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Combinatorial versus sequential auctions to allocate PPP highway projects

Pablo Mochon [a], Asuncion Mochon [b], Yago Saez [c,*]

[a] Avda. de Burgos 46, Madrid, 28036, Spain
[b] UNED, Paseo Senda del Rey, Madrid, 28040, Spain
[c] University Carlos III of Madrid, Avda. de la Universidad 30, Madrid, Leganés, 28911, Spain

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ABSTRACT

This article models a procurement process for allocating multiple related public-private partnership (PPP) highway projects. Traditionally, public infrastructure procurement processes have used a sequential allocation mechanism, despite the potential benefits of allocating all projects at once. The main contribution of this research is to address the question whether these projects should be auctioned individually, in sequential auctions, or at the same time, in a combinatorial auction. Our goal is to understand the impact of the allocation process in terms of efficiency and social welfare. In sequential auctions, bidders submit their offers for each project independently. However, in combinatorial auctions, contractors have the ability to bid for their preferred packages (combinations of projects), reflecting synergies or entry costs, if any, in their valuations. We have compared the impact in terms of efficient allocation and social welfare of both mechanisms in order to help policymakers to take future decisions when facing these processes. The methodology used to address these core questions in the multidisciplinary environment described is based on social simulations, which involves conducting analysis by means of computational simulations. For this work we have created a sophisticated valuation model adapted to the public infrastructure sector and we have developed a simulator which includes multiple types of bidders, projects and several scenarios. The experimental setup is based on the second wave of the Colombian 4G program, a case involving the allocation of 9 highway construction projects across the country. We have also included references to multiple examples of real markets in which these mechanisms could be implemented. Therefore, this research provides a valuable reference for policymakers chasing to enhance market design that could be applied in many real-world scenarios. The results reveal that the combinatorial mechanism improves the process in terms of optimal allocation and efficiency, yielding significant savings for all parties.

1. Introduction

Public-private partnership (PPP) projects have become increasingly widespread in recent years as part of attempts to boost the efficiency of collaboration between public entities that wish to develop infrastructure and private companies that design, finance, build and operate such projects. According to the definition of the European PPP Expertise Centre, *a PPP project is an arrangement between a public authority and a private partner designed to deliver a public infrastructure project and service under a long-term project. Under this project, the private partner bears significant risks and management responsibilities. The public authority makes performance-based payments to the private partner for the provision of the service (e.g., for the availability of a highway) or grants the private partner a right to generate revenues from the provision of the service (e.g., tolls from users of a bridge)*.[1]

PPP projects are carried out in many countries under different laws and structures, but the projects all share certain common characteristics. First, the cost of studying and preparing the offers is high, both for private participants and public administrations. Valila (2020) indicates that *the setting-up of the long-term contract between the government and the private partner is much more costly than the government contracting out asset construction and maintenance separately as short-term contracts*. Due to the projects' complexity, participants must be experienced; therefore, the number of competitors is relatively low. Furthermore, the range of the investment size is very high (usually hundreds of millions of dollars), and winning bidders are required to provide equity. Finally, the construction and operation periods are very long (usually between 10 and 20 years) in order to allow participants to recoup their investment and

* Corresponding author.
E-mail addresses: pablomochon@gmail.com (P. Mochon), amochon@cee.uned.es (A. Mochon), yago.saez@uc3m.es (Y. Saez).

[1] European PPP Expertise Centre: http://www.eib.org/epec/.

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make a profit. Feng (2019) presents a mathematical model to calculate the optimal concession period under a series of assumptions, and Jin et al. (2021), proposes a synthetic measure to determine the values of the concession period in relation with the revenues guaranteed by the government.

This situation leads governments to attempt to devise suitable mechanisms for the allocation of PPP projects, seeking the most appropriate way to distribute risks between public and private entities as well as promote competition. Governments are also concerned about avoiding project failures, which could result if the winning bidder has not done an adequate preliminary study or lacks sufficient experience or capacity to deal with the project.

Within this framework, it is necessary to reconcile public entities objective of executing and operating the infrastructure project at the best price and quality and private companies objective of obtaining an adequate profit. Therefore, a common question that governments must face is what the best way to design a PPP bidding process is.

In the transportation infrastructure sector, different mechanism types are implemented when multiple projects need to be allocated: sequential (one after another) or simultaneous (all at the same time) mechanisms, with one or multiple rounds (see Kerf et al. (1998)). Currently, the most widespread method used in this sector is a succession of auctions in which projects are allocated one by one in sealed-bid auctions to the participants that make the lowest offers, with the winning offer determining the amount that the public authority pays. However, there are many theoretical and empirical works that claim that allocating related projects through independent auctions generates inefficiencies. In the transportation sector, there are already some examples of services being allocated through combinatorial mechanisms in which participants can bid for packages of projects. Rassenti et al. (1982) worked on mechanisms for the awarding of airport time slots, and Caplice and Sheffi (2005) focused on truckload transportation. Furthermore, Song and Regan (2003) examined the benefits for shippers of using combinatorial auctions with respect to simple sealed-bid auctions.

Regarding the transportation infrastructure sector, some countries, aligned with this argument, are beginning to conduct simultaneous auctions in which all projects are offered at the same time. For example, the government of Argentina allocated six highways in 2018 through an auction in which participants could make offers on a combination of two projects.[2] Nevertheless, the main allocation mechanism in this sector is individual sequential sealed-bid auctions, and allowing bidding for a flexible combination of projects is still unusual.

Given the discrepancies between the new trends and the actual policies in the sector, this work attempts to provide a deeper understanding of the possible outcomes obtained by these two types of mechanisms in the allocation of multiple related highway projects. To achieve this goal, we have followed the methodology proposed by Cioffi-Revilla (2010) where social simulations are used in complex inter and multidisciplinary systems. Based on the theoretical models we have addressed key questions in order to understand the effect of sequential versus combinatorial auctions in terms of efficiency and public objectives. To this end, a complex valuation model is built to express the values and final offers for different types of participants involved in the process. Then, a simulator that implements both sequential and combinatorial auctions is developed. Finally, the results are analyzed and compared from different perspectives, looking for which variables increase efficiency and optimal allocation for both public administrations and private companies.

Our first contribution involves generating a sophisticated valuation model that is adjusted based on the case of the procurement process carried out in Colombia between 2013 and 2015. This case involved the allocation of 9 PPP projects in the second wave of construction of the so-called fourth-generation (4G) highways. The valuation model is constructed based on the author s deep knowledge of the sector and can be used for future valuation processes in the infrastructure transport sector. To generate values and final offers, we consider the projects main characteristics and types of participants to adjust them to each lot or package. Given the project specifications and geographical location of the highways for which the contractors provided offers, it is important to highlight that contractors may show complementarities or synergies in their valuation models; that is, the value of a set or bundle of connected projects may be higher than the sum of the individual values of each project (superadditive values).

Our second important contribution involves developing a specific simulator adapted to the allocation of these 9 projects through both sequential and combinatorial auctions. When comparing both mechanisms and to avoid a possible bias caused by the specific decisions made in the setup of the simulator, we test 9 different scenarios, namely, 5 main scenarios plus 4 additional scenarios designed to stress the effects of specific variables. Finally, as a robustness check, 50 simulations of each specific scenario are run by adding Gaussian noise to the valuations. Determining the winning participant and final price in sequential auctions is an easy task; it just involves selecting the lowest offer. However, in a combinatorial auction, participants can submit as many offers as possible combinations of projects, so calculating the winning combination is a NP-complete problem (see Sandholm (2002)). To deal with this task, a specific solver has been coded.

The primary goal of this work is to provide public policymakers with a benchmark with the advantages and disadvantages of each auction mechanism to improve decision-making in future processes in which multiple related PPP projects need to be awarded. Opting for a combinatorial auction implies that a considerable effort must be undertaken by authorities to simultaneously prepare all tenders at the beginning of the process. Likewise, the interaction and communication with private companies will also be more complex. However, our results reveal that combinatorial auctions allow participants to bid more aggressively for combinations of projects for which contractors have synergies or that would allow them to reach their optimal capacity. Conversely, in sequential auctions, such bidding strategies are not possible because winning one project does not guarantee winning a complementary one. Therefore, in light of the results achieved, it can be stated that a combinatorial auction enhances the procurement process in three main ways. First, this auction type improves in terms of optimal allocation as it lowers the price paid by public authorities while still delivering positive profits to participants. This increase in the final discount implies significant savings for public budgets. Second, this auction type enhance efficiency, as winners have the ability to express through their bidding strategies their values for combinations of projects and, therefore, have a higher probability of being awarded their desired project package. Third, a combinatorial auction tends to allocate projects to companies that are better prepared, thus reducing the likelihood of failure and having a positive effect on the critical success criteria for PPP projects presented by Osei-Kyei et al. (2017): effective risk management, fulfillment of output specifications, reliable and quality service operations, adherence to timelines, satisfaction of the needs of public facilities/services, long-term relationships and partnerships, and profitability.

This article is structured as follows. Section 2 presents the related work. Section 3 describes the fundamentals of sequential and combinatorial auction mechanisms. In Section 4, the selected context is outlined: the second wave of the 4G program in Colombia for allocating 9 highway construction projects. Section 5 offers an overview of the implemented methodology. Section 6 includes the specifications of the projects offered and the participants involved. Section 7 describes the valuation model, which is the way the final offer is computed for each participant and project, or combination of projects. A description of the different scenarios used for simulation is included in Section 8. Section 9 is focused on analyzing the obtained results on sequential versus

[2] Source: https://www.argentina.gob.ar/.

combinatorial auctions. With the aim of highlighting the applicability of the results obtained, Section 10 includes references to real markets in which one PPP contractor could be interested in multiple contracts that could be offered at the same time, so combinatorial auctions could be implemented. Finally, conclusions are drawn in Section 11.

2. Related work

There are many studies about PPP projects. We want to highlight the state-of-the-art research performed by Cui et al. (2018), Zhang et al. (2016) and Carbonara et al. (2012). Other authors have studied how entry barriers may promote efficiency in these processes: Osei-Kyei and Chan (2015) and Liu et al. (2016). Some studies, such as Hueskes et al. (2017), have also focused on how governments incorporate sustainability considerations into PPP infrastructure projects. Governments and international organizations have also conducted interesting studies, such as that by Kerf et al. (1998), explaining key factors in PPP projects. Carbonara et al. (2016) examined procurement processes to determine which ones minimize public costs. In this same area, Verweij and van Meerkerk (2020) analyzes the cost performance (in terms of costs for additional work caused by contract changes during project implementation) of PPP projects versus Design and Construct (DC) projects, finding that PPP-projects have a significantly better cost performance than DC projects, especially concerning costs for additional work due to technical requirements.

Regarding the capacity of having enough competition in the tender processes, Liu et al. (2014) illustrate the significance of the valuation to both host government and investors, and provide them with a clear reference when negotiating on the level of restrictive competition. Solino and De Santos (2010) compares Negotiated and the Open procedures, and analyzed the effects of high costs in both the preparation and follow-up phases. Finally, Carbonara et al. (2015) analyzed risk management in PPPs. Tiong (1996) shows that the financial and technical strength of the consortium awarded with the project is the most important critical success factor in a PPP tender, and that the PPP promoters must give high importance to the financial model to increase the chances of reaching a profitable PPP contract.

In the transportation sector, it is worth mentioning the book *Public private partnerships in transport: Trends and theory*, Roumboutsos (2015) and contributions focused on specific cases such as Chou et al. (2012) on high-speed rail in Taiwan, Verweij (2015) on the Dutch A15 highway, Macario et al. (2015) on the transportation infrastructure in Portugal, Garrido et al. (2017) on Spanish highways and Kumar et al. (2018) on Indian highways, who applies a standard risk-analysis model to the real-world PPP based Indian highway infrastructure projects. Lorenzen et al. (2001) reviews the positive experience of the Chilean toll road concessions program during the 1990s examining in detail the development of the regulatory framework and bidding process. Also in Chile, Vergara-Novoa et al. (2019) analyzes the revenues, cost, and capital structure of the Chile s highway concessionaires since 1995 to 2014.

Regarding the auction mechanism selected to allocate PPP projects, the work done by De Clerck and Demeulemeester (2014) and Carbonara et al. (2016) is worthy of mention. Furthermore, there are several studies that analyze the pros and cons of sequential auctions: Jofre-Bonet and Pesendorfer (2014), De Silva (2005) and Jofre-Bonet and Pesendorfer (2003). The advantages and disadvantages of using independent auctions have also been analyzed by Grimsey and Lewis (2007). Finally, De Clerck and Demeulemeester (2016) reviewed the beneficial effects of having a high enough number of projects to make it worth the economic effort of private companies to study all of them at the same time.

3. Description of auction mechanisms

In PPP procurement auctions, governments aim to allocate multiple projects among several private companies. This process can be done through multiple auctions held one after another (sequential auctions) or at the same time (simultaneous auctions). If the projects are offered simultaneously, the auctioneer can implement a combinatorial auction that allows participants to bid on any project or combination of projects at the same time. In this section, both mechanisms are explained in detail.

3.1. Sequential auctions

When an auctioneer wants to allocate multiple related projects J (1, 2, M) among several participants I (1, 2, N), she may do so through sequential auctions, that is, by offering the projects in different consecutive auctions. The auctioneer may choose the auction model that she prefers, either dynamic or single-round, but the auctions must be performed one after another. The main reasons to support sequential auctions are that they are easy to implement and that they reduce the risk of collusion.

In this article, we have implemented a first-price sealed-bid sequential auction as it is the mechanism most frequently used in the transportation sector and was the auction type implemented in the 4G Colombian process. In these auctions, the auctioneer offers M different but related projects in M sequential sealed-bid (single round) auctions. In each auction, a project j is offered, and each bidder i submits her offer for that project $b_{i,j}$. This offer $b_{i,j}$ determines the minimum amount of money the bidder is willing to earn to execute that project. Bidder i wins the project (q_{ij} 1) only if she submits the smallest offer: b_{ij} b_j, for which she will receive an amount equal to p_j, which will depend on the pricing rule selected. With the first-price rule, the winning participant will receive the amount of her offer (p_j b_j). However, if bidder i does not submit the lowest bid, she does not win the project (q_{ij} 0).

After all the sequential auctions are done, the government s payment to participant i is equal to the sum of the offers for her winning projects:

(1)

The total cost for the public authorities is equal to the sum of the payments to be made to all winning bidders:

(2)

where W is the set of winning participants.

The government s main goal is to design a process that allocates all the projects at the lowest price (R^*) but ensures quality. Although sequential auctions are still the most common mechanism implemented in this sector, they have important drawbacks when related projects are offered. One problem arises when participants have complementary values for the offered projects, as their bidding strategy cannot reflect this situation. Another problem with sequential auctions is that when participants are willing to win more than one project, bids submitted in the first auctions depend on the bidders estimations of the prices in future auctions. Therefore, participants may regret either winning a project at a low price in the first auctions or not having acquired their desired projects. Given this uncertainty, bidders predictions are frequently wrong, which translates into inefficient allocations.

3.2. Combinatorial auctions

In combinatorial or package auctions, the public authorities offer all the projects simultaneously in a single auction in which participants are allowed to send their offers for individual projects or any combination of projects that they may be interested in. For example, let us suppose a procurement auction offers 3 projects to bidders: A, B and C. Then, each participant could submit any of the following offers in a single round: A, B, C, AB, AC, BC, or ABC. These auctions are particularly suitable when substitute[3] and complementary[4] projects are offered because these valuations can be reflected in the package bidding strategy.

In combinatorial auctions, multiple related projects $J \quad (1,\ 2, \quad M)$ are offered to multiple participants $I \quad (1,\ 2, \quad N)$. Each participant i may submit as many offers as she likes for a project or combination of projects. The combination, known as a package, is represented by $S \quad J$. The offer from bidder i for package S is represented as $b_i(S)$.

Among all offers submitted by all participants, the auctioneer determines which offers win according to which packages minimize the total payment, that is, the feasible combination of bids that minimize the total price of the accepted offers under the constraint that each project is allocated to, at most, one participant. This allocation problem is known as the winner determination problem (WDP), which has the following mathematical formulation:

(3)

subject to:

1. $_{S\ \ j} \quad _{i\ \ I} x_i\ S \quad 1\ j \quad J$,
2. $_{S\ \ J} x_i(S) \quad 1\ i \quad I$,
3. $x_i\ S \quad 0\ 1 \quad S \quad J\ \ i \quad I$.

Solving this problem implies determining, among all possible combinations of offers, which one minimizes the government s payment.

Constraint (1) ensures that each project is awarded to, at most, one participant, that is, that a feasible allocation of projects is made. Restriction (2) limits the solution of the problem such that each bidder obtains, at most, one winning package, meaning that offers are mutually exclusive. This is called the XOR bidding language. Finally, $x_i(S)$ is a binary variable that is equal to one when a participant offers a winning bid and zero when none of her bids is accepted; see constraint (3). Solving the WDP is an NP-complete problem; see Sandholm (2002). Hence, advanced computational techniques must be used to solve this task.

After the winning combination is determined, the final payments to be made by the government to the winning bidders depend on the pricing rule. Just as in the sequential auction, the first-price rule is implemented for this model, such that each winning participant earns an amount equal to her winning bid:

(4)

The total payment that the auctioneer makes to the winning participants is equal to the sum of each winning offer:

(5)

where W is the set of winning participants. For a better understanding of combinatorial auctions, see Appendix A.

4. 4G program in Colombia

Procurement processes for PPP projects in the transportation sector in Colombia have been carried out since 1994 in a sequence of steps or ‘generations . These PPPs arose with the purpose of complementing public activity while curbing the deficit increases caused by the development of highways in Latin America. Since then, four generations of infrastructure projects have been executed in Colombia.

As mentioned above, this research is focused on the fourth generation (4G) that took place between 2013 and 2015, as it is the most recent and a great deal of information on it is available. The main goal of the 4G program was to build new highways to connect Colombia s main cities, production centers, ports and borders with each other, reducing transportation costs and time. This program proposed building more than 8,000 km of roads, including 1,573 km of highways, 159 tunnels, and 1,335 viaducts, among other infrastructure projects. Fig. 1 shows in red the new highways to be built during the 4G program compared with existing highways.

The 4G projects were divided into 3 groups, called waves. Each of these waves was tendered through sequential sealed-bid auctions, as described in Section 3, with the winner being the participant with the lowest bid.[5]

The first wave comprised 9 projects, the second wave another 9 projects, and the third wave 8 not-yet-completed projects.[6] Each project consists of several steps in the development of different stretches of highway in Colombia, from drafting the project, obtaining licenses, securing funds and executing the works to operating and maintaining an adequate service level on the highways for a certain period of time (between 15 and 25 years).

Procurement for the highway construction was divided into different projects so that a suitable economic balance between construction costs and expected revenues could be struck for each project. However, several projects are connected to each other, forming sections of the same highway. Therefore, although the projects were offered independently, participants might have exhibited complementary valuations (synergies) for these connected projects.

4.1. Second wave of the 4G program

The second wave of the 4G program, on which this research is focused, involves a total investment of 3.6 billion USD[7] and is composed of 9 highway projects with an approximate total length of 1,800 km. The government carried out the allocation of the projects through 9 independent sequential auctions, ignoring the relationships between the lots offered. In this second wave of 4G, the auctions were held between April and August 2015. As in the procurement process of the previous wave of the program, the same participants were involved in all auctions; the same tender rules were applied; and finally, the projects were all similar (construction of highways across the country). Fig. 2 shows the projects included in the second wave of the 4G program, which are numbered for further reference.

Given the characteristics of this process, the offered projects can be either substitutes or complements for the bidders involved:

Substitutes: Participants have diminishing marginal values, as the value of winning a set of projects is lower than the individual value of the projects included in the set. This situation can take place when participants establish a limit on the maximum number of projects to win because they have limited investment capacity or because they wish to diversify their project portfolios (see Jofre-Bonet and Pesendorfer (2014)). In our model, we set the maximum capacity for all bidders to 3 projects. This limit is aligned with participants real capacities in this sector. Furthermore, in the actual process, no one

[3] Projects are substitutes when the value of the combination is lower than the sum of the individual values.

[4] Projects are complements when the value of the combination is higher than the sum of the individual values.

[5] To compute the final score that determines the winning participant, the auction rules define both technical and economic criteria. Nevertheless, in the real process, all participants met the technical criteria, so only the economic criteria are considered in our model.

[6] The delay was due to the economic crisis caused by the drop in oil prices. In 2020 the government of Colombia launched the fifth Generation of PPP projects.

[7] Source: Agencia Nacional de Infraestructuras (ANI).

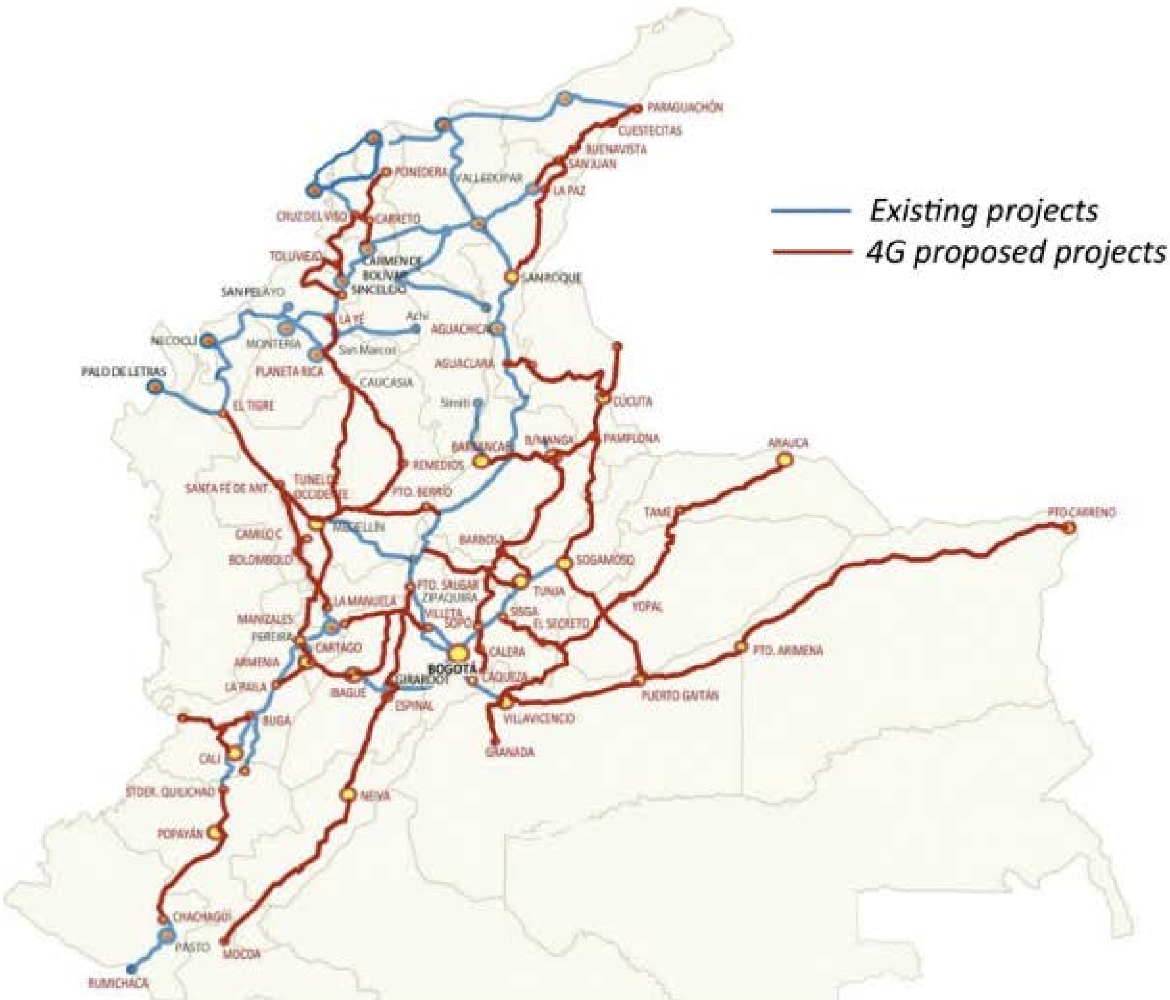

Fig. 1. Existing highway concessions compared with 4G. *Source: Agencia Nacional de Infraestructuras (ANI).*

Fig. 2. Geographic location and numbering of the 4G second wave projects. *Source: Compilation based on information from the ANI.*

won more than 3 projects. It is important to highlight that these projects require large investments and funds are limited in the infrastructure sector. Therefore, after reaching the maximum capacity, participants interest in successive projects is reduced.

Complements: Participants have increasing marginal values, as the value of winning a set of projects is higher than the individual value of the projects included in the set. As Solino and De Santos (2010) has pointed out, participants may be interested in winning and developing more than one project to have a higher turnover and greater EBITDA to amortize the investment made in studying the country, legislation and market. There may also be an additional complementarity effect between projects that are connected or very close to each other (see De Silva (2005)), generating economies of scale (savings on implementation costs, structure, etc.). In the projects included in our model, projects 2.2/2.3 and 2.6/2.9 are contiguous sections of the same highway (see Fig. 2). Therefore, they are considered complements for all participants in our model.

Substitute and complementary valuations can only be reflected in combinatorial auctions as bidders submit offers for packages of projects. In sequential auctions, projects are awarded individually, so these preferences cannot be incorporated into participants bidding strategies.

Table 1 depicts for each project the *ANI base value* (BV^{ANI}), which represents the starting price, that is, the amount set before the auction by the Agencia Nacional de Infraestructuras (ANI) as the maximum amount to be paid to the winning participant. Consultants hired by the ANI set these values based on participants experience and ratios of construction costs. Nevertheless, in the auction, each participant offers a lower amount, depending on the discount value that she can set with respect to the BV^{ANI}. The last two columns show the final discount and offer made by the winning participant in the actual auction. The base value and winning offers are in million USD, calculated based on the exchange rate of 0.000 3 USD/COP.

5. Methodology

The methodology used explores social sciences through the application of computer simulations. Social simulations have become an appropriate methodology in modern research when complex interdisciplinary environments are analyzed. In our work we have adopted the methodology proposed by Cioffi-Revilla (2010) for complex inter and multidisciplinary systems:

Linking together investigators from all disciplines and institutions: This is a multidisciplinary research team with members from different fields and a high expertise in PPP projects.

Key questions and theory: Based on the theoretical models of auction theory, core questions arise when implementing auctions to allocate real PPP related contracts: How does the award mechanism impact the efficient allocation? Should policymakers consider simultaneous combinatorial auction to allocate related contract instead of having a sequential process? What is the beneficial impact on public objectives of shifting the actual sequential mechanism to combinatorial auctions?

Computational models to address interdisciplinary research questions: To address these significant questions, we have formalized a complex model that simulates the selected market. Then, several scenarios have been set up to run multiple experiments. Advance computational techniques were needed to deal with combinatorial auctions (solving the winner determination problem, WDP). Finally, to validate results, a robustness analysis has been carried out by testing the impact of modifying multiple input variables introducing uncertainty as happens in real-world scenarios.

To address the key questions of this research, the following steps have been followed in order to develop an appropriate computational model.

1. Definition of lots, packages and participants: Based on the 9 projects included in the second wave of the 4G program, we identified the main variables related to the highway projects offered, such as investment, debt, equity and equity/investment ratio. Then, the variables that affect packages or combinations of projects, such as connectivity and optimum capacity, were also included. Afterwards, the basic characteristics of the bidders that participated in the actual auction were analyzed to generate a categorization of participants.
2. *Generation of the valuation model:* We developed an advanced valuation model adapted to the highway sector that generates different discounts with respect to the ANI base value and therefore final offers for each project and combination of projects. Final offers were adapted for each type of project and participant category based on the impacts of different variables.
3. *Setup of the experimental scenarios:* To provide a sensitivity analysis, we generated several scenarios in which the discounts applied by the participants are modified. This approach of having different variations provides robustness to our analysis, avoiding bias resulting from a specific setup. Each scenario was tested for both the sequential and combinatorial auction models and run 50 times.
4. *Analysis of the results:* Key variables in terms of final discounts and package allocation were compared for both auctions to determine the main advantages of the compared mechanisms.

Fig. 3 depicts the main stages followed in the methodology, which are also presented in detail in the next sections.

6. Definition of lots, packages and participants

In this section, we describe the main variables used to classify the projects and participants involved in the auction process.

6.1. Project key variables

For each of the projects included in the procurement process, the ANI reported the public information needed for the process. Using that information, we included the following data in our model:

Investment (I): Amount required to build each project.
Debt (D): Minimum debt amount to be raised from financial institutions by winning participants to develop the project.
Equity (E): Minimum equity amount that winning participants must contribute to the project.

Table 1
Actual outcomes in the 2015 Colombian second-wave 4G process.

Project	Date	*ANIBaseValue*[a](*BV^{ANI}*)	Winning Discounts	Winning Offer[a]
2.1	April 10th	102	18.98%	83
2.2	April 17th	162	23.61%	124
2.3	April 24th	388	17.40%	321
2.4	April 30th	298	1.97%	293
2.5	May 8th	320	13.10%	278
2.6	May 22[th]	441	18.00%	361
2.7	May 29th	314	21.99%	245
2.8	June 19th	455	20.64%	361
2.9	August 8th	466	15.67%	393

[a] Million USD. *Source: Compilation based on information from the ANI.*

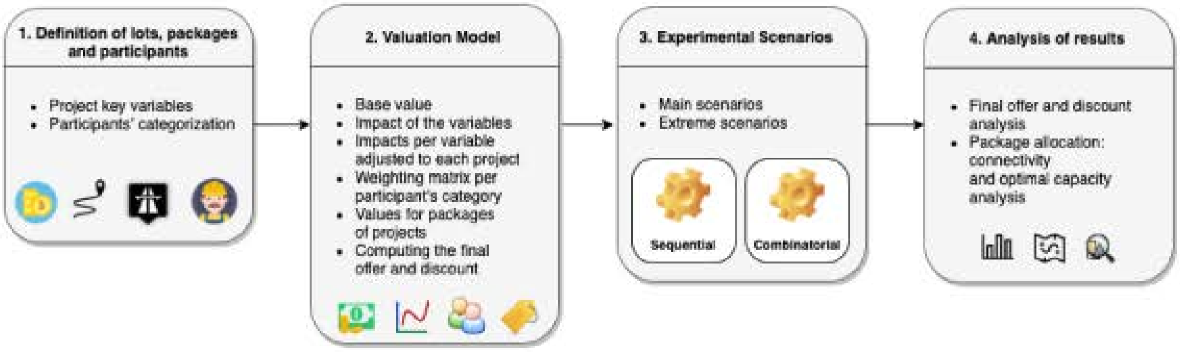

Fig. 3. Stages followed in the methodology.

- **Equity/Investment Ratio (*E/I*):** Percentage of equity with respect to the investment required per project.

The public value of each project published by the ANI is reported in Section 7.2. To set these amounts, the ANI completed a thorough process with the help of specialized advisors who studied key factors such as the cost of the infrastructure to be built, construction schedule, potential toll revenues, and possible financial structures. Furthermore, we identified two important variables that affect participants' values when submitting offers for a combination of lots:

- **Connectivity (*C*):** Geographical location of each project. Participants benefit from scale economies when building connected highways (see, e.g., De Silva (2005)).
- **Optimum Capacity (*OC*):** Optimal number of projects to win in one package. Depending on the type of bidder, each has a different optimum capacity.

All six variables were included in the valuation model to generate the final offers of each participant category per project in the different scenarios tested.

6.2. *Participant categorisation*

We classified the participants involved in the second wave of the 4G program by type according to the following features[8]:

- **Nationality:** Colombian, Asian or rest of the world.
- **Size:** Small, medium, large or very large. This classification was made based on the following variables: number of employees; turnover; and local, national or international company.
- **Business activity profile:**
  - Constructor: Participants whose main business activity is infrastructure construction. These participants are more likely to be interested in projects with a higher construction impact with respect to the investment needed, as they build the projects directly. In line with this idea, Ping (2013) developed the concept of the *profit tool*.
  - Investor: Participants, such as investment funds, whose main business activity is investment in assets with the objective of obtaining a long-term return.
  - Mixed: Participants comprising a consortium of companies in which two of them have a high stake (more than 49% each) in both construction and investment activities.

[8] When a participant comprised more than one individual company, the categories were defined based on the features of the company or set of individual companies with the majority (more than 50%) stake in the consortium.

Based on these features and the participants involved in the actual procurement process, we generated 15 participant categories that were included in the developed model (see Table 2). A total of 27 participants, representing 10 out of the 15 categories, took part in the second wave. We included this specific combination of categories in our model in order to replicate the real circumstances to the greatest extent possible.

7. Valuation model

The aim of the complex valuation model adapted to the sector is to generate different offers for each participant category on each individual project and each combination of projects. Specifically, the model computes the percentage of the discount to be made with respect to the base value and generates the final offer. The higher the discount is, the more competitive the offer will be and the greater the participant's chances of being a winner. The model is implemented according to the following steps:

1. Compute the *adjusted base value* (BV^A) based on the value given by the ANI (BV^{ANI}). The BV^A in our model is the potential offer submitted by a participant with a neutral preference for that specific project.
2. Set the impact that each of the six variables has in the different scenarios. The impact value ranges from 0% to 5% for the basic scenarios. Some variables are tested with a 12% value for extreme scenarios.
3. Adapt the impact value of each variable to each project. The adjustment coefficient value ranges from −1 to +1.
4. Particularize the effect that each variable produces over each participant category using a weighting matrix. The value ranges from −1 to +1.
5. Compute values for projects and combinations of projects.

Table 2
Participant categories.

Nationality	Size	Business activity	category	# participants
Colombian	Small	Constructor	1	5
	Medium	Constructor	2	2
	Large	Constructor	3	2
	Very large	Constructor	4	–
	Very large	Investor	5	2
	Very large	Mixed	6	–
Asian	Large	Constructor	7	2
	Very large	Constructor	8	2
	Very large	Investor	9	–
Rest of the world	Medium	Constructor	10	6
	Large	Constructor	11	–
	Large	Mixed	12	3
	Very large	Constructor	13	1
	Very large	Investor	14	2
	Very large	Mixed	15	–

6. Compute the final discount with respect to the BV^A and hence, the offer to be made by each type of participant for each project or combination of projects.

Fig. 4 shows the steps followed in the valuation model to generate final offers per participant and project. A detailed description of these steps is presented in the following sections.

7.1. Base value

Before the allocation process, the ANI set BV^{ANI} for each project. After the process, the winning discount and offer of the participants that actually won each project were published. Introducing these values in our model, we found that winning participants had a more aggressive bidding strategy than neutral participants. Therefore, the BV^{ANI} value was adjusted, generating the BV^A equal to the potential offer submitted by a neutral preference bidder. The BV^A used in our model is equal to BV^A BV^{ANI} 0.855 6. This means that a neutral bidder would have submitted an offer with a discount of 14.44% with respect to the BV^{ANI}. It is important to highlight that the same value was used to adjust all projects; therefore, it has no effect on the comparisons made, but it helps us to set the results closer to the market value.[9]

The BV^A values used in the developed model are expressed in USD, using an exchange rate of 0.000 3 USD/COP. Table 3 shows the values for BV^{ANI} and BV^A per project in million USD.

7.2. Impact of variables used to generate scenarios

As described in Section 6.1, we identified four variables affecting the valuation of individual projects (investment (I), debt (D), equity (E), and equity/investment ratio (E/I)), plus two additional variables affecting the valuation of packages (connectivity (C) and optimal capacity (OC)). These variables are represented in the model as V (1, 2, V), where I (v 1), D(v 2), E(v 3), E/I(v 4), C(v 5) and OC(v 6). The specific values for the first four variables affecting individual projects were reported by the ANI and are summarized in Table 4. The values of the last two variables depend on the composition of the packages.

To test the impact that each of these variables can have on the participants offer and, consequently, in the final allocation, we defined different sets of impact values. The impact value for each variable is represented as I_v. Each set of impact values depends on a specific hypothesis and yields an experimental scenario. The impact value range is 0% I_v 5% for the basic scenarios and up to 12% for extreme case testing. A total of 9 scenarios were prepared and are described in Section 8.

In each scenario, the value of the impact variables is the same for all projects and participants. The adaptation of each impact to a specific project was done using an adjustment coefficient, and the adjustment of the impact to each participant category was done using the weighting matrix, both described in the following sections.

7.3. Adjusted impacts of variables for each project

The 9 projects included in the process have similar characteristics but are not equal. Therefore, the impact value of each variable v needed to be adjusted to each project j by using an adjustment coefficient $_{v,j}$. Given that this adjustment was made for each individual project, it was only computed for the first four variables.

Table 5 depicts the $_{v,j}$ values, which have the following interval: 1 $_{v,j}$ 1. To compute the $_{v,j}$ values, we first considered the values given by the ANI for each variable and project; see Table 4. Then, for each variable, a 1 was applied to the project with the highest value for that variable and a 1 to the lowest value. Then, a proportional rule was used for the remaining projects.

The adjusted impact that variable v has on all participants for project j is equal to (I_v $_{v,j}$). The next step was to incorporate the effect on each participant category.

7.4. Participant category weighting matrix

The incorporation of the effect of variable v on participant i was done through a weight factor ($W_{v,i}$) that has values in the following range: 1 $W_{v,i}$ 1. The weighting matrix for each variable and participant category is included in Table 6.

The combinations of weights set for the different participant categories were determined based on the authors expertise in this specific sector and the following criteria:

- Constructors give a higher weight to projects that require more I, as they build the projects themselves and can make additional markups within the construction contract. Conversely, investors have to hire third companies, so they give a relatively lower weight to projects with a higher level of I.
- Investors are usually capable of raising higher amounts of debt at a lower price, so they give a higher weight to projects that require a higher amount of D.
- Investors can obtain funds more easily, so they give a higher weight to projects that require more E.
- Constructors give a higher weight to projects with a lower E/I ratio, as they want to maximize the work to be done with respect to the equity invested.
- Larger companies with just one business activity give a higher weight to projects with higher I, D or E than do smaller companies.
- All participants give the same weight to C, as it is equally beneficial for all of them.
- Investors and the largest companies have higher OC than smaller companies do, as their capacity to invest and develop several projects at the same time is higher. Nevertheless, all participants have the same weight if they reach their own OC.

The way each variable for independent projects (v 1, , 4) affects the final offer of each participant category (i) on project (j) is expressed in equation (6). Values for packages, which include the last two variables, are described in the following section.

(6)

7.5. Values for packages of projects

When multiple projects are being considered in a combinatorial auction, connectivity and optimal capacity must be taken into account to compute the package s value.

- Connectivity: The connectivity value for the projects included in package S is represented by C_S and takes a value of 1 when the package includes connected highways and 0 otherwise. The impact of the connectivity value is expressed as (1 I_5C_S). As we mentioned before, the impact value for I_5 is set in each scenario.
- Optimal capacity: Based on the participant categories described in Section 6.2, we gave each type of participant an optimal capacity (OC_i), that is, the optimal number of projects each participant wants to be awarded (see Table 7). Therefore, each bidder i has a $OC_{i,S}$ value for package S that depends on how close it is to OC_i. The value of $OC_{i,S}$ can be 0, 0.5 or 1, depending on the absolute value of the difference between the number of projects included in package S with respect to OC_i. Finally, the impact of the optimal capacity value

[9] The adjustment was made using the $_{i,j}$ value of the winning participants in the actual process. A full description of how to compute $_{i,j}$ is presented in the following sections.

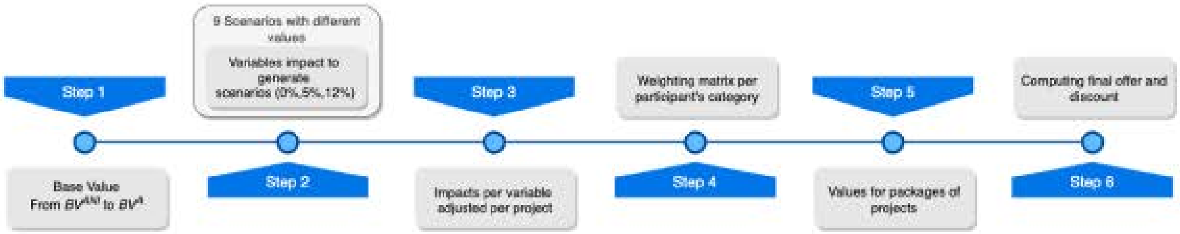

Fig. 4. Steps in the valuation model.

Table 3
ANI and adjusted base values (million USD).

Project	BV^{ANI}	BV^{A}
2.1	102	87
2.2	162	139
2.3	388	332
2.4	298	255
2.5	320	274
2.6	441	377
2.7	314	269
2.8	455	389
2.9	466	87
Total	2,947	2,522

Table 4
Variable values in USD for each project.

Project	$I(v = 1)$	$D(v = 2)$	$B(v = 3)$	$E/I(v = 4)$
2.1	135	57	36	27%
2.2	165	87	59	40%
2.3	586	308	209	39%
2.4	467	265	133	30%
2.5	370	230	156	43%
2.6	471	290	113	25%
2.7	523	265	148	29%
2.8	508	317	206	43%
2.9	460	299	131	31%

Source: Compilation based on information from the ANI.

Table 5
Adjusted coefficient values by variable and project.

Project	$\beta_{1,j}$	$\beta_{2,j}$	$\beta_{3,j}$	$\beta_{4,j}$	$\beta_{5,j}$	$\beta_{6,j}$
2.1	−1.0	−1.0	−1.0	−0.8	0	0
2.2	−0.9	−0.8	−0.7	0.7	0	0
2.3	1.0	0.9	1.0	0.5	0	0
2.4	−0.5	0.6	0.1	−0.5	0	0
2.5	0.0	0.3	0.4	1.0	0	0
2.6	0.5	0.8	−0.1	−1.0	0	0
2.7	0.7	0.6	0.3	−0.6	0	0
2.8	0.7	1.0	1.0	1.0	0	0
2.9	0.4	0.9	0.1	−0.3	0	0

Source: Compilation based on information from the ANI.

for package S is expressed as $(1-I_6OC_{i,S})$, where I_6 is set in each scenario.

7.6. Computing the final offer and discount

The final offer that participant i submits for package S in our model is equal to:

$$O_{i,S} = \sum_{j\in S}\frac{BV_j^A}{1+\sum_{v=1}^{4}(I_v\beta_{v,j}W_{v,i})}(1-I_5C_S)(1-I_6OC_{i,S}), \tag{7}$$

where j represents the projects included in package S. Equation (7) can also be expressed as:

$$O_{i,S} = \sum_{j\in S}\frac{BV_j^A}{\frac{1+\sum_{v=1}^{4}(I_v\beta_{v,j}W_{v,i})}{(1-I_5C_S)(1-I_6OC_{i,S})}}. \tag{8}$$

Equation (8) can be simplified as:

$$O_{i,S} = \sum_{j\in S}\frac{BV_j^A}{\Omega_{i,j}}, \tag{9}$$

where $\Omega_{i,S}$ is the value used to adjust VB^{ANI} and obtain VB^{A} using the real auction data, as explained in Section 7.1.

Once the final offer is computed, we can also calculate the discount that participant i proposes on package S with respect to VB^{ANI} according to the following equation:

Table 6
Weighting matrix by variable and participant category.

Participant Category	$W_{1,i}$	$W_{2,i}$	$W_{3,i}$	$W_{4,i}$	$W_{5,i}$	$W_{6,i}$
1	0.5	−1.0	−1.0	−1.0	1	1
2	0.5	−0.5	−1.0	−1.0	1	1
3	0.5	−0.5	−0.5	−0.5	1	1
4	1.0	0.5	−0.5	−0.5	1	1
5	−0.5	1.0	0.5	0.5	1	1
6	0.5	0.5	−0.5	−0.5	1	1
7	0.5	−0.5	−1.0	−1.0	1	1
8	1.0	0.5	0.5	0.5	1	1
9	0.5	1.0	1.0	1.0	1	1
10	−0.5	−0.5	−1.0	−1.0	1	1
11	0.5	−0.5	−0.5	−0.5	1	1
12	−0.5	0.5	0.5	0.5	1	1
13	0.5	−0.5	−1.0	−1.0	1	1
14	−0.5	1.0	1.0	1.0	1	1
15	0.5	0.5	0.5	0.5	1	1

Table 7
Optimal capacity by participant category.

Participant Category	OC_i^*
1	1
2	2
3	2
4	3
5	3
6	3
7	1
8	3
9	3
10	1
11	2
12	2
13	2
14	3
15	3

(10)

8. Experimental scenarios

The described valuation model was used to set the offers submitted by the participants in the different scenarios. To avoid biased results, in each scenario, we ran 50 simulations in which the final offers were multiplied by a noise factor of between 3% and 3%, selected using a Gaussian distribution. Then, for each simulation, the allocation process was solved for both sequential and combinatorial auctions.

As we outlined in Section 7.2, the scenarios were generated by setting different values for the impact that each variable can have on the offers (I_v). Each set of impact values yields a scenario in which I_v ranges from 0% to 5%, except for cases of extreme testing, in which I_v is 12%.

8.1. Main scenarios

The main scenarios tested in this work include the following:

Basic scenario:

Scenario 1: We assumed that all variables have the same impact, I_v 3% for all v. This is a balanced scenario, where all the variables have a reasonable impact on the participants decisions. We consider this scenario to be aligned with real-world behaviour based on our expertise and the outcome of the real process.

Scenarios with variations per project:

In the following two scenarios, we changed the balance between the variable that has a positive effect on contractors (I_1) and the variables that have a negative effect on them (I_2, I_3 and I_4).

Scenario 2: The impact of the investment amount needed to build a project is lower than that of the other variables: I_1 1% and I_2 I_3 I_4 5%.

Scenario 3: The impact of the investment amount needed to build a project is higher than that of the other variables: I_1 5% and I_2 I_3 I_4 1%.

Scenarios with variations by package:

We modified the balance between the impact value of the variables that only affect individual projects (I_1, I_2, I_3 and I_4) versus that of variables that affect packages (I_5 and I_6). This change helped us to understand the outcomes when optimal capacity or connectivity is zero.

Scenario 4: The variables that affect the package valuations have no effect at all: I_1 I_2 I_3 3% and I_5 I_6 0%.

Scenario 5: Only the variables that affect package valuation have an impact on the final offer: I_1 I_2 I_3 0% and I_5 I_6 3%.

A summary of the I_v values included in the main scenarios appears in Table 8.

Table 8
Main scenarios.

I_v	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
I_1 (*I*)	3%	1%	5%	3%	0%
I_2 (*D*)	3%	5%	1%	3%	0%
I_3 (*E*)	3%	5%	1%	3%	0%
I_4 (*E/I*)	3%	5%	1%	3%	0%
I_5 (*C*)	3%	3%	3%	0%	3%
I_6 (*OC*)	3%	3%	3%	0%	3%

8.2. Extreme scenarios

In addition to the main scenarios, we wanted to test the final outcome assuming great deviations from our prior assumptions in some of the variables. To this end, we included four additional scenarios with large variations from the basic scenario (Scenario 1) for some specific variables:

Scenario 1a: The investment needed to develop a project has a substantial effect, I_1 12%.

Scenario 1b: Debt and equity have a major effect, I_2 I_3 12%.

Scenario 1c: Having connected projects in a package has a great impact, I_5 12%.

Scenario 1d: Optimal capacity has a substantial effect, I_6 12%.

Table 9 shows the scenarios with extreme variations for several variables.

9. Analysis of results

For each scenario, 50 simulations were performed to generate final offers for all participants. Then, the offers were submitted to the model using the two different auction mechanisms: sequential and combinatorial. Finally, the solver generated the outcome for each auction format, yielding the winning participants and final price paid by the government. The results are compared in detail in the following sections.

9.1. Final offer and discount analysis

Analyzing the results, the winning offers in the combinatorial auctions are lower than the winning offers in the sequential auctions, which implies that the combinatorial auction yields significantly higher discounts.[10] To check whether these differences in final offers and discounts are statistically significant, we performed both a *t*-test and a Mann-Whitney test, finding that the differences are statistically significant for all the scenarios tested, with a p_{value} 0.000 0. The results obtained are summarized in Table 10.

When comparing the details of the final outcomes of each scenario, we obtained the following findings:

Scenarios 1 to 3: The combinatorial mechanism yields a 26% or 27% discount with respect to the base value, which implies a 4% additional discount over that obtained with the sequential auction. This case implies savings of more than 100 million USD for the government in the complete process when this combinatorial mechanism is chosen. The final average discount in the real process was 17%, so the combinatorial mechanism adds an extra 9% or 10% to the discount. The fact that the three scenarios yield a similar output shows

Table 9
Extreme scenarios.

I_v	Scenario 1*a*	Scenario 1*b*	Scenario 1*c*	Scenario 1*d*
I_1 (*I*)	12%	3%	3%	3%
I_2 (*D*)	3%	12%	3%	3%
I_3 (*E*)	3%	12%	3%	3%
I_4 (*E/I*)	3%	3%	3%	3%
I_5 (*C*)	3%	3%	12%	3%
I_6 (*OC*)	3%	3%	3%	12%

[10] The discount percentage is measured with respect to the base value reported by the ANI for all the projects included in the model: $_{j\ 1}^{9}BV^{ANI}$ 2 947 million USD (see equation (10)).

Table 10
Winning offers and discounts by scenario.

Scenario	Auction type				Difference	
	Sequential		Combinatorial			
	Price[a]	Discount	Price[a]	Discount	Price[a]	Discount
1	2,303	22%	2,182	26%	121	4%
2	2,273	23%	2,154	27%	119	4%
3	2,306	22%	2,195	26%	111	4%
4	2,328	21%	2,257	23%	71	2%
5	2,322	21%	2,222	25%	100	3%
1a	2,237	24%	2,125	28%	202	4%
1b	2,176	26%	2,041	31%	135	5%
1c	2,303	22%	2,044	31%	259	9%
1d	2,159	27%	1,985	33%	174	6%
Avg.	2,277	23%	2,134	28%	144	4%

[a] Price measured in million USD.

that the model is robust, regardless of the impact value of the variables I_1, I_2 and I_3.

Scenario 4: This scenario reports the smallest difference between both auction mechanisms, as the impact values for the connectivity and optimal capacity variables are set to zero (I_5 I_6 0%). Nevertheless, even in this case, the combinatorial auction still yields a 2% higher discount with respect to the sequential option. It is important to note that this scenario proves that the combinatorial auction is more efficient than the sequential auction, even if the connectivity and optimal capacity values are not included in the model.

Scenario 5: In this scenario, only the impact values for the connectivity and optimal capacity variables are positive, while the others are set to zero (I_1 I_2 I_3 I_4 0%). Again, the combinatorial auction yields a higher discount than does the sequential auction.

Scenarios 1*a* and 1*b*: The outcomes in these scenarios are very similar to those obtained in scenarios 1, 2 and 3. All of them present an extra 4% in the discount in the combinatorial auction with respect to the sequential auction (except scenario 1*b*, with a 5%). This result reveals that setting extreme values for the impact of the investment, debt or equity variables (I_1, I_2 and I_3) does not modify the final outcome significantly from the baseline scenario.

Scenarios 1*c* and 1*d*: In these scenarios, an extreme value is given to the connectivity and optimal capacity variables: I_5 12% and I_6 12%, respectively. This means that the synergy values from projects being connected or participants reaching their optimal number of projects have a higher impact than do the other variables. As expected, these assumptions have a positive effect on the combinatorial mechanism, as the participants can express their preferences for combinations of projects. Hence, we obtain an extra 9% in the discount in scenario 1*c* and an extra 6% in scenario 1*d* with respect to the discount in the sequential auction outcome.

Fig. 5 exhibits the box plot of the final offers submitted in the 50 simulations for the 9 scenarios for both allocation mechanisms. As the figure shows, the combinatorial auction always yields a significantly lower winning offer, which implies an important savings for the government.

This outcome implies that the combinatorial auction improves the allocation procurement process from the point of view of optimality. *Optimal auctions* are those that minimize the total price that the auctioneer needs to pay to the winning participants. According to the results obtained, the combinatorial mechanism always yields an allocation that significantly reduces the final price paid by the government with respect to the traditional model used in the sector. Specifically, on average, the combinatorial mechanism entails 128 million USD savings with respect to the sequential mechanism and 314 million USD savings with respect to the actual prices paid in the 4G Colombian process.[11]

The results are similar when comparing the final discounts to the base value. Fig. 6 displays the discounts obtained in all the scenarios. Again, the combinatorial mechanism yields higher discounts with respect to the base value reported by the ANI. On average, the combinatorial mechanisms imply a 28% discount with respect to the base value, an extra 4% with respect to the discounts yielded by the sequential mechanism and an extra 11% discount with respect to the those yielded in the real procurement process. This increase in the discount reduces public spending and has a positive effect on the public budget. Based on these results, we argue that shifting from the sequential auction mechanism to the combinatorial one would have a substantial beneficial impact on public budget objectives, resulting in significant cost savings.

9.2. Package allocation: connectivity and optimal capacity analysis

We conducted further analysis of the package allocation from three angles: how connected projects are allocated, what the status of the participants capacity is after the allocation, and how packages are distributed among the winners.

Allocating connected projects: Implementing the sequential mechanism implies that, on average, connected projects are allocated to the same winners only 4% of the time, resulting in very low synergy values. Nevertheless, the combinatorial mechanism allocates connected projects to the same bidder 82% of the time. This value reaches 100% in scenario 1*c*, in which the impact value of having connected projects is set to I_5 12%, and falls to 24% in scenario 4, in which the impact value of having connected projects is set to I_5 0%.

Increasing the number of connected projects allocated to a winning participant has a positive effect both for governments and participants, as increasing the synergy values reduces the overall cost for everyone: companies are willing to take on projects for a lower price, and governments use less of the public budget, resulting in a more efficient process for all players.

Reaching optimal capacity: Under the sequential mechanism, the participants only reach their optimum capacity (OC OC^*), on average, 38% of the time. By contrast, the combinatorial mechanism leads to optimal capacity use up to 74% of the time, on average, among all scenarios. These values increase to up to 99% of the time in scenario 1*d*, in which the impact of reaching the optimum capacity takes an extreme value I_6 12%. It is interesting to highlight that in scenario 4, in which this variable is set to zero, I_6 0%, although the number of bidders that reach their optimum capacity falls to 49%, this value is still noticeably above that produced by the sequential mechanism, just because of the ability to bid for packages in the combinatorial format.

Reaching participants optimal capacity also increases the efficiency of the process, as winners can amortize the cost of studying the projects and achieve their desired amount of capital investment.

Concentration of winners: The outcome of the sequential mechanism reveals that after the 9 projects have been allocated, on average, there are 7.2 winners. On the other hand, the combinatorial outcome yields a higher concentration of winners, as only 4.1 participants win

[11] The total winning offers in the Colombian process added up to 2,458 million USD, with a 17% discount on average.

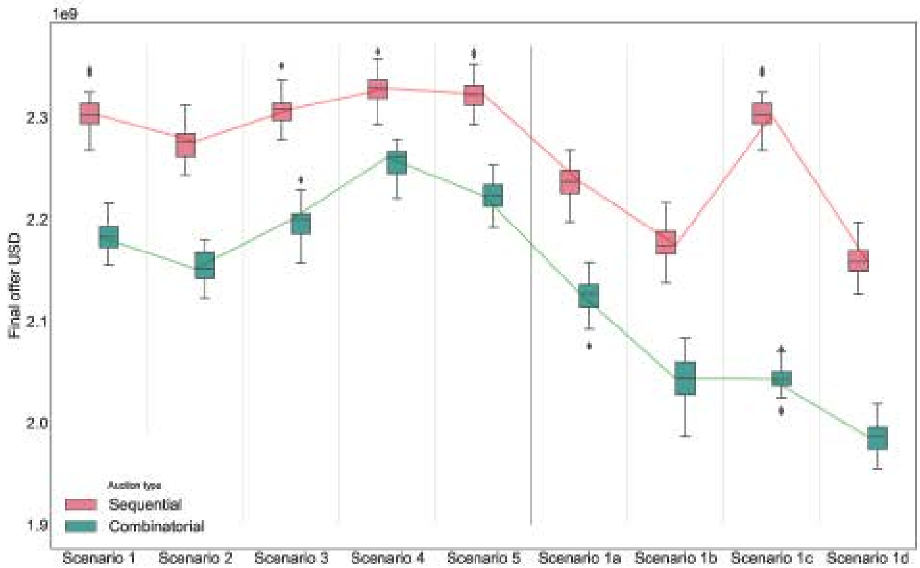

Fig. 5. Final offers.

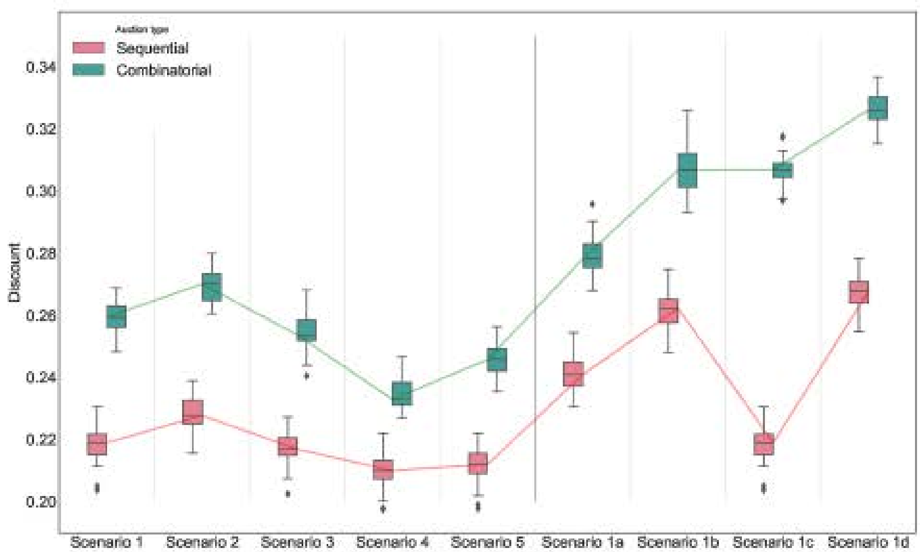

Fig. 6. Final discount.

at least one project. This result is consistent with the previous outcome, as winning larger packages implies reducing the number of winners.

The package allocation results are summarized in Table 11.

Table 11
Package allocation by scenario.

Scenario	Sequential			Combinatorial		
	% connected	Winners with OP=OP*	# winners	% connected	Winners with OC=OC*	# winners
1	2%	33%	7.5	98%	74%	3.9
2	0%	37%	7.4	82%	74%	4.1
3	2%	42%	7.8	88%	76%	4.0
4	4%	27%	7.5	28%	49%	4.3
5	2%	42%	7.5	90%	69%	4.1
1a	2%	36%	7.3	84%	78%	4.3
1b	10%	47%	5.8	82%	70%	4.6
1c	2%	33%	7.5	100%	79%	3.8
1d	8%	51%	6.1	90%	99%	3.6
Avg.	4%	38%	7.2	82%	74%	4.1

10. Real markets

The results obtained reveal that combinatorial auctions is a market design that can noticeably improve the actual allocation systems in terms of efficiency and public expenditure, when multiple related projects are auctioned. To highlight how these results could be transferred to real markets, this section includes a description of multiple examples in which one contractor could be bidding in multiple PPP contracts at the same time, and therefore, expressing his synergy values through this bidding strategies. In all these examples policy makers could have implemented combinatorial auctions and obtained all the benefits of offering all the contracts at the same time, instead of doing it sequentially.

In recent years we can find multiple examples of PPP projects that meet the features needed to implement a combinatorial auction, however, in all cases, they were auctioned through a sequence of auctions.

Between 1998 and 2000 the Spanish Ministry of Development awarded 9 sections of toll roads, under a PPP scheme, see Table 13 inside Appendix B. Six of these projects where awarded to consortium participated by a company (Abertis). Other relevant Spanish companies, as Sacyr, Dragados and Ferrovial participated in the consortium awarded with 2 of the contracts.

Between 2004 and 2007 the Ministry of Health of the Community of Madrid developed a program for the construction of 7 hospitals under the model of public-private collaboration PPP, see Table 14 included in Appendix B. Nowadays, the Sacyr is shareholder of 2 of them, and the UK investment fund Aberdeen is shareholder of 3.

In Chile, between 1996 and 1998, 8 sections of the country s backbone from north to south, Route 5, were awarded, also under a PPP scheme, representing around 1,500 km of road, and which were conceived with a level of quality standards and equivalent rates, see Table 15 in Appendix B.

Initially, the Chilean government thought of tendering the entire route as a single package (Lorenzen et al. (2001)), but was dismissed due to concerns about the effect that possible monopolistic incentives could have on final prices.

The tenders for all those projects were launched by the same auctioneer, in a short period of time and under the same law and rules. In this example, we can observe again that one contractor was interested in multiple PPP contracts at the same time. Specifically, the companies Sacyr and Ferrovial, which were awarded with 3 projects in one geographical area (La Serena Los Vilos, Río Bueno Puerto Montt, Santiago Valparaíso) and other 2 projects in another area (Temuco Río Bueno, Collipulli Temuco), respectively.

Sarmento and Renneboog (2021) analyzed the bidding process for 21 PPP highways in Portugal in the last two decades. They identified 25 companies that made at least one bid (alone or as part of a consortium) and collectively made 282 bids. Thus, in average, each company submitted bids for 11,28 of the 21 PPP projects.

Canada is one of the most advanced countries in terms of PPP markets. In the period between 2006 and 2007, Infrastructure Ontario launched the tender of 20 projects. Those projects where awarded to 8 different companies (see Table 16 included in Appendix B), where 5 of those 8 companies were awarded with more than one project: 1 company won 2, 3 companies won 3 projects each, and 1 company won a total of 6 projects.

In the procurement process of the 9 projects of the second wave of the 4G processes of Colombia, which has been analyzed in this article, the ANI developed a previous process of qualification.[12] Some companies were qualified for several projects. In Table 17, included in Appendix B, we can see that the 9 most relevant companies were qualified for 3 or more projects.

There are many other examples in which offering multiple projects at the same time could have been implemented in the past: tender of 49 roads under PPP contract by the National Highways Authority of India (NHAI) between the years 2016 and 2018; 6 motorways by the Transport Infrastructure of Ireland between 2006 and 2007; 3 motorways in Italy in 2007; 4 Hospitals by the Mexican Social Security Institute in 2018; 7 motorways by the government of Portugal between 2008 and 2009; among many others.

These examples, in multiple countries and real markets, evidence that, in the PPP sector, there are many processes in which one contractor could be bidding in multiple contracts at the same time. The ability to do so, would improve his bidding strategy and therefore, the allocation process. Therefore, policy makers should identify these situations in future PPP processes in order to improve in terms of efficient allocation and social welfare.

As an example of this evolution, public authorities all over the world have implemented simultaneous mechanisms instead of sequential processes to allocate radio spectrum licenses. The telecommunications sector is probably the main market in modern economies in which market design has had a deeper impact in the allocation mechanism. Mochon and Saez (2017) present an extensive review of combinatorial auctions applied to this sector in multiple countries.

11. Conclusion

In the transportation infrastructure sector, the main allocation mechanism still used for awarding multiple related PPP projects is a sequence of individual sealed-bid auctions. Nevertheless, there are many arguments and experiences in many other sectors that indicate that allocating all projects through a combinatorial auction improves the final outcome. At this juncture, the main goal of this research is to provide policymakers with a reference for comparing the possible outcomes of both auction mechanisms using models based on real data to support future processes.

In this work, we have implemented the methodology proposed by Cioffi-Revilla (2010) in which computer simulations are applied to understand complex multidisciplinary environments. Based on auction theory, we have analyzed many different outcomes that arise when comparing the allocation process of multiple related contracts sequentially versus simultaneously by combinatorial auctions. By means of computer simulations we have compared the impact in terms of optimality and efficiency of both mechanisms. To this end, we designed a sophisticated valuation model based on the procurement process conducted in Colombia between 2013 and 2015 that involved the allocation of 9 PPP projects of the 4G highway initiative. The model includes all the actual specifications of the sector (projects and participants). To test how these valuations would perform in the real world, we have developed a simulator implementing both sequential and combinatorial auctions. To avoid possible bias depending on the calibration of the valuation model, we have created 5 basic scenarios, plus 4 more focused on extreme variations of certain weights. Finally, 50 simulations with different lot and package valuations drawn from Gaussian distributions were run for each scenario.

[12] Through that process the government makes a pre-selection, for each project, a maximum of 10 companies or consortium eligible to submit their bids between all the ones that presented their proposals to this previous qualify stage.

After analyzing all the described scenarios, we have concluded that the combinatorial auction improves the procurement allocation process in two main aspects:

Optimality of the mechanism: Optimal auctions are those that minimize the total price that the auctioneer needs to pay to the winners. In our model, the combinatorial mechanism yields lower winning offers for all scenarios with respect to the sequential mechanism. It implies higher discounts and important savings for public expenditure. Hence, shifting from the sequential mechanism to the combinatorial mechanism would have a beneficial impact on public objectives and, therefore, society.

Efficiency of the allocation: Efficient auctions are those that allocate the items to those participants that value them most. Unlike in sequential auctions, in combinatorial auctions, participants have the ability to express their values for combinations of projects. Therefore, in the presence of synergies, the super-values of winning complementary projects can be reflected in the submitted offers. As in many other procurement processes, in our model, participants have synergies in regards to carrying out connected projects and reaching their optimum capacity. Therefore, because of these two features, the combinatorial mechanism allows projects to be allocated to those participants who value them most. Roumboutsos (2020), in her analysis of the competition for infrastructure projects through traditional procurement and PPPs in Europe, states: *there is a common factor through which competition for the market may be achieved: Most of the factors may be influenced by the knowledgeable contracting authority creating conditions of market attractiveness*

Another important finding is that the combinatorial mechanism reduces the number of winners at the end of the procurement process. Conversely, sequential auctions tend to increase the number of participants allocated to at least one project. On the one hand, having fewer winners that nonetheless are stronger companies with higher capabilities has the advantage of reducing the risk of default. On the other hand, a reduced number of winner may be undesirable for governments concerned about increasing competition or giving opportunities to local companies. If this is the case, they can implement many rules to prevent this outcome. Some examples of these potential rules that have already been implemented in many sectors are the following:

The auctioneer can set a cap, that is, a maximum number of projects to be allocated to the same bidder, to guarantee a wider distribution of projects among participants.

If the governments is concerned about encouraging smaller players, new entrants, national companies, or any other firm with a particular public interest, it can apply a multiplying factor that improves those bidders offers in terms of allocation but does not modify the final prices.

This study provides valuable findings that can help optimize future PPP procurement processes of related infrastructure projects. As we mentioned in Section 10, it is important to stand out that there are many real markets that could effectively improve by allocating multiple related projects simultaneously instead of sequentially. Therefore, policymakers should take into consideration the results found because choosing a specific mechanism has significant impacts on all players. Although implementing combinatorial mechanisms involves a substantial effort to be undertaken by public authorities (to prepare the tenders) and companies (to study them), it is worth the effort, as it helps improve performance on the so-called critical success criteria: effective risk management, fulfillment of output specifications, reliable and quality service operations, adherence to timelines, satisfaction of the need for public facilities/services, long-term relationships and partnerships, and profitability (see Osei-Kyei et al. (2017)). Specifically, governments can generate large savings by implementing a combinatorial mechanism, and companies can benefit from winning projects with synergies by expressing these synergy values in their bidding strategy.

One remaining challenge to improve and extend this research involves comparing the outcomes after the introduction of new pricing rules, such as the second-price rule, or alternative modifications in the combinatorial allocation processes. Such studies would help to establish the best process for procurement in the transportation infrastructure sector.

CRediT authorship contribution statement

Pablo Mochon: Methodology, Investigation, Resources, Writing original draft. **Asuncion Mochon:** Conceptualization, Validation, Writing review & editing, Project administration. **Yago Saez:** Software, Formal analysis, Data curation, Visualization, Supervision.

Appendix A. Combinatorial auctions and the WDP

The following example shows how to solve the WDP in a combinatorial auction in which the following items are offered: A, B, and C. Each bidder may submit up to seven offers, one for each item and each combination of items: A, B, C, AB, AC, BC, and ABC. Assuming that there are three bidders in this auction, Table 12 presents the bids made by each of them in a sealed-bid (single-round) combinatorial auction in which the first-price rule is established.

With the submitted bids, there are many possible ways to allocate the items. However, solving the WDP requires identifying, among all of the possible solutions, the one that minimizes the sum of the accepted offers.

One possible combination would be to award the AB items to the first bidder and the C item to the second bidder. With this allocation, the WDP value is equal to $b_1\ AB\quad b_2\ C\quad 190\quad 100\quad 290$. Although this combination is feasible (the same item is not awarded to different bidders) and meets the condition of XOR bids (each bidder wins at most one bid), this is not an efficient allocation, as it does not minimize the sum of the accepted bids. In this example, the combination of winning bids that solves the WDP is $b_1\ A\quad b_2\ B\quad b_3\ C\quad 80\quad 80\quad 80\quad 240$.

Another combination with the same WDP value is $b_1\ A\quad b_1\ B\quad b_3\ C\quad 80\quad 80\quad 80\quad 240$. However, this combination does not satisfy the restriction of having exclusive bids; bids are not XOR because the first bidder has won two different bids.

Table 12
Offers submitted by all bidders for all projects.

S	b_1	b_2	b_3
A	80	100	100
B	80	80	100
C	100	100	80
AB	190	219	220
AC	250	300	275
BC	300	400	300
ABC	500	520	550

Appendix B. Examples of related PPP contracts

In this appendix we have included several real examples of specific contracts that were auctioned sequentially, although they were related projects, and one same bidder won more than one contract.

Toll roads in Spain

Table 13 shows the tolls partition contracts auctioned during 1998 and 2000.

Hospitals in Madrid

Table 13
Toll roads under concession awarded in Spain between 1998 and 2000.

Project	Year of Tender
Alicante - Cartagena	1998
Estepona - Guadiaro	1999
R3 Madrid - Arganda and R5 Madrid - Navalcarnero	1999
Santiago - Alto de Santo Domingo	1999
Avila - Villacastin	1999
Segovia - El Espinar	1999
Leon - Astorga	2000
R2 Madrid - Guadalajara	2000
R4 Madrid - Ocana	2000

Source: Compilation based on public information.

Table 14 includes the hospitals concessions auctioned sequentially in 2005.

Route 5 in Chile

Table 14
Hospitals under concession awarded for the Autonomous Community of Madrid Spain in 2005.

Project	Year of Tender
H. del Henares (Coslada)	2005
H. Infanta Cristina (Parla),	2005
H. del Tajo (Aranjues)	2005
H. Infanta Leonor (Vallecas)	2005
H. Infanta Sofia (San S. de los Reyes)	2005
H. del Sureste (Arganda)	2005
H. Puerta de Hierro (Majadahonda)	2005

Source: Compilation based on public information.

Between 1997 and 1998 Chile awarded 8 road tolls projects, see Table 15.

Health infrastructure in Ontario

Table 15
Concession toll roads awarded in Chile between 1997 and 1998.

Road	Stretch	Investment (MMUSD)	year Bid
15/57	Santiago - Los Andes	146	1997
5	La Serena Los Vilos	265	1996
5	Temuco Río Bueno	203	1996
5	Chillan Collipulli	224	1996
5	Río Bueno Puerto Montt	210	1997
5	Collipulli Temuco	241	1997
68	Santiago Valparaíso	400	1996
5	Santiago Talca	750	1998

Source: Compilation based on *information* from the Chilean government.

PPP health projects for infrastructures in Ontario in 2006 and 2007, see Table 16.

Consortium pre-qualified in multiple projects in Colombia

Table 16
Winners of PPP health tenders between 2006 and 2007. Infrastructure Ontario.

Year	Number of projects	Project	winner
2006	14	Rouge Valley Health System - Ajax and Pickering Hospital	ABCON
		Runnymede Healthcare Centre Toronto	Bondfield Construction Company
		St. Joseph s Health Care - Governor St. Site Phase 1	D. Grant and Sons
		Niagara Health System - St Catharine s Hospital	PCL Construction and others

(continued on next page)

Table 16 (*continued*)

Year	Number of projects	Project	winner
		Trillium Health Centre Redevelopment	EllisDon
		Hospital Regional de Sudbury Regional Hospital	EllisDon
		Bluewater Health - Sarnia Hospital	EllisDon
		Hamilton General Hospital	EllisDon
		London Health Sciences Centre/St. Joseph s Health Centre	EllisDon
		Sault Area Hospital	EllisDon and others
		Henderson General Hospital - Hamilton	Fengate Capital, Hamilton Health Sciences
		Quinte Healthcare Corporation Belleville Site	M. Sullivan and Son
		Ottawa Hospital Regional Cancer Centre	PCL Construction
		Sunnybrook Health Sciences Centre	Vanbots Construction
2007	6	Toronto Rehabilitation Institute - University Avenue Site	AECON
		Lakeridge Health Redevelopment	AECON
		Credit Valley Hospital Phase II	Bondfield Construction Company
		Kingston Hospital Developments	PCL Construction
		Royal Victoria Hospital - Barrie	Vanbots Construction
		Windsor Regional Hospital Western Campus	Bondfield Construction Company

Source: Compilation based on Infrastructure Ontario website.

2nd wave 4G Colombia. Consortium pre-qualified in more than 3 projects, included in Table 17.

Table 17
2nd wave 4G Colombia. Consortium pre-qualified in more than 3 projects.

Name/Main members of Consortium	N pre-qualifications
EP13 infraestructura vial para Colombia	4
Concesionaria vías del desarrollo 3	3
EP OHL Concesiones	5
Grupo Odinsa and others	4
EP Shikun y Binui - Grodco	3
Infraestructura concesionada - Infracon	3
Concesiones 4G Eurolat	5
Construtora Andrade Gutierres and others	3
Sacyr and others	5

Source: Compilation based on information from ANI.

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