on reducing average costs. If a firm wins a non-exclusive first auction, it may secure between 75% and 95% of the total auction volume rather than exactly 75%, making it challenging to assert the exact effect of the volume increase on marginal costs. Consequently, this study focuses on determining the existence and significance of the synergy effect rather than quantifying the reduction in average costs associated with each incremental volume percentage.

Figure 3.4 – Distribution of volume ratios of non-exclusive auctions over its exclusive pair



4 Methods

This chapter outlines the empirical strategy used in the study. Section 4.1 focuses on the application of Regression Discontinuity Designs to evaluate whether small firms experience internal economies of scale. Section 4.2 discusses sample restrictions imposed to guarantee a clean interpretation of the estimates.

4.1 Regression Discontinuity Designs

This thesis employs a Regression Discontinuity Design (RDD) to evaluate whether small firms experience internal economies of scale. Lee & Lemieux (2010) give a comprehensive "guide to practice" to implement RDDs in Economics, from which this study will base its methodological background.

To give a brief introduction, based on Lee & Lemieux (2010), an RDD describes a non-experimental data generating process and can be used to estimate causal effects in situations where treatment is assigned based on a running variable and a predetermined cutoff point in the running variable. In RDDs, units on either side of the cutoff point receive different treatments, and the discontinuity in outcomes at the cutoff is interpreted as the causal effect of the treatment. RDDs are particularly useful because when treatment is determined by an arbitrary cutoff, it creates a situation analogous to a randomized experiment near the cutoff. This interpretation of a locally randomized experiment is conditional on two assumptions: (1) units cannot precisely change their placement around the cutoff point; and (2) units just above and below the cutoff are nearly identical in all aspects, except for the treatment.

In the context of this study, the running variable for the RDD is defined as the difference between the running time of the second auction and the end time of the first auction. Specifically, let $R = t_S - T_F$ represent the running variable, where t_S is the current time of the second auction and T_F is the ending time of the first auction. The treatment is defined as the knowledge of the first auction's outcome. Consequently, the cutoff used to evaluate the discontinuity occurs at $R = 0$, when the first auction ends and firms in the second auction gain knowledge of the first auction's outcome. The dependent variable, affected by the treatment, is the normalized bid (NB). It is defined as the percentage decrease of the reference value (RV) that the bid (b) does, such that

$$NB = \frac{RV - b}{RV} \tag{4.1}$$

Therefore, bigger NBs indicate a more aggressive behavior from the bidder. The final component of the RDD is the sample window used for regression estimations. In line with the recommendations of Lee & Lemieux (2010), the RDD is estimated across different windows to show robustness. Due to the limited number of observations, windows smaller than a 12-second window are too narrow for reliable estimates. Therefore, RDDs are estimated for windows ranging from ± 12 to ± 20.

The primary objective of this study is to assess whether firms experience internal economies of scale by comparing the treatment effects on the normalized bids of a firm knowing it has won or lost the first auction. A difference in these effects would indicate that firms respond differently after learning the auction outcome. The analysis is further divided between exclusive and non-exclusive second auctions: when competing in exclusive second auctions, after the cutoff point, firms have won (or lost) at least 75% of the sales volume in the non-exclusive first auction; when competing in non-exclusive second auctions, after the cutoff point, they have won (or lost) at most 25% of the sales volume in the exclusive first auction. This distinction allows for a more precise examination of how firms adjust their bidding strategies depending on the auction format and the stakes involved.[1] However, inaccuracies in the ratio of auction volumes complicate interpreting the magnitude of synergies and their relation to the firm's cost structure. While this limitation does not affect the identification of an information effect on bidding, it undermines comparisons between the information effect on winners in exclusive and non-exclusive auctions, as asserted in Section 3.2. Additionally, firms winning exclusive auctions may differ significantly from those winning non-exclusive auctions. Consequently, this study will focus exclusively on determining the existence of these effects rather than quantifying the average cost reduction a firm experiences after winning an additional volume of goods.

Since the ending time of the first auction is random, firms cannot

[1] In terms of the model described in Equation 4.2, one could propose to compare $\beta^W_{0,E}$ and $\beta^W_{0,NE}$ to examine the impact of varying quantities on the cost scale.

strategically time their bids in the second auction to fall before or after the first auction's conclusion. This randomness ensures that firms cannot precisely manipulate their bid positions around the cutoff. Figure 3.1 illustrates the empirical distribution of ending times, confirming it follows a uniform distribution. The same figure also displays the empirical distribution of first auctions' ending times, showing a continuous distribution. Given that the Running Variable is based on the first auction's ending time, this continuity ensures that the Running Variable itself is continuous around the cutoff at $R = 0$. As outlined by Lee & Lemieux (2010), this condition is sufficient to prevent firms from manipulating their bids around the cutoff, thereby supporting Assumption (1).

In summary, each RDD will be defined by two key factors: the second auction type — either exclusive or non-exclusive; and the firm situation — the firm's status as a winner or loser of the first auction. Hence, a total of four regression discontinuities are estimated. The following equations outline the regressions estimated for winners (W) and losers (L):

$$NB_{i,\ell} = \alpha^h_{0,k} + \alpha^h_{1,k} R_\ell + \beta^h_{0,k} \mathbb{1}\{R_\ell > 0\} + \beta^h_{1,k} R_\ell \mathbb{1}\{R_\ell > 0\} + u_{i,\ell} \quad (4.2)$$

where k $\in$ {E, NE}, h $\in$ {W, L}, $NB_{i,\ell}$ is the normalized bid of the i-th firm in the ℓ-th second auction, R_ℓ is the running variable of auction pair ℓ and $\mathbb{1}\{R_\ell > 0\}$ is a binary variable that equals one when $R_\ell > 0$ and equals zero otherwise.

The key coefficients are $\beta_{0,k}^{W}$ and $\beta_{0,k}^{L}$, which indicate the discontinuity in the bidding behavior of winning and losing firms, respectively, on auction type k. Therefore, the effect of the information treatment on winners versus losers is assessed by comparing these coefficients within each auction type.

To compare the causal discontinuity in regressions of winning firms with that of losing firms, it is crucial to ensure that these firms are similar in all aspects, except for the fact of winning the first auction. Ideally, data on various firm characteristics would be available to verify a balanced baseline between winning and losing firms. However, since such data is unavailable, an alternative approach is required. Given the random nature of the auction's ending time, when competition is active, the winner is simply the last firm to place a lower bid, which occurs randomly, as the ending time follows a uniform distribution. If that is the case, it is reasonable to assume winning firms and losing firms are similar in all relevant aspects that explain their cost structure. On the other hand, if there is no competition near the end of the first auction, it could indicate that the winning firm differs from losing firms in other characteristics, such as being significantly more cost-efficient, to the point of outbidding all other firms before the end of the auction. Section 4.2 explains how this comparison is guaranteed through sample restrictions.

4.2 Sample Restrictions

To understand all subsequent sample restrictions, one must consider the study's objective: to measure the impact of winning an extra volume of production in the first auction on firms' bids in the second auction.

To observe a clear discontinuity in their behavior, firms must learn their outcome at the exact moment the first auction ends. If firms discover the outcome at different times, it becomes impossible to observe the desired discontinuity at a single cutoff point. One might suggest setting the cutoff at the time of the last bid — instead of the auction end —, but this would eliminate the randomness of the cutoff point, undermining the assumptions required for the RDD validity. And more importantly, firms may be uncertain of their win at the time of the last bid, as they believe other bids could still be placed in the remaining seconds. However, once the auction ends, all firms are certain of the random phase outcome. It is also essential that firms compete in both auctions until the end of the first auction, ensuring that their belief towards their situation is only updated when the first auction ends — i.e. at the cutoff point.

Besides the initial selection of bids that were exclusively made during the random phase, bids that were ignored by competitors are excluded — specifically, the lowest bid in an auction where at least five higher bids followed, so long as the bid was not made by the auction winner.[2] It is important not to remove all bids followed by five

[2] 0.07% of the remaining sample were excluded due to this restriction.

higher ones, since firms often compete for second place. Removing such bids could exclude winning bids or those that were not ignored in the competition for first place. The lowest bid should also not be removed simply because it was not made by the winning firm, as the overall winner is often determined outside the random-phase competition, typically during subsequent negotiation phases.

After removing ignored bids, non-competitive bids are excluded. These are defined as bids that do not lower the current winning bid — i.e. are bigger than the lowest current bid.[3] Such bids may arise from a lack of understanding of the auction mechanics, technical or manual errors, or competition for second place. Competing for second place can be rational, as firms with the lowest bid may sometimes fail to fulfill the contract, prompting the government to select the second-lowest bidder. Though less frequent, competition for third or lower positions can also occur for similar reasons. These bids are removed because they are not competing for the win. If only second-place competition is happening in an auction, the lowest bidder may already know they have won before the auction ends, making the the lowest bidder change its belief before the cutoff.

After non-competitive bids are removed, pairs of auctions with differing starting times are excluded. This restriction ensures that firms lack prior information about which auction will end first. As auctions' ending times are uniformly distributed, firms may adjust their expectations regarding each auction's ending time if one auction starts before the other. Additionally, auction pairs with identical ending times

[3] 15.15% of the remaining sample was excluded due to this restriction.

are removed to maintain the treatment effect in the second auction. If both auctions close simultaneously, firms cannot adjust their behavior in the second auction based on the outcome of the first, as both results are revealed at once.[4]

Following the removal of auctions with invalid starting or ending times, auctions where the last bid was placed sixteen or more seconds before the auction's end are removed, as this indicates no competition occurred in the final seconds and firms already gained information on the auction outcome.[5] Removing such auctions ensures that no firm knows the outcome before the cutoff point. The choice of a 16-second threshold is justified by the mean reaction time, shown in Figure 3.3.

Similarly, losing firms that did not compete until the end of the first auction should be excluded from the sample, as they do not serve as effective controls for winning firms. For a valid control group, losing firms must compete alongside winning firms until the auction's conclusion, ensuring that the only difference between them is whether their bid happened to be the standing bid at the random closing moment. To ensure this, losing firms that did not place a bid within the last 32 seconds — twice the average reaction time — of the first auction are removed from the sample.[6]

Finally, firms that did not participate in both auctions are excluded.[7] By design, firms that won the first auction and appear in

[4] The removal of auctions with either an invalid starting time or ending time cuts 40.98% of the remaining bid sample.

[5] Due to this restriction, 65.83% of the remaining bid sample was excluded.

[6] Applying this restriction resulted in the removal of 23.44% of the remaining bid sample, representing a removal of 35.58% of the remaining bids from losing firms.

[7] Due to this restriction, 6.12% of the remaining bid sample was excluded.

the regression participated in both auctions, but firms that did not win the first auction may have either lost or simply not participated. Small firms that only took part in the second auction may not be comparable to those that participated in both. For instance, a firm so small and inefficient that it cannot coordinate participation in two auctions would not be comparable to one capable of doing so.

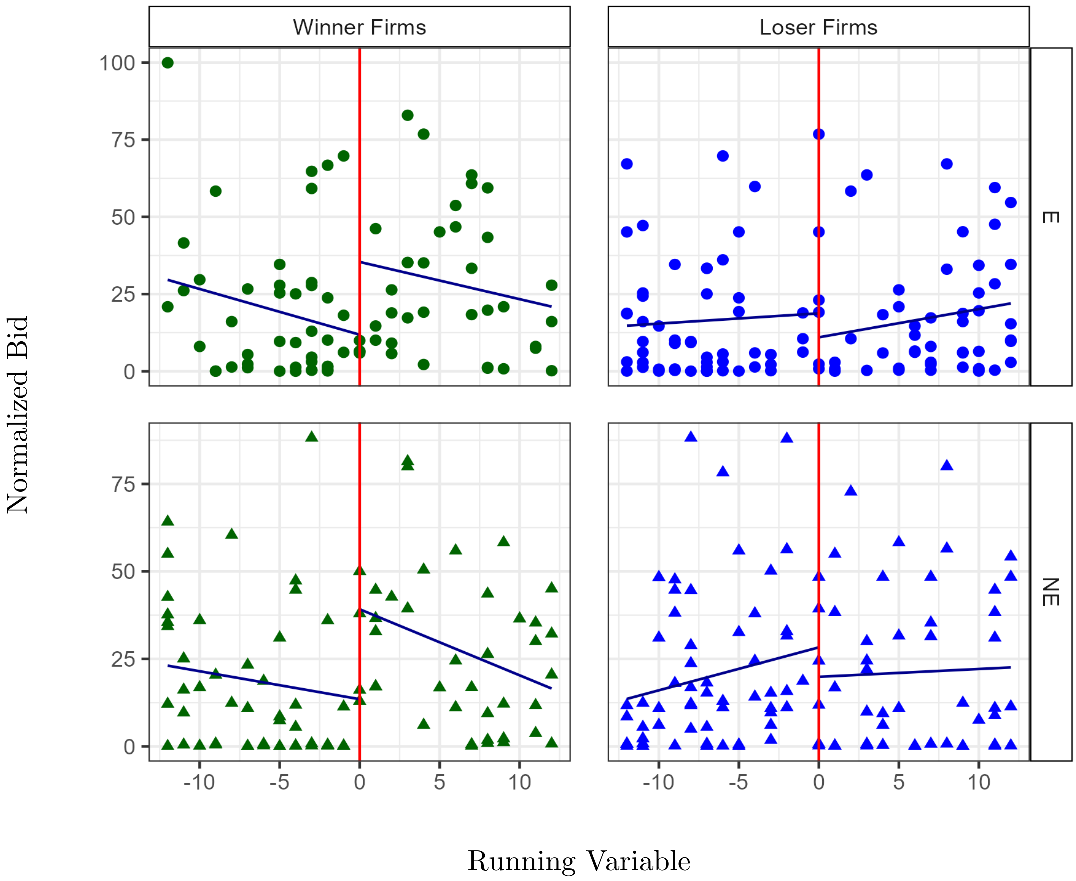
Once all restrictions are applied, it is reasonable to say Assumption (2) holds, as firms are uncertain of their outcomes in the first auction until it ends. This ensures that firms are similar in all respects around the cutoff, apart from the information gained at $R = 0$. The restrictions also ensure winning firms and losing firms within a same auction type are comparable, as it is fair to say they are similar in all aspects, except for the treatment.

5 Results

This chapter presents results for the RDDs described in the previous chapter, along with robustness checks to ensure the reliability of the findings. An attempt to examine sector heterogeneity is provided in Appendix A. As we will show in the Appendix, due to a lack of observations, results are not robust for sector RDDs.

The estimated RDD results are illustrated in Figure 5.1, where estimated lines are plotted alongside data points to highlight any discontinuities. Windows of 12 seconds are used, as smaller windows yield unreliable results due to the limited amount of observations.

Figure 5.1 – Visualization of the Regression Discontinuity Design



Clear discontinuities appear in the regressions for winning firms, indicating that these firms became more aggressive after learning of their winning outcome in the first auction. In contrast, no such discontinuity is observed in the regressions for losing firms, suggesting they did not increase their bid aggressiveness following the losing outcome. Assuming that winning and losing firms are similar in all relevant aspects, as argued in Section 4.2, this effect must come from the sole difference between them: the belief of producing a bigger goods volume than what is being auctioned in the second auction.

Table 5.1 presents the RDD coefficient estimates across four specifications. Columns (1) and (3) display the RDDs for winning firms, while columns (2) and (4) show those for losing firms. Additionally, columns (1) and (2) correspond to exclusive auctions' RDDs, indicating that the first auction was a non-exclusive auction. Thus, columns (3) and (4) correspond to non-exclusive auctions' RDDs, indicating that the first auction was an exclusive auction. The discontinuity estimates are represented by Δ Intercept.

As expected, both exclusive and non-exclusive winner RDD estimates ($\beta^W_{0,k}$) exhibit a statistically significant discontinuity, while the corresponding losing firms' estimates ($\beta^L_{0,k}$) are not statistically different from zero. Additionally, the estimates show that, on average, firms reduce their bids by approximately 23.6% [1] of the reference value after winning a non-exclusive first auction and by approximately 25.7%[2]

[1] With a 95% confidence level, this coefficient ranges from 4.5% to 42.6%. For that reason, relying solely on the point estimate may not be yield accurate estimates of the true effect. Nonetheless, even if the true effect is at the lower bound of 4.5%, the impact remains economically significant, given that it represents 4.5% in a scale of billions of R$.

[2] With a 95% confidence level, this coefficient ranges from 7.1% to 44.3%. As with the previous

Table 5.1 – Regression Discontinuity Designs

	(1)	(2)	(3)	(4)
Intercept ($\alpha^h_{0,k}$)	11.849*	18.756***	13.480*	28.295***
	(5.559)	(5.340)	(5.560)	(5.511)
Slope ($\alpha^h_{1,k}$)	-1.480	0.332	-0.799	1.228
	(0.962)	(0.685)	(0.743)	(0.761)
Δ Intercept ($\beta^h_{0,k}$)	23.556*	-7.761	25.710**	-8.420
	(9.572)	(8.935)	(9.356)	(8.579)
Δ Slope ($\beta^h_{1,k}$)	0.274	0.583	-1.090	-1.004
	(1.498)	(1.108)	(1.225)	(1.173)
Winner	X		X	
Exclusive	X	X		
Num.Obs.	82	104	87	108
R2	0.082	0.014	0.085	0.025
R2 Adj.	0.047	-0.015	0.052	-0.003
RMSE	22.14	19.28	20.63	21.83

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Window: [-12,12]

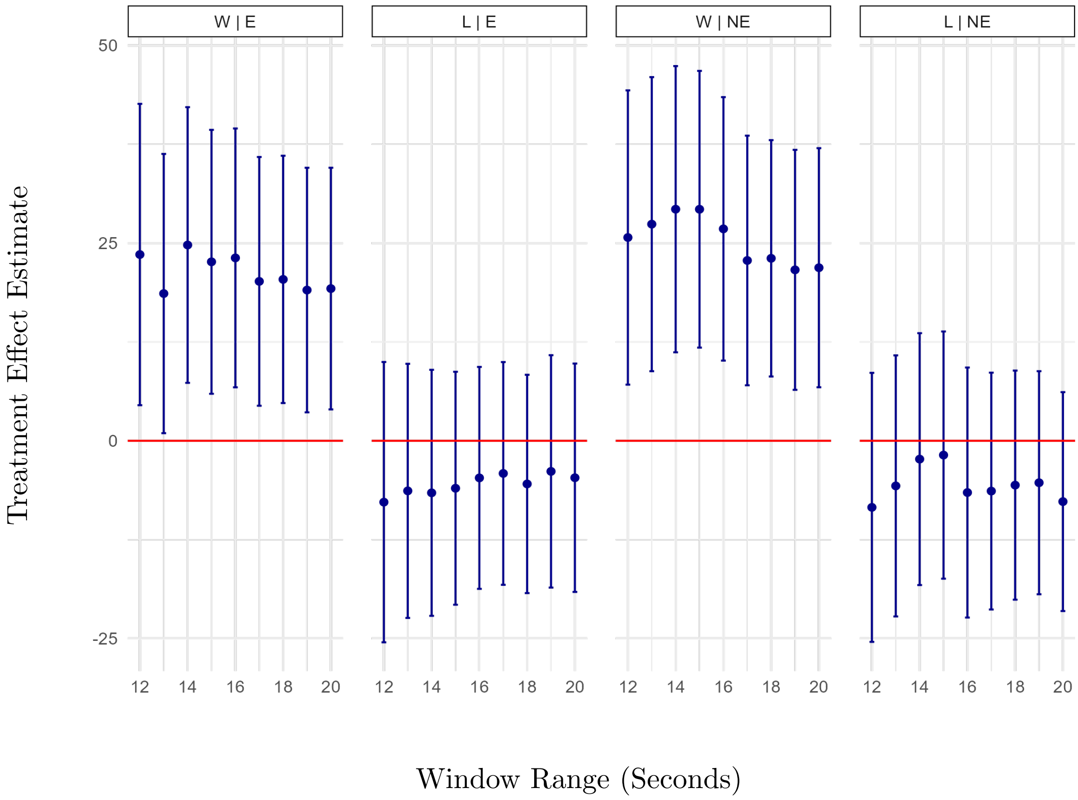
after winning an exclusive auction. These results are not only statistically significant but also of high economic relevance.

To assess robustness, Figure 5.2 illustrates how the $\beta^h_{0,k}$ estimates change with variations in the window width used for the corresponding RDD estimation. Columns labeled with W denote winner RDDs, while columns labeled with L represent loser RDDs. Similarly, E columns correspond to exclusive second auctions, and NE columns to non-exclusive second auctions.

As shown, the results remain robust across all windows. Both exclusive and non-exclusive winner discontinuities are statistically significant throughout, while exclusive and non-exclusive loser discontinuities consistently show no statistical difference from zero. Point

estimate, even a lower bound of 7.1% remains economically significant given the large scale of auction values involved.

Figure 5.2 – Estimates of treatment effects across a 12 to 20 seconds window range



estimates remain relatively close, showing only minor variations.

As a final robustness check, additional RDDs were estimated by aggregating exclusive and non-exclusive auctions, thus distinguishing only between winner and loser firms. This increases the sample size and allows the use of 10-second windows.

Table 5.2 presents the Δ Intercept estimates for both 12-second and 10-second windows. The results are specially interesting as they highlight the average information effect of the first auction's outcome on subsequent bidding strategies. With a 12-second window, the coefficient shows that, on average, firms reduce their bids by approximately 24.38% of the reference value after winning, whether in an exclusive or non-exclusive first auction. The result is coherent with previous findings, falling between the exclusive and non-exclusive RDD estimates.

For the 10-second window, the coefficient suggests an average bid reduction of around 19.72% of the reference value. Although lower, this effect remains economically significant, with a 95% confidence interval lower bound of approximately 5.24%.

Table 5.2 – RDD estimates aggregating Exclusive and Non-Exclusive auctions

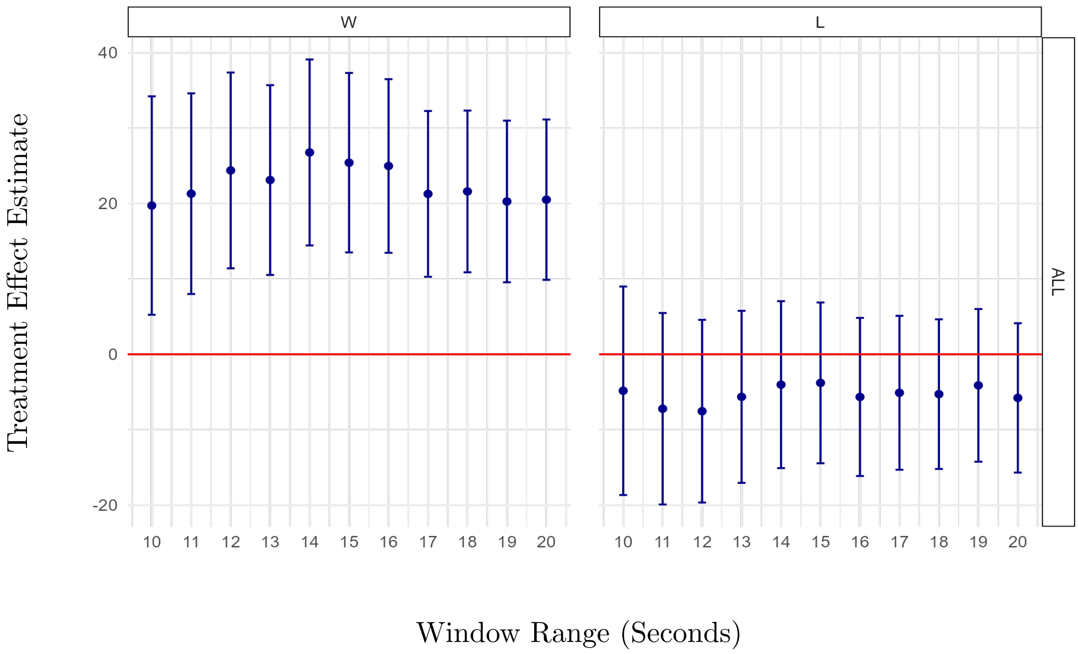
	(1)	(2)	(3)	(4)
Intercept (α_0^h)	13.014***	24.041***	17.402***	23.693***
	(3.843)	(3.832)	(4.212)	(4.277)
Slope (α_1^h)	-1.019+	0.827	0.332	0.720
	(0.573)	(0.510)	(0.802)	(0.695)
Δ Intercept (β_0^h)	24.378***	-7.550	19.720**	-4.839
	(6.574)	(6.145)	(7.323)	(7.001)
Δ Slope (β_1^h)	-0.570	-0.384	-1.839	-0.850
	(0.929)	(0.799)	(1.294)	(1.121)
Window	12s	12s	10s	10s
Winner	X		X	
Num.Obs.	169	212	140	167
R2	0.080	0.015	0.102	0.008
R2 Adj.	0.063	0.001	0.082	-0.010
RMSE	21.43	20.76	21.19	21.20

+ p < 0.1, * p < 0.05, *** p < 0.001

Figure 5.3 displays the estimated coefficients across a bigger range of windows, demonstrating that the estimates remain highly consistent in this scenario and the results are robust across different sampling choices and window specifications.

Therefore, it is fair to conclude firms become more aggressive in the second auction after knowing a winning outcome in the first auction, while firms do not seem to change their behavior on the second auction after knowing a losing outcome in the first auction. Implications of these results for auction designs are discussed in Chapter 6.

Figure 5.3 – Estimates of treatment effects across a 12 to 20 seconds window range aggregating exclusive and non-exclusive auctions



6 Conclusion

This chapter discusses the findings of the previous chapter and why are they important for auction designers. It also discusses limitations to the study and what future inquiries could be made.

Firstly, Chapter 5 concludes that knowledge of a winning outcome in the first auction leads bidders to adopt a more aggressive strategy in the second auction, whereas a losing outcome does not produce the same effect. As previously argued in Chapter 4, winning firms can be assumed to be similar to losing firms in all respects except for the belief that they have secured a production volume in the first auction. The increase in bidding aggressiveness must therefore be a result of that belief. Assuming firms base their bids in relation to their expected average cost, such aggressive behavior would imply a reduction in the expected average cost. Thus, the expectation of producing a larger volume of goods would result in a decrease in average cost, provided all assumptions hold. In this case, bidding behavior serves as an indicator of an underlying causal link: the expectation of increased production leads firms to adjust their belief in a way that reflects a reduction in average costs. Consequently, the findings demonstrate the presence of internal economies of scale within these firms.

As discussed in Section 2.1, set-aside programs, such as the one analyzed in this study, are often justified by auction designers as mechanisms to create a more competitive environment. The argument is that, without these programs, larger firms would dominate the auction, crowding out smaller competitors. However, existing studies supporting that argument frequently overlook the potential impact of internal economies of scale, which can lower costs for firms that win the full volume allocated by the set-aside program. This study contributes to the literature by emphasizing the importance of considering internal economies of scale in auction designs.

Determining whether the set-aside program increases or reduces government procurement costs, however, requires a more comprehensive analysis. This study does not evaluate the consequences of removing the set-aside program and consolidating the entire purchase volume into a single non-exclusive auction. Such a change could have mixed effects: the increased volume might lower costs due to internal economies of scale, encouraging firms to bid more aggressively, or it could crowd out smaller firms, reducing competition and potentially increasing costs for the government. Disentangling all possible effects that may affect bidding behavior is not a trivial task.

Additionally, while this study demonstrates that small firms experience internal economies of scale, it does not address whether larger firms benefit from similar cost efficiencies. Extending these findings to larger firms would require further, more detailed investigation. Finally, the results are based on a restricted sample comprising only 104 winning firms and 108 losing firms, representing a small fraction of the firms operating in Brazil. As such, an attempt to generalize these findings to other auctions or broader contexts should be approached carefully.

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A Sector Results

This appendix extends the analysis conducted in Chapter 5 to sector-specific data. Although the results lack statistical robustness due to the limited number of observations, the analysis highlights potential directions for future research.

Initially, auctions were classified into seven sectors. However, the scarcity of observations in some sectors made it impossible to estimate regressions, as the number of regressors would often exceed the available data points. As a result, the analysis was limited to two sectors: Civil Construction Machinery and Equipment (MCC) and IT, Electrical, and Office Materials (MIE). Nonetheless, as Table 3.2 illustrates, even these sectors contained too few observations within the estimation window.

Figures A1 and A2 replicate the analysis of Figure 5.1 for the MCC and MIE sectors, respectively. Although the figures suggest a potential information effect in some regressions, Table A1 confirms that none of the regressions produces a statistically significant estimate for Δ Intercept at the 5% significance level.

Figure A3 presents an estimation across a range of windows, replicating the analysis conducted in Figure 5.2. The results indicate that no coefficient is consistently different from zero across the examined window range, for the 5% significance level.

Table A2 reproduces the analysis in Table 5.2, by aggregating exclusive and non-exclusive auctions, distinguishing only between winners and losers. The table only presents results for the 12-second window. Once again, the results are not statistically significant, although the point estimates remain comparable to those in Table 5.2.

Figure A4 presents the estimated coefficients from Table A2 across a broader window range. Although none of the coefficients are consistently statistically significant at the 5% level, the point estimates for winners remain consistently higher than those for losing firms, particularly in the MCC sector. This suggests weak evidence of internal economies of scale in both the MCC and MIE sectors. The weakness of this evidence is caused by two key issues: (1) the limited number of observations, which reduces the reliability of the estimates, and (2) the sector assignment process, which relies on a soft match of product descriptions and may result in inaccuracies.

To address the first issue, future research could analyze auctions that do not follow the set-aside format, as these are more frequent and provide a larger dataset for analysis. Evidently, this would imply in a change of methodology, as this study relies on the paired-auction feature of some procurement auctions. For the second issue, a more precise sector classification could be achieved by using CNAE data, which links firm IDs to sectors, allowing for a more accurate categorization of auctions.

Figure A1 – Visualization of the Regression Discontinuity Design for the Civil Construction Machinery and Equipment sector

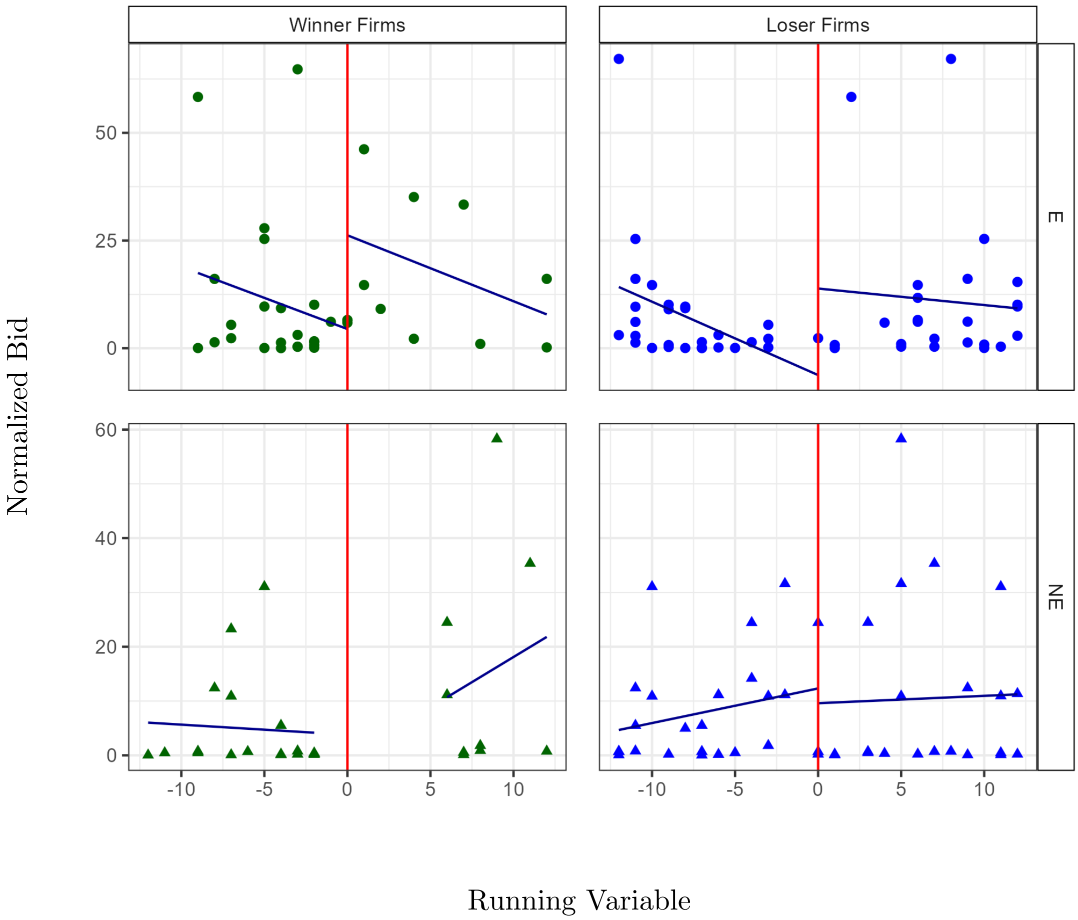

Figure A2 – Visualization of the Regression Discontinuity Design for the IT, Electrical and Office Materials sector

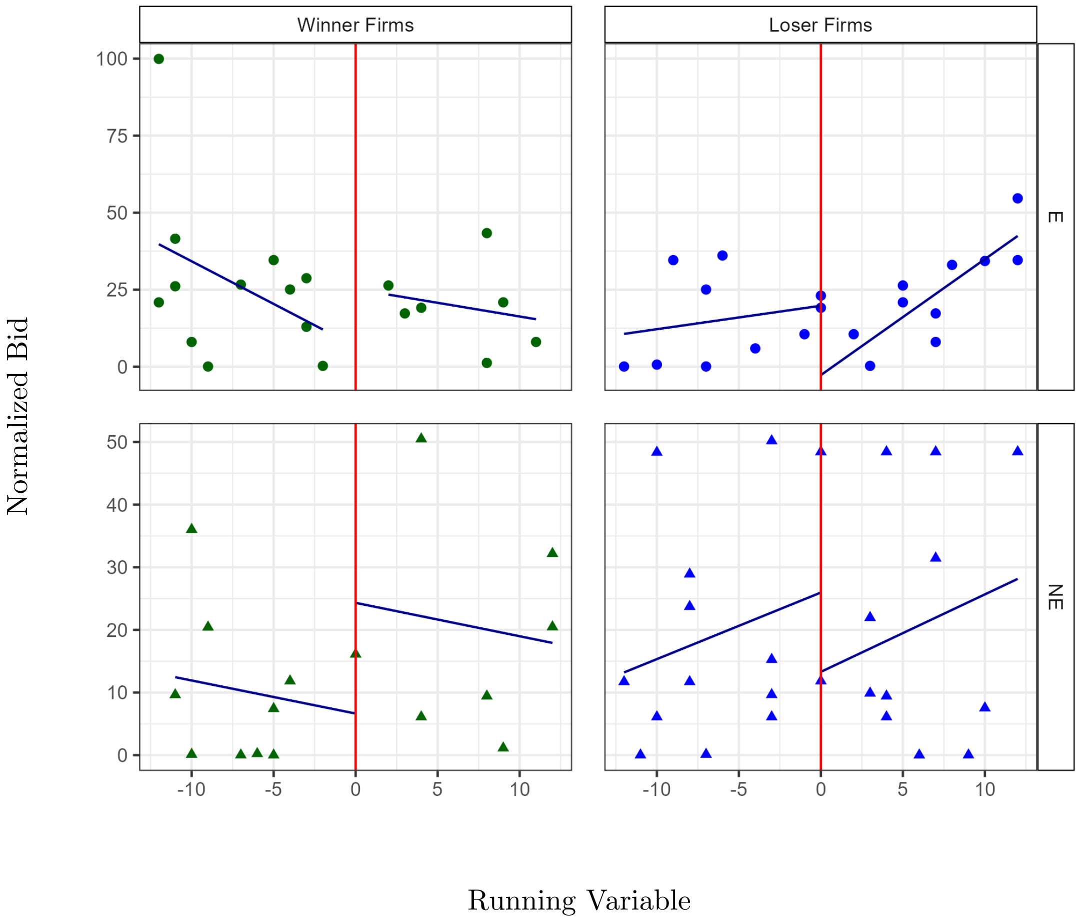

Table A1 – Sector-specific Regression Discontinuity Designs

	MCC				MIE			
	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Intercept ($\alpha^h_{0,k}$)	4.448	-6.247	3.799	12.321*	6.541	19.788**	6.647	25.964*
	(5.850)	(7.706)	(7.286)	(5.084)	(14.422)	(6.664)	(11.365)	(9.505)
Slope ($\alpha^h_{1,k}$)	-1.446	-1.704+	-0.185	0.638	-2.768	0.761	-0.528	1.063
	(1.225)	(0.908)	(1.109)	(0.669)	(1.742)	(0.966)	(1.528)	(1.306)
Δ Intercept ($\beta^h_{0,k}$)	21.765+	20.098+	-4.198	-2.723	18.644	-22.509+	17.676	-12.662
	(11.156)	(10.767)	(21.452)	(7.715)	(23.906)	(11.388)	(20.489)	(16.702)
Δ Slope ($\beta^h_{1,k}$)	-0.085	1.320	2.036	-0.502	1.880	3.003+	-0.005	0.174
	(1.830)	(1.290)	(2.630)	(1.019)	(3.181)	(1.525)	(2.467)	(2.378)
Winner	X		X		X		X	
Exclusive	X	X			X	X		
Num.Obs.	35	52	27	47	19	20	16	25
R2	0.113	0.086	0.134	0.029	0.174	0.452	0.122	0.050
R2 Adj.	0.028	0.029	0.021	-0.039	0.009	0.349	-0.097	-0.086
RMSE	15.68	14.40	13.13	12.68	19.75	11.01	13.50	17.49

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001
Window: [-12,12]

Figure A3 – Sector-specific estimates of treatment effects across a 12 to 20 seconds window range

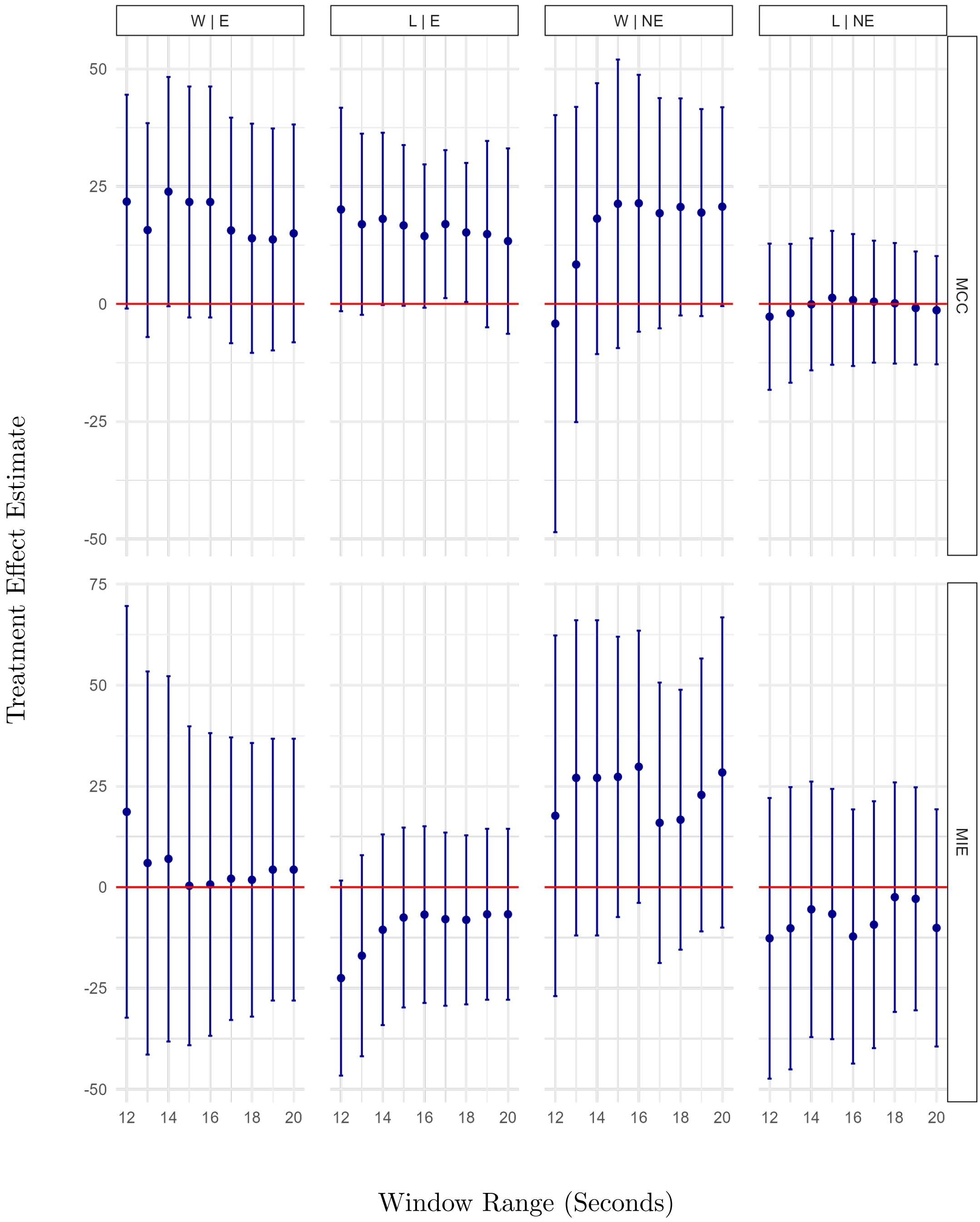

Table A2 – Sector-specific RDD estimates aggregating Exclusive and Non-Exclusive auctions for 12-second windows

	MCC		MIE	
	(1)	(2)	(3)	(4)
Intercept	5.658	14.953**	4.364	28.598***
	(4.437)	(4.553)	(9.458)	(6.130)
Slope	-0.498	0.526	-2.120+	1.012
	(0.795)	(0.584)	(1.196)	(0.835)
Δ Intercept	16.824+	-0.689	20.035	-5.835
	(9.387)	(7.050)	(16.092)	(9.323)
Δ Intercept	-0.410	-0.803	1.470	-0.740
	(1.330)	(0.897)	(2.026)	(1.223)
Winner	X		X	
Num.Obs.	62	116	35	71
R2	0.074	0.009	0.096	0.027
R2 Adj.	0.026	-0.017	0.009	-0.016
RMSE	15.12	16.58	18.49	18.06

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Window: [-12,12]

Figure A4 – Sector-specific estimates of treatment effects across a 12 to 20 seconds window range aggregating exclusive and non-exclusive auctions