Market Transparency, Relational Contracts and Collusion in the Colombian Electricity Market *

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Abstract

This paper tests for, and quantifies the value of, collusive arrangements supported by relational contracting in the Colombia energy sector. We take advantage of the introduction of a market reform that extended the delay with which information about bids submitted to the industry regulator by energy generators would be disclosed to other market participants. By reducing market transparency, this reform makes harder for firms to sustain a collusive arrangement. We show that bids submitted by a subset of firms in the market collapsed immediately after the *announcement* of the reform, before it was was implemented. This suggests that some of these firms might have been part of an informal collusive arrangement that was made unsustainable by the regulation. Using factor analysis, we construct a proxy for cartel membership based on unit characteristics *a priori* correlated with incentives and ability to collude. Within an event-study framework, the resulting proxy captures well the observed drop in bids following the announcement. We rule out confounders and provide detailed forensic evidence of how the cartel functioned, uncovering both the incentives to collude and the mechanism through which firms colluded. A calibration of the dynamic incentives compatibility constraints associated with collusion confirms that a collusive arrangement was sustainable before, but not after, the reform. The cartel lead to a substantial increase in the price paid for electricity. A back-of-the-envelope calculation suggests that the average consumer paid 4% higher energy bills as a result of the cartel.

Keywords: Relational Contracts, Collusion, Transparency, Regulation, Energy Markets.

JEL Codes: L14, L41, O13, L94

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No one has the right, and few the ability, to lure economists into reading another article on oligopoly [...] The present paper accepts the hypothesis that oligopolists wish to collude to maximize joint profits. It seeks to reconcile this wish with facts, such as that collusion is impossible for many firms and collusion is much more effective in some circumstances than in others. [...] The reconciliation is found in the problem of policing a collusive agreement, which proves to be a problem in the theory of information. (Stigler (1964), p. 44)

1 Introduction

Formal contract enforcement is often impractical – if not altogether absent (Greif (1993); Djankov et al. (2003)). Parties therefore rely on relational contracts – informal agreements sustained by the future value of the relationship (Baker et al. (2002)) – to support trade. While these arrangements provide mutual advantages to their participants (Macchiavello and Morjaria (2015)), there is no guarantee that they benefit the market as a whole. The most prominent example of this possibility is perhaps given by the case of horizontally competing firms colluding to raise prices (Green and Porter (1984); Rotemberg and Saloner (1986)): collusion benefits the participants at the expense of competitors, customers or suppliers with the losses usually outweighing the benefits (see, e.g., Tirole (1988)).[1] Such distortions might be particularly severe in developing countries, where markets are often thinner and more concentrated (Mitton (2008); Djankov et al. (2002); Leone et al. (2022)) and competition authorities weaker – if at all existent (see, e.g., World Bank (2016); Besley et al. (2020)).

Despite the policy relevance, evidence on cartels in low income countries – and on how they are sustained by relational arrangements – remains scarce. As the majority of empirical studies focus on cartels investigated by competition authorities, which tend to be weaker in developing countries, fewer documented examples exists.[2] In addition to these data challenges, however, it is also difficult to identify behaviour sustained by relational contracts – as those are based on promises about future behaviour that are not observed and that make it hard to rule out confounding explanations.

This paper shows how a relational arrangement sustained collusion in the Colombia energy market. Access to adequate sources of reliable and cheap energy is a critical engine for development

[1] Other prominent examples include buyers and sellers using informal relationships to foreclose markets to rivals (see, e.g., Rey and Tirole (2007)) and various forms of organized crime (Gambetta (1993); Dixit (2003)).

[2] For example, data from the Private International Cartel database (Connor, 2020) reveal that only 5% of proven cartels are in Africa (and, of those, 72% were proven in South Africa alone), 7% in Latin America and 11% in Asia.

(Greenstone et al. (2014)) and a key determinant of firms' productivity (see, e.g., Allcott et al. (2016)). Besides its intrinsic relevance, the context of our study offers two advantages to understand how relational contracts are used to support collusive arrangements. First, wholesale electricity markets are inherently incomplete, imperfectly competitive and thus regulated (Wilson (2002)). The Colombian wholesale electricity spot market is no exception and, as many other markets around the world, is regulated as a uniform price multi-unit procurement auction.[3] Detailed data on the bidding behaviour and costs of all market participants are thus available. Second, for identification purposes we exploit a regulatory change. Specifically, we study the effect on bidding behaviour of a change in regulation that significantly delayed the availability of information on other market participants' bids. Conventional wisdom (see, e.g., Whinston et al. (2008)) holds that such a regulatory change can make collusion harder to sustain by inhibiting cartel members' ability to "police" the agreement, i.e., detect, and punish, deviating members.

We find compelling evidence that a subset of firms in the market relied on a relational contract to collude and raise the price of electricity. Critically to our identification strategy, we show that a subset of the firms in the market lowered bids by a number between 43% and 31% immediately after the *announcement* – and well before the actual implementation – of the regulatory change. That is, a subset of market participants reacted in anticipation of *future* market conditions that could (potentially) make a cartel unsustainable. Inter alia, this strategy allows us to rule out several confounders, including the fact that changes in market transparency itself could lead firms to change their bidding behaviour. Besides ruling out confounders, we also provide detailed forensic evidence of how the cartel functioned, uncovering both the incentives to collude and the mechanism through which firms colluded. We calibrate the dynamic incentives compatibility constraints required to sustain the cartel and confirm that they were satisfied before, but not after, the reform. The results, which point at a potentially sizeable welfare loss due to the cartel, also yield policy implications and a cautionary message to efforts to boost market transparency in other contexts (e.g., agriculture, e-commerce) in developing countries.

Section 2 provides background information on the Colombia wholesale electricity market, the regulatory change and the data used in the analysis. In the Colombian Electricity Market – a moderately concentrated oligopoly – generation units declare, once a day, their available supply for each hour and a unique bidding price for the next day.[4] *XM*, the system operator, minimizes

[3] Other examples of markets that have used the multi-unit uniform auction are the Mexican treasury Bill, Swiss Bonds and Texas and UK electricity sectors.

[4] The 47 units are owned by 15 firms. Since we focus on bids, which are submitted by units, we consider generation

the cost of fulfilling the demand for each hour, by arranging bids in an increasing order.[5] This process, which does not consider transmission network restrictions, generates an hourly *spot* price (the bidding price of the marginal generation unit necessary to fulfill the demand) and gives rise to the *ideal dispatch*. Due to constraints to the transmission network, however, *XM* implements a different set of production assignments, the *real dispatch*. Differences between the *ideal* and *real dispatches* yield positive and negative reconciliations. A generation unit receives a positive reconciliation when the real dispatch allocation is greater than the ideal dispatch, and a negative reconciliation if it is lower. As we describe momentarily, reconciliations play a key role in our analysis.

The market witnessed a significant increase in bidding prices during 2008. During a meeting on January $6^{th}, 2009$ (the *announcement* date), the regulator – concerned with the price increase – decided to invite Professor Peter Cramton for advice. At that time, the operator used to disclose all information (bids, availability and allocation) to all market participants with two days delay. While such a transparent market can increase the efficiency of bidding behavior and simplify monitoring and implementation, Cramton had previously advised regulators on how transparency also facilitates collusion and was thus expected to recommend a tightening of the transparency policy. Indeed, Cramton recommended to increase to 90 days the delay to disclose information to market participants during a presentation delivered on January $24^{th}, 2009$. The regulator adopted the recommended change on January $30^{th}, 2009$, with effect from February $6^{th}, 2009$ onward (the *implementation* date).

Section 3 presents the main evidence and rules out potential confounders. The average bid in the market sharply decreased right after the *announcement* date. The average decline, however, masks significant heterogeneity: not all units lowered their bids. Unlike some studies which rely on proven cartels (Porter and Zona, 1993; Asker, 2010; Igami and Sugaya, 2021), we do not know the identity of the firms participating in the collusive arrangement. Yet, such information, or a proxy for cartel participation, would allow us to sharpen our empirical test and investigate mechanisms. We thus construct a proxy for cartel membership. We put forward four factors that we conjecture to be *a priori* (i.e., theoretically) correlated with units' incentives, and ability, to collude and use factor analysis to classify firms into two groups.[6] This simple classification isolates a group of 15

units as the relevant unit of analysis. We use information on firms' ownership of generation units for robustness checks and to gain further insights into the operation of the cartel.

[5]For more information see http://informacioninteligente10.xm.com.co/Pages/Default.aspx.

[6]The four factors are whether the unit is *a*) privately owned (instead of public); *b*) thermal (as opposed to hydro); *c)* located in the North Atlantic (a region characterized by particularly poor governance and corruption); *d*) involved in forward contracting in 2008. Section 3 explains the rationale for focusing on these four characteristics and performs

thermal units – henceforth, the *cartel* – that belong to 6 private firms and are all located in the North Atlantic region. Using both DID and more flexible event-study specifications, we show that the average bid for cartel units falls by a number between 43% and 31% after the announcement date, and before the implementation of the regulatory change. No fall in bids is detected for the remaining units in the market.[7]

Our preferred interpretation is that firms in the cartel were artificially increasing their bids to benefit from higher prices. As in standard oligopolistic markets, lower bids increase the likelihood of winning the auction and constitute a potentially profitable deviation that the cartel has to police. As any relational contract, the collusive agreement rests on the premise that current temptations to deviate are deterred by future punishments. The transparency regime allowed firms in the cartel to police the agreement, by detecting and – if needed – punishing deviations. The *announcement* of the regulatory change altered members' expectations about their *future* ability to enforce the cartel: even before the regulatory change was implemented, cartel members knew that future punishment was no longer possible and the cartel unravelled. Alongside the baseline DID and event-study specifications, we present several robustness checks and placebos. We rule out several potential confounders, e.g., costs, changes in forward markets and other common shocks and explore robustness to alternative definitions of cartel membership. We find that results are very robust.

Section 4 conducts forensic analysis to uncover the incentives, and strategies used, to collude. We argue that units in the cartel colluded to increase bids so as to increase their profits in the positive reconciliations market. Our argument unfolds in three steps. In the first step, we note that cartel units – which are all thermal – have high production costs and would anyway be unable to be allocated production in the ideal dispatch. Given this, these units try to maximize benefits in the only possible remaining way: the positive reconciliation market. In the second step, we indeed confirm that the positive reconciliation market functions as a standard oligopolistic market in which firms have incentives to coordinate price increases and in which increases in the likelihood of positive reconciliations raises higher bids. In the third step, we show that cartel units coordinated bidding behaviour: units in the cartel increasing their bids particularly so at times in which certain other units bid low prices and declare unavailability after winning the ideal dispatch, thereby generating positive reconciliations for the high bidders in the cartel.

several robustness checks. Note that, provided our classification is positively correlated with actual membership in the cartel, miss-classification of units into (and out of) the cartel leads to attenuation bias, making it harder for us to detect collusive behaviour (see Mirenda et al. (2022) for a similar argument.

[7] Connor and Bolotova (2006) provides a meta-analysis of cartel overcharges and finds, in a sample of 395 documented cartel episodes for which overcharges are available, a median (average) overcharge of 19% (29%).

We support the results of our forensic analysis in two ways. First, we use data from the minutes of the meetings of the Association of Generating Units (CNO in Spanish). The association holds regular meetings to discuss engineering problems (and solutions) related to technical difficulties and constraints on the network. Of course, bidding behaviour is not to be discussed at those meetings. We downloaded the minutes of all the meetings in 2008 (during the cartel) and 2009 (after the announcement date). Within a DID framework, we find that after the announcement date, units in the cartel stopped sending employees from the commercial area (i.e., those involved in setting bids) to the meetings after the announcement date. This lends support to the regulator's concerns that the meetings of the associations might have been used to discuss bids and collude. Second, if the forensic analysis is correct, we expect that revenues and profits from positive reconciliations (but not from the ideal dispatch) fall relatively more for cartel units after the end of the cartel. As a sanity check, we confirm this to be the case within the baseline DID analysis.

Section 5 quantifies the incentive to collude for each unit and the cost of the cartel for consumers. First, we calibrate the optimal static bidding strategy and show that, before – but not after – the announcement date, cartel units could increase static profits by deviating from the collusive agreement. In contrast, non-cartel units would not be able to increase profits by bidding differently. We then embed such deviations into a dynamic incentive compatibility constraint. For reasonable parametrization of the discount factor, we show that such deviations are not incentive compatible under the old transparency rule, but they become profitable under the new rule. This calibration thus lends further support to the DID results in Section 3: the (announcement of the) reform made collusion unsustainable and caused the cartel to unravel.

Counterfactual bids and allocations allow us to provide a lower bound of the excessive costs paid by consumers for electricity in the second semester of 2008. The cartel artificially increased the price paid for electricity in the wholesale market. In particular, the cartel increased by 15% the price paid for positive reconciliations. Positive reconciliations account for approximately 10% of the electricity procured by the regulator, but since they are paid above the spot price this led to an overall increase in costs of 3%. Assuming a full pass-through of the cost increase to consumers, the cartel increased the average monthly bill paid by a Colombian households by 1,500 COP , i.e., around 4%. Finally, Section 6 discusses policy implications of our results.

Related Literature

This paper contributes to three branches of the literature, with a particular focus on developing countries: relational contracts, collusive arrangements and energy markets.

Relational Contracts Markets in developing countries are often characterized as having weaker formal contract enforcement and governance, making the study of relational contracts particularly important (see, e.g., McMillan and Woodruff (1999); Fafchamps (2004) and Macchiavello (2021) for a review).[8] The key difficulty in testing models of relational contracting is that neither the *future* value of the relationship nor the *current* temptations to deviate are typically observed. Macchiavello and Morjaria (2015) tests the implications of a relational contracting model exploiting information on temptations to deviate and an exogenous supply shock in the Kenya flower sector. Blouin and Macchiavello (2019) uses unanticipated increases in temptations to deviate to test for, and quantify, the extent of opportunistic behaviour in relationships between exporters and importers in the international coffee market. We contribute to this literature a novel test for relational contracting that relies on changes in *current* behaviour in anticipation of changes in the *future* value of the relationship – a central implication of relational contracting models.[9]

Collusion We also contribute to the empirical literature on collusion (see Asker and Nocke (2021) for a recent, comprehensive, review). Two branches of the literature can be distinguished. The first branch studies known cartels to gain insights into their functioning and quantify associated efficiency losses. Within this branch, important examples include Porter and Zona (1993, 1999); Pesendorfer (2000); Asker (2010). Studying the international vitamin C cartel, Igami and Sugaya (2021) calibrate the dynamic incentive compatibility constraint associated with the collusive arrangement to perform counterfactual and is thus particularly related to our paper.

A second branch designs empirical tests to detect anti-competitive behavior in contexts in which a cartel has not been proved. Porter (2005) and Harrington (2008) provides overviews of the literature and Hendricks and Porter (1988); Bajari and Ye (2003); Baldwin et al. (1997); Ishii (2009); Athey et al. (2011); Conley and Decarolis (2016); Chassang et al. (2022a,b) examples. Chassang and Ortner (2019) study of procurement in Japan derive a test from the dynamic incen-

[8] Relational contracts between firms are important in developed countries as well, see, e.g., Corts and Singh (2004); Barron et al. (2020); Gil and Zanarone (2017); Gil et al. (2022) for examples and reviews.

[9] Ghani and Reed (2022) study how relationships evolved in response to an increase in supply in the Sierra Leone market for ice, Macchiavello and Morjaria (2021) finds that higher competition inhibits relational contracting in the Rwanda coffee chain.

tive compatibility constraint and is thus particularly related to our paper. They note that, if firms collude through a relational agreement, higher minimum prices can make collusive punishment less effective and lead to a drop in the right tail of winning bids. Instead, we exploit the fact that a *future* change in market transparency which lowers members ability to police the cartel, leads to the instantaneous demise of the cartel.

We thus also contribute to the literature on collusion and market transparency. Conventional wisdom holds that transparency facilitates collusion (see, e.g., Whinston et al. (2008); Perloff and Carlton (1999)). A number of notable contributions, e.g., Genesove and Mullin (2001) study of the sugar cartel in the U.S. and Albæk et al. (1997) analysis of the Danish antitrust authority's decision to publish firm-specific transactions prices of ready-mixed concrete in three regions, support this view. The evidence and theoretical literature on the matter, however, is less conclusive. Sugaya and Wolitzky (2018) argue that transparency can hinder cartels by helping firms devise more profitable deviations and discuss examples in which that appears to have been the case. We thus contribute evidence to the ongoing debate. We do so in a developing country context. This might be particularly valuable given the general perception that cartels are widespread (World Bank (2016)) and the limited available evidence.[10]

Energy Markets Finally, we contribute to the empirical literature on energy markets. The literature is vast (see, e.g., Kellogg and Reguant (2021) for a recent and comprehensive review) and, therefore, we focus our discussion on studies in developing countries.[11] Rud (2012), Lipscomb et al. (2013), Greenstone et al. (2014) and Allcott et al. (2016) show that energy is one of the key inputs for productivity and development. Intrinsic features of electricity markets make them prone to abuse of market power and even collusion – evidence on which policies improve market efficiency is thus particularly valuable. For example, through counterfactual simulations, Ryan (2021) finds that a more integrated grid would increase surplus by 22% in the Indian market.[12] A few recent papers study the Colombian electricity market, albeit with a different focus (Camelo et al. (2018) on centralized unit commitment, Fioretti et al. (2021) on substitution between fossil fuels and hydropower, and Suárez (2022a,b) on the interaction of market power and public ownership).

[10] In a recent review of the literature Asker and Nocke (2021) cites only two studies on collusion in developing countries (Bergquist and Dinerstein (2020) on Kenya maize and Barkley (2020) on Mexican insulin).

[11] Relevant examples of collusive practices in electricity markets in developed countries are Fabra and Toro (2005) and Mercadal (2022).

[12] Ryan (2020) finds that contract renegotiations are widespread, and induce significant efficiency costs, in the procurement of power generation units in India. Improving contract enforcement would have significant pro-competitive effects.

2 Institutional Setting & Background

This section provides a general overview of the Colombian wholesale electricity market and details the timeline of the events that surrounded the regulatory change used in Section 3 to detect the collusive arrangement. The Section concludes with a brief discussion of the data used in the paper.

2.1 Electricity Demand and Generation

Demand The average daily generated electricity in Colombia was 149.81 GWh in 2009.[13] The energy demand fluctuates at different times of the day with 7 p.m. being the peak hour while 3 a.m. the one with the lowest demand. Given its location in the tropic, demand does not vary significantly across the different months of the year.

Supply (Generation) Electricity sold on the wholesale Colombian market in 2008/2009 was produced by 47 generation units. Among all these generation units, about 30% of production is done by publicly-owned generation units. The rest, 32 private units are owned by 11 firms. The market was a moderately concentrated oligopoly in 2008/2009. The Herfindahl-Hirschman index of the installed capacity was around 1306.[14] The 4 largest firms (EMGESA, EEPPMM, ISAGEN and GECELCA) accounted for 65% of installed capacity. As we explain below, bids to supply electricity in the wholesale market are submitted by individual generation units. Most of our analysis therefore considers these units, rather than firms, as the relevant decision making units. However, we use information on firms' ownership of generation units for robustness checks and to gain further insights into the functioning of the collusive agreement.

Electricity is generated using different technologies. In Colombia, the share of different generation technologies over the installed capacity in 2008 was as follows: 66.7% hydro-power, 32.9% thermal generation (20.4% gas-fired, 7.3% coal-fired and 5.2% other fuels) and 0.4% of other small units (co-generation and wind).

Hydro-power generation relies on availability (head and flow) of water stored in reservoirs (hydroelectric basins). Water availability depends on seasonal rainfall patterns (Colombia has three main rain periods: dry (December to February), wet (April to June) and normal (the other 6 months)) and other meteorological events (e.g., El Niño, during which dry weather conditions lower hydroelectric resources, and La Niña during which the opposite occurs).

[13] As reference, the Gwh daily electricity generation in other countries in 2009 was: 1277,15 in Brazil, 340,82 in Argentina, 260,93 in Pakistan, 54.18 in Nigeria, 24.54 in Ghana, 937,02 in the UK and 10822,82 in the US.

[14] See Comisión de Regulación de Energía y Gas (CREG) (2009a).This value is in the range of other developing countries, for instance Kenya was 3.500, Peru 2,300 and Pakistan 677) (World Bank).

Thermal generation relies on gas and coal. The most important source of gas for Colombian producers is the basin Guajira, located on the northern coast of the country. In 2009, 82% of gas consumption for electricity generation came from that source. During the sample period, the Colombian Government set a maximum price for gas from the Guajira basin (gas from alternative sources was not regulated at the time). Colombia was the fourth worldwide largest exporters of Coal in 2009.[15] Most of the coal-fired generation units are closely located to large coal mines. In the coal market, transactions are usually governed by long-term contracts and prices bilaterally negotiated.

2.2 Colombian Wholesale Electricity Market

Market Format and Ideal Dispatch Electricity markets are characterized by volatile demand, prohibitively high storage costs and economies of scale. They are thus incomplete and imperfectly competitive (Wilson (2002)). To improve efficiency, encourage participation and minimize expected payments to generators, many countries trade electricity through auction mechanisms. The Colombian wholesale electricity spot market works as a uniform price multi-unit procurement auction.[16] Once a day, companies submit for each generation unit their availability for each hour and a unique bidding price for the next day. Although only one bidding price is allowed for each unit per day, the Colombian wholesale electricity market clears every hour. The heterogeneity of hourly spot prices within a day is explained by differences in the availability of the units and hourly demand fluctuations. There are not intra-day balancing markets and there is only one pricing node for the whole market, i.e. the same spot price is paid in all the regions.

Once the generation units have submitted their daily bids, *XM*, the system operator, minimizes the cost of fulfilling the demand for each hour, by arranging in an increasing order the submitted bids. This process does not consider transmission network restrictions. For each hour, the price that clears the market, the *spot* price, is the bidding price of the marginal generation unit necessary to fulfill the demand. This process gives rise to the *ideal dispatch*, which establishes for each generation unit, how much and at which hour, it should supply energy to the system.

Real Dispatch: Positive and Negative Reconciliations Once the ideal dispatch has been determined, contingencies such as transmission constraints may arise and make infeasible the initial planned allocation. As a consequence, *XM* proposes a different set of production assignments,

[15] See https://www.iea.org/data-and-statistics/charts/total-coal-exports-by-major-exporters-1978-2020.

[16] Examples of uniform price multi-unit auctions electricity markets studied in the literature include Spain (Fabra and Toro (2005)), Texas (Hortaçsu and Puller (2008)) and U.K. (Crawford et al. (2007)).

called the *real dispatch*. Units that were initially called upon to produce but cannot supply electricity to the network do not do it, while units that were not called upon may be called in. To compensate the generators for the differences between the *ideal* and *real dispatches*, the market operator has a scheme called positive and negative reconciliations.

A generation unit receives a positive reconciliation when the real dispatch allocation is greater than the ideal dispatch. In that case, the system compensated each energy unit at a price equal to the minimum between a cost-based regulated price and the generation unit's bidding price. In case that two or more units could replace the production obligations of another unit and be called for positive reconciliations, the system regulator selects the one with the lowest bidding price.

A negative reconciliation arises when the real dispatch generation is less than the ideal dispatch generation. In 2009, the system compensated each of those units at a price equal to the average between the spot price and the generation unit' bid.

2.3 Change in Transparency Policy

Figure 1 shows that during 2008 there was a strong increase in the average bid in the wholesale electricity market. The bid increase was at odds with hydro-electricity generators having received an unusually high level of rainfalls. The electricity market regulator thus begun to suspect that, among the potential reasons to explain the sharp increase, anti-competitive practices such as collusion might have been playing a role.[17]

Figure 2 summarizes the timeline of events of the actions taken by the regulator which, ultimately, led to the policy change. To deal with the price increase, the authorities held a meeting on January 6th 2009, a date that we label *announcement date*, to discuss which measures could be taken to prevent anti-competitive behaviors. During this meeting, they decided to hire Professor Peter Cramton (University of Maryland) as consultant for the case.

Before the Colombian regulators asked for his advice, Cramton had already advised regulators on the design of different types of auction markets. In particular, and likely common knowledge among Colombian market participants, Cramton consistently mentioned the importance of considering the relative costs and benefits of having a market with full transparency of bids. One the one hand, it may provide efficiency benefits but on the other hand it facilitates collusion. In those cases where the market is expected to suffer from collusion, Cramton argued against a fully-transparent policy. (Cramton and Wilson, 1998; Cramton and Schwartz, 1998a,b).

[17] For more details see (Comité de Seguimiento del Mercado Mayorista de Energía Eléctrica, 2008) and Comisión de Regulación de Energía y Gas (CREG) (2009a), page 74.

On January 24th 2009, as expected, Cramton recommended changing the bidding disclosure policy. Before the implementation of the policy, day t production schedules (ideal and real dispatches) and bidding prices were released as public information *two* days after (in $t+2$). Cramton recommended to reveal all bids only 90 days after the auction took place–instead of 2 days after–. The aim of this policy was to make harder to collude as the delay in observability of others' actions would make harder punishing deviation from collusive behaviors (Klemperer, 2002; Cramton and Wilson, 1998).

Following his advice, regulators approved a law on January 30, 2009 with effect on February 6th, 2009 (Comisión de Regulación de Energía y Gas (CREG), 2009a). The law mandated that day t production schedules and bidding prices were public information, only ninety days after (in $t+90$). The spot price for each hour of day t was still available to everyone, two days after. Privately though, each generation unit was informed whether or not they won in the multi-unit auction or they had any type of reconciliations. The measure also mandated that the generating units kept their bidding programs' information secret from other units. The law did not specify how long the policy would last.[18]

2.4 Data

In this paper we use three main sources of data. The first one, available from the webpage of *XM*, contains detailed information on market variables of the Colombian wholesale electricity market from August 2008 to July 2009. The database has the universe of submitted bidding programs, the forward contracts hourly sales of each generation unit, the hourly demand and spot price, the daily water intakes of the reservoirs for each hydro unit, the quantities and revenues from positive and negative reconciliations and the contingencies of the transmission infrastructure.

The second dataset provides time-varying marginal costs for each generation unit. To construct them, we follow a standard engineering methodology (Green and Newbery, 1992; Wolfram, 1998, 1999; Wolak, 2000; Fabra and Reguant, 2014) that uses technical specifications of each generation unit (i.e. heat rate), fuel prices and transportation costs. Similar methods have been implemented in the literature on electricity markets (see Appendix B for details).

Finally, we hand-collected minutes of meetings of the electricity-generators association and

[18] In the second semester of 2009 El Niño event affected the production capacity of the hydro-power units. The Colombian regulators thought that changing the information disclosure policy would facilitate facing the meteorological event ((Comisión de Regulación de Energía y Gas (CREG), 2009b)). Due to water availability being a stock, bidding behaviour for hydro-units is inherently dynamic. Better information on market conditions allow hydro-units to improve the inter-temporal allocation of scarce water capacity. Therefore, the 90-days disclosure rule was eliminated on December 4, 2009 and the market went back to the same two-days disclosure policy.

search for the CV of all of the attendees of these meetings.

3 Detecting Relational Collusive Agreement

This Section provides evidence that a cartel was likely operating in the Colombia wholesale electricity market. We begin explaining the logic of our empirical test. We then describe the sudden decrease in bids around the time of the reform . We introduce a proxy for cartel membership and present DID and event-study specifications. Finally, we perform several robustness checks and rule out confounding explanations.

3.1 The Logic of the Test

We now detail the logic of our test for collusive behaviour sustained by relational contracts. The argument has two parts. First, we review theoretical arguments regarding the role of information in auction markets and its role in facilitating collusion. Second, we argue that a central implication of relational contracting models is that shocks to parties *future* ability to punish deviations should lead to *instantaneous* changes in behaviour. This highlights the relevance of distinguish between the *announcement* and the *implementation* date of the regulatory change.

Market Transparency & Collusion A critical aspect of market-design is to determine what type of information, if any, should be revealed to bidders. As noted above, during the first part of our sample period, i.e., throughout 2008 and the very beginning of 2009, the Colombian market had a fully transparent process. The market operator, *XM*, was revealing all the information (bids and allocations) to all market participants with minimum delay.

Transparency can potentially increase efficiency and simplify implementation (see, e.g., Cramton and Wilson (1998)). First, transparency can increase the efficiency of individual bidding behavior. For example, better knowledge of the residual demand allows hydro units to improve the inter-temporal allocation of scarce water resources. Second, transparency simplifies implementation. The regulator simply needs to release the information, rather than paying the cost to assure that certain information is only communicated to specific units and not communicated between units. Furthermore, with perfect transparency, the regulator need to worry about regulator's employees or generation units not keeping information secret from other market participants.

Transparency, however, can also facilitate collusion. The conventional wisdom thus holds that the less the information provided on the outcomes of the auction, the more difficult it is for a

cartel to operate (see, Perloff and Carlton (1999); Porter (2005); Kovacic et al. (2006); Whinston et al. (2008)). Cramton and Schwartz (1998a,b) discuss concrete examples. For instance, if the regulator reveals the bids of all bidders, then a bidding ring faces a much easier problem in policing its agreement.[19]

Testing for Relational Contracting While models of relational contracting differ in many important respects (see, e.g., Mailath et al. (2006) and Watson (2021) for reviews), they all share the common insight that the *future* value of the relationship is needed to deter *current* temptations to deviate. The future value of the relationship is given by the discounted (expected) difference in the payoffs following cooperation and defection respectively. The current temptation to deviate is instead given by the difference in payoff between deviating from the agreement and sticking to it. In the context of cartels, it is *a priori* difficult to know how cooperation and punishment play out in practice (e.g., firms might coordinate on bidding rings, or they might punish each other entering price wars). In most cases, however, defection will take the form of either an increase in quantity sold in the market and/or a lowering of the price.

The key difficulty in testing models of relational contracting is that neither the *future* value of the relationship nor the *current* temptations to deviate are typically observed (see Macchiavello (2021) for a discussion). The former depends on, inter alia, on discount rates, on beliefs about other players' future behaviors on- and off-the-equilibrium-path. The latter also depends on the off-the-equilibrium-path payoffs associated with defection. Discount rates are notoriously difficult to estimate, beliefs rarely observed and off-the-equilibrium-path actions (and payoffs) are not meant to be observed in the data.

A key implication of relational contracting models, however, is that a worsening of parties ability to detect defection – e.g., induced, as in our case, by regulatory changes in market transparency – increases the future payoffs associated with defection and lowers the value of the relationship. Holding constant current temptations to deviate, this makes it harder to satisfy the dynamic incentive constraint and increases the likelihood of opportunistic behaviour. That is, we expect that the change in transparency policy leads to lower bids by firms in the cartel.

In practice, changes in market transparency could potentially influence behaviour through a variety of channels. For example, more information might lead firms to have more precise estimates of their residual demand curve and alter bidding behaviour. A key implication of relational contract

[19] Sugaya and Wolitzky (2018) however show that cartels can sometimes sustain higher profits under less transparency because better information can hinder collusion by helping firms devise more profitable deviations.

models, however, is that it is the *future* value of the relationship that deters current temptations. The ideal test thus relates anticipated changes to *future* relationship value to *current* behaviour. This logic can be implemented in our context exploiting the difference between *announcement* and *implementation* date:

Test for Collusion: *Units that belong to a cartel sustained by a relational contract lower their bids after the announcement, and before the implementation, of the regulatory change.*

3.2 The Main Fact

Figure 1 shows a large drop in the average bidding price around the policy change. Figure 3 zooms in around the policy change plotting the time-series of the bidding price. The average bid in the market sharply decreased right after the *announcement* date. The average decline, however, masks significant heterogeneity: not all units lowered their bids. Splitting units into two groups – the ones that we label for simplicity cartel units and the rest – and deferring the explanation of how we assign units to the two groups to the next subsection, we note that Figure 3 shows a sharp decrease in the average bidding price right after the *announcement* date *only* for cartel units. The average price for these firms falls in about 43% – the price for other units barely moves.

3.3 Proxying for Cartel Membership

We now explain how the use of factor analysis helped us finding the two groups displayed in Figure 3. Unfortunately, we do not know the identity of the firms participating in the collusive arrangement. Yet, such information, or a proxy for cartel participation, would allow us to sharpen our empirical test and investigate mechanisms. We thus construct a proxy for cartel membership. To implement the procedure, we put forward four variables that we hypothesize to be theoretically correlated with the probability of being in a collusive agreement: governance, forward obligations, culture around illicit behavior and type of production technology. The rationale for each of the four variables is as follows:

1. *Private*: Whether a unit is privately-owned or not. Private units maximize profits while public firms maximize welfare or other objective functions (Barros and Modesto, 1999). While the former is managed by private boards, the latter has a board composed by different members including some of the electricity sector regulators. We expect that private firms are more likely to be in a collusive agreement than public firms.

2. *The ratio forward contracts/availability.* This variable captures the incentive to modify short-term market aggregates. If a unit has all its energy production capacity contracted with a specified price, quantity and other conditions, there is not a strong incentive to modify market parameters such a spot price or revenue for positive reconciliations (Wolak, 2007). We expect that the larger the fraction of energy through forward contracts the less likely to be in a collusive agreement.

3. *Atlantic* Whether a unit is located in the Atlantic area of Colombia. This variable captures the culture around illicit behavior. Among all the generation units working in 2008/2009 in Colombia, the Atlantic area, composed by six states (Atlantico, Bolivar, Cesar, Cordoba, Guajira, Magdalena and Sucre) is the most corrupt geographical area (see for instance, Duque (2014); CTpC (2010, 2017)). We expect that units belonging to the Atlantic area are more likely to belong to a collusive agreement than other generating units.

4. *Thermal* Whether a unit is thermal or not. This variable measures the type of production and cost technologies of the production unit. We expect that units with larger marginal costs such as thermal units, have more to win from a collusive agreement and therefore they are more likely to collude than hydro-power units characterized by very low marginal costs (Knittel and Stango, 2003).

We use factor analysis to classify firms into two groups. Factor analysis is a statistical method used describe variability among correlated variables in terms of a potentially lower number of unobserved variables, called factors. Factor analysis is thus used to reduce the set of variables in a dataset. Figure A1 shows the scores of the first two factors for each unit. Our baseline definition takes the units with positive values for both factors (top-right quadrant) as candidates for members of the collusive agreement. This baseline classification isolates a group of 15 thermal units – henceforth, the *cartel* – that belong to 6 private firms and are all located in the North Atlantic region (see Figure A2 for the geographical location of all of the generation units).

The procedures thus allows us to define a dummy variable, $Cartel_i$, that takes the value one for units that we assign to the cartel and zero otherwise. This dummy allows us to perform more rigorous tests, e.g., by running DID and more flexible event-study specifications.

It is important to note that our classification *does not* rely on unit's bidding behaviour around the time of the policy change – there is thus no mechanical correlation between variation used to proxy for cartel membership and bidding behaviour around the time of the reform. Of course,

this doesn't make our proxy perfect: both type-I and type-II errors are a real possibility. The classification might miss units that did instead belong to the cartel, it can also assign units to the the cartel that were not part of it. Provided our proxy is moderately positively correlated with actual membership in the cartel, miss-classification of units into (and out of) the cartel leads to attenuation bias, making it harder for us to detect collusive behaviour (see Mirenda et al. (2022) for a similar argument in the context of organized crime infiltration). Nevertheless, for all these reasons we explore alternative baseline definitions of the cartel proxy, relying both on variation in the factor analysis, on information of firm's ownership of units and on placebos.

Table 1 presents descriptive statistics for the units classified to be in the collusive agreement and the rest for two different periods: before and after the announcement date. As expected, and with respect to other units, they are more likely to be privately-owned, they have a lower fraction of forward contracts and they are more likely to belong to the Atlantic area. There are also some changes to highlight across top and bottom panels for cartel firms. First, the bids decrease after the announcement of the policy. Second, the probability of getting a positive reconciliation increases. Third, the revenue for positive reconciliations decrease. Other non-cartel units have lower bids and earn much less in positive reconciliations than cartel units.

3.4 Market Transparency, Cartel Membership & Bidding Behaviour

We use a difference-in-differences specification to quantify the differential change in bidding behaviour across the two groups around the time of the reform. We distinguish the announcement and the implementation of the non-transparency policy, controlling for time invariant heterogeneity across units and common time effects. The baseline equation specifies the log bidding price of unit i at date t according to:

$$ln(b_{it}) = \beta_1 \mathbb{1}\{Collusive\}_i \times \mathbb{1}\{Announ\}_t + \beta_2 \mathbb{1}\{Collusive\}_i \times \mathbb{1}\{Trnsp\}_t + \lambda_i + \mu_t + X_{it} + \epsilon_{it} \quad (1)$$

Where $ln(b_{it})$ is the logarithm of the bidding price, the dummy variable $\mathbb{1}\{Cartel\}_i$ takes the value of one if i is a unit in the collusive agreement group and zero otherwise, the dummy variable $\mathbb{1}\{Announ\}_t$ take the value of one if t is a date after the announcement date (January 6th, 2009) and zero otherwise, the dummy variable $\mathbb{1}\{Trnsp\}_t$ take the value of one if t is a date after the implementation of the transparency policy (February 6th, 2009) and zero otherwise. λ_i are unit fixed effects and μ_t are date fixed effects, which control for common market conditions (such as demand and input prices). Standard errors are two-way clustered by date and generation unit.

Table 2 presents the regression results. We find a statistically significant decrease in bidding prices of production units linked with the announcement of the policy by a number between 43% and 31% (i.e. $\exp(-0.558) - 1 = -0.427$). The coefficient for $\mathbb{1}\{Cartel\}_i \times \mathbb{1}\{Trnsp\}_t$ in this specification is negative and statistically significant at 10% of significance, equivalent to a decrease in bidding prices of about 16%. The estimates are identical regardless of whether we exclude (column 1) or include (column 2) unit and date fixed effects as controls. A potential concern is that time-varying shocks vary across units in ways that are not captured by the common date fixed effects. Columns 3 to 6 in the table however show that the result is robust if we also control for input costs, demand, forward contracts, and date fixed effects that are common to units with the same technology, geographical position and ownership.

Figure 4 reports estimates from a more flexible event-study specification. In particular, we extend the specification in column 2 of Table 2 including interactions between dummies for leads and lags relative to announcement date and the $Cartel_i$ dummy. First, the specification rules out differences in pre-trends in bidding behaviour between units assigned and not assigned to the cartel. Second, coefficients drop after the announcement and remain negative for the rest of the sample. Similar results are found when we use alternative specifications from Table 2.

Our preferred interpretation is that firms in the cartel were artificially increasing their bids to benefit from higher prices. As in standard oligopolistic markets, lower bids increase the likelihood of winning the auction and constitute a potentially profitable deviation that the cartel has to police. As any relational contract, the collusive agreement rests on the premise that current temptations to deviate are deterred by future punishments. The transparency regime allowed firms in the cartel to police the agreement, by detecting and – if needed – punishing deviations. The *announcement* of the regulatory change altered members' expectations about their *future* ability to enforce the cartel: even before the regulatory change was implemented, cartel members knew that future punishment was no longer possible and the cartel unravelled.

3.5 Robustness & Alternative Mechanisms

Before investigating more direct evidence of why, and how, firms in the cartel colluded in Section 4, this subsection explores the robustness of our results. We first explore robustness to alternative definitions of cartel membership. We then argue that the differential drop in prices for cartel units is unlikely explained by confounders on the demand and supply sides.

3.5.1 Alternative Definitions of Cartel Membership

Our factor analysis has classified units and not firms. To know the extent of which this can biases our results, Figure 5 reports estimated coefficients of the interaction between the dummies for announcement, $\mathbb{1}\{Announc\}_t$, and implementation, $\mathbb{1}\{Trnsp\}_t$, with four alternative definitions of cartel membership: Baseline, Refined, Extended and Placebo units.

The first group comprises the 15 units that come from the factor analysis. The second group has only 10 units. Those are the units that belong to firms for which *all* their units were initially classified in the baseline Cartel. The extended units group, with 23 units, includes the baseline units plus other units that also belong to the firms that have at least one unit in the baseline definition of the cartel. To conduct the placebo exercise, we drop all of the units from the extended group and in each step randomly allocate 15 units as cartel units and the rest to the control group. We repeat this procedure 1000 times.

Figure 5 shows two main patterns. First, for the refined and extended units groups, both the announcement and implementation coefficients are significantly lower than 0. The coefficient of the interaction term of the announcement is lower than the coefficient of the interaction term of the implementation for both groups. Second, the previous pattern is different for the placebo exercise. Units randomly allocated to the cartel group sometimes have an increase and sometimes a decrease in bidding prices after the announcement or the implementation period.[20]

3.5.2 Demand Confounders: Forward Contracting

The incentives to collude depend on the level of the fixed-price forward contracts obligations signed by the generation unit. The supplier must serve these obligations, independently of the level of the spot price. If its forward contract obligations are less than its energy production, the firm is a net seller in the spot market. Hence, an increase in the spot price increases its profits. On the other hand, if its forward contract obligations are greater than its energy production, the firm is a net buyer in the spot market. Hence, an increase in the spot price decreases its profits (Wolak, 2000, 2007; McRae and Wolak, 2009).

Figure A3 plots the daily average ratio forward contracts committed over total availability for both, the units in the collusive agreement and the rest.[21] Two patterns emerge. First, given the

[20] Table C1 shows that results are robust if we define cartel membership using only the first factor.

[21] As the availability and contracts variables are set for each hour, we simply sum across hours to have a daily measure. We have dropped some outliers (4% of the observations) of this ratio when the denominator was close to zero. We considered as an outlier an observation with a ratio beyond the third quartile plus 3 times the interquartile range or beyond the first quartile minus 3 times the interquartile range.

differences in levels of contract commitments, cartel firms have more incentives to collude than the rest of the units. Second, the drop in bidding prices of the collusive units is unlikely related to a sudden change in the profile of forward contracting around the dates of the transparency policy as those contract obligations did not change significantly around the policy change.

3.5.3 Supply Confounders: Cost Shocks

Table 1 reveals a drop in marginal costs after the announcement date. To understand to what extent the differential drop in bids can be explained by the change in these costs, Figure A4 presents the time-series of the mark up ($Bid - Mg.Cost$) for the units in the collusive agreement and the rest. This figure shows an abrupt fall in the margin for units in the collusive agreements but not for the rest of the units, on the dates after the announcement. Table A1 and Figure A5 replicate Table 2 and Figure 4 respectively and show that the using the earned margin instead of the bidding price provides qualitatively similar results as those in the previous section.

In sum, changes in marginal costs and/or positions in the forward market cannot explain the drop in bidding prices of units in the collusive agreement right after the announcement date.

4 Incentives to Collude & Inner Functioning of the Cartel

The evidence in the previous Section shows that a subset of units in the market likely entered a collusive agreement to increase bids. This Section provides further evidence on cartel units' incentives to enter the agreement and on the inner working of the cartel. In subsection 4.1 we show that cartel units had incentives to enter a cartel to increase payments in the positive reconciliation market. The argument unfolds in two steps. First, we show that cartel units have costs so high that they wouldn't be able to earn the right to supply electricity through the ideal dispatch if they were to bid competitively. Given this, they maximize profits through the positive reconciliation market. Second, we qualitatively confirm that, indeed, incentive to collude exists in the positive reconciliation market. In particular, we show that revenues and profits are inverted-U shaped in bids: beyond a certain point, raising bids lowers the likelihood of being called upon for positive reconciliation as cheaper units might be available. Units thus benefit from a coordinated increase in bids.

Subsection 4.2 provides additional forensic evidence on the functioning of the cartel. First, we show that cartel units coordinated bids increase, particularly so when the probability of being called for positive reconciliation increases. Concretely, the cartel worked as follows: certain low cost units

win in the ideal dispatch auction and, from time to time, generate positive reconciliations to declare unavailability. Given network restrictions, these positive reconciliations are awarded to other cartel units that coordinated increases in bids to maximize revenue from positive reconciliations. Second, we complement the forensic analysis using data from the minutes of the meetings of the Association of Generating Units (CNO in Spanish). Finally, consistent with a cartel being at work, we confirm that, after the announcement of the regulatory change, profits from the reconciliation market (but not from the ideal dispatch) decreased relatively more for cartel units than for other units.

4.1 Incentives to Collude

Cartel Units are Unlikely to be in the Ideal Dispatch Figure 6 shows the comparison of the distribution of calculated marginal costs and average spot price for cartel units and other units separately. The average marginal cost of the units in the collusive agreement tend to be larger than the average spot price. This contrasts with the units that are not in the collusive agreement. For them, there is a significant mass of bids lower or equal than the average spot price.

Given the large differences in marginal costs across cartel and not cartel units, cartel units try to make profits in the only remaining possible way: the positive reconciliations market. As a sanity check, Table A2 shows that under different scenarios the profits that cartel units obtain in the positive reconciliation market are larger than what they would obtain in the counterfactual case in which they bid their marginal costs and try to win in the ideal dispatch.

Revenues and Profits from Positive Reconciliations are Inverted-U Shaped in Bids Incentives to collude on prices arise when uncoordinated price increases lower profits. We thus need to check that the positive reconciliation market features the usual price setting trade-off: higher prices increase margins, but reduce quantity (in this case, the likelihood of being called for a positive reconciliation). Table 3 shows that the revenue for positive reconciliations is increasing in the submitted bid when we control for unit and time fixed effects as well as aggregate demand and input prices. However, as the quadratic effect term shows, there is an inverted-U shape relationship. The coefficients can be interpreted as follows: If the prices are very low, the unit is not called for positive reconciliations as it would be allocated the right to produce in the ideal dispatch. However, when the prices increase, also the potential payment, but when these prices are too high, the regulator would prefer to call different units with lower bidding prices. The last column of the table shows that the estimates for profits closely track that on revenues.

4.2 Inner Working of the Cartel

Bids are Larger when Units Expect to Have Positive Reconciliations The first step to understand how the cartel worked is to check that, indeed, units bid strategically and increase bids when they anticipated a higher likelihood of being called for a positive reconciliation. If a unit expects to be called for a positive reconciliation, there are lower incentives to bid competitively to win the ideal dispatch. Note that this incentive is, in principle, present for both cartel and non-cartel units.

We thus investigate the relationship between bidding behaviour and the likelihood of being awarded a positive reconciliation. Obviously, we can not test the hypothesis using a simple OLS regression: the time-varying and unit specific likelihood of being awarded a positive reconciliation it is not directly observed and must be proxied with actual positive reconciliations. However, those are endogenous to bidding behaviour. We therefore instrument (the probability of receiving) positive reconciliations for unit i at date t constructing a proxy for exogenous market contingencies. We construct a proxy that varies across time *and* units using information on network overcharges. When market contingencies affect the system, they tend to do so for a prolonged period as repairing the network takes time. We thus use the lag instead of the current level of the probability of positive reconciliations.[22]

Table 4 presents the results of this exercise. The table shows that units increase their bids when they have a positive reconciliation in the previous period. Column 1 reports a very strong first stage: conditional on unit and date fixed effects, shocks to the infrastructure significantly increase the probability that the unit is awarded a positive reconciliation. Column 2 reports the second stage. We find a large, and statistically significant, increase in bids for units that are more likely to be awarded positive reconciliations due to shocks to the transmission network. Finally, Column 3 show the OLS – note that the OLS can be either upward or downward biased as a higher bid can either increase (the unit is less likely to win the ideal dispatch) or decrease (the unit, if eligible, is less likely to be called in) the likelihood of being awarded a positive reconciliation.[23]

[22] The logic of the instrument is as follows. The generation to guarantee security (The security generation) is the amount of energy that the generation unit must generate due to contingencies in the transmission system. This amount, which can be on merit or out of merit (i.e., based on the ideal dispatch) is independent of the bidding price. When security generation is needed and the unit is out of merit, then a positive reconciliation arises. Hence, the security generation explains well the likelihood of a positive reconciliation (first stage) but is independent of the bid (exclusion restriction).

[23] Add results with interactions or separate for cartel?

Coordination of bids and positive reconciliation across cartel units The previous exercise shows that there are incentives to increase bids in anticipation of positive reconciliations. We now show that cartel units likely coordinated to increase bids precisely when other cartel units generated positive reconciliations by winning the ideal dispatch and then declaring unavailability.

In order for units in the cartel to be able to profitably coordinate to win the auction and then declare unavailability to generate positive reconciliations for other units that submitted high bids, two conditions are necessary. First, it must be the case that the cartel comprises specialized units that are able to win in the ideal dispatch, at least sometime. The top-left panel in Figure 7 shows that some of the units in the cartel actually do have low costs, submit relatively low bids, and are sometime awarded capacity in the ideal dispatch. This same figure on the top-right shows the number of unavailabilities that each group of firms have in the second semester of 2008, i.e., during the cartel. Low bid units declare more than 8 times more often unavailable than high bid units. Finally, the bottom of the figure shows that the probability that high price cartel units receive positive reconciliations when low price cartel units win is much larger than the probability for the same high price cartel units when low price no cartel units win.

The second ingredient is to show that units are indeed able to coordinate. To check whether this is the case, for each unit i we define "friends" as those units who are more likely to get a positive reconciliation when unit i has a negative reconciliation. For each unit i, we rank the "friends" by the probability of receiving positive reconciliations. Top 1 denotes the "friend" with the largest probability while Top 3 means the three "friends" with the largest probability. We focus on observations 6 months before and 6 months after the announcement date.

We then investigate whether the average bid of i's friends increase when the real availability unit i is below its awarded ideal generation. Real availability is the actual availability that the unit was able to produce while the ideal generation depends on the expected availability. The actual availability can be lower than the expected availability due to strategic decisions of the unit (unit i decides to produce less than declared to the regulator ahead of the auction) or exogenous reasons (e.g., if unit i suffers production shocks). While we are unable to separate these two motives, an interesting pattern emerges. Figure 8 presents the baseline results when we focus on the "Top 1" friend of each unit and shows that only the friends of cartel units increase their bids when a positive reconciliation can be expected and that the effect is present (and significant) in the period before the announcement. The coordination of bids and declared availability between cartel units

and their friends appeared only after the likely beginning of the cartel period.[24]

Summary In sum, we have gathered evidence that the cartel worked as follows: 1. There are two types of units in the cartel: low and high marginal bids. 2. Low-price units try to win the auction and declare unavailable from time to time. Given network restrictions, the right to allocate usually is assigned to other units in the cartel. As a consequence, the cartel was being profitable for the parties involved by having units with low costs that allow those with high costs to make profits in the reconciliations market.

Minutes Evidence We complement our forensic analysis using novel, hand-collected, data from the minutes of the meetings of the Association of Generating Units (CNO in Spanish). Regulators were suspicious about the possibility that members of the cartel were conducting coordinating actions in 2008 in meetings of a generating units association (CNO in Spanish).[25] For its engineering nature, this association held meetings to find problems and solutions related to technical difficulties and constraints of the system. As a consequence, workers related to the division that set prices, the commercial area, were not invited to those meetings.

We downloaded the minutes of all of the meetings that occurred in 2008 and 2009. We are interested in understanding whether or not there was any behavior in these meetings that cartel units had different from non-cartel units before and after the policy change.

For this purpose, we use two main dependent variables: a dummy that takes the value of 1 if the unit sends someone to the meeting and a dummy that takes the value of 1 if the unit sends someone from the commercial area to the meeting. For each of the attendees-minutes, we categorize the participants as belonging to the commercial area if at the moment of the minute their CV (accessed through websites such as LinkedIn) reports they belong to any commercial area. We have two independent variables. The interaction term Cartel*2009 and a dummy for the presence of a regulator.

Table 6 shows that when the regulator attended those meetings, generation units were more

[24]These results are robust to different exercises. Figure A6 shows that results do not change if we consider the 'Top 3' friends instead of 'Top 1'. Figure A7 shows the results are robust to the sample period: when defining friends using observations for the period 2005-2008 instead of a one year period around the reform. Third, in the baseline results we consider all of the cases in which the real availability is lower than the ideal generation. Figure A8 shows the results when we focus only on 50% of those cases where the difference between the real and ideal generation availability is the highest. Unfortunately, data on real availability are unavailable after 2008. This prevents us from checking that the estimated relationship reverts back to insignificant *after* the end of the cartel.

[25]For more information, see https://www.cno.org.co/content/quienes-somos and the report from the regulators (Superintendencia Delegada para Energía y Gas, 2008)

likely to send someone to those meetings but less likely to send someone from the commercial area. Table 6 also shows that cartel units were less likely to send someone from the commercial area to those meetings after the announcement period. While the evidence is only suggestive, this is consistent with units knowing that attendance to the meeting of employees involved in setting bids isn't allowed (or, at least, discouraged) and that attendance of such employees was relatively more likely for units in the cartel during the period in which the cartel was in force.

Lower Profits from Positive Reconciliations After the End of the Cartel Finally, the hypothesis of an implicit agreement in the bidding scheme implies that after the break of the agreement the profits and revenues of the collusive agreements units should decrease. As a sanity check, we therefore revisit our baseline specifications presented in Section 3.4 and consider the following dependent variables: Daily revenues from positive reconciliations, Daily profit from positive reconciliations, Daily total revenue and share of the revenues from positive reconciliations.

Table 5 shows that the revenue and profits from positive reconciliations as well as the total revenue and the percentage of revenue coming from positive reconciliations sharply decreases for the collusive group after the announcement date.

5 Quantifying the Value of the Collusive Agreement

In this section, we quantify the incentive to collude of each unit and the cost of the cartel for consumers. In order to do so, we need to construct counterfactual bids and profits under three scenarios: competition, collusion, and optimal deviation from collusion. We conduct this exercise in three steps. First, we show empirically that cartel units could increase static profits by deviating from the collusive agreement and by submitting lower bids. Second, we construct counterfactual profits and show that such deviations are not incentive compatible under the old transparency rule due to the future value of the cartel, but they become profitable under the new 90 days rule. Third, we use such estimate to provide a back-of-the-envelope estimate of the cost of the cartel for consumers.

5.1 Bidding Strategy

The existence of a cartel involves departures from static Nash equilibrium for its members, which implies a short run incentive to deviate from the cartel. The sustainability of a cartel depends on whether such deviations are incentive compatible or not, that is whether the gain from short

run deviations compensate the loss of future gains from colluding. However, before verifying the incentive compatibility of such deviations, we empirically show the existence of deviations to increase static profits. Our hypotheses are that non-cartel units set bids to maximize their individual static profits while cartel units do not. In particular, cartel bids should be larger than static profits-maximizing bids. We test these hypotheses with the following three-step procedure: First, since the cartel operates on the market for positive reconciliations, we need to select a suitable comparison group of non-cartel units that are also more likely to make profits with positive reconciliations. Second, we estimate how the amount of positive reconciliations that a unit gets changes if the unit had submitted a different bid. Third, we use these estimates to compute the bid that maximizes static daily profits from positive reconciliations and compare it to the observed ones.

In the first step, we identify a suitable comparison group of non-cartel units using the following criteria. (i) Thermal units, because all cartel units are thermal and because their production costs can be estimated with engineering formulas. (ii) Private units, because publicly owned units might not be profit maximizers (Barros and Modesto, 1999). (iii) Units that are not owned by a cartel firm, because we want to limit the possibility of considering units that are actually in the cartel or pursuing different goals, as in the robustness exercise on the cartel definition presented in Section 3.4. This criteria leaves us with a comparison group consisting of four non-cartel units.[26] We focus on a one year period: six months before the policy change and the six months after the policy change. For these two periods, we compare observed bids with static profits maximizing bids for both cartel and non-cartel units.

We compute, for each day, the amount of positive reconciliations that a unit would have got had it submitted a counterfactual bid. In the spirit of Porter and Zona (1993), our analysis is based on the rank of bids rather than bids themselves. We follow a two steps estimation procedure to accommodate the non-linearity between bids and quantities: We first model the probability of receiving some positive reconciliation, and then we model the expected amount of positive reconciliation conditional on receiving some.[27] Since, due to transmission network constraints, the

[26] If we do not impose the third restriction, we obtain a comparison group consisting of nine units and similar results (see Figure A11).

[27] In practice, we model the probability of receiving some amount of positive reconciliation with a binary response model and use the rank of the bid of a unit with respect to its competitors, its squared value, unit and time fixed effects as regressors. Since our goal is to make predictions, we estimate the model with maximum likelihood assuming the errors follow a logistic distribution. Then, we regress the logarithm of the awarded quantity of positive reconciliation conditional on being awarded some quantity with a linear model using the same covariates as in the first step. We estimate the second model with OLS. The expected quantity is then given by the product of the probability of being awarded some positive reconciliations with the expected amount conditional on being awarded some positive reconciliations.

geographical position of a unit is crucial in determining who gets a positive reconciliation, and since cartel and non-cartel units are located in different regions, we estimate the two models separately for cartel and non-cartel units. In particular, for cartel units the rank of bids is computed with respect to all the others cartel units, while for non-cartel units the rank of bids is computed with respect to all the others non-cartel units. Figure A9 presents in-sample predictions from this estimation procedure versus observed quantities. We further compare the distribution of our predictions and of observed quantities in figure A10. Both diagnostic figures suggest that our model is able to replicate fairly well the amount of positive reconciliations awarded.

Given these estimates, we simulate, for each unit and day, alternative bids to the observed one and the corresponding quantities of positive reconciliation conditional on other units' bids. We then compute counterfactual profits and select the bid yielding the highest static daily profits. At the unit-day level, we compute the ratio between the observed bids and the static profits maximizing bids and plot the density of this ratio separately for the two groups of units and the two periods of time.

Under the assumption that units aim to maximize static profits from positive reconciliations, we expect the mass of the density to be centered around one. If units are colluding to raise prices in the positive reconciliation market, instead, we expect significant mass above one. Figure 9 presents the results of this exercise. Before the policy change, the distribution computed for cartel units is bimodal and displays a peak at a ratio around four (significantly larger than one), i.e., cartel bids are often much larger than their static profit maximizing bids. For non-cartel units, instead, the distribution is single-peaked with most of its mass closely around a ratio equal to one. After the policy change, instead, for both cartel and non-cartel units the density is centered around one, suggesting that both groups are now bidding competitively.

5.2 Dynamic Incentive Compatibility Constraints

The previous subsection provides evidence that cartel units could increase daily profits by deviating from the collusive bidding strategy. However, cartel sustainability relies on the fact that deviations are not profitable due to the future value of the collusive agreement. In this subsection, we check the mechanism through which the policy change undermined cartel sustainability. Similarly to Igami and Sugaya (2021), we check that the incentive to collude is positive for all cartel units under the old transparency rules, but negative for at least one unit under the new ones.

We assume that deviation of a unit from the collusive agreement triggers competition. Under

the old transparency rule, this implies that a unit can unilaterally deviate for two days and undercut other cartel's bids to increase static profits. But, from the third day onward, cartel units would bid competitively. However, under the new transparency rule, a unit can unilaterally deviate for 90 days before competition is triggered because only then the deviation becomes common knowledge. We thus define static profits for unit i at time t as π_{it}^{j} under three alternative scenarios: j = C (collusion), N (competition), D (optimal deviation from the collusive agreement). We assume that units hold static expectations and denote with β the daily discount factor. We define the dynamic incentive compatibility (DIC) constraint under the old (2) and new (3) transparency rule as follows

$$\frac{1}{1-\beta}\pi_{it}^{C} - \frac{1-\beta^{2}}{1-\beta}\pi_{it}^{D} - \frac{\beta^{2}}{1-\beta}\pi_{it}^{N} > 0 \qquad \text{For all units} \tag{2}$$

$$\frac{1}{1-\beta}\pi_{it}^{C} - \frac{1-\beta^{90}}{1-\beta}\pi_{it}^{D} - \frac{\beta^{90}}{1-\beta}\pi_{it}^{N} < 0 \qquad \text{For at least one unit} \tag{3}$$

Our hypothesis is that the DIC in (2) is satisfied for *all* cartel units for all periods t before the policy change, while the DIC in (3) is not satisfied for *at least* one cartel unit after the policy change. We empirically test this hypothesis as follows.

We focus on cartel units one year around the policy change and on the profits they can make with positive reconciliations.[28] Given the evidence presented above, we assume that cartel units where colluding before the announcement of the policy change and competing after the implementation. Thus, for each unit and day in these two periods we observe bids and quantities under one of the three possible scenarios. We then need to compute bids and quantities for the other two counterfactual scenarios. From August 2008 until the announcement of the new policy we observe bids and quantities under collusion and need to compute bids and quantities under competition and deviation from collusion, while from the policy implementation until June 2009 we observe bids and quantities under competition and need to compute bids and quantities under collusion and deviation from collusion. For the period between the announcement and the implementation we remain agnostic about the moment in which each unit moved from collusive to competitive bids, and we construct counterfactual variables for all the three scenarios.

To simulate counterfactual bids and quantities we follow the approach presented in the previous subsection. Given these bids and quantities, we compute profits using the estimates for the production costs introduced above and compute the incentive to deviate for each unit at any point in time according to the definitions in (2) and (3). Below we provide details on the steps for this exercise.

[28] We do not consider the unit Proelectrica 2 because it was never awarded positive reconciliations in the considered period of time. We thus focus on 14 of the 15 cartel units.

First, we need counterfactual competitive bids b_{it}^N for the pre-reform period and counterfactual collusive bids b_{it}^C for the post-reform period. We model bids a function of market fundamentals similarly to Pesendorfer (2000): We regress observed bids on unit fixed effects, production costs, the logarithm of the total amount of positive reconciliation in the previous day, and the logarithm of the total amount of ideal generation (that is the two exogenous quantities that are known at the time of submitting bids). We estimate this regression separately for the pre and post-reform periods and use these estimates to simulate counterfactual bids. Table 7 presents the results. As argued by Porter and Zona (1993) and Ishii (2009), our estimates suggest that the levels of bids do not necessarily reflect the underlying market fundamentals when units are colluding, but they do when units are competing. In order to assess the goodness of our method, in Figure A12 we plot in-sample predictions versus observed bids for the collusive and competitive period separately, and the respective distributions in Figure A13. Our model seems to replicate well how cartel units set bids under both scenarios.

We also need counterfactual competitive quantities q_{it}^N for the pre-reform period and counterfactual collusive quantities q_{it}^C for the post-reform period. However, to correct for differences in units' availability and transmission problems, we also simulate q_{it}^C for the pre-reform period and q_{it}^N for the post-reform period instead of relying on observed ones. In practice, we thus simulate both counterfactual quantities - collusion and competition - for all days and units. We model how awarded quantities of positive reconciliation depends on the rank on the bids and rely on the same method used in the previous exercise. We then predict q_{it}^C using observed bids for the pre-reform period and using simulated bids for the post-reform period. We do the opposite for q_{it}^N. Figures A14 and A15 show the goodness of in-sample predictions.

Given simulated and observed bids, estimated costs, and simulated quantities, we predict profits π_{it}^C and π_{it}^N for all days and units. We finally need bids and quantities under the optimal deviation scenario to compute the corresponding profits. For each unit and day separately, we simulate quantities and profits for different possible values of a deviation bid b_{it}^D (above production cost and below the collusive bid) and select the one yielding the highest profits π_{it}^D. Figure A16 presents the resulting average profits under the three different scenarios. By construction, for each units, deviation yield the largest average profits, competition the lowest with the collusion payoff in the middle. The Figure reveals significant variation in how much units stand to gain from collusion relative to competition. Given these counterfactual profits, we can compute the incentive to collude for each unit. We average profits at the monthly level and compute the incentive to collude in

each month assuming static expectations (results are similar if we aggregate at the daily or weekly level). In the top part of Figure 10 we report the *smallest* incentive to collude across cartel units over time, assuming a daily discount factor $\beta = 0.9997$ ($\beta^{365} = 0.90$, the interest rate in 2008 and 2009 was around 10%). We use the definition in (2) for the period until the reform in January 2009 and (3) afterwards. The figure shows that all cartel units were better off colluding until January 2009, but that afterwards the cartel became unsustainable as it was more profitable for at least one unit to deviate from the collusive agreement. As it happens, our estimates reveal that the dynamic incentive compatibility constraint (2) was violated for four units after the reform.

A potential concern is that the sudden drop in the incentive to collude as of January 2009 might have been driven by other changes in the market rather than the reform itself. To rule out this possibility, in the bottom part of Figure 10 we report the DIC according to (2) and (3) separately for the entire considered period. The figure shows that if deviations were possible only for two days, the smallest incentive to collude across cartel units would be positive both in the pre and post-reform period. However, if deviations were possible for 90 days, some units would have an incentive to deviate both before and after the reform. That is, the drop in the incentive to deviate observed in January 2009 and the cartel collapse are only driven by the policy change and not by other differences between the pre and the post-reform periods. As an additional robustness exercise, in Figure A17 we report the result for slightly higher and lower values of the discount factor.

5.3 Cost of the Cartel

The exercise we conducted above allows us to quantify the cost of the cartel for consumers. That is, the additional cost consumers paid for the electricity produced due to the high cost imposed by the cartel to the reconciliations market. For this exercise, we focus on the second semester of 2008, and compare the total cost paid for positive reconciliations to cartel units with the total cost that would have been paid if the cartel firms had behaved competitively. The former quantity is observed, while the latter is deduced from the counterfactual variables in the previous section.

To advance in this direction, we make the simplifying assumption that the total amount of positive reconciliations produced by the cartel is independent of its members colluding or competing. The collusive behavior only changes the particular allocation of production of energy to units. The assumption relies on two observations. First, cartel units are concentrated in a particular geographical area (see Figure A2), and thus transmission problems that generate positive recon-

ciliations effectively create a separate market. Furthermore, even if the previous assumption is not satisfied, our measure provides a lower bound estimate of the benefit of competition. The rationale of why this is the case is that if cartel units decrease the price, they, as a whole, may increase the total amount of positive reconciliations being awarded. But this implies that if we allow for the possibility of increasing the awarded positive reconciliations, the total cost that customers pay would be even *lower* because the bids of cartel firms cannot be larger than the bids of the non cartel units that previously were winning the right to produce.

In practice, to conduct the estimation of the cost of the cartel, we multiply bids and amounts at the unit-day level and then sum over units. As before, we aggregate costs at the monthly level and present the results in Figure 11. The two lines (scale on the left axis) refer to the total cost paid to cartel and non-cartel units for positive reconciliation under collusion and competition. The bars (scale on the right axis) show the percentage increase in cost due to the existence of the cartel. The figure shows that the cartel generated an additional cost of around 15 billion COP per month, which corresponds to an increase of around 15% with respect to the competitive scenario. Positive reconciliations account for approximately 10% of the electricity procured by the regulator, but since they are paid above the spot price this lead to an increase in overall costs of about 3%. Around 10 million households lived in Colombia in 2008. If all the energy allocated via positive reconciliations is bought by households, and assuming a full pass-through of the cost increase to consumers, the average household paid 1,500 COP in excess per month in the second semester of 2008 due to the collusive agreement (with many household living with less than a minimum wage of 461.500 COP).

6 Conclusions and Final Discussion

To be added

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7 Figures

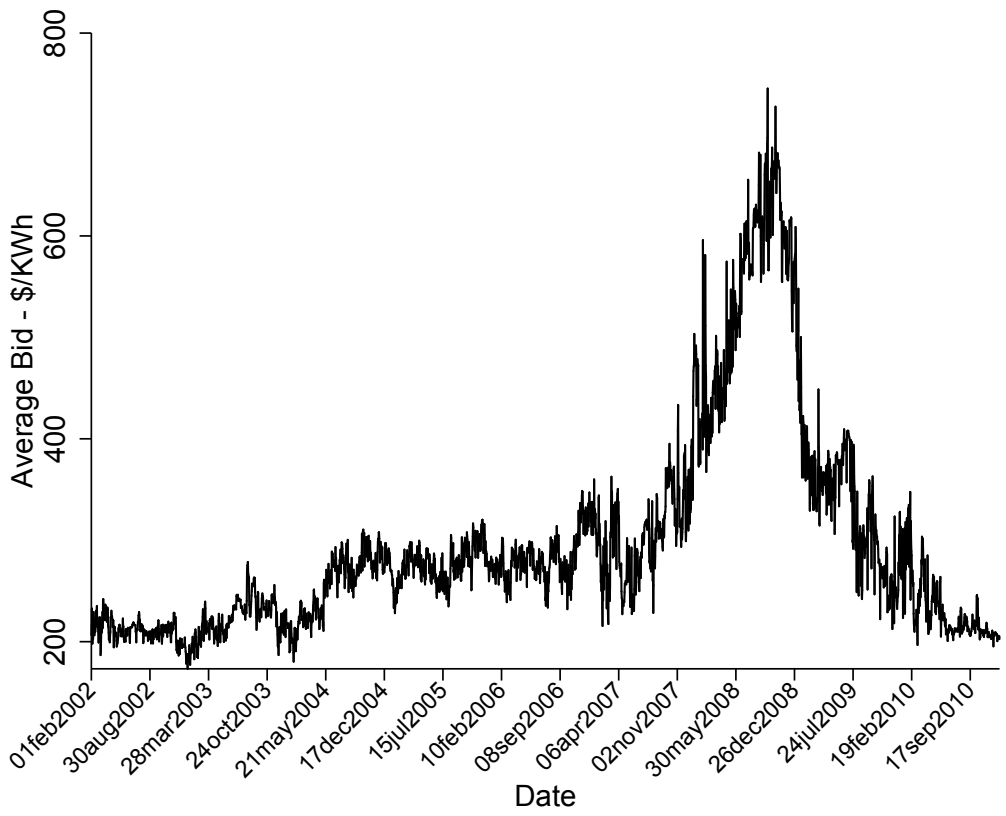


Figure 1: Average bid time series.

Note: Daily time series of the average bid from 2002 to 2010 in the Colombian wholesale electricity market.

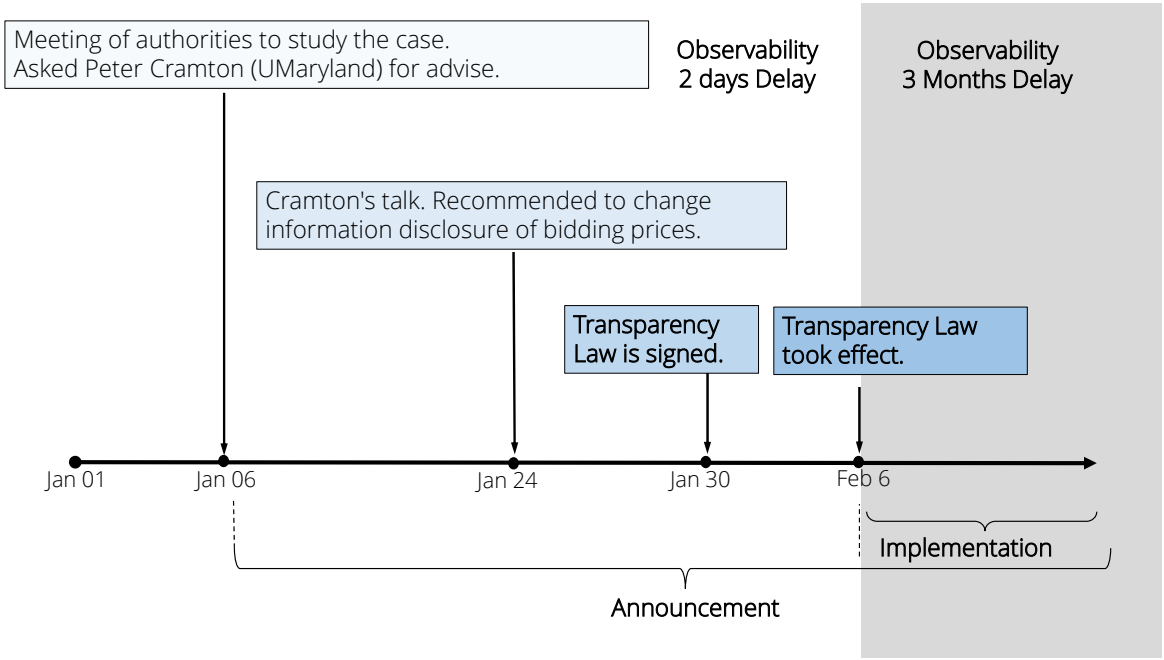


Figure 2: Timeline.

Note: Timeline of the announcement and implementation of the transparency policy.

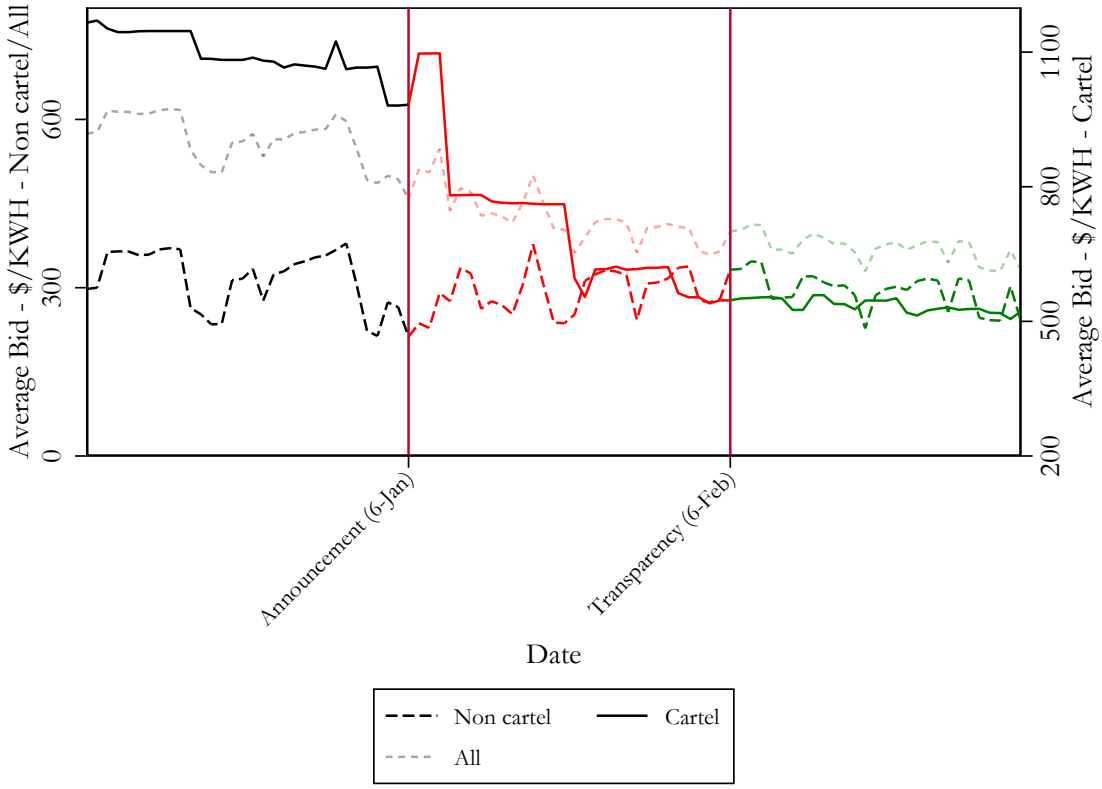


Figure 3: The Main Fact: Cartel and non cartel groups bids.

Note: Time series of the average bid of the cartel (solid line, right axis) and non-cartel groups (dashed line, left axis) around the dates of announcement and implementation of the transparency policy. In transparency we also report the overall average (right axis). The vertical lines point out the key dates of the transparency policy (announcement and implementation).

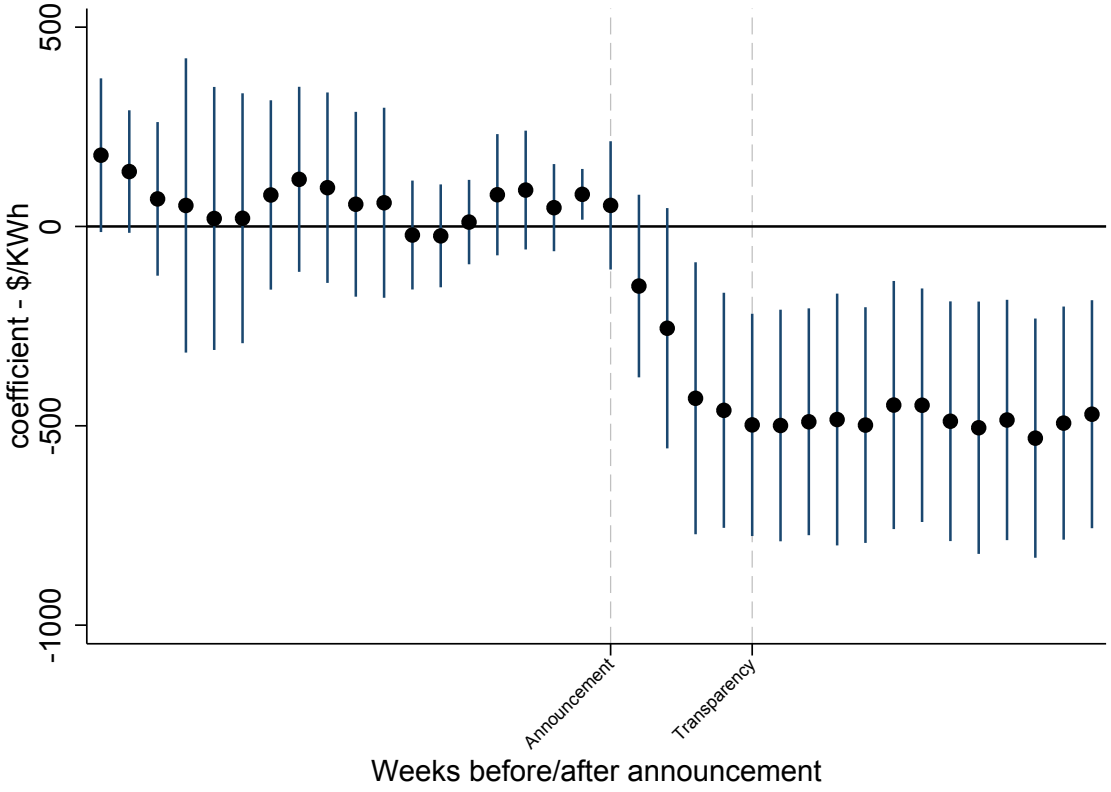


Figure 4: Event study representation of the differences-in-differences model.

Note: The figure presents the event study representation of the difference-in-difference model using the bid as the dependent variable. We performed a two-way fixed effects model including a specific treatment effect for each week of the period studied. The x-axis represents weeks before and after the announcement of the transparency policy. The y-axis represents the difference in the bidding price with reference to the week of the announcement of the transparency policy. The black dots represent the estimated differences and the surrounding vertical lines represent the 95% confidence intervals. The zero (omitted) coefficient corresponding to the week of the announcement of the transparency policy is not presented in the figure. The dotted line labeled as "Announcement" represents the next week to the announcement of the transparency policy. The dotted line labeled as "Transparency" represents the next week to the implementation of the transparency policy.

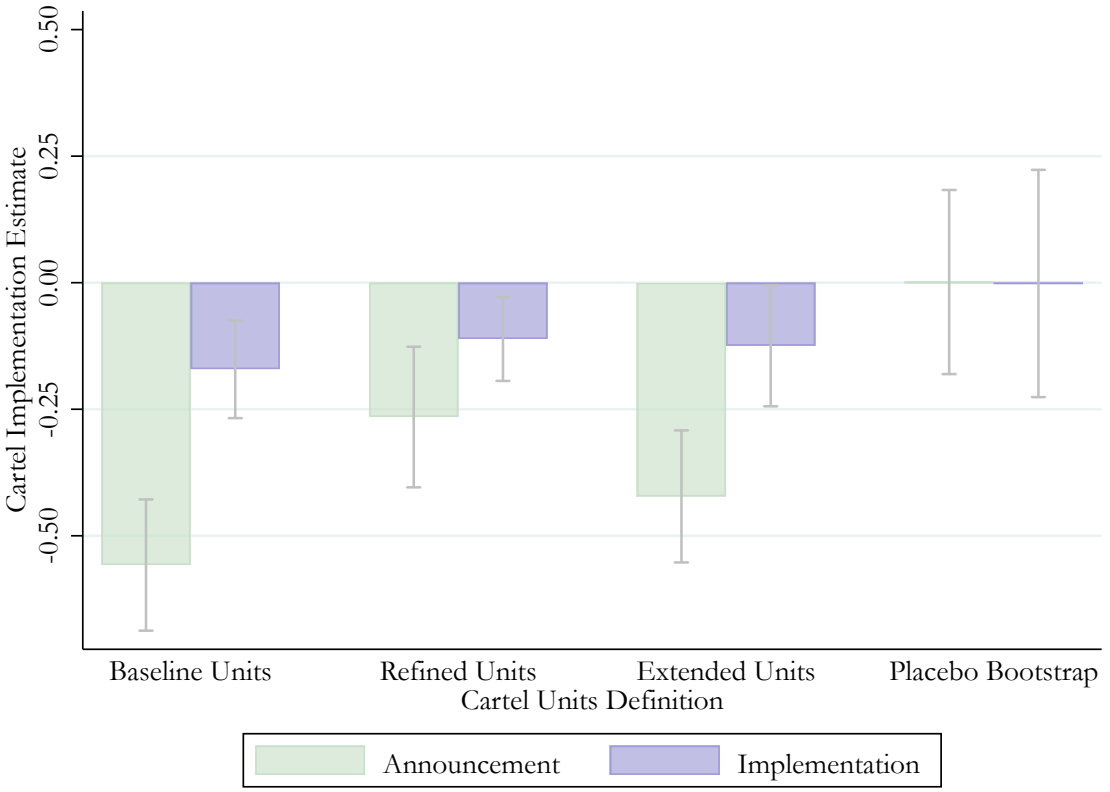


Figure 5: Robustness Exercises.

Note: The figure shows the coefficients and standard errors of the announcement and implementation parameters from 4 different estimations. Baseline units shows the 15 units we include in the main estimations. The refined units group only includes units (total treated=10) that belong to firms that has all their units in the cartel. The extended units group includes all of the units of firms for which at least one unit belong to the baseline cartel definition (total treated=23). Placebo test includes all of other units that are different from the extended units. For this exercise, the treated group consists of 15 units. All of the estimations control for Water Intake, Coal Price and Colombian Guajira Index as well as a battery of unit and date fixed effects.

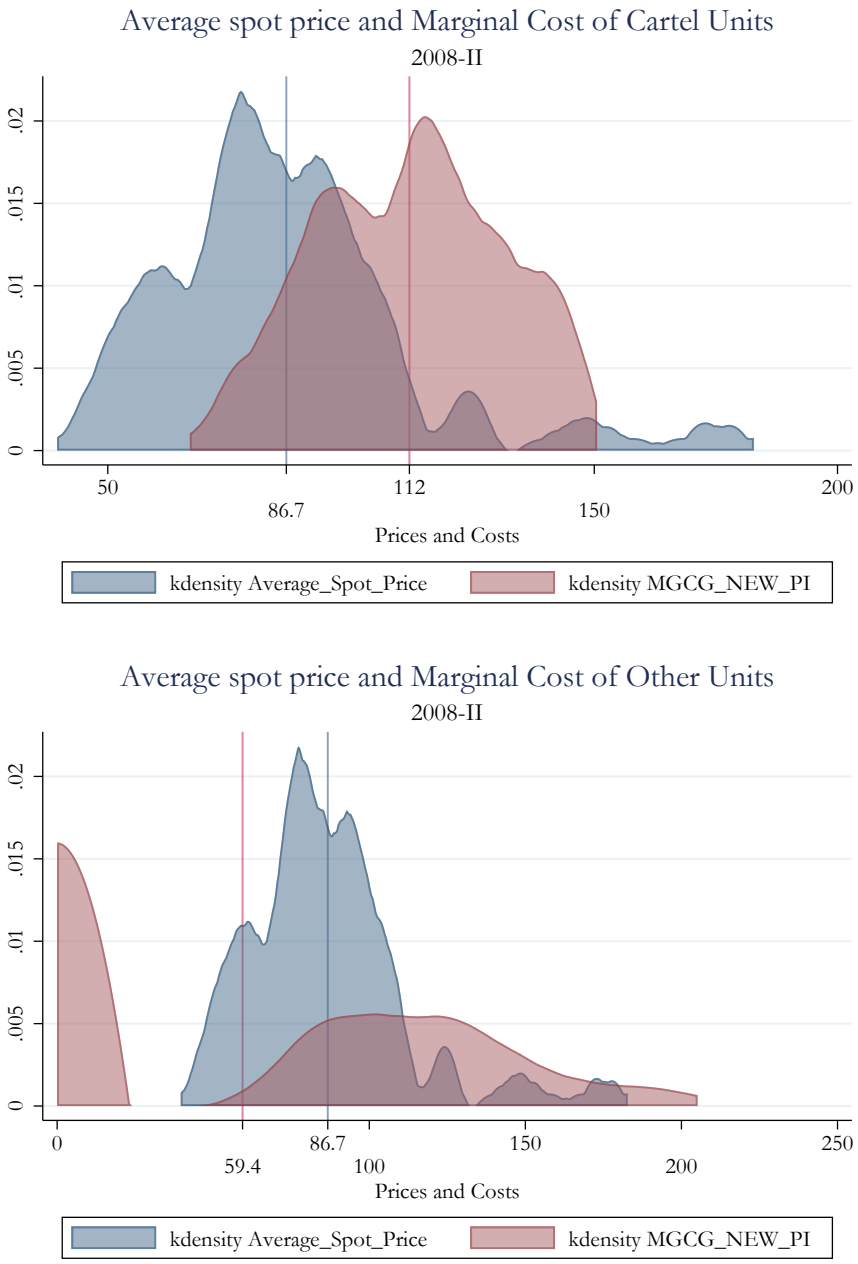


Figure 6: competitiveness of the cartel and non-cartel units.

Note: The panels in the figure present the kernel densities of the daily spot price (blue shaded density) and the marginal cost (red shaded density) in the second semester in the year 2008. The top panel presents the kernel densities of the cartel group units and the bottom panel presents the kernel densities of the no-cartel group. The vertical blue line indicates the average spot price and the red vertical line indicates the average marginal cost for the corresponding group.

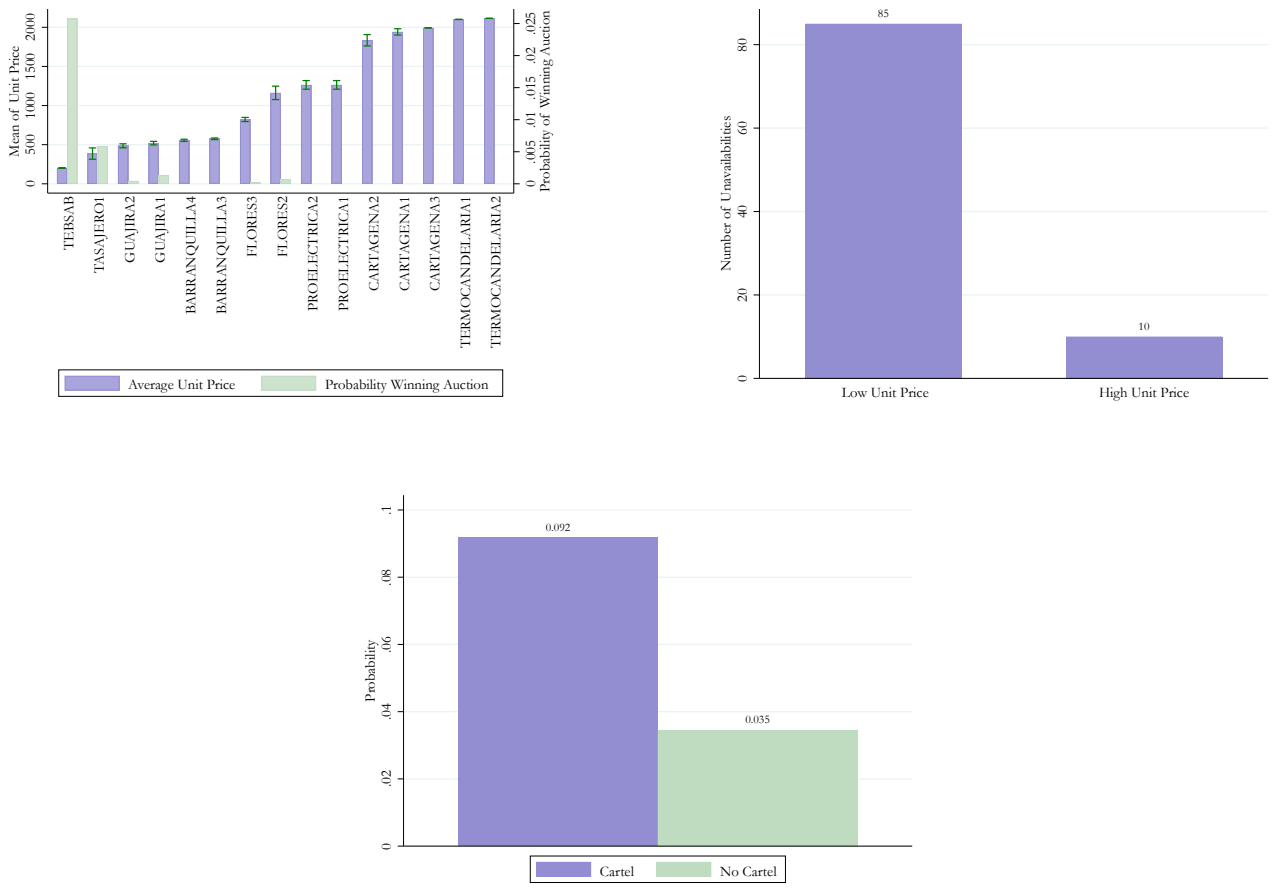


Figure 7: Inner Working of the Cartel

Note: The top left figure shows the average unit prices for the cartel units and their probability of winning the auction in the second semester of 2008. The top right figure shows the number of unavailabilities of high and low bid cartel firms. The bottom figure shows the probability that high price cartel units receive positive reconciliations when low price cartel units win, or low price no cartel units win for the second semester of 2008.

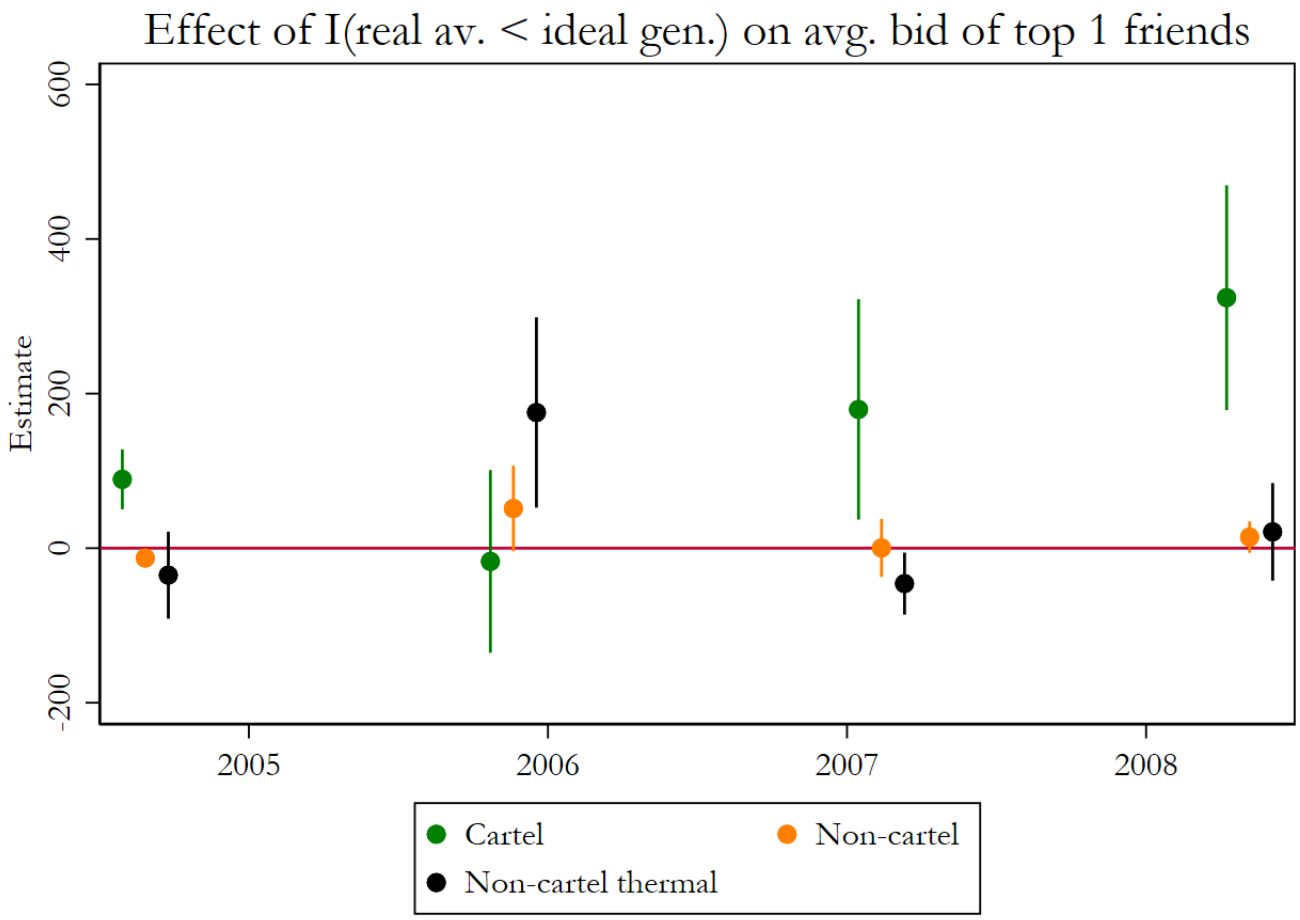


Figure 8: Baseline Friends' Exercise.

Estimates from a regression where the outcome variable is the average bid of the friends of unit i and the explanatory variables is an indicator for unit i declaring a level of real availability below the ideal generation quantity it was awarded. We run 3 separate regression for the 3 groups (cartel, non-cartel, non-cartel thermal).

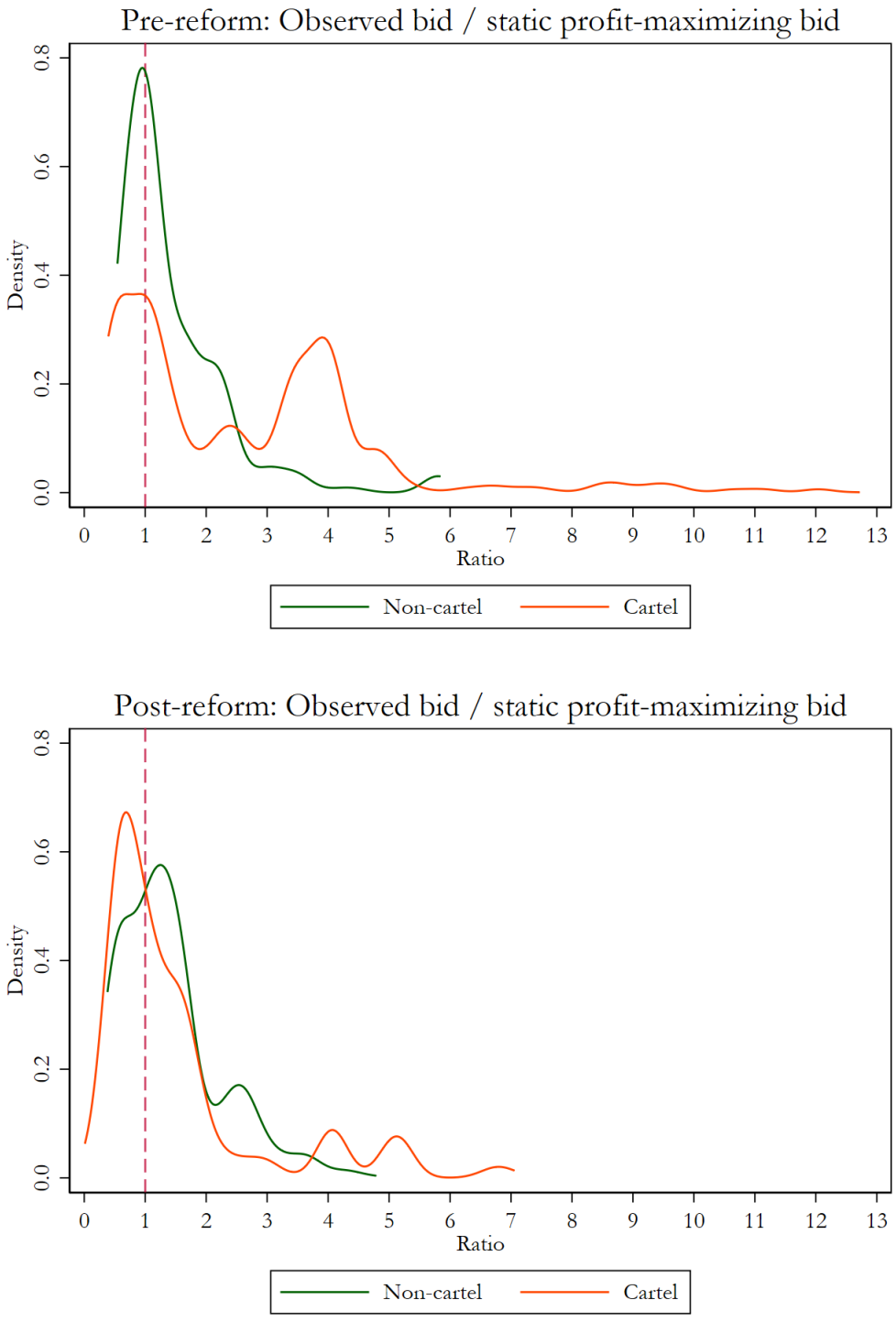


Figure 9: Density of the ratio between unit-daily observed and static profits maximizing bids for cartel and non-cartel units over two different six month periods.

Note: For cartel and non-cartel units, we simulate counterfactual bids and the corresponding amount of positive reconciliations and select the static profit maximizing bids. We then compare it with the observed bid: At the unit-day level, we compute the ratio between the observed bid and the profit maximizing bid. We plot the density of this ratio. The top figure presents the density using data from the six months before the policy change; the bottom figure refers to the six months after the policy change.

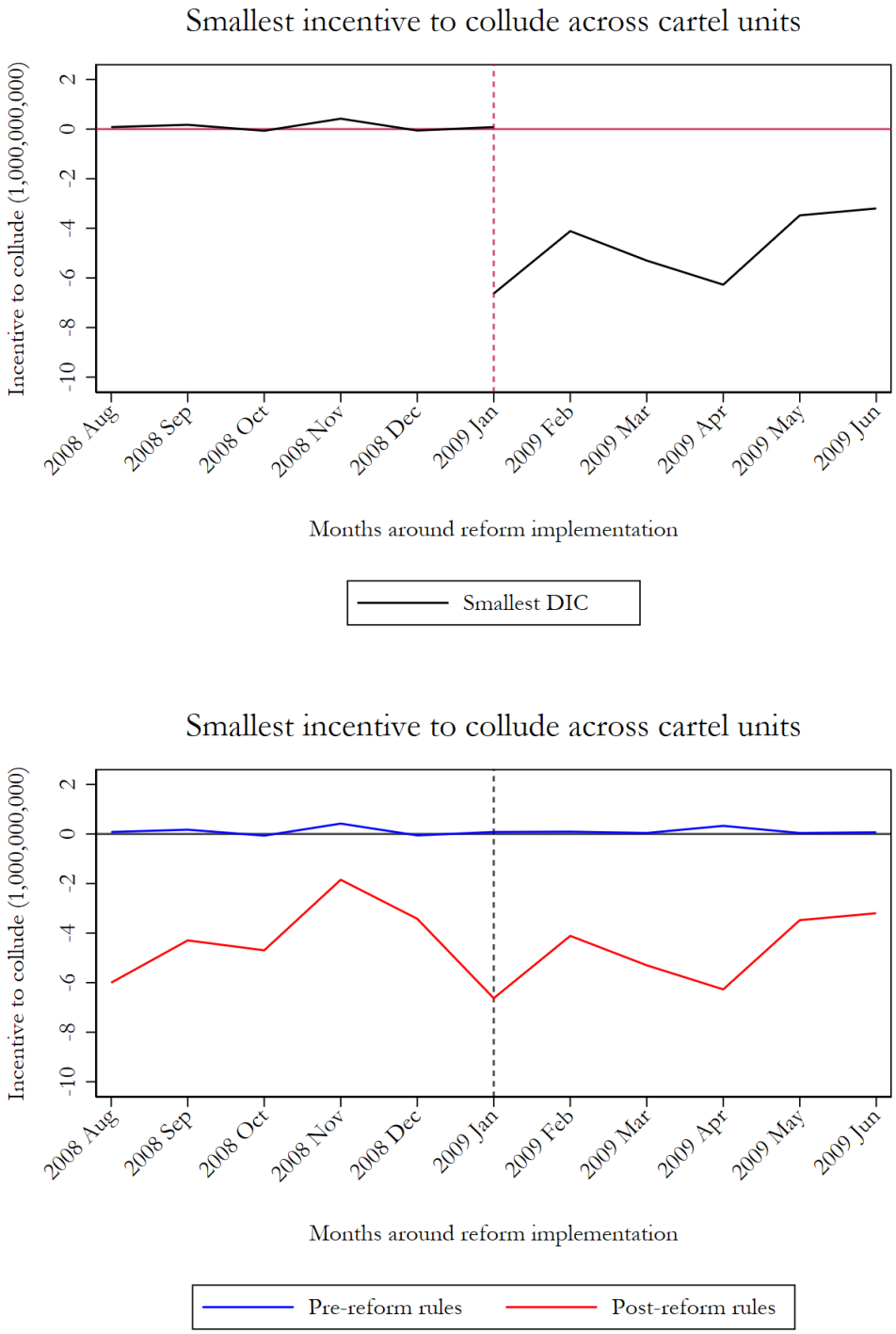


Figure 10: Smallest incentive to collude across cartel firms. β=0.9997, 0.9997^{365} = 0.90.

Note: For each cartel unit we compute the incentive to collude in each month from August 2008 to June 2009. In the top panel, up until January 2009 the incentive to collude is computed assuming that a unit can unilaterally deviate for two days before triggering competition; from January 2009 a unit can deviate for 90 days. In this figure we plot the smallest incentive to collude across cartel units in each month. In the bottom panel, we plot the smallest incentive to collude across cartel units assuming that a unit can unilaterally deviate for two days before triggering competition (blue line) or for 90 days (red line).

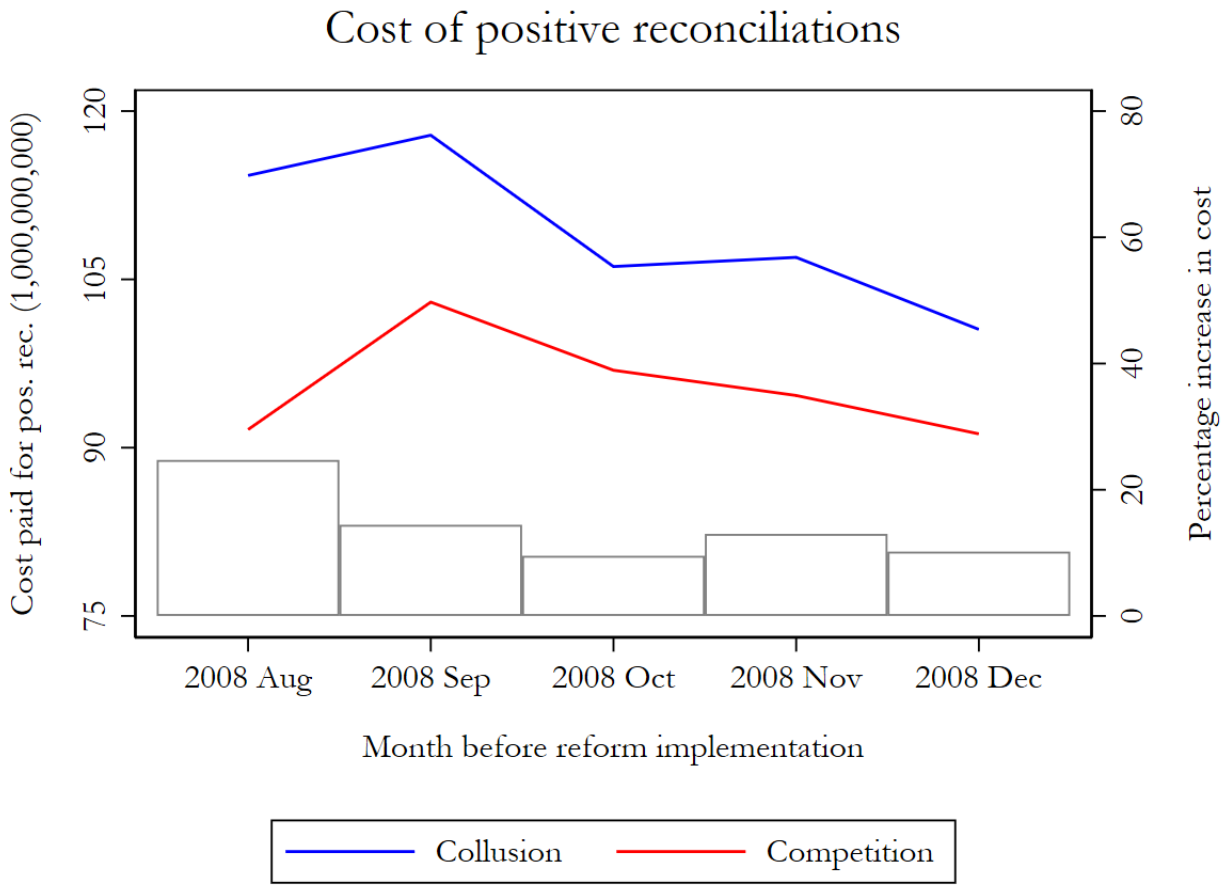


Figure 11: Total cost of positive reconciliations paid to cartel and non-cartel units under collusion and competition.

Note: The blue line (scale on the left axis) represents the total cost paid to cartel and non-cartel units for positive reconciliations in every month between August and December 2009. The red line (scale on the left axis) represents the counterfactual cost assuming cartel units were competing rather than colluding. The bars (scale on the right axis) present the percentage increase in the cost paid for positive reconciliations with respect to the competitive scenario.

8 Tables

		Before 06/01/2009					
		Cartel			No Cartel		
Variable	Unit	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Bid	COP/KWh	2370	1159.92	731.58	5056	360.59	558.07
Ratio forward contracts/ availability	%	2351	0.37	0.33	4907	0.93	1.19
Probability positive reconciliation	Probability	2370	0.16	0.34	5056	0.22	0.33
Average Positive reconciliation	KWh	2370	23673	74089	5056	9280	29416
Revenue from Positive reconciliation	Millions COP	2370	108.78	336.59	5056	14.58	47.37
Average Availability	KW	2370	127541	159186	5056	286861	303097
Location in Atlantic zone	Dummy	2370	0.93	0.25	5056	0.03	0.17
Public firm	Dummy	2370	0.33	0.47	5056	0.53	0.50
Estimated Marginal Cost	COP/KWh	2370	110.22	21.48	5056	58.96	63.45
Demand	GWh	2370	148.50	10.60	5056	148.50	10.60
Hydro generation	Dummy	2370	0.00	0.00	5056	0.50	0.50
Gas generation	Dummy	2370	0.93	0.25	5056	0.25	0.43
Coal generation	Dummy	2370	0.07	0.25	5056	0.25	0.43
		After 06/01/2009					
		Cartel			No Cartel		
Variable	Unit	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Bid	COP/KWh	3105	551.57	486.40	6624	294.05	469.98
Ratio forward contracts/ availability	%	3103	0.37	0.34	6594	1.23	1.80
Probability positive reconciliation	Probability	3105	0.19	0.36	6624	0.25	0.35
Average Positive reconciliation	KWh	3105	21485	69440	6624	11258	37928
Revenue from Positive reconciliation	Millions COP	3105	75.42	252.60	6624	20.53	69.20
Average Availability	KW	3105	136324	170578	6624	287086	304480
Location in Atlantic zone	Dummy	3105	0.93	0.25	6624	0.03	0.17
Public firm	Dummy	3105	0.33	0.47	6624	0.53	0.50
Estimated Marginal Cost	COP/KWh	3105	78.84	15.82	6624	49.56	54.31
Demand	GWh	3105	147.90	10.71	6624	147.90	10.71
Hydro generation	Dummy	3105	0.00	0.00	6624	0.50	0.50
Gas generation	Dummy	3105	0.93	0.25	6624	0.25	0.43
Coal generation	Dummy	3105	0.07	0.25	6624	0.25	0.43

Table 1: Descriptive Statistics

Note: The table presents the descriptive statistics of the cartel and non-cartel groups for two different period before and after the announcement of the policy. Columns 3 to 5 present information of the cartel group while columns 6 to 8 present information of the non-cartel group. The top panel presents information for the period 1st August of 2008 until 6th January of 2009. The bottom panel starts on the 6th January of 2009 and ends 31st July 2009.

VARIABLES	(1) LnBid	(2) LnBid	(3) LnBid	(4) LnBid	(5) LnBid	(6) LnBid
Cartel Announcement	-0.56***	-0.56***	-0.56***	-0.56***	-0.38***	-0.38***
	(0.12)	(0.13)	(0.12)	(0.13)	(0.06)	(0.06)
Cartel Implementation	-0.17**	-0.17*	-0.17**	-0.17*	-0.05	-0.07
	(0.08)	(0.10)	(0.08)	(0.10)	(0.06)	(0.06)
Announcement	0.01		-0.00	-0.00		
	(0.06)		(0.06)	(0.07)		
Implementation	-0.11		-0.07	-0.07		
	(0.08)		(0.06)	(0.08)		
Observations	17,155	17,155	17,155	17,155	16,790	16,790
R-squared	0.27	0.82	0.27	0.81	0.84	0.84
Unit FE	NO	YES	NO	YES	YES	YES
Date FE	NO	YES	NO	NO	NO	NO
Inputs Control	NO	NO	YES	YES	NO	NO
Demand Control	NO	NO	YES	YES	NO	NO
Date-technology-atlantic-public FE	NO	NO	NO	NO	YES	YES
Forward Control	NO	NO	NO	NO	NO	YES

Robust SE clustered by Unit and Date in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 2: Difference-in-difference estimates

Note: The table presents the estimation results of the difference in difference model proposed in expression 1 in sub-section 3.4 using the logarithm of the bid as the dependent variable. The model presented in column 1 controls by cartel/non-cartel groups, announcement period, and implementation period. The model in column 2 applies two-way fixed effects. The model in column 3 control by cartel/non-cartel groups and by time-variant input supply variables common to all units as well as aggregate demand. The model in column 4 applies unit fixed effects and controls by time-variant aggregate demand as well as input supply variables common to all units. The model in column 5 controls for unit and date-technology-atlantic-public fixed effects. The model in column 6 further controls for forward contracts. Robust standard errors clustered by unit and date are presented in parenthesis.

VARIABLES	(1) LnRevenues	(2) LnRevenues	(3) LnRevenues	(4) LnRevenues	(5) LnProfits
Ln(Bid)	1.33***	8.48***	8.47***	9.40***	9.39***
	(0.28)	(1.22)	(1.22)	(1.40)	(1.43)
Ln(Bid) 2		-0.68***	-0.68***	-0.78***	-0.78***
		(0.11)	(0.11)	(0.12)	(0.12)
Observations	6,725	6,725	6,725	5,978	4,715
R-squared	0.59	0.62	0.62	0.71	0.67
Unit FE	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	NO	NO
Day of the Week FE	YES	YES	YES	NO	NO
Inputs Control	NO	NO	YES	NO	NO
Demand Control	NO	NO	YES	NO	NO
Date-technology-atlantic-public FE	NO	NO	NO	YES	YES
Units	ALL	ALL	ALL	ALL	ALL

Robust SE clustered by Unit in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Revenues and Profits from Positive Reconciliations

The table presents the estimation results of the linear regression models proposed in 4.1 using the logarithm of the daily revenues (and profits) from positive reconciliation as the dependent variable. The sample is restricted to the observations with positive values of positive reconciliations. The models control by unit, week of the sample, and day of the week fixed effects. They also control by time-variant input supply covariates common to all units and total demand of the generation system. Robust standard errors clustered by unit are presented in parenthesis.

VARIABLES	(1) $ProbabilityRec.Pos._{(t-1)}$	(2) $LnBid$	(3) $LnBid$
$Infrastructure Shock_{(t-1)}$	0.00113***		
	(0.000023)		
$ProbabilityRec.Pos._{(t-1)}$		0.623***	-0.2
		(0.169)	(0.130)
Observations	17,041	17,041	17,041
Unit FE	YES	YES	YES
Date FE	YES	YES	YES
Sample	2008	2008	2008
Estimation	First Stage	Second Stage	OLS

Robust standard errors in parentheses. First column coefficients multiplied by 10K.
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Positive Reconciliations and Electric Network Contingencies

Note: The table presents the two-stage instrumental variables regression of the logarithm of the bid price on the first lag of the probability of positive reconciliation for the year 2008. The first column presents the first stage of the estimation. We use the contingencies in the transmission system as instruments of the lag of the probability of positive reconciliation. The coefficient and the standard error of this column are multiplied by 10.000 for illustrative purposes. The second column presents the second stage of the estimation. The third column presents the results of the regression by OLS. All the columns control by two-way fixed effects. The Probability of positive reconciliation in day t: is the *mean* across the hourly dummies $DummyPR_{iht}$. Robust standard errors clustered by unit are presented in parenthesis.

VARIABLES	(1) Revenues PR	(2) Profits from PR	(3) Total revenues	(4) % Revenues from PR	(5) Bid
Cartel Announcement	-129.62*	-89.16*	-215.95**	-0.19***	-160.58**
	(74.21)	(44.36)	(81.88)	(0.06)	(64.08)
Cartel Implementation	-68.95*	-31.19	192.63**	-0.06	-61.04
	(38.10)	(20.31)	(81.45)	(0.07)	(55.53)
Observations	6,765	6,765	6,746	6,746	6,765
R-squared	0.75	0.68	0.74	0.58	0.56
Unit FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES

Robust SE clustered by Unit and Date in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Effects of announcement on revenues and profit

Note: The table presents the estimation results of the difference in difference model proposed in expression 1 in sub-section 3.4 using several dependent variable and controlling by two-way fixed effects. The estimation is conditional to receiving positive reconciliations. Column 1 presents the estimates for the revenues from positive reconciliations. Column 2 presents the estimates for the daily profit from positive reconciliations. It was calculated as the difference of the daily revenues from positive reconciliations minus the total cost. Total cost was computed as the product of the quantity of positive reconciliations multiplied by the marginal costs. Column 3 presents the estimates for the daily total revenue. This variable is computed as the daily sum of the hourly revenue from sales in the spot market and the hourly revenue from positive reconciliations. The hourly revenue from sales in the spot market is computed as the product of the spot price and the ideal generation. The hourly revenue from positive reconciliations is the value of the positive reconciliation paid to each unit. Column 4 presents the estimates for the daily share of the revenues from positive reconciliations. Column 5 presents the estimates for the Bid. Robust standard errors clustered by unit and date are presented in parenthesis.

VARIABLES	(1) Someone	(2) Someone	(3) Someone Commercial	(4) Someone Commercial
Cartel x 2009	0.0370	0.0571	-0.136*	-0.146*
	(0.0415)	(0.0420)	(0.0707)	(0.0714)
Regulator Presence		0.342***		-0.166**
		(0.0741)		(0.0606)
Observations	460	460	460	460
R-squared	0.720	0.733	0.472	0.478
Unit FE	YES	YES	YES	YES
Meeting FE	YES	YES	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Meetings Minutes Evidence

Note: The table presents the relationship between having someone or someone from commercial area on two variables: an interaction term cartel*post and the regulator presence. Cartel takes the value of 1 for the units classified in the baseline collusive agreement and 0 otherwise. Post is 1 for minutes in 2009 and 0 otherwise. The dummy regulator presence takes the value of 1 when the minute reports having at least one regulator.

VARIABLES	(1) Pre-reform	(2) Post-reform
Cost	0.715	1.756
	(1.205)	(1.376)
L.Ln Q PR	56.79	-21.82**
	(71.75)	(10.01)
Ln Q ideal	43.45	-90.33***
	(90.05)	(26.27)
Constant	-1,268	2,259***
	(2,771)	(545.8)
Observations	2,685	2,715
R-squared	0.843	0.943
Unit FE	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Estimation of bids on market fundamentals

Note: The table presents the estimates of the model proposed in section 5.2 in order to predict the bids of cartel units. We regress bids on costs, the lagged value of the logarithm of the total amount of positive reconciliations, and the logarithm of the total amount of ideal generation. We use observations from cartel units from a one year period around the reform (six months pre and six months post-reform in columns 1 and 2 respectively).

VARIABLES	(1) Logit	(2) OLS
Rank	-0.942***	0.431**
	(0.265)	(0.147)
$Rank^2$	0.0319	-0.0347***
	(0.0224)	(0.0104)
Constant	2.141	11.10***
	(2.176)	(0.624)
Observations	4,560	1,333
Unit FE	YES	YES
Date FE	YES	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Estimation of the positive reconciliation quantities model

Note: The table presents the estimates of the models proposed in section 5.2 in order to predict the expected quantity of positive reconciliations for cartel units. In the first column, we present the logit estimates of a binary model where we regress a dummy for receiving positive reconciliations in a day on the rank of the bid, its squared value, unit and date fixed effects. The second column presents the OLS estimates of a linear model where we regress the logarithm of the amount of positive reconciliations in a day on the same covariates as above, using only observations with some amount of positive reconciliations. We use observations from a one year period around the reform.

A Appendix: Additional Figures and Tables

A.1 Figures

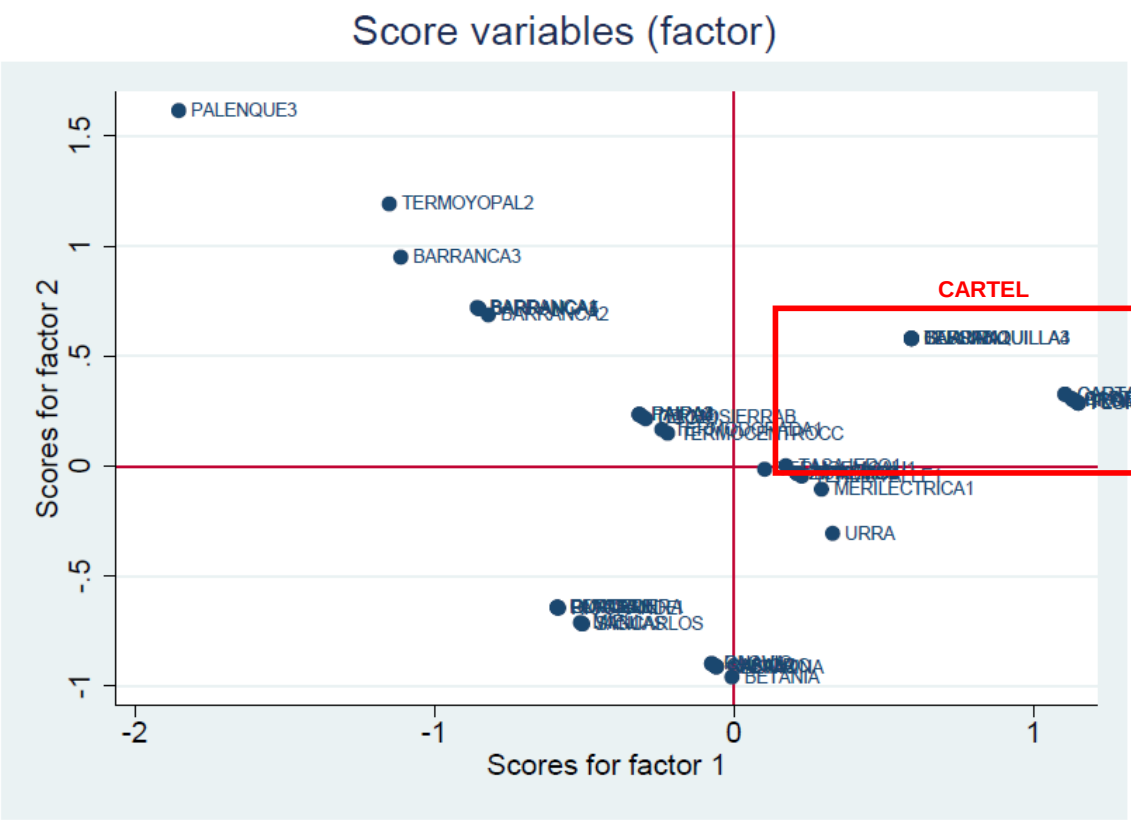


Figure A1: Results factor analysis.

Note: We implemented factor analysis as the baseline methodology for cartel group selection. The figure represents the estimates for each unit of scores for the two factors used for cartel detection. The x-axis represents the scores for factor 1 and the y-axis represents scores for factor 2. Each point represents the factor 1 and 2 scores corresponding to each unit. The units in the cartel group are those with positive values for both factor 1 and 2. The red square in the north-east (first) quadrant encloses the units in the cartel group.

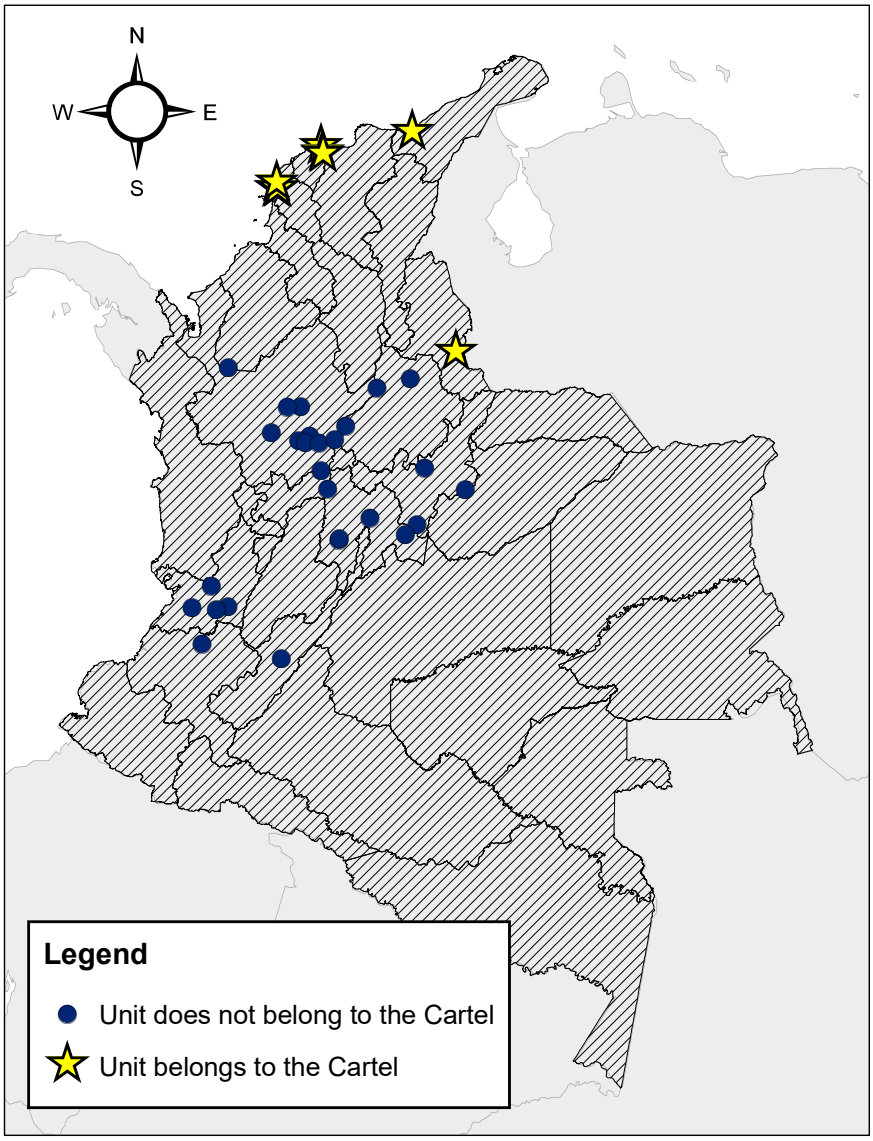


Figure A2: Geographical location of cartel units.

Note: The figure presents Colombia's map and the location of the electricity generation units participating in the wholesale electricity market. The dark shaded area represents Colombian territory. The black thick line represents the division of the country in political units called "departamentos". The star shaped yellow marks locate the cartel generation units and the circle shaped blue marks locate the non-cartel units.

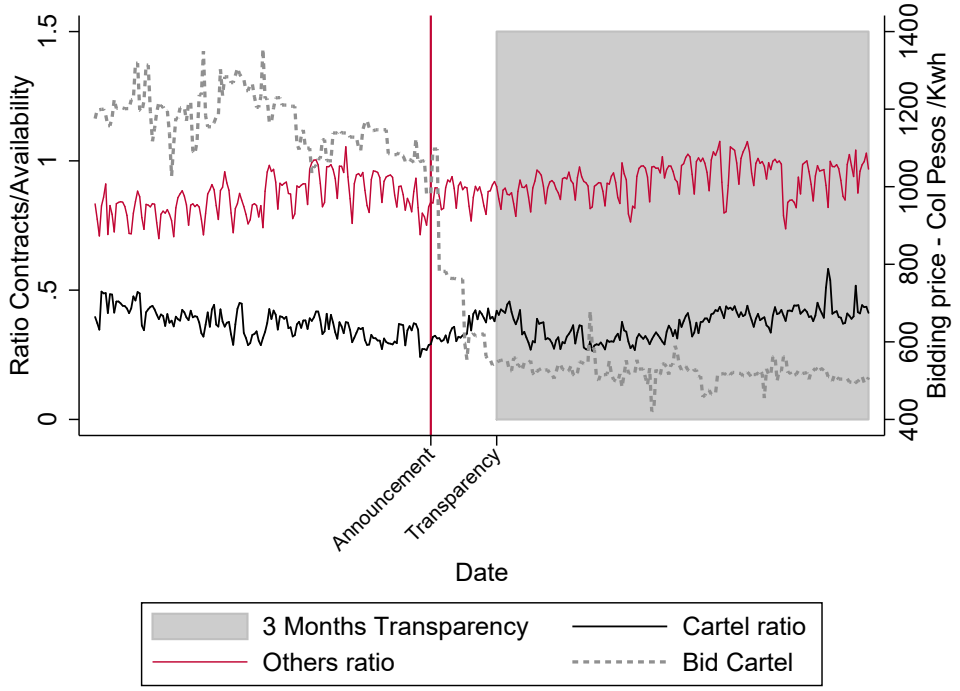


Figure A3: Time Series of Forward Contracts for Cartel and Non-Cartel Members

Note: The figure presents the time series of the portion of capacity sold through forward contracts of the cartel and non-cartel groups around the dates of announcement and implementation of the transparency policy. This portion is computed as explained in subsection 3.5.2. The top panel presents the time series from February 2006 to March 2010 and the bottom panel presents the time series from August 2008 to July 2009. The shaded area represents the period with the transparency policy in place. The black line represents the cartel group time series, the cranberry line represents the non-cartel group time series and the dotted line represents the average bidding price time series.

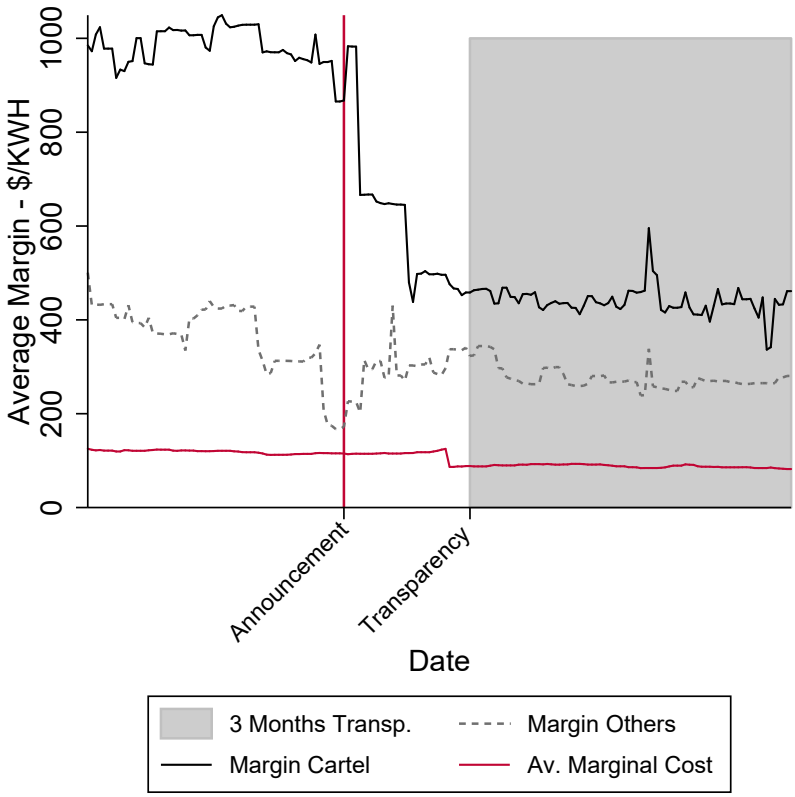


Figure A4: Average margin time series.

Note: The figure presents the time series of the average margin of the cartel (solid black line) and non-cartel (dotted grey line) groups around the dates of announcement and implementation of the transparency policy (From November 2008 to April 2009). The margin is computed as the difference of the bid minus the marginal cost. It also presents the time series of the average marginal cost of the cartel units (solid red line). The shaded area represents the period with the transparency policy in place.

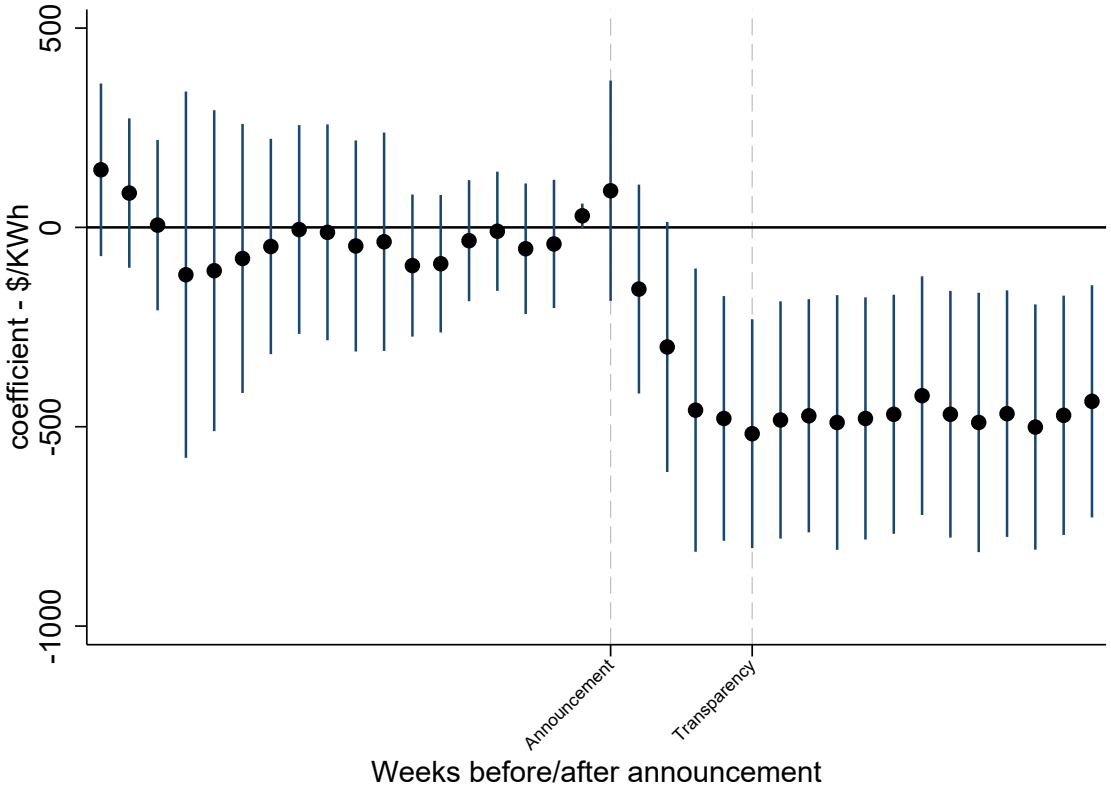


Figure A5: Event study representation using margin as the dependent variable

Note: The figure presents the event study representation of the difference-in-difference model using the margin as the dependent variable. The margin is computed as the difference of the bid minus the marginal cost. Only thermal units are included in the sample. We performed a two-way fixed effects model including a specific treatment effect for each week of the period studied. The x-axis represents weeks before and after the announcement of the transparency policy. The y-axis represents the difference in the bidding price with reference to the week of the announcement of the transparency policy. The black dots represent the estimated differences and the surrounding vertical lines represent the 95% confidence intervals. The zero (omitted) coefficient corresponding to the week of the announcement of the transparency policy is not presented in the figure. The dotted line labeled as "Announcement" represents the next week to the announcement of the transparency policy. The dotted line labeled as "Transparency" represents the next week to the implementation of the transparency policy.

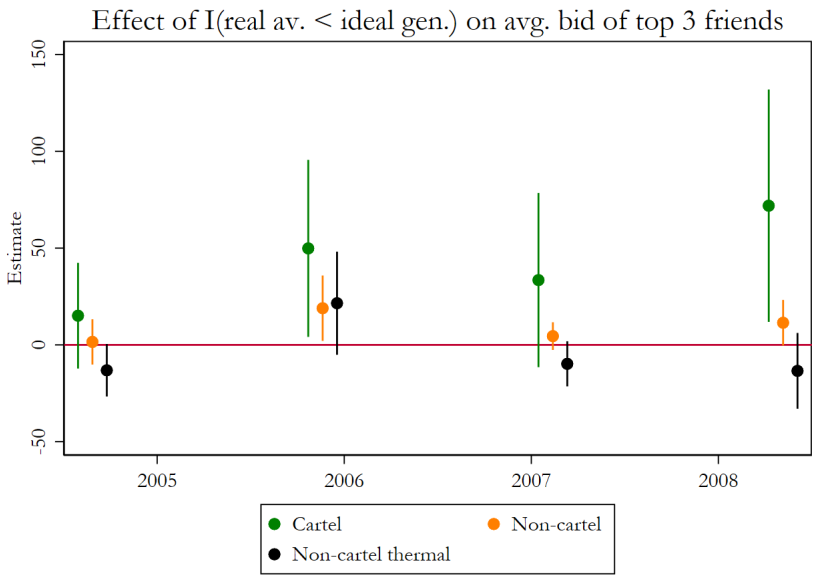


Figure A6: Robustness 1: Top 3 friends instead of top 1.

Note: Estimates from a regression where the outcome variable is the average bid of the friends of unit i and the explanatory variables is an indicator for unit i declaring a level of real availability below the ideal generation quantity it was awarded. We run 3 separate regression for the 3 groups (cartel, non-cartel, non-cartel thermal). Compared to the baseline analysis, here we consider the 'top 3' friends instead on only the first one.

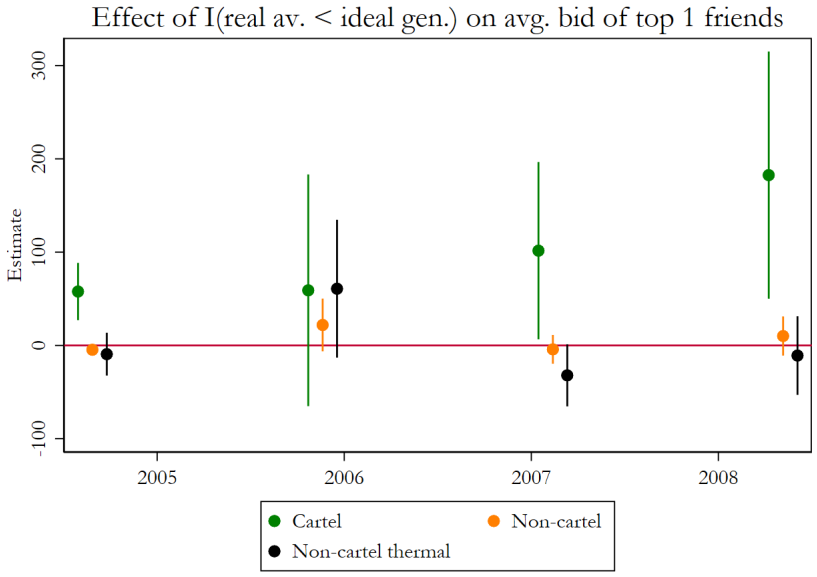


Figure A7: Robustness 2: Friends defined over the years 2005-2008.

Note: Estimates from a regression where the outcome variable is the average bid of the friends of unit i and the explanatory variables is an indicator for unit i declaring a level of real availability below the ideal generation quantity it was awarded. We run 3 separate regression for the 3 groups (cartel, non-cartel, non-cartel thermal). Compared to the baseline analysis, we define 'friends' using observations from the period 2005-2008 instead of a one year period around the policy change.

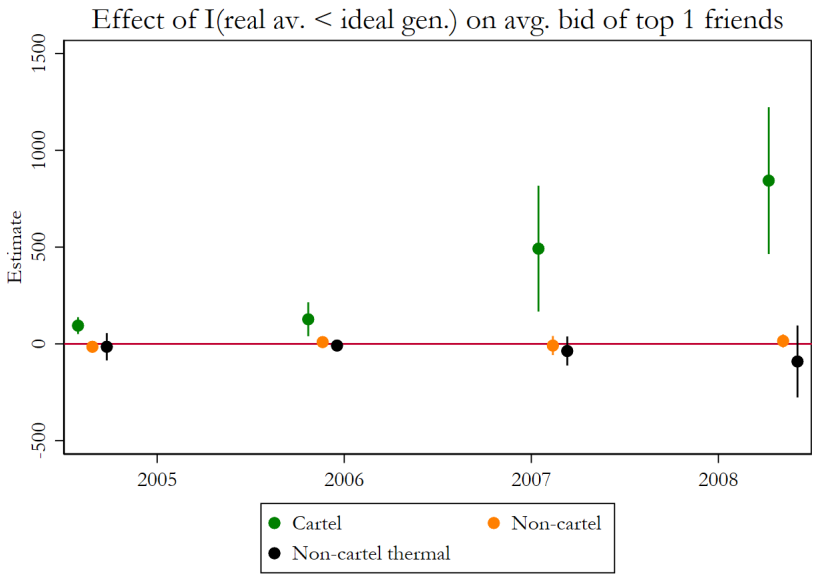


Figure A8: Robustness 3: Focus on the 50% cases when the negative difference between real availability and ideal generation is largest in absolute value.

Note: Estimates from a regression where the outcome variable is the average bid of the friends of unit i and the explanatory variables is an indicator for unit i declaring a level of real availability below the ideal generation quantity it was awarded. We run 3 separate regression for the 3 groups (cartel, non-cartel, non-cartel thermal). Compared to the baseline analysis, here we focus on the 50% cases when the negative difference between real availability and ideal generation is largest in absolute value.

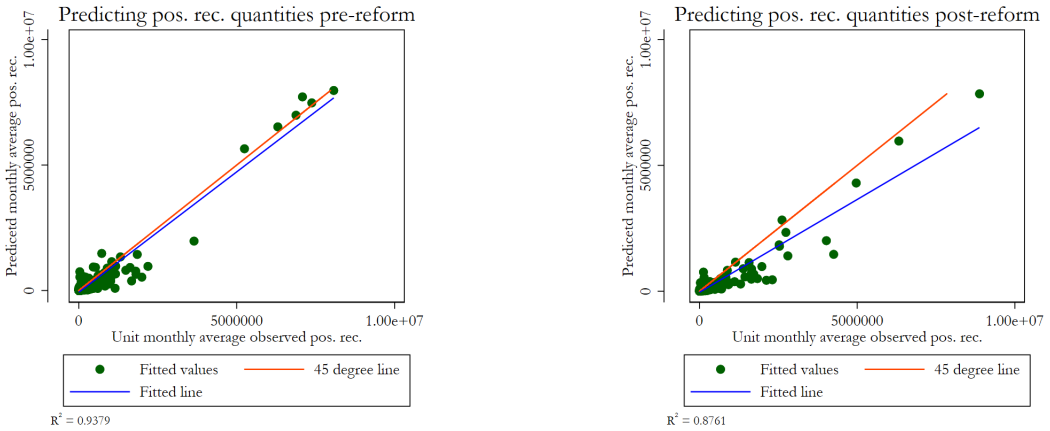


Figure A9: Comparing observed quantities of positive reconciliations with in-sample predictions for cartel and non-cartel units in the pre and post-reform periods.

Note: We use the method described in Section 5.1 to estimate how the quantity of positive reconciliation awarded to a unit depends on the rank of its bid. We use both cartel and non-cartel units in this exercise. We use these estimates to make in-sample prediction and average at the monthly level for each unit. We compare the average predicted quantity (y-axis) with the average observed one (x-axis). The left figure refers to observations from the six months before the reform; the right figure refers to the six months after the reform.

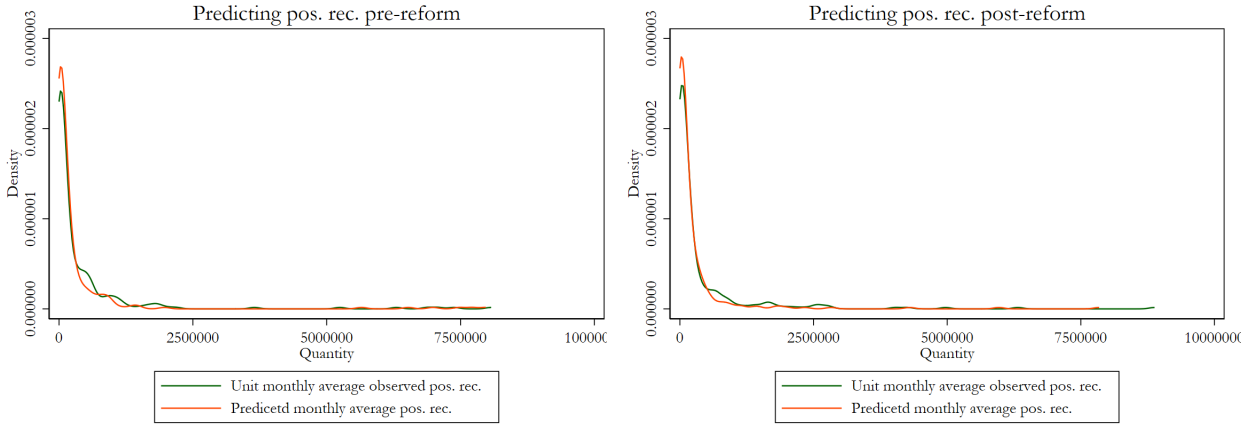


Figure A10: Comparing the distribution of observed quantities of positive reconciliations with in-sample predictions for cartel and non-cartel units in the pre and post-reform periods.

Note: We use the method described in Section 5.1 to estimate how the quantity of positive reconciliation awarded to a unit depends on the rank of its bid. We use both cartel and non-cartel units in this exercise. We use these estimates to make in-sample prediction and average at the monthly level for each unit. We compare the density of the average predicted quantity (orange line) with the density of the average observed one (green line). The left figure refers to observations from the six months before the reform; the right figure refers to the six months after the reform.

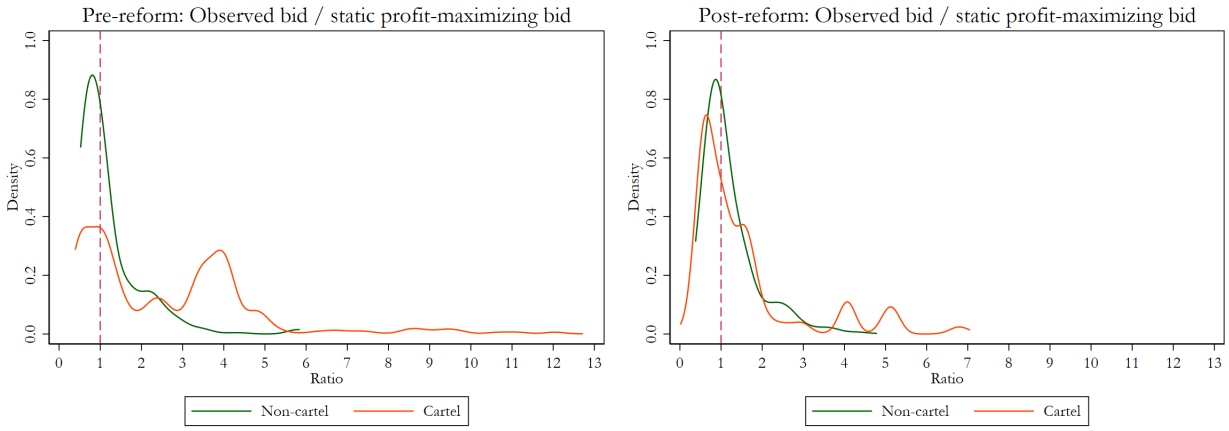


Figure A11: Robustness check: Results when not imposing the third restriction for non-cartel units (to exclude non-cartel units owned by a cartel firm). Density of the ratio between unit-daily observed and static profits maximizing bids for cartel and non-cartel units over two different six month periods.

Note: For cartel and non-cartel units, we simulate counterfactual bids and the corresponding amount of positive reconciliations and select the static profit maximizing bids. We then compare it with the observed bid: At the unit-day level, we compute the ratio between the observed bid and the profit maximizing bid. We plot the density of this ratio. The top figure presents the density using data from the six months before the policy change; the bottom figure refers to the six months after the policy change. Compared to the baseline analysis, here we include non-cartel units that are owned by a firm which also own some cartel units.

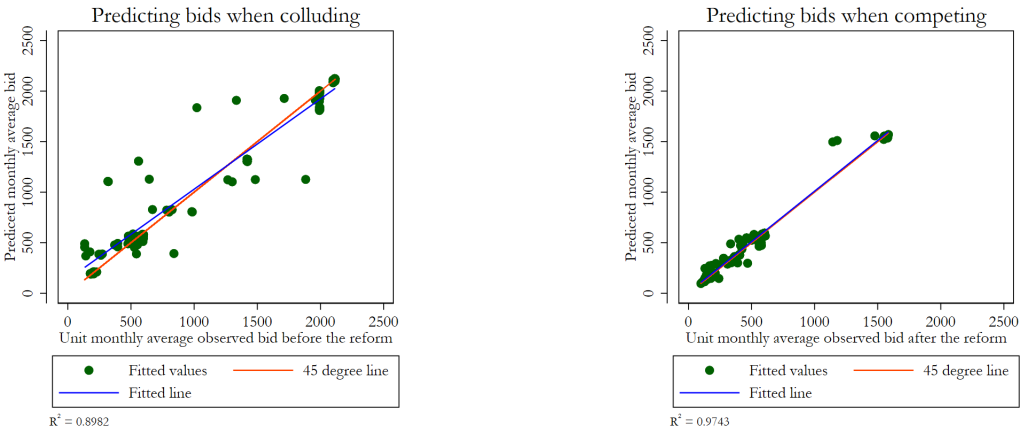


Figure A12: Comparing observed bids with in-sample predictions.

Note: We use the method described in Section 5.2 to estimate how cartel units set bids by regressing bids on costs, the lagged logarithm of the total amount of positive reconciliations, and the logarithm of the ideal generation quantity. We use these estimates to make in-sample prediction and average at the monthly level for each unit. We compare the average predicted bid (y-axis) with the average observed one (x-axis). The left figure refers to observations from the six months before the reform; the right figure refers to the six months after the reform.

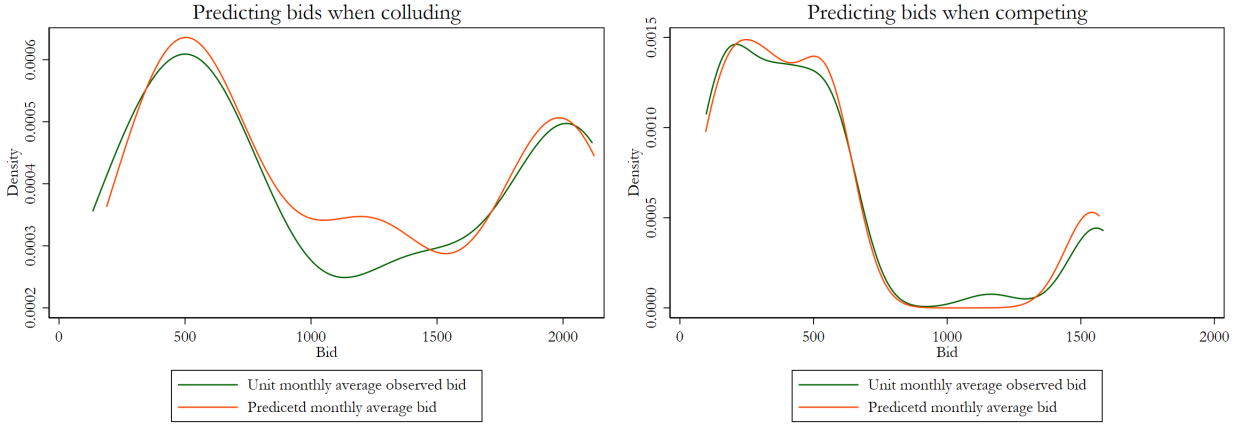


Figure A13: Comparing the distribution of observed bids with in-sample predictions.

Note: We use the method described in Section 5.2 to estimate how cartel units set bids by regressing bids on costs, the lagged logarithm of the total amount of positive reconciliations, and the logarithm of the ideal generation quantity. We use these estimates to make in-sample prediction and average at the monthly level for each unit. We compare the density of the average predicted bid (orange line) with the density of the average observed one (green line). The left figure refers to observations from the six months before the reform; the right figure refers to the six months after the reform.

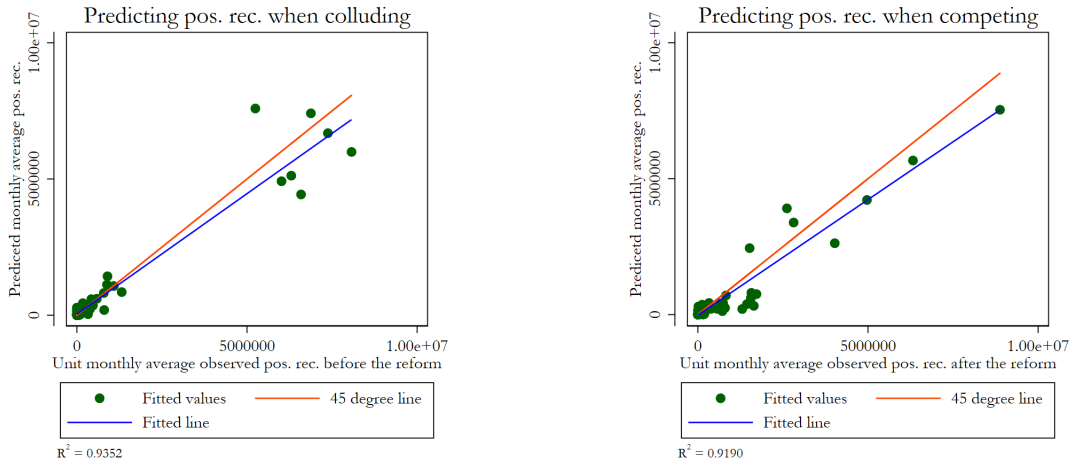


Figure A14: Comparing observed quantities of positive reconciliations with in-sample predictions for cartel units in the pre and post-reform periods.

Note: We use the method described in Section 5.2 to estimate how the quantity of positive reconciliation awarded to a unit depends on the rank of its bid. We focus on cartel units in this exercise. We use these estimates to make in-sample prediction and average at the monthly level for each unit. We compare the average predicted quantity (y-axis) with the average observed one (x-axis). The left figure refers to observations from the six months before the reform; the right figure refers to the six months after the reform.

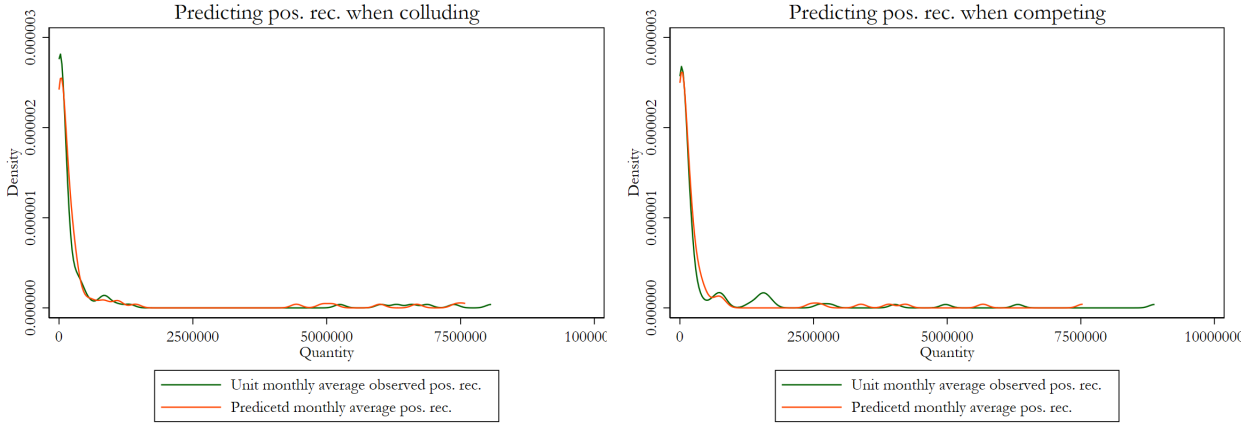


Figure A15: Comparing the distribution of observed quantities of positive reconciliations with in-sample predictions for cartel units in the pre and post-reform periods.

Note: We use the method described in Section 5.2 to estimate how the quantity of positive reconciliation awarded to a unit depends on the rank of its bid. We focus on cartel units in this exercise. We use these estimates to make in-sample prediction and average at the monthly level for each unit. We compare the density of the average predicted quantity (orange line) with the density of the average observed one (green line). The left figure refers to observations from the six months before the reform; the right figure refers to the six months after the reform.

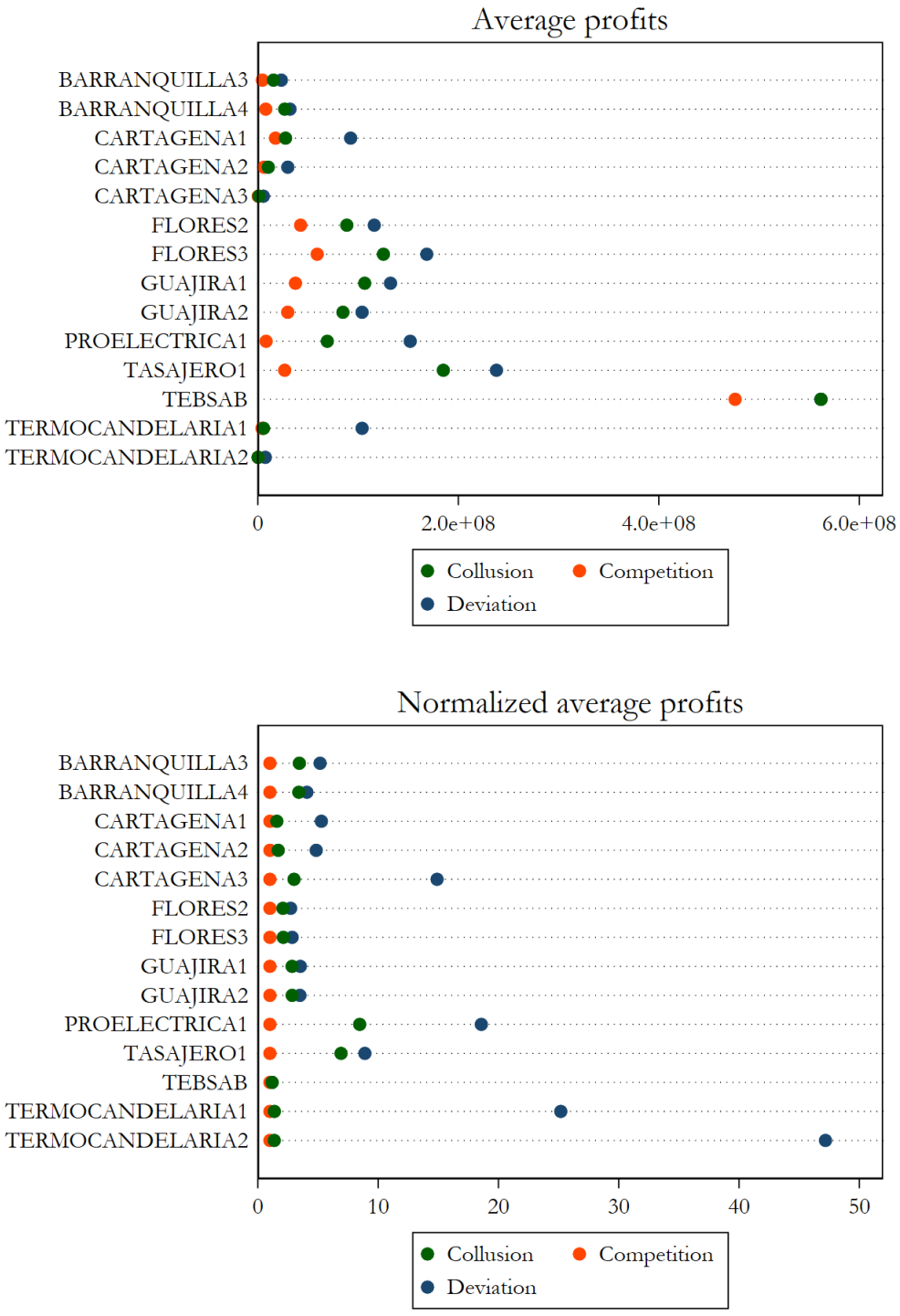


Figure A16: Average profits of cartel units under competition, collusion, and optimal deviation.

Note: We use the methods described in Sections 5.1 and 5.2 to construct counterfactual bids and quantities under three alternative scenarios: Collusion, competition, and optimal deviation from collusion. Based on these variables we construct profits for each unit under the three scenarios and average over a one year period around the reform. The top figure reports the level of the average profits, while the bottom one reports the ratio with respect to competitive profits.

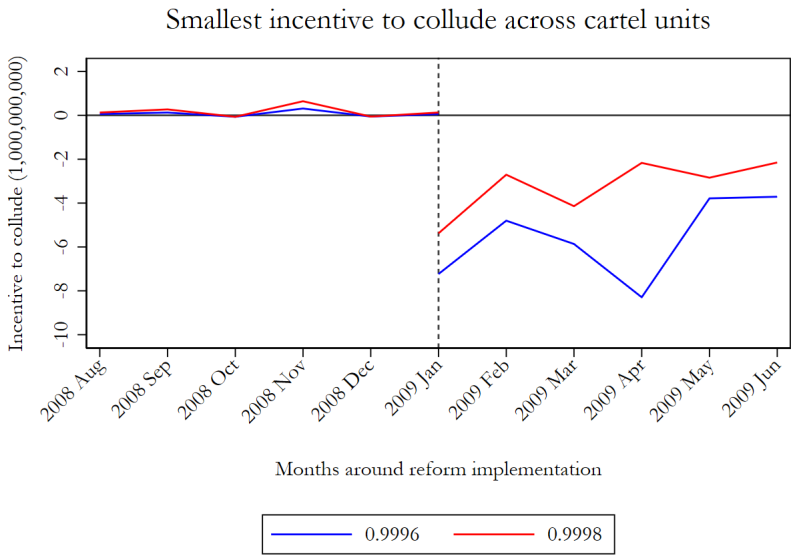


Figure A17: Smallest incentive to collude across cartel firms for different values of the discount factor. $0.9996^{365} = 0.86, 0.9998^{365} = 0.93$

Note: For each cartel unit we compute the incentive to collude in each month from August 2008 to June 2009. Up until January 2009 the incentive to collude is computed assuming that a unit can unilaterally deviate for one day before triggering competition; from January 2009 a unit can deviate for 90 days. In this figure we plot the smallest incentive to collude across cartel units in each month. In the baseline analysis we use a daily discount factor $\beta = 0.9997$; here we present the results using a daily discount factor of 0.9996 (blue line) and 0.9998 (red line).

A.2 Tables

VARIABLES	(1) Margin	(2) Margin	(3) Margin	(4) Margin	(5) Margin	(6) Margin
Cartel Announcement	-315.79**	-315.79**	-315.79**	-315.79**	-148.42***	-153.51***
	(119.51)	(124.38)	(119.54)	(124.32)	(40.39)	(41.91)
Cartel Implementation	-134.61***	-134.61**	-134.61***	-134.61**	-17.48	-4.67
	(47.40)	(57.18)	(47.56)	(57.02)	(13.94)	(25.72)
Announcement	-122.78***		-115.85***	-115.85**		
	(43.70)		(41.10)	(45.66)		
Implementation	-34.84		38.05	38.05		
	(26.61)		(32.51)	(48.09)		
Observations	11,315	11,315	11,315	11,315	16,790	16,790
R-squared	0.20	0.82	0.20	0.82	0.84	0.84
Unit FE	NO	YES	NO	YES	YES	YES
Date FE	NO	YES	NO	NO	NO	NO
Inputs Control	NO	NO	YES	YES	NO	NO
Demand Control	NO	NO	YES	YES	NO	NO
Date-technology-atlantic-public FE	NO	NO	NO	NO	YES	YES
Forward Control	NO	NO	NO	NO	NO	YES

Robust SE clustered by Unit and Date in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table A1: Difference-in-difference estimates - Margin

The table presents the estimation results of the difference in difference model proposed in expression 1 in sub-section 3.4 using the margin as the dependent variable. The margin is computed as the difference of the bid minus the marginal cost. Only thermal units are included in the sample. The model presented in column 1 controls by cartel/non-cartel groups, announcement period, and implementation period. The model in column 2 applies two-way fixed effects. The model in column 3 control by cartel/non-cartel groups and by time-variant input supply variables common to all units. The model in column 4 applies unit fixed effects and controls by time-variant input supply variables common to all units. The model in column 5 controls for unit and date-technology-atlantic-public fixed effects. The model in column 6 further controls for forward contracts. Robust standard errors clustered by unit and date are presented in parenthesis.

Scenario	Variable	Obs	Mean	Std. Dev.	Min	Max	Frec. Negative	T-Test
Scenario 1	Actual profit	2295	60.03768	194.8847	-29.83928	1275.529	.0013072	14.40
	Counterf spot market profit	2295	2.881308	15.72966	0	269.273		
Scenario 2	Actual profit	1140	61.08083	202.0675	0	1139.433	0	7.66
	Counterf spot market profit	1140	21.74932	46.23523	0	357.1698		
Scenario 3	Actual profit	1140	61.08083	202.0675	0	1139.433	0	10.21
	Counterf spot market profit	1140	0.0073915	.1629634	0	4.913246		
Scenario 4	Actual profit	1155	59.00808	187.6077	-29.83928	1275.529	.0025974	5.31
	Counterf spot market profit	1155	35.77655	68.62892	0	691.9288		
Scenario 5	Actual profit	1155	59.00808	187.6077	-29.83928	1275.529	.0025974	10.34
	Counterf spot market profit	1155	2.51874	16.88746	0	246.2969		

Table A2: Comparison of profits form positive reconciliation and counterfactual competition

We performed a comparison between the profits that the units of the cartel group obtained from the positive reconciliation collusive agreement and the profits that those units would obtain in the counterfactual case in which they bid their marginal costs and try to win in the ideal dispatch. First, we computed the profits from the positive reconciliation collusive agreement as the value of income from positive reconciliations minus the cost of generating the energy. Second, for computing the counterfactual of the profits if the units bid as a competitive firm, we assumed that if cartel firms would bid competitively it had the same probability of being in merit than the competitive units. Hence, we computed the probability of being on merit of the no cartel units. We computed the counterfactual profits for cartel units as the product of the probability of being on merit (if the unit is competitive) multiplied by the profit obtained by the unit if it would sell its energy at the spot price and would generate its declared availability. We allow the possibility of inaction of the unit. Hence if the profit above is negative we replace it by zero. For this computation we only consider thermal units. We use the data of second semester 2008. We compute five counterfactual scenarios. **Scenario 1**: Average spot price and average hydro resources condition. The spot price used for computation is the average spot price. All the days in the sample are considered. **Scenario 2**: High spot price and high hydro resources condition. The spot price used for computation is the spot price in the higher demand hour (7 p.m.). Only the days with hydro resources higher than the median are considered. **Scenario 3**: Low spot price and high hydro resources condition. The spot price used for computation is the spot price in the lower demand hour (3 a.m.). Only the days with hydro resources higher than the median are considered. **Scenario 4**: High spot price and low hydro resources condition. The spot price used for computation is the spot price in the higher demand hour (7 p.m.). Only the days with hydro resources lower than the median are considered. **Scenario 5**: Low spot price and low hydro resources condition. The spot price used for computation is the spot price in the lower demand hour (3 a.m.). Only the days with hydro resources lower than the median are considered.

B Calculation Marginal Costs

We calculated marginal costs of thermal plants using the heat rate, fuel costs and fuel transportation costs with the following formula:

$$\underbrace{Exchange\ R._t}_{\frac{COP\$}{US\$}} \times \Big[\underbrace{Heat\ R._i}_{\frac{MBTU}{KWh}} \times \underbrace{(Transp.\ fuel\ cost_i + Fuel\ cost_t)}_{\frac{US\$}{MBTU}} \Big] = \underbrace{Marginal\ Cost_{it}}_{\frac{COP\$}{kWh}}$$

Where *COP* are Colombian pesos, *MBTU* are one thousand of the British thermal unit, *US* are United States dollars and *KWh* is one kilowatt per hour. The heat rate is a measure of the thermal efficiency of the generation unit. It represents the quantity of fuel measured in *MBTU* necessary to generate one kilowatt per hour. The parameters of the heat rate of thermal electricity generation units were extracted from reports of the Mines and Energy Planning Unit (UPME) (Unidad de Planeación Minero Energética (UPME), 2003).

In the case of gas fired units, we use as fuel cost the price of the gas from the basin Guajira which is the most important gas supply source for Colombian thermal generation. Since September 1995 Until August 2013, the Colombian Government regulated the prices of gas coming from this gas source. The regulation consist in imposing a maximum sale price of gas. This maximum price at period t, p_t, is given by the formula $p_{t-1}[index_{t-1}/index_{t-2}]$ where $index_{t-1}$ is the average of the last semester of the New York Harbor Residual Fuel Oil 1.0 % Sulfur LP Spot Price according to the series that was published by the Energy Information Administration of the United States. A period t is defined as semester and it changes 1st February and 1st August of each year [29] .This price is given in *US dollars/MBTU*.

We calculated the Guajira regulated price applying the formula presented above and converting the resulting price *(US dollars/MBTU)* to *Colombian pesos/KWh*. The exchange rate data was obtained from the Colombian central bank (Banco de la República)[30].

Consequently, for gas fired units, we take as transportation costs the sum of the fees for the use of each segment of the gas transmission network necessary to take the gas from Guajira well to the respective generation units. These fees are regulated by the CREG and are published in regulatory acts (Comisión de Regulación de Energía y Gas (CREG), 003a,b).

Regarding the coal fired units, given that Colombia is a net exporter of coal we use the weighted average FOB export price as fuel cost. We computed it as the ratio between the total value of

[29] The formula was established in Resolution 119/2005 of CREG (Comisión de Regulación de Energía y Gas (CREG), 2005)

[30] See:https://www.banrep.gov.co/es/estadisticas/trm

coal exportation (in *US dollars*) and the quantities exported (Tons) according to the data from the non-traditional exports report of the National Department of Statistics (DANE). The price in dollars per ton was transformed to dollars per $MBTU$ units, multiplying for a calorific value of the Colombian thermal coal of 1,370 btu per pound (Source: regulation 2009 180507 Colombian Ministry of Energy and Mines (Ministerio de Minas y Energía (MME), 2009)). For computing the coal transportation costs, an importation parity approach is adopted. According to this criteria, we estimate it as the road freight transportation fee from the closest importation port to the respective location of the generation unit. These fees were extracted from the system of information of efficient costs for road freight transportation provided by the Transportation Ministry of Colombia [31].

[31] See: https://www.mintransporte.gov.co/publicaciones/359/sistema_de_informacion_de_costos_eficientes_para_el_transporte_automotor_de_carga_sicetac/

C Appendix: Results with only one score

VARIABLES	(1) LnBid	(2) LnBid	(3) LnBid	(4) LnBid
Cartel Announcement	-0.50***	-0.50***	-0.50***	-0.50***
	(0.11)	(0.12)	(0.11)	(0.12)
Cartel Implementation	-0.15	-0.15	-0.15	-0.15
	(0.11)	(0.12)	(0.11)	(0.12)
Announcement	0.08		0.06	0.06
	(0.08)		(0.08)	(0.09)
Implementation	-0.09		-0.05	-0.05
	(0.10)		(0.08)	(0.10)
Observations	17,155	17,155	17,155	17,155
R-squared	0.23	0.82	0.23	0.81
Unit FE	NO	YES	NO	YES
Date FE	NO	YES	NO	NO
Inputs Control	NO	NO	YES	YES
Demand Control	NO	NO	YES	YES

Robust SE clustered by Unit and Date in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

Table C1: Difference-in-difference estimates - Only one factor

Note: The table presents the estimation results of the difference in difference model proposed in expression 1 in sub-section 3.4 using the logarithm of the bid as the dependent variable and only one factor for detecting the firms in the cartel. The model presented in column 1 controls by cartel/non-cartel groups, announcement period, and implementation period. The model in column 2 applies two-way fixed effects. The model in column 3 control by cartel/non-cartel groups and by time-variant input supply variables common to all units. The model in column 4 applies unit fixed effects and controls by time-variant input supply variables common to all units. Robust standard errors clustered by unit and date are presented in parenthesis.

	(1) Revenues PR	(2) Profits from PR	(3) Total Revenues	(4) % Revenues from PR	(5) Bid
Cartel Announcement	-90.52	-64.65*	-228.3***	-0.177***	-138.5***
	(54.50)	(33.05)	(67.67)	(0.0598)	(44.14)
Cartel Implementation	-48.24	-20.79	189.7***	-0.0623	-55.32
	(28.75)	(15.22)	(68.51)	(0.0835)	(53.77)
Observations	6,765	6,765	6,746	6,746	6,765
R-squared	0.739	0.677	0.743	0.582	0.562
Unit FE	YES	YES	YES	YES	YES
Date FE	YES	YES	YES	YES	YES

Robust standard errors clustered by unit and date in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table C2: Effects of announcement on revenues and profit - Only one factor

Note: The table presents the estimation results of the difference in difference model proposed in expression 1 in sub-section 3.4 using only one factor for detecting the firms in the cartel. The estimation is conditional to receiving positive reconciliations. Column 1 presents the estimates for the revenues from positive reconciliations. Column 2 presents the estimates for the daily profit from positive reconciliations. It was calculated as the difference of the daily revenues from positive reconciliations minus the total cost. Total cost was computed as the product of the quantity of positive reconciliations multiplied by the marginal costs. Column 3 presents the estimates for the daily total revenue. Column 4 presents the estimates for the daily share of the revenues from positive reconciliations. Column 5 presents the estimates for the Bid. Robust standard errors clustered by unit and date are presented in parenthesis.