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Abstract

We study sequential auctions in which bidders demand multiple units. We collect a novel data set on sequential water auctions for the empirical study. Although water units are identical, two features from the empirical setting create a trade-off whereby units of water end up being complements or substitutes. First, there is a water loss that is only incurred for the first unit, generating a sunk cost. Second, subsequent units of water exhibit decreasing marginal returns. Units of water are complements or substitutes depending on the relative importance of the sunk cost and decreasing returns. Weather seasonality provides us with the required variation (in sunk costs relative to decreasing returns) to perform the empirical investigation. When units are complements, one bidder wins all units by paying a high price for the first unit, thus deterring others from bidding on subsequent units. When units are substitutes, different bidders win the units with positive probability and pay prices of similar magnitude, even when the same bidder wins all units. We analyze this stark pattern of outcomes not investigated in the literature before. We recover individual demand consistent with this pricing behavior and confirm it is not collusive, but consistent with non-cooperative behavior. Demand estimates are biased if one ignores these features.

JEL Codes: D44, C13, L10, L40

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1 Introduction.

There are many instances in the real world where several units of the same or similar goods are allocated sequentially or periodically using auctions. Examples include timber, procurement of public goods, electromagnetic spectrum, and treasury bills. The nature of the goods at auction and the firms bidding determine whether the goods are complements (increasing marginal returns) or substitutes (decreasing marginal returns). In many cases, goods are complements because firms incur fixed costs to realize the full value of purchased goods. This is the case of the machinery and workers needed to fell trees or build highways. Firms also experience decreasing marginal returns due to limited capacity to hire more workers or buy more machinery. Decreasing marginal returns also arise as a consequence of the downward sloping demand for the firms' final products. Once a firm has a valid spectrum for a given county, the value of another tranche of the spectrum decreases substantially. We expect firms to have increasing marginal returns if the first effect dominates, decreasing marginal returns if the second effect dominates, and hill shaped marginal returns if both effects are important.

By affecting the valuation of subsequent units, fixed costs and decreasing returns determine bidder behavior and price dynamics. Price dynamics are central to connect observed bids to the underlying distributions that characterize individual demand, which is fundamental to discuss positive and normative questions. For instance, variation in prices caused by a high sunk cost will affect even relatively simple tasks such as measuring the dispersion in individuals' private valuations. Moreover, in such a case, a competitive environment could be incorrectly interpreted as collusive.

The existing literature on sequential auctions has provided little empirical evidence on the effect that complementarities or substitutabilities in the valuation of subsequent units has on price behavior. The main reason for this lack of evidence is the challenge of finding sufficient variation in the degree of complementarity. Our aim is to address this empirical gap. To that end, we examine a unique panel data set that exploits large changes in the degree of complementarity across seasons: variation in the importance of sunk costs relative to decreasing returns. We use this variation to analyze bidding behavior in sequential auctions in which buyers' preferences for multiple units exhibit both sunk costs and decreasing marginal returns. We investigate its implications for price dynamics and price competition.

The data in this paper comes from sequential water auctions from a self-governed community of farmers in Mula, Spain. The data allows to exploit a unique scenario to analyze a stark pattern of outcomes not previously documented in the literature. Sometimes, winning prices exhibit a standard competitive pattern. In this scenario, winning prices are similar in magnitude, regardless of whether the same or different bidders (farmers in our case) win the sequential units.[1] Other times, one farmer wins all the units, pays a high price for the first unit, deters other farmers from entering subsequent auctions, and thus pays a very low price

[1]Declining prices for identical objects is an empirical regularity known as the *declining price anomaly*, which was first documented by Ashenfelter (1989) in his seminal paper.

for the remaining units. We call this the *deterrence* effect. We show that this pattern of outcomes is consistent with a non-cooperative equilibrium, where the observed price dynamics are competitive, not collusive.

The data for our analysis consist of individual winning bids and auction covariates. These covariates include the amount of rainfall. The basic unit of sale is the right to use three hours of water (432,000 liters) for irrigation. For each weekday, eight units are sold for each schedule: *four* for daytime (7AM-7PM) and *four* for nighttime (7PM-7AM) irrigation. The auctioneer sells first the twenty units corresponding to nighttime and then the twenty units corresponding to daytime. This leaves ten *four-unit* sets of auctions that are sold in order. (The ten sets of *four-unit* auctions are: Monday-nighttime, Tuesday-nighttime, and so on until Friday-daytime.) Thus, the relevant unit of analysis for investigating individuals' demand and the pattern of outcomes is *four-unit* auctions. But units within each *four-unit* set are not conditional-independent due to the presence of sunk costs. Observing the winner's identity allows us to estimate the model, as outlined in Section 6. Local weather conditions determine the relevant agricultural irrigation technology and, hence, water demand. Additionally, as less rain falls in summer than in winter in southern Spain, the presence of seasonalities provides us with the variation in sunk costs relative to decreasing returns necessary to perform the empirical investigation.

The interpretation of the data based on our economic model is fundamental to our approach. We model the environment as a sequential (ascending price) English auction along the lines of Engelbrecht-Wiggans (1993) and von der Fehr (1994) in which bidders, by incurring a participation cost, decide whether to attend each sale. We focus on the symmetric conditional-independent private values paradigm that has dominated the literature (Donald and Paarsch 1996). We incorporate two features from our empirical setting. First, a sunk cost is incurred for the first unit bought because water flows through a channel dug into the ground. Some water is lost when the channel is dry (the first unit), but the loss is negligible for subsequent units. Engineers have estimated that 20% of the water of the first unit that travels through a dry channel was lost (González-Castaño and Llamas-Ruiz 1991). Second, decreasing marginal returns are present for subsequent units because the amount of irrigated land is fixed.

The relative importance of sunk costs and decreasing marginal returns generates a tradeoff, whereby buyers' bidding behavior depend on whether different units are complements or substitutes. When goods are complements, the same bidder wins all the objects paying a high price for the first unit equal to the valuation for the whole bundle (*four* times the second highest valuation for the first unit, adjusted for the complementarity effect and participation cost). By doing this, the winner of the first unit deters others from bidding on the remaining three units, allowing this bidder to pay very low prices (close to zero) for the remaining three units. The resulting price pattern, along with the same bidder winning all the units, may lead to an incorrect collusive interpretation. When goods are substitutes, different bidders win the objects with a positive probability and pay prices of similar magnitude, even when the same bidder wins all the objects. We provide empirical evidence for the key features of our model: participation and sunk costs. We argue that bidders are better informed than the seller, whose mechanism ignores bidder preferences for multiple units. Nevertheless, a sequential English auction achieves *ex-ante* efficiency, as we discuss in Subsection 7.2.

The price patterns that our model predicts provide us with a straightforward empirical method to determine the regime being played (complements or substitutes). When goods are complements, very low prices are paid by the same winner (the winner of the first unit) for the second, third, and fourth units. This allows us to separate the data for each regime using the procedure outlined in Section 5.

We estimate the distribution of private valuations by maximum likelihood using an exponential distribution and the English structure for the auction. To estimate sunk cost and decreasing marginal returns, we form moment conditions based on the structural equations of the model. We infer participation costs using data from auctions in which bidders were present, but no one placed bids. This method gives us bounds on participation costs.

Our empirical work establishes three main results. First, we recover individual demand—characterized by private valuations and the model's structural parameters—that is consistent with the described price patterns and the *deterrence* effect in particular. Second, the equilibrium price dynamics are consistent with competitive behavior. Non-cooperative behavior is not only consistent with the *deterrence* effect, but also predicts such price differentials. Incentives to deviate from a collusive strategy are higher in spring and summer, when water is more valuable. However, it is in spring and summer when we observe non-cooperative behavior more often. Finally, we show that estimates that ignore the importance of participation and sunk costs will be biased. We test whether price variations, conditional on covariates, are better explained by our proposed model or a standard English auction model without participation costs, using that the latter is encompassed by the former. The approach of Haile and Tamer (2003), that relies on two basic behavioral assumptions, provides a robust structural framework for inference. These minimal assumptions are not satisfied in the present context. We discuss how Haile and Tamer's structure can be interpreted in the current setting.

In the next section, we describe the related literature. Section 3 discusses the auction system, the empirical regularities, and the modeling assumptions required in our context. Section 4 presents the model. Section 5 discusses regime determination. Section 6 examines the estimation procedure. Section 7 presents the results, analyzes the importance of sunk costs, and the interpretation of complementarities. Finally, Section 8 concludes. Additional data description is provided in Section A in the online appendix. All proofs and extensions of the model are in Section B in the online appendix.

2 Contributions and Related Literature.

In this section we describe the related literature and highlight how our paper contributes to the current body of work. This paper is most similar to the empirical literature investigating the predictions of strategic bidding in sequential auctions with multi-unit demand. To best of our knowledge, the price dynamics that we investigate (see Section 3) have not been documented in the literature before. Most of the literature do not consider participation costs in their analysis. We show that participation costs affect equilibrium outcomes. We then use our model to partially identify participation costs and estimate informative bounds.

Numerous empirical studies have highlighted the importance of complementarities (Anton and Yao 1987; Gandal 1997; Wolfram 1998; Pesendorfer 2000; Marshall, Raiff, Richard, and Schulenberg 2006).[2] Substitutabilities are a major component in several industries such as sequential highway construction procurement auctions (Jofre-Bonet and Pesendorfer 2003), sequential timber auctions (List, Millimet, and Price 2004), or sequential cattle auctions (Zulehner 2009). Several authors have studied cases of either complements due to synergies among auctioned goods, or substitutes due to decreasing marginal utility (Black and De Meza 1992; Branco 1997; Liu 2011). Selling goods in a bundle increases a seller's revenue when goods are complements (Palfrey 1983; Levin 1997, Armstrong 2000). Our setting differs from these scenarios in that we consider sequential, instead of simultaneous, auctions.[3]

Prior investigations of the relationship between sequential auctions and the complementarity or substitutability between identical units are more scarce (*e.g.* Jeitschko and Wolfstetter 2002; Jofre-Bonet and Pesendorfer 2012). Jeitschko and Wolfstetter 2002 analyze optimal sequential auctions in a binary-valuations case. They find that English auctions extract more rent than first-price auctions. Our model differs as we consider the class of continuous valuation distributions. Jofre-Bonet and Pesendorfer 2012 allow for complementarities and substitutabilities in a model of sequential auctions. They find that while first-price auctions give greater revenue than second-price (English) auctions when the goods are substitutes, the opposite is true for complements. Both mechanisms are efficient in their model. Their predictions about price trends are consistent with previous findings. Contrary to our analysis with participation costs, where buyers are better informed than the seller, Jofre-Bonet and Pesendorfer 2012 examine the effect of capacity constraints on bidding behavior in procurement auctions using a two-period auction game where sellers have private information about their costs. Balat (2013) and Groeger (2014) analyze dynamic auctions in the highway procurement market. Balat (2013) extends the model from Jofre-Bonet and Pesendorfer 2012 by

[2] Outside the auction literature, Gentzkow (2007) studies the value of new goods using a model encompassing the possibility of both complementarities and substitutabilities.

[3] See Milgrom (2000) and Ausubel (2004) for recent contributions to this literature. Edelman, Ostrovsky, and Schwarz (2007) study the properties of a "generalized English auction" used to sell Internet advertisements and show their proposed mechanism has a unique equilibrium. Kagel and Levin (2005) experimentally investigate multi-unit demand auctions with synergies, and compare behavior in sealed-bid and ascending-bid uniform-price auctions. See Kagel (1995) for a survey on laboratory experimental auction markets.

allowing endogenous participation and unobserved heterogeneity. Groeger (2014) analyzes bidder learning in the entry stage of an auction game.[4] Finally, Hendricks and Porter (1988) conducted an early and influential investigation on how interdependencies among auctioned objects affect the auction's outcome. They analyze auctions for drainage leases and show that better informed firms (which hold tracts neighboring the drainage tracts that were auctioned) earned higher rents than uninformed ones.

This paper makes a methodological contribution by developing an empirical model of sequential English auctions with participation costs that allows units to complement and substitute for the *same* bidder depending on seasonalities. The model produces distinguishable price pattern predictions in each regime. This feature allows us to determine the regime under which the game is being played using end-digit preferences. This allows us to weaken the behavioral assumptions, such as the specification of bidders' beliefs, that would be necessary to solve the whole game (see Sections 4 and 5). Similar to the work of Hendricks and Porter (1988) and Haile (2001), we show evidence inconsistent with the equilibrium predictions of standard models and supportive of a model that captures sunk costs, decreasing marginal returns, and participation costs. Not accounting for these features may lead to the incorrect interpretation of a competitive market as collusive.

We build upon the existing literature on participation costs and entry fees (McAfee and McMillan 1987; Engelbrecht-Wiggans 1993; von der Fehr 1994) by constructing a sequential English auction model similar to that of Von der Fehr. However, our set-up differs in that bidders are allowed to buy more than one unit of the good. von der Fehr 1994 considers the case when goods are independent and finds the same equilibrium as that of our complementarities case.

While the auction literature has studied price dynamics and the relationship between sequentially auctioned goods (for example, Weber 1983; McAfee and Vincent 1993; Benhardt and Scoones 1994; Engelbrecht-Wiggans 1994), to the best of our knowledge, we analyze a stark pattern of outcomes not investigated in the literature before. Sometimes, when goods are substitutes, winning prices exhibit a standard competitive pattern: regardless of whether the same or different bidders win the sequential units, winning prices are similar in magnitude. Other times, when goods are complements, the same bidder wins all units by paying a high price for the first unit, deterring others from bidding on subsequent units.[5] We show that this pattern of outcomes is consistent with a competitive market structure. We are not aware of any study where identical units may complement *and* substitute within the same market and for the *same* bidder.[6] In addition to recovering the structural parameters that characterize

[4]In contrast, we investigate a stark price dynamics not documented before (see Section 3). In our empirical setting, the same identical units sometimes complement and other times substitute for the same bidder. We show that these price dynamics are not collusive, but consistent with non-cooperative behavior. In addition, we infer participation based on two simple assumptions that provide us informative bounds.

[5]Declining or downward price trends in sequential auctions, the results we describe in Subsection 3.3, have been broadly documented (for example, Ashenfelter 1989; Ashenfelter and Genesove 1992; McAfee and Vincent 1993).

[6]The literature in multi-unit auctions can be divided into sequential auctions, in which the auctioneer

individual demand and confirming it is consistent with non-cooperative behavior, which are of interest to the literature on empirical auctions, we collect a unique panel data set to examine a market institution that was active and stable for eight centuries in a self-governed community of farmers in southern Spain.[7] Understanding this strategic non-cooperative behavior of bidders in this stable market institution is of independent interest.

3 Background on the Market.

The data in this paper come from all water auctions in Mula, Spain, from January 1954 through August 1966, when the last auction was run.[8] On August 1^{st}, 1966, the allocation system was modified from an auction to a two-sided bargaining system. In the bargaining system, the *Heredamiento de Aguas* (water-owners holding) and *Sindicato de Regantes* (land-owners association) arranged a fixed price for every *cuarta* of water (the smallest unit auctioned). Gradually, the *Sindicato de Regantes* bought shares in the *Heredamiento de Aguas* association until they finally merged in 1974. Thereafter, water was allocated to each farmer following a fixed quota with each piece of land entitled to some proportion of the water every year.

The reasons for focusing on the period from 1954 to 1966 are, first, that it represents the final period of the auction allocating system in use for at least eight centuries in this region. Second, the government conducted a special agricultural census in 1954/55, providing detailed information about the farmers who bid in this period's auctions

The study of these sequential auctions introduces a unique circumstance for analyzing a stark pattern of outcomes not previously documented in the literature. Sometimes, winning prices exhibit a standard competitive pattern where, regardless of whether the same or different farmers win the sequential units, prices are similar in magnitude (Figure 1). Other times, one farmer wins all sequential units: he pays a high price for the first unit, *deterring* other farmers from entering subsequent auctions, thus paying a very low price for the remaining units (Figure 2).[9] This stark pattern of outcomes is consistent across the whole sample (see

sells the units following a series of sequential steps using a single-unit auction each time, and simultaneous auctions, in which the auctioneer uses a complex mechanism to allocate all units simultaneously. For recent contributions see Kastl (2011), who investigates bidders submitting step functions as their bids in multi-unit treasury bills auctions, and Reguant (2013), who studies complementarity bidding mechanisms used in wholesale electricity auctions. Implementing a simultaneous auction requires a strong commitment from the auctioneer either to not renege in the promised mechanism, or to use the information elicited in the process to demand a higher price for the good. This also imposes technical difficulties in the way bidders frame their contingent bids (Cramton, Shoham, and Steinberg 2006). Neither of these conditions are satisfied in our setting. Hortaçsu (2011) discusses recent progress in the empirical study of multi-units auctions. See Kagel and Levin (2001) for an experimental investigation when bidders demand multiple units in sealed bid and ascending auctions.

[7] In the lead article of the first issue of the *American Economic Review,* Coman (1911) provides an early discussion of the same institution that is analyzed in detail in this paper. For an extensive study of self-governed irrigation communities see Ostrom (1992).

[8] Data available in the historical archive of Mula go back to 1803.

[9] In terms of purchasing power, one peseta from 1950 is approximately equivalent to 0.43 U.S. dollars from

Table 1 and Figure 5 that we describe in Subsection 3.3).

3.1 Water Auctions as Allocation System.

Although the process of allocating water in Mula has varied slightly over time, the basic structure has essentially remained unchanged since the 15^{th} century. Land in Mula is divided into *regadío* (irrigated land) and *secano* (dry land). Irrigation is only permitted in the former. A channel system directs water from the river to *regadío* lands.[10] *Regadío* are fertile lands close to rivers, and thus allow a more efficient use of the water in the region. Since it is forbidden to irrigate lands categorized as *secano*, only the farmers that own a piece of *regadío* land in Mula are allowed to buy water.

The mechanism to allocate water to those farmers was a sequential outcry ascending price (or English) auction. The auctioneer sold by auction each of the units sequentially and independently of each other. The auctioneer tracked the name of the buyer of every unit and the price paid by the winner.[11]

The basic selling unit is a *cuarta* (quarter), which is the right to use water that flows through the main channel for three hours. Water storage is done in the *De La Cierva* dam. Water flows from the dam through the channels at approximately 40 liters per second. As a result, one *cuarta* carries approximately 432,000 liters of water. Traditionally, auctions were held every 21 days to complete a *tanda* (quota), the basic aggregate unit of irrigation time. During our sample period, auctions were carried out every Friday.

During each session, 40 *cuartas* were auctioned: four *cuartas* for irrigation during the day (from 7:00 AM to 7:00 PM) and four *cuartas* for irrigation during the night (from 7:00 PM to 7:00 AM), for each weekday (Monday to Friday). The auctioneer first sold the 20 *cuartas* corresponding to the night-time, and then the 20 *cuartas* corresponding to the day-time. Within each day and night group, units were sold beginning with Monday's four *cuartas*, and finishing with Friday's.

3.2 The Dataset.

We combine data from four sources. The first is auction data, that we collected from the historical archive of Mula.[12] Based on bidding behavior and water availability, auction data

2013 (for details see Section A in the online appendix).

[10]The channel system was expanded from the 13^{th} to 15^{th} century as a response to the greater demand for land due to population increase. The *regadío* land structure has not changed since the 15^{th} century.

[11]The farmers could not store water in their plots. Reselling water was forbidden. While a farmer could steal water by opening the gate next to his own parcel, the technology for detection of this crime was effective as irrigation was done by flood irrigation (more on this in Subsection 4.2). It was easy to determine who stole water just by identifying a flooded parcel from a farmer who did not buy water in the auction for that specific day-schedule (conditional on rainfall). The *Tribunal de los Hombres Buenos* (Council of Good Men), composed by elected members among the farmer community, was responsible to adjudicate conflicts between the farmers. Conflicts mostly arose over unpermitted irrigation. We investigate this behavior in Donna and Espin-Sanchez (2013b).

[12]From the section *Heredamiento de Aguas*, boxes No.: HA 167, HA 168, HA 169, and HA 170.

can be divided into three categories: (i) Regular periods, when the name of the winner, price paid, date and time of the irrigation for each auction transaction was registered; (ii) No-supply periods, when no auctions were conducted due to water shortage in the river or damage to the dam or channels, usually due to intense rain; and finally (iii) No-demand periods, when auctions were held but no one bid, leaving the registration auction sheet blank. The sample for this study includes nearly 13 years of auction data spanning January 1954 to August 1966. Every week, 40 units (corresponding to 40 *cuartas*) were sold, with the exceptions being when no auction was run (no-supply) or no bids were observed (no-demand). A total of 17,195 auctions were run during the period under analysis. [13]

We link auction data to the data that we collected from the 1954/55 agricultural census from Spain, which provides information on individual characteristics of farmers' land.[14] The census was conducted by the Spanish government to enumerate all cultivated soil, production crops, and agricultural assets available in the country. Individual characteristics for the farmers' land (potential bidders which we link with the names in the auctions data) include the type of land and location, area, number of trees, production, and the price at which this production was sold in the census year. Figure 3 shows a sample card for one farmer from the census data. During the 13-year period under analysis, there were approximately 500 different bidders in our sample. The number of bidders who won auctions during a specific year was considerably lower—the mean for our sample is around 8 (see table 5, discussed in Subsection 6.2)—and conditional on participation, each farmer won on average 22 units per year. This is consistent with the census data, where mean land extension is 5.5 ha. with an average of 33 trees per ha.[15]

We also link auction data to daily rainfall data for Mula and monthly price indices for Spain, which we obtain from the *Agencia Estatal de Metereología*, AEMET (the National Meteorological Agency), and the *Instituto Nacional de Estadística de España*, INE (the National Statistics Institute of Spain), respectively.

[13]Table A1 on page A-3 in the online appendix displays the frequency distribution of units in the auctions disaggregated by the units bought sequentially by the same farmer.

[14]From the section *Heredamiento de Aguas* in the historical archive of Mula, box No. 1,210.

[15]Average annual rainfall during the period is 320 mm. Recent irrigation studies on young citrus plantings have shown a water use of 2-5 megalitres per hectare annually (Chott and Bradley 1997). Water savings are possible if irrigation can be allocated to similar units of production, such as young trees or reworked sections of a property. In arid regions, like Murcia, water requirements are around 20% less and they are lower for mature trees. Some farmers that are part of water-owner holding use their own water instead of selling it through auctions. Although water stress during droughts affects the quality of production, trees would hardly die as a result. During a normal year without drought, trees could survive the whole year from rainfall alone. For further details see, for example, Chott and Bradley (1997), Wright (2000), and du Preez (2001). Finally, note that although the average number of trees per farmer is 161 (see Table A2 in Subsection A in the online appendix), the average number of trees per hectare in our sample is 33, a lower number compared to the conventional agricultural standard spacing for citrus trees that is 100 trees per hectare.

3.3 Summary Statistics.

Mediterranean climate rainfall occurs mainly in spring and autumn. Peak water requirements for the products cultivated in the region are reached in spring and summer, between April and August. Soaring demand is reflected by the frequency of *auctions where the same farmer buys all four consecutive units* (4CU), which reaches its peak during these months (see Figure 14 and the discussion in Subsection 7.2). The frequency of 4CU is not homogenous over time, but is related to seasonal rainfall, as can be seen in Figure 4. Overall, 42% of the units were sold in 4CU.[16] There are no observations where the same farmer buys more than four consecutive units, nor observations where the same farmer buys consecutive units across days (*e.g.* there are no observations where the same farmer buys the last units of a day-auction, and the first units of the night-auction).

We only observe the transaction price (winning bid) and the identity of the winner (name). (We do not observe all bids.) There is substantial price variation, both within and across four-unit auctions. Winning prices range from 0.05 pesetas (*ptas*) to 4,830 *ptas*, with a mean of 271.6 *ptas*. As expected, winning prices and the frequency distribution of 4CU are strongly correlated with past rainfall (Figure 4). Table 1 exhibits the distribution of winning prices by both the number of consecutive units bought by the same individual (1CU, 2CU, 3CU, or 4CU) and by sequential auction (1^{st}, 2^{nd}, 3^{rd}, or 4^{th}). The greater variation that we observe for 4CU (with respect to non-4CU) has a well defined pattern. While mean prices for the first auction in 4CU are considerably higher than for non-4CU (Table 1, Panel 2: 677.6 *ptas* for 4CU against 211.1 *ptas* for 1CU, 305 *ptas* for 2CU, or 410 *ptas* for 3CU), mean prices for fourth auctions in 4CU are the smallest (Table 1, Panel 5: 210.1 *ptas* for 4CU against 233.4 *ptas* for 1CU, 239.6 *ptas* for 2CU, or 311.6 *ptas* for 3CU). Median and maximum prices display similar patterns.

Figure 5 presents price variation by number of consecutive auctions won by the same individual (left panel) and by sequential auction (right panel). The figure shows that the stark pattern of outcomes from Figures 1 and 2 is consistent across the whole sample. On the one hand, in the top panel of Figure 5 we can see that price dispersion—as well as the mean and median price—is higher when the same farmer wins all four consecutive units (in the top panel, last vertical box labeled 4). On the other hand, in the bottom panel, where we further disaggregate each box from the top panel by unit (first unit, second unit, third unit, and fourth unit), we can see that the higher price dispersion for unit 4 in the top panel—as well as the higher mean and median—is generated by the greater variation in prices for first units in the lower panel (not by prices in second, third, and fourth units).

This particular pattern in prices is caused by the above mentioned *deterrence* effect whereby farmers exhibit different behavior based on seasonality and rainfall, *i.e.,* residual demand for water. During high demand and low rainfall months, the same farmer buys

[16] Table A1 in Section A in the online appendix displays the frequency distribution of units sold by number of units bought by the same farmer.

all four sequential units, paying a high price for the first unit (with respect to the median or average price conditional on rain) and very low prices for the remaining units. During months when demand is not high due to farming seasonalities or when rainfall is high, winning prices for all units are similar in magnitude, regardless of whether the same farmer wins all sequential units (4CU) or different farmers win subsequent units (1CU, 2CU or 3CU).

Aggregate prices over time display consistent trends with the ones found in the empirical literature on sequential auctions. Figure 6 shows that, on average, per unit prices decline by sequential unit (being the first unit of each day higher than second to fourth units), and by day of the week (prices decline from Monday to Friday). Figure 6 also shows that per unit prices are slightly higher during the day than during the night. High water requirements for citrus during summer causes prices to soar during those months (Figure 7). As expected, prices are also higher during droughts, after conditioning on seasons (Figure 8).[17]

Table 2 shows that these correlations are robust after conditioning on past rain, unit, weekday, schedule, week-of-the-year, month, and individual fixed effects. The table displays the results obtained by regressing daily unit prices on a seven-day-rain moving average (*Rain MA7*), the rain on auction day, and the mentioned fixed effects. The estimated coefficients on *Rain MA7* have the expected sign and are statistically significant at the 1% level. From column 1, a 10 millimeter (*mm*) increase in average rain in the previous week is associated with a decrease of 40.5 *ptas* in the equilibrium price paid in the auction. The regression in column 2 adds unit, weekday, and schedule fixed effects. The estimated coefficient on *Rain MA7* increases in magnitude and also has the expected sign. This regression also shows that, as noticed in previous figures, price declines within day and across units (both for day-time and night-time auctions) and across schedules (price is on average 110 *ptas* lower for night-time auctions than for day-time auctions). The estimated coefficients show that equilibrium prices decline monotonically within the week (Figure 6). Columns 3 and 4 add, respectively, month seasonal dummies and individual fixed effects (we have 537 different individuals in our sample) to the specification in column 2. The estimated coefficient on *Rain MA7* in column 3, though smaller, again has the expected sign and is statistically different from zero. Similar qualitative results are obtained in column 4; however, the estimated coefficient on *Rain MA7* has increased. Note that the goodness of the fit in the last regression is 36%, indicating that average (or *ex-ante*) prices are explained relatively well by observables such as rain in the previous week and time of the allocation. This evidence supports the idea the observable (common knowledge) components of prices in drives four-unit auctions. Although not reported, we performed an analogue analysis using average daily prices within schedule as a robustness exercise and obtained similar results.

[17] See the online appendix for a discussion on droughts.

4 The Model.

As noted above, bidding behavior is a result of a complex decision process. There are three main features from the empirical setting that need to be accounted by the model: (i) sunk costs that farmers incur when they buy their first unit, (ii) decreasing marginal returns of subsequent units of water, and (iii) participation costs of farmers in this market.

Sunk Costs (SC). Water is allocated during the auction and is distributed on the specific day and time of the irrigation accordingly. Water stored in the dam is delivered to the farmer's plot on this date using the channel system. Except the main canal, all channels are dug into the ground (Figure 9). On the day of the irrigation, a guard opens the corresponding gates to allow the water to flow to the appropriate farmer's land. These channels are land-specific in the sense that different areas and lands have their own system of channels which only carry water when the corresponding gates are opened. A concern is that farmers whose lands lie next to each other may be buying different sequential units for the same auction. In this case, the SC would only be incurred by the first farmer for his first unit but not for the second farmer for his first unit. We use data on the specific location of the farmers that we match to auction winners to analyze these situations in Subsection 7.2. There is a water loss that is incurred because water flows over a dry channel. Engineers have estimated this loss to be between 15% and 40% (20% on average) of the water carried by one *cuarta* when the channel is completely dry (see Vera Nicolás 2004). This is the SC incurred by the bidder for his first unit. The SC is only incurred once, for the first unit, since water losses associated with a wet channel are negligible. The channel dries out after approximately 12 hours without water (González-Castaño and Llamas-Ruiz 1991). In 1974 the system of sub-canals was made of concrete, instead of just dug in the ground, to prevent such losses (González-Castaño and Llamas-Ruiz 1991).

Decreasing Marginal Returns (DMR). The second feature refers to the decreasing marginal returns (DMR) effect. The classic textbook case for DMR is appropriate for our empirical application. Given that the amount of land owned by each farmer is fixed, marginal productivity of subsequent units of water is decreasing. When assessing the relative importance of DMR, the impact in summer would generally be greater than in autumn. More generally, one would expect DMR to be affected by season and rain. When water requirements are high, the slope of the marginal productivity function will be relatively flat, as in the left panel in Figure 10. This is likely to occur in spring and summer. On the other hand, when water requirements are low, the slope of the marginal productivity function will be steeper, as in the right panel in Figure 10. This is likely to happen in autumn or winter.

Participation Costs. There are several reasons why farmers face participation costs in this market. The first component is opportunity cost. Farmers who value their time may prefer not to participate in the whole auction session. Auctions were run on Fridays during work hours. Attending the auction entailed alternative use of working time for the farmer. This type of cost affects the number of farmers that participate in the auction, which we do not observe, but not the behavior of the farmer during the auction.

The second component of participation costs correspond to the hassle costs associated with active bidding. Only a fraction of the individuals who attended a Friday auction were actively engaged in the bidding for a particular sequential auction of water and not everyone who was present participated in every auction (Botía, Francisco, personal interview, Murcia, June 17, 2013).[18] As von der Fehr (1994) points out, a reasonable assumption for why only a portion of attendees participate may be that they consider it so unlikely to that they will win at a price below what they will be willing to pay, that they are not willing to bother to engage in bidding. We expect this type of costs to be very small but positive.[19]

Empirical evidence from our data is consistent with the assertion that farmers dislike participation, facing positive entry costs as they do. We observe multiple weeks per year when auctions were run, farmers showed up and bought the first units of water, but no one bid for the last units. Since there was no reservation price and the minimum bid increment was cents, they could have potentially won all the remaining units bidding one cent. To the contrary, they decided not to bid and instead left the auction. For example, on January 22, 1954, units 1 to 16 were sold to seven different farmers but no one bid for units 17 to 20 (Figure 12). In 1954 we observe similar behavior for 14 weeks,[20] and this is consistent along the remaining years in our sample. To infer participation costs, we use $2,423$ auctions where some bidders where present and no one bid for the last units, *i.e.,* auctions similar to the one in Figure 12. Our interpretation is that the utility for all bidders is smaller than the participation cost, conditional on covariates. We use this information to partially identify participation costs (see page 24).

4.1 Set Up.

We use the three main specific features from the empirical setting to build our model. A SC is incurred only for the first unit bought while DMR are present for second to fourth units. The relative importance of the SC and DMR generate a trade-off, whereby bidders coordinate their behavior based on whether different units are complements or substitutes. A simple way to show this intuition is by assuming that the initial SC is proportional to the value of water, and DMR are linear in the number of units bought. We parametrize the SC effect by $(1 - \rho_1)$, whose interpretation is the percentage of water loss from the first unit because water is flowing through a dry channel (hence, proportional to the valuation of the bidder for

[18]A summary is available online in the online appendix at http://www.jdonna.org/water-auctions-web.

[19]Note that the results would be the same if participation costs were zero. However, the equilibrium when goods are complements would not be unique (see Subsection 4.2).

[20]Weeks of January 22, February 5, April 5, May 1, May 8, May 15, May 22, May 29, June 5, June 12, July 3, July 10, November 26, and December 3.

the unit of water). One would expect that, conditional on rain, water loss would be constant within season with relatively more importance (lower ρ_1) in summer.[21] We parametrize the DMR of unit k by ρ_k for $k = 1, 2, \ldots, K$. Let ρ be the vector of parameters that characterizes marginal utilities, *i.e.* $\rho \equiv (\rho_1, \rho_2, \ldots, \rho_K)$. Then, the marginal utility for bidder i for each unit k is:

$$MU_{ki} = \rho_k \cdot v_i,$$

where v_i, only known by bidder i, is a scalar that captures the valuation that the bidder assigns to their first (complete) unit of water, *i.e.,* when $\rho_1 = 0$ we have $MU_{1i} = v_i$.

We consider v_i to be independent and identically distributed on the interval $\mathbb{R}_+$, according to the cumulative distribution function $F(v_i)$, for all bidders $i = 1, \ldots, N$. We assume that $F(v_i)$ admits a continuous density $f(v_i) > 0$ and has full support. It is assumed that $E[v_i] < \infty$. The distribution $F(v_i)$ is fully characterized by the parameter μ. The assumption that the support of $F(v_i)$ is bounded below by 0 is not restrictive, since bidders with negative valuations will not enter the auction. The private valuation, v_i, is only known by bidder i, and it is learned before entering the first auction.[22]

The seller wants to allocate K identical units. These units are auctioned off sequentially by the seller using an English (ascending price) auction for every unit. All participating bidders observe the total number of individuals who take part of the auction, N. After every auction, each participant observes both the price paid by the winner and the winner's identity. The seller continues to run subsequent auctions sequentially until all the units are allocated. We assume that all bidders share the same utility function, $U(\cdot)$. The primitives of the model, (K, N, μ, ρ), are common knowledge.

The strategy set for every bidder is the vector $\sigma \equiv \left(y_i^k, b_i^k\right)_{i=1,\ldots,N}^{k=1,\ldots,K}$, where $y_i^k \in \{0,1\}$, $y_i^k = 1$ indicates that bidder i participates in the auction for unit k ($y_i^k = 0$ if bidder i does not participate in the auction for unit k), and b_i^k is the maximum amount that bidder i is willing to pay for unit k. Bidders play sequentially, or stage by stage. This means that they choose $\sigma_i^k = \left(y_i^k, b_i^k\right)$ after learning the outcome of the previous $(k-1)$ auctions. Bidders participating in auction k observe the price at which each bidder is no longer active (bids are observable) except for the winning bid. The information transmission is consistent with the auction being an English (or ascending price) auction rather than a second price auction.[23]

[21] We discuss variation of SC across auctions (conditional on covariates) in page 21 in the paper.

[22] We do not consider the case where farmers might have different valuations for different units of water. The reason for this is that the units are identical and we condition on observables that may affect the price of water in the econometric specification (see Section 6.1). We obtained similar results by allowing the valuation for subsequent units to be different draws from the same distribution. The exposition of the model, however, becomes more cumbersome.

[23] We model the game as in a button auction. Each bidder holds a button while the price continuously rises. A bid for bidder i is the value at which bidder i stops holding the button. When there are only two bidders active (holding the button) and one of them releases the button, the auction ends. The active bidder wins the object and pays the price at which the runner up stopped. See Cassady (1967) and Milgrom and Weber (1982) for details.

The seller allocates the unit to the highest bidder: $x_j^k \in \{0,1\}$ and $x_j^k = 1$ when $j = \underset{i}{argmax}\left(b_i^k\right)$ (and 0 otherwise), at a price equal to the second highest bid: $p^k = b_l^k$, where $l = \underset{i \neq j}{argmax}\left(b_i^k\right)$. Let $X_i^k \equiv \sum_{j=1}^{j=k} x_i^j$.be the number of units that bidder i has won before participating in auction k. If only one bidder participates in a specific auction this bidder obtains the object for free. Each object is either allocated to one of the N bidders, or it is lost if none of the bidders decide to participate in the auction.

Participation decisions in each auction are done simultaneously by all bidders. To take part in every auction each bidder incurs a participation cost, $c > 0$, at the beginning of the period. We assume that participation in the first auction is free.[24] If only one bidder participates, this bidder obtains the object for free but he bears the participation cost, c, nonetheless. The process is then repeated in every period.[25]

As discussed in previous subsection, the assumption of positive entry costs is consistent with the data in our empirical setting, where we observe no demand for some of the units, even though the reservation price is zero. The interpretation is that, in those situations where no-demand is observed, the value that bidders assign to that unit is smaller than the participation cost, c.[26]

The utility for a bidder who buys l units and participates in m auctions is:

$$U_i\left(l, m, v_i; \rho, c\right) = \sum_{k=1}^{l} \rho_k \cdot v_i - \sum_{k=2}^{K} y_i^k \cdot c = \sum_{k=1}^{l} \rho_k \cdot v_i - (m-1) \cdot c.$$

In the remainder of the paper we refer to $v_{N:N}$ as the highest realization of the random variables $v_1, \ldots, v_n$ drawn independently from CDFs $F_1, \ldots, F_N$ (one draw from each distribution), and $v_{N-1:N}$, as the second highest realization. More generally, $v_{j:N}$ is the j^{th} order statistic for a sample of size N from the distribution $F\left(v_i\right)$.

4.2 Four-Unit Auctions.

The most comprehensive independent unit of analysis that could be considered is the weekly auctions, encompassing all 40 units sold per week. This would be the relevant definition to answer questions related to demand fluctuations generated by supply shocks, such as no auctions due to drought or excessive rain, on an aggregate level. Alternatively, the narrowest

[24] Allowing for a positive cost in the first auction will not affect the results qualitatively. However, the estimated distribution then will not be the original distribution of valuations $F\left(v_i\right)$ but the distribution of valuations conditional on v_i being greater than some minimum threshold for entering the first auction v^*, i.e., $F^*\left(v_i\right) \equiv F\left(v_i | v_i > v^*\right)$. Alternatively, we could impose some restrictions on the distribution of valuations to ensure that all bidders enter the first auction as in von der Fehr (1994).

[25] Bidders enter the auction if, and only if, the expected utility they obtain from the game is positive. See von der Fehr (1994) for a discussion of entry when the goods are complements or the conditions needed for entry when the entry cost in the first auction is positive.

[26] We later use this information to partially identify participation costs (see page 24). See above in this section for justification of this assumption in our specific empirical setting.

possible unit purchased is a *cuarta* (1 of the 40 weekly units). As discussed above in this section, the presence of SC and DMR indicate that *cuartas* within a day-schedule are not conditional-independent. Moreover, they are not the relevant unit of analysis to investigate individual farmers' demand, nor the price pattern described above.

Our original question is motivated by the price behavior caused by the *deterrence* effect. This particular behavior is observed within four-unit auctions and is the relevant unit of analysis in the model. This is an implication of the way the auction is structured: twelve hours of water (subdivided into four *cuartas* of three hours each) during day-time and twelve hours of water during night-time, each weekday. The logic behind this structure is related to water requirements in the area. First, water scarcity in the region made water accountability crucial. The standard unit used to measure surface area in Mula is called *tahúlla*. One *tahúlla* is, by definition, the surface area which can be irrigated in such a way that water level rises 1-foot high in 1 minute.[27] The surface area from one-*tahúlla* varies from one town to another, depending on soil conditions.[28] A four-consecutive units auction—half day, twelve hours of irrigation—is, in that sense, the amount of water that absorbed by a regular *parcela* (individual piece of land). Water requirements could and actually do differ (a) across farmers depending on farming trees and land extension, and (b) for the same farmer over time depending on past rainfall.

Second, the irrigation technique used in Mula is flood irrigation. The farmer builds small embankments in his *parcela* and water is delivered to the land by the channel system that simply flows over the ground through the crop. Flood irrigation requires a minimum of water delivery that, for a regular *parcela*, is captured by one *tahúlla.*

Finally, a supply-side consideration also plays a role. The reason to supply water for 12 hours (during day-time and during night-time) is to guarantee a particular and homogenous quantity for each *cuarta* (which depends on water pressure since water units are defined in hours). Given that the *De La Cierva* dam is continuously filled with water from the river, spreading the supply provision across weekdays ensures the homogeneity of water units.

Our data confirm these three points, validating the relevant unit of analysis for individual demand as four-consecutive units. The most frequent quantity purchased by farmers is twelve hours of water (42% of sold units are 4CU). There are no observations where the same farmer buys more than four consecutive units, nor observations where the same farmer buys consecutive units across days (*e.g.* there are no observations where the same farmer buys the last units of a day-auction, and the first units of the night-auction).

The next two assumptions allow us to determine the regime under which the game is being played.

[27] Although close in magnitude, the traditional Murcian measure of foot is not exactly the same as the foot measure used in the U.K. and the U.S. (Valiente 2001).

[28] The surface area of 1-*tahúlla* is 1,118 square meters in Murcia and 1,185 square meters in the old *Kingdom of Aragón*, except the region of *Pías Fundaciones*. The *tahúlla* has been used in *regadío* lands since the reign of Charles IV (king of Spain from 14 December 1788 until his abdication on 19 March 1808). In *secano* lands the surface area measure used is the *fanega* and the *celemín*. For further details see Vera Nicolás (2004).

Assumption 1 [A1]: $\rho_1 \leq \rho_4$.

Assumption 2 [A2]: $\rho_1 + \rho_2 \leq \rho_3 + \rho_4$.

When $K = 4$, we call it a *strict complements regime* when A1 and A2 holds. We call a *weak substitutes regime* when neither A1 nor A2 holds. The following results summarize equilibrium winning price behavior as a function of the model's primitives (valuations, SC, DMR, and participation costs). We later use these results for the estimation. We only consider pure strategy symmetric Perfect Bayesian Equilibrium (PBE).[29] All proofs and extensions are in Section B in the online appendix.

Proposition 1. *In a* strict complements regime *(i.e., when A1 and A2 hold) the pure strategy symmetric PBE is:*

- *First auction:*
  - *Participation: bidder i will always participate in the first auction,* i.e. $y_i^1 = 1$.
  - *Bidding Strategy:* $b_i^1(v_i) = \sum_{k=1}^{4} \rho_k \cdot v_i - 3c$.
- *Second, third, and fourth auctions:*
  - *Participation: bidder i participates in each auction if, and only if, she won the first auction,* i.e. $y_i^k = 1$ *if, and only if,* $x_i^1 = 1$.
  - *Bidding Strategy: If bidder i participates in each auction ($y_i^k = 1$ for $k = 2, 3, 4$), she will continue bidding until the price reaches its own valuation for that individual unit,* $b_i^l(v_i) = \sum_{k=1}^{4} \rho_k \cdot v_i - (4 - l)\, c$.

Corollary 1. *In a* strict complements *regime (i.e., when A1 and A2 hold) the total utility of the winner satisfies:*

$$\sum_{k=1}^{4} p^k = \sum_{k=1}^{4} \rho_k \cdot v_{N-1:N} - 3c. \tag{1}$$

Lemma 1. *In a* weak substitutes *regime (i.e., when neither A1 nor A2 holds) the probability that a bidder different from the winner enters the last auction is decreasing in the participation cost, c. Moreover, this probability goes to 1 when c goes to zero,* i.e.*:*

$$\underset{c \to 0}{Lim} \left\{ Pr\left(y_i^K = 1 \mid x_j^1 = 1, i \neq j \right) \right\} = 1.$$

[29] When $K = 2$, cases where $\rho_2 \leq 0$ and $\rho_1 = \rho_2$ are equivalent to von der Fehr (1994), in Subsections 3.2 and 3.4, respectively. Uniqueness, however, is not proved by von der Fehr in any of those cases.

Corollary 2. *In a* weak substitutes *regime (i.e., when neither A1 nor A2 holds) the marginal utility of the winner in the last auction, depending on how many units the winner won, satisfies:*

If the winner won all four units:

$$p^4 = \rho_1 \cdot v_{N-1:N} - c. \tag{2}$$

If the winner won three units, two out of the first three, and the last one:

$$p^4 = \rho_2 \cdot v_{N-1:N} - c. \tag{3}$$

5 Regime Determination and End-Digit Preferences.

When goods are strict complements, very low prices—or, according to the auctioneer who ran the auctions, symbolic prices (Botía, Francisco, personal interview, Murcia, June 17, 2013)[30]— are paid for the second, third, and fourth units by the winner of the first unit (Figure 2 and Table 1). This feature allows us to determine the regime (strict complements or weak substitutes) under which the game is being played using end-digit preferences and without specifying further assumptions on the model's primitives. When goods are strict complements a key prediction from proposition 1 is that the same bidder will win all units, pay his valuation for the whole bundle in the first auction, and pay a price of zero for the second, third, and fourth units. We do not observe zero prices (for second, third, and four units in the data), but very low prices (relative to the first price). These are symbolic prices. Although there is no reserve price in the actual auctions, we interpret the minimum price as a general agreement to bid a symbolic price in subsequent auctions. A common effect in our data is that farmers bid certain preferred end-digits prices substantially more often than others. We use this information to determine both regimes.

Studies of digit distribution go back to Benford (1938) who documented that in large data sets, leading digits are not distributed evenly (1 is the most common and 9 the rarest), and proposed a distribution for first digits of numbers in naturally occurring data. Abrantes-Metz, Villas-Boas, and Judge (2011) use Benford's second digit reference distribution to track the daily London Interbank Offered Rate (Libor) from 2005 to 2008 and find that in two periods, Libor rates depart significantly from the expected Benford reference distribution; collusion or rate manipulation appear as likely outcomes to this behavior, the authors suggest. Cramton and Schwartz (2000) also use end (trailing) digits to investigate collusive bidding in the spectrum auctions. Rauch, Goettsche, Braehler, and Engel (2011) use a Benford test to investigate the quality of macroeconomic data relevant to the deficit criteria reported to Eurostat by the European Union member states; they find that the data reported by Greece shows the greatest deviation from Benford's law among all euro states.

[30] A summary is available online in the online appendix at http://www.jdonna.org/water-auctions-web.

In regards to end-digit preferences, Kandel, Sarig, and Wohl (2001) use Israeli IPO auctions to present evidence that investors have end-digit preference for round numbers (prices that end with 0 or 5), and that prices that end with 0 are used more often than those ending with 5.[31] End-digit preferences and systematic age misreporting are important and broadly studied issues in demography, particularly in survey and census data when respondents inaccurately report ages or dates of birth (Myers 1940; Das Gupta 1975; Coale and Li 1991; and Siegel, Shryock, and Swanson 2003). The concern in these cases is, typically, heaping on particular ages such as those ending in 0 or 5. Crayen and Baten (2009) use some of these techniques to investigate the phenomenon of age heaping, and to test the hypothesis that an unequal distribution of human capital reduces welfare growth. Baker (1992) focuses on digit preferences in CPS unemployment duration data, where he raises the question of what can be said without making any specific assumptions concerning the true nature of end-digit preference in the CPS, and shows that employment duration is sensitive to the choice of a corrective for end-digit preference. Finally, end-digit preference has also been studied in the medical literature pertaining to individuals reporting body weight and height, blood pressure, and cigarette consumption (Bopp and Faeh 2008).

Table 3 shows in column 2 the frequency distribution by the last digit of price for first-unit prices.[32] We observe strong preferences for 0 and 1, and somewhat weaker preferences for 5. In 32.1% of the cases we see a multiple of 10, in 32.2% we see a price ending in 1, while 8.4% report a multiple of 5. The frequencies also show some preference for 2 and 6, but not a marked one. After taking into account these effects, we find that 48% of the first-unit price observations are inconsistent with a uniform distribution in each digit.[33] That is, we would need to reclassify 48% of the cases to obtain a uniform distribution by digit. This is clearly not the case for our underlying distribution. We interpret these results as strong end-digit preference for 0 and weak end-digit preference for 5.

Strong preference for digit 1 is not, in general, an indication of a preference for this digit *per se* but, instead, a sign of competition. According to our model, first-unit prices are always competitive (in the sense that all N bidders will enter the auction when no information has yet been revealed), regardless of the regime. Nevertheless, second to fourth-unit prices are not competitive in the strict complements regime (competition in this regime takes part in the first unit where they bid for the whole bundle, and then pay a symbolic price for the second to fourth units since it is optimal for the remaining $N-1$ bidders not to enter in these sequential auctions). Hence, end-digit preference for 1 in second to fourth-unit prices, as a sign of competition, are indicative of a weak substitutes regime. Alternatively, end-digit preference for 0 for second to fourth-unit prices are indicative of a strict complement regime.

[31] See Backus, Blake, and Tadelis (2013) for a recent application to negotiation in eBay auctions.

[32] We obtain similar patterns if we restrict the sample by month or schedule (day-time or night-time) or both.

[33] This number corresponds to the value of the Whipple's concentration index (Siegel, Shryock, and Swanson 2003). In the absence of digit preference one would expect 10% in each terminal digit.

Moreover, in the strict complement regime the model predicts that all second, third, and fourth consecutive prices will simultaneously behave in this fashion. Column 3 in Table 3 display the frequency distribution by the last digit of price for the second to fourth units. Prices exhibit a pattern consistent with this description.

This behavior provides us with a natural lower bound for the strict complements regime, namely, second, third, and fourth unit prices within the same four-unit auction show a strong end-digit preference for 0. We use this behavior, along with the model, to identify the two regimes.[34]

Figure 11 displays the histogram of the percentage change of first price against the median of second to fourth price, by regime.[35] It can be seen in the figure that end-digit preference behavior (as defined above) also captures, in general, the other empirical prediction from the model, namely, that prices are competitive in the weak substitutes regime but exhibit the deterrence effect in the strict complements one (the way to see this in the figure is that percentage change from the first to the second, third or fourth prices is high when goods are strict complements). This is remarkable as the end-digit preference behavior used to identify the regime is unrelated *a priori* to this second empirical prediction. This provides further evidence in favor of the model.[36] Regime identification is done by using the strongest version of the empirical prediction to identify the strict complements case, *i.e.,* the case in the left panel in Figure 11.

A final robustness check further shows that the approach in this section consistently identifies both regimes in terms of our model. Columns 1 and 2 (first unit) in Table 4 display, by regime, the frequency distribution in terms of end-digit prices for first-unit, among each four-unit auction. As emphasized above, both regimes should exhibit competition for first-unit prices according to our model. This competition is captured by the same distribution among ending digits in both regimes. This is what we observe in columns 1 and 2 (first unit). Columns 3 and 4 in Table 4 (fourth unit) show that, as predicted by the model, fourth-unit prices for weak substitutes are also competitive: 29.5% of preference for 0 vs. 39.7% for 1.

[34]We could also use weaker or stronger definition of end-digit or round-number preferences to obtain different bounds for the empirical distributions of prices in each regime. We could, for example, assume that in the strict complements regime second, third, and fourth unit prices within the same four-unit auction show simultaneously a strong end-digit preference for 0 or 5. Our results are robust to include end-digit preference for 5 as well.

Note that the strongest version of the empirical prediction is be that all second, third, and fourth prices display an end-digit preference for 0 in any given four-unit auction for the same individual. A weaker version would be that two out of the three (among second to fourth) prices show an end-digit preference for 0. The weakest version is that just one of these three prices exhibit an end-digit preference for 0. The last (weakest) specification only provides us an upper bound for strict complements regime identification since, as shown in Table 3, the underlying distribution displays an end-digit preference for 0 even in the weak substitutes regime.

[35]The figure looks similar if we use the second, or the third, or the fourth, or the average of second to fourth prices.

[36]Using a modified version of this assumption that differentiates end-digit preference for prices ending in 0 that exhibit more frequency (for example, prices like 100 are more frequent than 150) yields almost identical results.

Note that, in column 3 (strict complements), the percentage of observations with last digit 0 is 100% by construction.

6 Estimation.

6.1 Econometric Specification.

We estimate the model via maximum likelihood using an exponential distribution for the individual valuations. In this subsection we describe how the likelihood is formed and how we account for rain expectations and auction heterogeneity.

Regime Determination. When goods are strict complements, very low prices—or, according to the auctioneer who ran the auctions, symbolic prices (Botía, interview)— are paid, by the winner of the first unit, for the second, third, and fourth units (Figure 2). The predicted price pattern by our model for each each regime (strict complements and weak substitutes) provides us with a straightforward empirical method to determine them (see Section 5). This allows us to separate data into four categories:

a) Same bidder wins all four units and goods are in a strict complements regime (*i.e.* when A1 and A2 hold),

b) Same bidder wins all four units and goods are in a weak substitutes regime (*i.e.* when neither A1 nor A2 holds),

c) Last winner also bought two out of the first three units, three units in total, and goods are in a weak substitutes regime (i.e., when neither A1 nor A2 holds),

d) Otherwise.

Categories a, b, and c define the three mutually exclusive regions of the likelihood. In region a, winning prices are determined by equation 1. In region b, winning prices are determined by equation 2. In region c, winning prices are determined by equation 3. Let D^a be an indicator variable that equals 1 if the winning price is in region a, and 0 otherwise. Define analogously D^b, D^c for regions b, and c, respectively (so $D^a + D^b + D^c = 1$). See subsection 6.2 for a discussion about the regions of the likelihood and the covariates.

Identification. For the case of an English auction, the conditional distribution of private valuations is non-parametrically identified when the transaction price and the number of bidders are observable (Athey and Haile 2002). This result is immediately useful in our sequential English auction model where bids are conditional-independent draws from a distribution $F_V(.)$ and the equilibrium (observed) transaction price is a function of the second highest valuation, $v_{N-1:N}$. Consider the strict complements regime. Winning prices are determined by equation 1. The distribution of valuations is identified up to the multiplying constant, $\sum_{k=1}^{4} \rho_k$, using equation 1 and the result from Athey and Haile 2002. Identification of the remaining parameters, ρ_k, would require four additional independent restrictions (in addition to equation 1). Two additional restrictions are provided by the model from corollary 2 (equations 2 and 3). But we only observe winning bids in the data. Then, two of the ρ_k, $k = 1, \ldots, 4$, are not identified without further structure. So we use a specification with linear decreasing marginal returns due to the mentioned data limitation. Linear decreasing marginal returns impose two additional restrictions. First, we define $\rho_1 = 1 - \alpha$ and $\rho_2 = 1 - \beta$. (Note that these are not restrictions on the parameter space.) We then restrict the parameter space by assuming that $\rho_3 = 1 - 2\beta$ and $\rho_4 = 1 - 3\beta$ (*i.e.* linear decreasing marginal returns). Hence, we have three independent restrictions (equations 1, 2, and 3) and three parameters to estimate (μ, α, β), where μ is a parameter that fully characterizes the distribution of valuations.[37] With observability of all bids (not just the winning bids as in our empirical setting), ρ_3 and ρ_4 would be identified and we would not need to impose the linearity assumption on marginal returns.[38]

Farmers' Expectations of Future Rain. For our estimation we allow DMR, β_t, to vary across auctions holding fixed SC, α (more about this below). We allow β_t to vary with farmers' expectations of rain in each auction $t = 1, \ldots, T$. We proxy these expectations by actual (*i.e.* observed) future rain, so $\beta_t = \beta_0 + \beta_1 R_t^F$, where R_t^F is a dummy variable (defined next) that is linked to expectations about future rain in t, and β_0 and β_1 are parameters. $R_t^F = 1$ if farmers expect that rain is going to be positive (for the day for which they are buying water) and zero otherwise. We further let β_t have different intercepts in each regime:

$$\begin{aligned} \beta_t^S &= \beta_0^S + \beta_1^S R_t^F \\ \beta_t^C &= \beta_0^C + \beta_1^C R_t^F \end{aligned} . \tag{4}$$

Table 6 provides an heuristic argument to understand the reasons behind this equation. The table presents probit regressions of a dummy variable identifying the regime (strict complements *vs.* weak substitutes) on future rain and other covariates. We interpret future rain in these regressions as a proxy for aggregate expected future rain for the farmers. Table 6 shows that low expected rain and high demand months (May to August) significantly increase the likelihood of being in a strict complements regime. The interpretation is that farmers have some information (expectations) about future rain. While the idiosyncratic component of this information is captured by their type, v_i, the common component is captured by β_t. When farmers expect, on aggregate, no rain in a given day, they will coordinate to play in the strict complements regime. Seasonality also affects the demand for water and affects the position of a farmer in the production curve (Figure 10). The results in Table 6 show that it is the slope on the marginal return effect that drives the change of regime, holding fixed SC.

In our parametrization we fix α across auctions and season but we allow β_t to vary. We

[37] Note, however, that the distribution of private valuations is non-parametrically identified from the result from Athey and Haile 2002.

[38] Note that assumptions A1 and A2 are equivalent to assume that $\alpha \geq 4\beta$.

expect α to vary across auctions and seasons as well. But this variation is not separately identified from the variation on β_t because it is the relative magnitude of the effects that matters. The rationale for why we let β_t vary (instead of α) is that a regime switch is driven by the (residual) demand for water by the farmers, as determined by rain and seasonal effects. Therefore, the estimated changes in β_t should be interpreted relative to changes with respect to α.[39]

The Likelihood. The econometric problem consists of finding the parameter that characterizes the common distribution of valuations F and the structural parameters that best rationalize the bidding data. As discussed in the previous section, the bid levels at which bidders drop out of the auctions are not observed, except the bidder with the second-highest valuation. We estimate the model *via* maximum likelihood assuming that farmers draw independent and private valuations from an exponential distribution at each four-unit auction, conditional on observed auction-specific covariates. (We discuss the assumptions below in Subsection 6.2.)

Our model and the context of the market under analysis provide insight on how the characteristics of farmers and auctions should affect private values, but it offers little guidance on the functional form of this distribution. We assume that farmers' valuations, v_i, follow an an exponential distribution for each four-unit auction.[40] In Subsection 7 we report the results from a Kolmogorov-Smirnov test where the null hypothesis that the distribution of private valuations are draws from an exponential distribution cannot be rejected.

Let $v_i \sim F(v;\mu)$, where $F(v;\mu) = (1 - e^{-\mu v})\, \mathbf{1}\{v \geq 0\}$ is the CDF of an exponential distribution that is characterized by the scalar $\mu > 0$. Equations 1, 2, 3, and 4 jointly identify the parameter vector $\left(\mu, \alpha, \beta_0^C, \beta_0^S, \beta_1^C, \beta_1^S\right)$, conditional on the regime (see Section 5) and exogenous covariates, R_t^F. The full system of equations is given by:[41]

[39] We obtained similar results to the ones on Tables 7 and 8 fixing β and allowing α_t to vary in each auction $t = 1, \ldots, T$.

[40] In our earlier working paper Donna and Espin-Sanchez 2012 we used an Exponentiated Gamma (EG) distribution The EG distribution gives us a closed-form solution for the PDF of the j^{th} order statistic and is characterized by a single parameter. Additionally, the PDF of the j^{th} order statistic of a EG is a weighted average of several PDF of EG. This implies that the PDF of any order statistic of an EG distribution also has a closed-form solution.

[41] The third equation in the system is, actually, $p_b^4 = Max\left\{(1-\alpha)v_{N-1:N}, (1-\beta)\, v_{N-2:N}\right\}$, since we do not know whether the runner-up in the last auction was the bidder who already won one unit or a bidder without previous purchases. However, when N is large, $(1-\alpha)v_{N-1:N} < (1-\beta)\, v_{N-2:N}$ if $\beta \simeq \alpha$. But, in the case that $\beta \simeq \alpha$, the same bidder will not win three out of four units. That is, in an auction where N is large and the same bidder wins three out of four units, we expect β to be significantly greater than α. Therefore, the equation can be simplified to $p_b^4 = (1-\alpha)v_{N-1:N}$.

$$
\begin{aligned}
\sum_{k=1}^{4} p_a^k &= \left[4 - \alpha - 6\beta_t^C\right] v_{N-1:N} - 3c \\
p_b^4 &= (1-\alpha) v_{N-1:N} - c \\
p_c^4 &= (1-\beta_t^S) v_{N-1:N} - c \\
\beta_t^S &= \beta_0^S + \beta_1^S R_t^F \\
\beta_t^C &= \beta_0^C + \beta_1^C R_t^F .
\end{aligned}
\tag{5}
$$

Let $\theta \equiv (\alpha, \beta_0^C, \beta_0^S, \beta_1^C, \beta_1^S)$ and let v_i be a conditional-independent draw from $F(\cdot;\mu|\theta, R_t^F)$. Then, the likelihood function is given by:

$$
\begin{aligned}
L(\cdot;\mu \mid \theta, R_t^F) = \prod_{t=1}^{T} f_{N-1:N}\left(\frac{\sum_{k=1}^{4} p_t^k}{4-\alpha-6(\beta_0^C+\beta_1^C R_t^F)};\mu \mid \theta, R_t^F\right)^{D_t^a} \times \\
f_{N-1:N}\left(\frac{p_t^4}{1-\alpha};\mu \mid \theta, R_t^F\right)^{D_t^b} \times \; f_{N-1:N}\left(\frac{p_t^4}{1-\beta_0^S+\beta_S^C R_t^F};\mu \mid \theta, R_t^F\right)^{D_t^c},
\end{aligned}
\tag{6}
$$

where $f_{N-1:N}(v;\mu)$ is the probability density function (PDF) of the $(N-1)^{th}$ order statistic from a sample of N from the exponential distribution of valuations F, $D_t^a + D_t^b + D_t^c = 1$ $\forall t$, and D_t^a, D_t^b, D_t^c are, respectively, indicator variables for cases a, b, and c, as defined above at the beginning of this subsection .

Auction Heterogeneity. We allow the mean of the distribution of valuations to depend on various characteristics that are drawn from the data. We assume that observed prices follow a linear function of the following exogenous variables and estimate all parameters using the likelihood function:[42]

$$
\mathbb{E}\left(v_t^i\right) = Z_t'\gamma = \gamma_0 + \gamma_1 R_t^P + \gamma_2 \left(R_t^P\right)^2 + \gamma_3 Night_t + \sum_{k=2}^{5} \gamma_{2+k} Day_t^k + \sum_{k=2}^{12} \gamma_{6+k} Month_t^k . \tag{7}
$$

The first exogenous variable, R_t^P, refers to *Past Rain*, a moving average of the daily rain beginning seven days prior to the date of the auction; we include a quadratic term to allow for non linearities in past rain. The second variable is a dummy variable that equals one if the water was bought for night use. The next four variables are a set of dummy variables for each weekday. Finally, the last eleven variables are a complete set of monthly dummy variables to condition on seasonality. Water prices soar in this market during the dry summer and drop in

[42] Laffont, Ossard, and Vuong (1995) assume that private values follow a log-normal distribution and let the mean of the logarithm of the valuations be a linear function of exogenous characteristics. Haile and Tamer (2003) condition on covariates by constructing the conditional empirical distribution functions using Gaussian kernels. See Hickman, Hubbard, and Saglam (2011) for a recent guide to the literature on structural econometric methods in auctions.

winter. We accommodate these shocks to demand with seasonal monthly dummy variables. See Sections D and E in the online appendix for details about the estimation procedure.

Identification and Estimation of Participation Costs. Although, throughout the previous estimation procedure, participation costs, c, have been fixed at an arbitrary small magnitude, we recover them from our data. We use our model and data where auctions were run, no bids observed and farmers were present, along with the structural estimates. Participation costs are identified by the necessary condition for a bidder to bid in the first auction that is given by:

$$(1-\alpha)v_{N:N} < c.$$

More generally, a condition that additionally involves second, third, and fourth marginal utilities for the case where the bidder also enters the individual auctions for two, three or four units should be considered. In these cases, participation costs are also greater than the average marginal utility for second, third, and fourth units. Formally:

$$Max\left\{(1-\alpha), \frac{(2-\alpha-\beta_t)}{2}, \frac{(3-\alpha-2\beta_t)}{3}, \frac{(4-\alpha-3\beta_t)}{4}\right\} v_{N:N} < c. \tag{8}$$

Note that, when $\alpha < \beta_t$, the former condition is sufficient, implying the latter. In our econometric specification the structural parameter α is fixed while the parameter β_t varies according to the farmers' expectations of (exogenous) future rain. One would expect to observe auctions without bids when farmers' expectations for rain, as captured by actual future rain, are high (which in the model is represented by a relatively high β_t). Therefore, absence of bids will only occur when $\alpha < \beta_t$, thus, the former identification restriction is sufficient.

Analogously, using the model and the remaining data not used in the structural estimation, we obtain an upper bound using that participation cost are lower than the minimum registered price (conditional on covariates, sunk cost, and decreasing marginal returns).

6.2 Discussion.

Conditional Independent Private Valuations (CIPV). For the estimation we assume that farmers have independent and private valuations at each four-unit auction, conditional on observed auction-specific covariates. The first justification for CIPV is that each bidding farmer (who may or may not be a water-owner) has his own land extension, and his own mixture of trees and crops. This eliminates a strict common value scenario. In addition, in the econometric specification we account for observables that affect all farmers in a similar way such as (past and future) rainfall, schedule of the auction, day of the week, weather seasonality, etc. (see subsection 6.1 for details). Second, the products sold are units of water. Assuming that farmers have private information from other farmers about the characteristics of this product is not in line with the homogeneous nature of water units. Finally, the conditional-independence assumption is the most credible in our context, given the varying nature of farming products and soil conditions across farmers. To understand why, recall that sellers in the water market are a holding formed by the water owners and buyers are farmers that own fertile land. Around 500 different farmers are observed to win auctions in our sample. Not all of these farmers show up at every auction or decide to participate if they are present. Farming products cultivated in the area are mainly fruit and citrus trees (lemon, orange, peach, mandarin, and apricot), and vegetables (tomato, lettuce, and onion). The amount of water required by the trees depends on the time of the year and type of crop (citrus trees should not be irrigated daily). Moreover, and given that we condition on seasonality, water requirements vary across products. For example, water needs for grapefruit and lemons are about 20% higher than those for oranges, while water requirements for mandarins are about 10% less. Ground conditions (which also vary across areas where different farmers have their land) also affect water necessity.[43] The variations across farmers generated by these factors provide support for the fact that the conditional-independence assumption seems satisfied, given that each day the market is quite specific and since we work with data for four-consecutive auctions as a unit of analysis (sequential auctions).[44]

Auction Heterogeneity. Observed heterogeneity across auctions arises due to seasonal effects, rain, and the day and time of the week when the auction occurs. This means that the distribution of private values for the t^{th} auction, $F_t(\cdot)$ is not constant across auctions. In our estimation, we recover the family of distributions $F(\cdot|Z_t, \gamma)$. That is, we assume for every four-unit auction that $F_t(\cdot) = F(\cdot|Z_t, \gamma)$, where $\gamma \in R^k$ is a parameter vector and Z_t is a vector of fully observed characteristics describing the environment of the t^{th} auction. We described the inclusion of these covariates above.

Number of Potential Bidders. The number of potential bidders in each auction, N_t, is not observed. Moreover, it is not identified (Athey and Haile 2002). We assume that it is constant for every four-unit auction, $N_t = N$. Table 5 displays the timing structure for different bidders in our sample. For our estimation, we let the number of potential bidders in each auction be the yearly average of different farmers who won auctions in our sample.[45]

[43] Table A3 in the online appendix displays appropriate intervals for watering citrus.

[44] Our justification of the CIPV paradigm is in line with the literature on empirical auctions. For first price descending auctions see, for example, Laffont, Ossard, and Vuong (1995) in an application to agricultural products (greenhouse eggplants in Marmande, France) where the number of bidders vary between 11 and 18. For English auctions, Haile and Tamer (2003) apply their limited structure model to U.S. Forest Service timber auctions, where the number of bidders vary from 2 to 12.

[45] The agricultural products that are cultivated in the area are mainly citrus trees, which are harvested once per year. The number of different bidders who bought at least one unit during a specific year constitutes a good approximation of the number of farmers who were actively bidding in each four-unit auction during that year. The monthly average of different bidders who bought water in the sample (years 1954 to 1966) is 8.31 (Table 5).

We estimate the model using different values of N for robustness.[46]

Unobserved Heterogeneity. Throughout, we have assumed that the vector Z_t of covariates is fully observed by the econometrician. In our environment, unobserved heterogeneity implies that the distribution of bids may not be conditional-independent across t. All farmers may, for example, observe some factor unobservable by the researcher that shifts the location of the distribution values. This unobserved heterogeneity could lead to correlation among bidders' valuations, causing an identification problem and inconsistent estimates to arise.[47] Modeling unobserved heterogeneity may require additional assumptions on the behavior of unobservables, such as independence, separability, strict monotonicity, and is beyond the scope of this paper.[48]

Dynamic Strategic Considerations. The way in which the auction system is carried out every week raises the question of the importance of dynamic strategic considerations between four-unit auctions both among days (Monday to Friday for a specific schedule) and between schedules (day-time vs night-time for a specific day). Tables 1 and 2 show that winning prices decline across days (for a given schedule) and at night (for a given day), which is consistent with the literature on empirical sequential auctions. These dynamic strategic considerations are outside the scope of the present investigation, and we abstract from them in the model.[49] However, it is important to note that, even if present, dynamic behavior considerations do not invalidate the model's assumptions. As emphasized above, the conditional-independent units of analysis are four-unit auctions (not day-auctions of eight units or week-auctions of 40 units) which, conditional on covariates, are homogeneous goods. As can be seen from the correlations presented in Table 2, previous patterns are consistent along the whole sample and robust to the inclusion of a whole set of fixed effects and covariates. The principal difference between prices in these four-unit auctions is related to the uncertainty of future rain. As it is explained above, we include covariates for schedule, day-of-the-week, and past rain in our structural estimation that capture technological or strategic effects. Future rain, on the other hand, is also included as a proxy for farmers'

[46] In Table 7 we present the results for $N \in \{8, 10\}$. We have performed a sensitivity analysis to different values of N_t that are consistent with the pattern observed in Table 5 and the evidence described in Section 3. In addition, we broke the sample into four periods and performed the estimation independently in each period allowing the mean value of N_t to vary by period. We obtained similar results to the ones reported in Table 7.

[47] From the agricultural census data we observe individual characteristics of the farmers which we are able to link to the winning bids. Given the structure of the agricultural water market we are modeling, it does not appear to be an important concern once we consider the homogeneity of the selling good and the observed characteristics we introduce in our estimations (seasonality, past and future rain, among others).

[48] For a discussion on this issue see, among others, Athey, Levin, and Seira (2011) for an application to timber auctions, and Krasnokutskaya (2011) for a semi-parametric approach to Michigan highway procurement contracts. Roberts (2009) uses information contained in reserve prices to allow bidders' private signals to depend on the realization of the unobserved heterogeneity. Balat (2013) allows for unobserved heterogeneity using dynamic auctions in the highway procurement market.

[49] For a broader discussion see Donna and Espin-Sanchez 2013a.

beliefs to account for these possible strategic behaviors unaccounted by previous covariates. In that sense, our estimates should be interpreted as four-unit day-schedule specific auctions, conditional on past rain and seasonality. It seems implausible that after accounting for these observables and unobservables,[50] and given that the relevant unit of analysis is the four-unit auction, dynamic behavior would affect our results concerning individual demand.[51]

Regions of the Likelihood and Covariates. Another concern may be selection in the regions of the likelihood. As emphasized in subsection 6.1, categories a, b, and c define the three mutually exclusive regions of the likelihood. (In region a, winning prices are determined by equation 1. In region b, winning prices are determined by equation 2. In region c, winning prices are determined by equation 3.) Table A4 in the online appendix displays a comparison of the covariates in the three regions of the likelihood. As expected, prices are higher in the strict complements regime (region a) relative to the weak substitutes regime (regions b and c). This is because the amount of rainfall is lower under the strict complements regime (region a) relative to the weak substitutes regime (regions b and c). Rainfall is lower in region a) (relative to regions b and c) due to weather seasonalities: the percentage of observations in Apr-May (when the agricultural products need the water the most) is substantially higher in region a) (strict complements) relative to regions b) and c) (weak substitutes). The opposite is true during the low demand season (Jan-Mar and Oct-Dec). Finally, note that there is no substantial variation (between the strict complement and weak substitutes regimes) in terms of the percentage of observations by Schedule (day or night) and Weekday (Mo, Tu, We, Th, and Fr).

7 Results.

7.1 Maximum Likelihood Estimates.

In this section we present the estimation results under various econometric specifications. We present the structural estimates obtained using a tolerance level of $1.0e-12$. We let private valuations for each four-unit auction follow an exponential distribution, and follow the described estimation procedure. As discussed above, the number of bidders, N, is determined by the monthly average of different bidders who bought water in the sample (years 1954 to 1966). In this 13-year sample, the average is slightly above 8. Each of these farmers regularly won auctions. It is reasonable to assume that they attended the auctions. Tables 7 and 8 present our estimation results. Columns 1, 3, and 5 present the estimates for $N = 8$, while

[50] While farmers use their reasonable good predictions in their decisions, we use actual future rainfall in our estimation.

[51] Once we condition on these covariates, the concern that a bidder's outside option would vary according to the day of the week (or schedule) is addressed by redefining the idiosyncratic individual valuation in such a way that the new one be the original valuation net of the outside option. By normalizing the outside option of Friday-night to zero the model's assumptions remain valid.

columns 2, 4, and 6 do it for $N = 10$.[52] For each specification, we present the estimates of the model's structural parameters in Table 7 and the estimates of the covariates in Table 8. Table 8 is the continuation of Table 7. That is, for each specification (column) in Table 7, Table 8 displays the estimates of the covariates in that specification.

All parameters have the expected signs. We use the estimate of the parameter γ (that characterizes the distribution of private valuations), to compute the mean valuation of the first complete unit of water. In the case of column 3, the value of the first complete unit of water is 152.93 *ptas*. As expected, in the specification in column 4 (with 10 different bidders), the mean value of the first complete unit of water is slightly lower, 138.9 *ptas*.

The parameter β_1^R, $R \in \{C, S\}$ captures the effect of future rain. As farmers' expectations of future rain increase, DMR are more severe ($\beta_1^R > 0$, $R \in \{C, S\}$). This increases farmers' likelihood of coordinating in a not-strict complements regime (see Table 6) and thus reduces their valuation of subsequent units of water ($\frac{\partial p_t^i}{\partial R_t^F} < 0$). Predicted DMR are obtained by adding the estimates of intercepts, $\hat{\beta}_0^R$, $R \in \{C, S\}$, to the estimates of the slope, $\hat{\beta}_1^R$, $R \in \{C, S\}$, conditional on the rain on the day of the auction. When evaluated at the average future rain from each regime, the following null hypothesis (joint test) that overall DMR are lower in the strict complements regime (as predicted by the model) cannot be rejected (*p-value* above 10%). $H_0: \ \hat{\beta}_0^S + \hat{\beta}_1^S \hat{\mathbb{E}}_s(R_t^F) > \hat{\beta}_0^C + \hat{\beta}_1^C \hat{\mathbb{E}}_c(R_t^F)$, where $\hat{\mathbb{E}}_s(R_t^F) = \frac{1}{T_s} \sum_{t:D_t^a=0} R_t^F$, $\hat{\mathbb{E}}_c(R_t^F) = \frac{1}{T_c} \sum_{t:D_t^a=1} R_t^F$, T_s, and T_c are the number of auctions in not-strict complements and strict complements regimes, respectively.

The estimates of the SC parameter, α, are statistically significant in all specifications. Given the choice of parametrization for sunk costs, the parameter estimates can be interpreted as the percentage loss in terms of a complete unit of water (Section 4). For our estimate in column 3 this represents a loss of 4.6 *ptas* (using the mean value of 152.9 *ptas* for a complete unit).

The estimated coefficients for covariates have the expected sign. For specification 3, for instance, prices in August (February) are significantly 234 *ptas* higher (11 *ptas* lower) than on January. This is consistent with the conventional wisdom that water is more (less) valuable during these months because of high (low) water demand. Also as expected, past rain decreases observed prices in the data. For specification in column 3, an increase in the average rainfall by 1 *mm* from the previous week (with respect to the day of irrigation), decreases average conditional price of a unit of water by 1.7 *ptas*.

[52] In their simulated Non Linear Least Squares (NLLS) estimation, Laffont, Ossard, and Vuong (1995) search for the best value of N by minimizing a lack-of-fit criterion (proposition 4). Note that, as discussed in Subsection 6.1, identification of the distribution of valuations and structural parameters of our model requires observation of the total number of bidders. The rationale for this is straightforward: whether second highest realization of the random variable v_i is from a sample of size $N = 10$, or from a sample of size $N = 100$, it is crucial to interpret the second highest bid (observable in our data). Although observation of an additional order statistic can eliminate this requirement (Song 2004), this would require imposing further structure on the distribution of beliefs in our model (to interpret auctions where, for example, three different farmers win auctions), which is outside the scope of this investigation. Moreover, we only observe winning bids in the data (see Section 3).

Participation cost are recovered using data where auctions were run with farmers present, but no bids were placed, along with the identifying restriction that holds in such cases.[53] Out of the $3,203$ auctions where no bids were placed, we use the $2,423$ where some bidders where present (auctions similar to the one in Figure 12). We obtain the following interval estimate using specification 3: $0.0082 < \hat{c} < 0.1431$. That is, participation costs are positive but small (less than 14 cents of a *peseta*). This is in line with the intuition from the model: hassle or opportunity costs because farmers value their time.

7.2 Discussion.

Robustness and Goodness of the Fit. In comparing columns 1-2 and 3-4, it is clear that the model with covariates outperforms the model without, as shown by the significance of past rain and seasonal dummy estimates, the increase in the likelihood function, and the improvement in the goodness of the fit. The main reason is the dependence of prices on seasonal factors, which we capture in our specification with seasonal dummy variables. From the residual analysis we find no evidence that the increase in the log likelihood function is due to the parametric misspecification of the value distribution itself. Our specification survives the Kolmogorov-Smirnov test, so that the exponential distribution of private valuations cannot be rejected (for the specification in column 3 the *p-value* of the test is 39%).[54]

As regards the goodness-of-fit, our specification in column 3 performs quite well. The $pseudo - R^2 = 53\%$ is obtained by computing predicted prices by our model: $pseudo - R^2 = 1 - \frac{\sum_{t=1}^{T}(p_t - \hat{p}_t)^2}{\sum_{t=1}^{T}(p_t - \bar{p})^2}$, where $\hat{p}_t$ are prices predicted by the model and $\bar{p}$ is the mean of prices. These results are in line with the R^2 obtained in the reduced-form regressions. Although not directly comparable given the distribution assumptions in the structural approach, the $R^2 = 23\%$ in the reduced-form specification with all covariates (column 3 in Table 2) can be heuristically interpreted as the proportion of variability in the data set that is accounted for by the covariates. The proportion accounted for by the model without covariates displayed in column 1 in Table 7 is $R^2 = 28\%$.[55] As can be seen in Figure 13, our model allows us to follow winning prices accurately.[56] The figure displays real prices against predicted prices using three different models: (i) our structural model (specification 3 in Table 7), (ii) a standard English auction model (specification 5 in Table 7, that we discuss in the next subsection), and (iii) a reduced-form model (specification 4 from Table 2 that includes as regressors *Past Rain* and multiple fixed effects, including individual fixed effects).

[53]See page 24.

[54]We perform the nonparametric test to evaluate the equality of two distributions of valuations: our sample of private values with a reference from an exponential distribution.

[55]If we additionally add individual fixed effects to the reduced-form specification, the R^2 just increases from 23% to 36% (column 4 in Table 2).

[56]We describe how we compute the predicted prices in section C in the online appendix. See also section C in the online appendix for a high definition version of this figure.

Understanding the Importance of the Model. We proceed now to analyze our model's implications with respect to the importance of SC and DMR. Suppose that the researcher neglects the dynamics that arise from the model and, instead, estimates a standard English auction model. Suppose, for instance, that we are in the strict complements regime and that valuations follow a distribution with mean, μ_v, and standard deviation, σ_v. Then, the estimated mean of the distribution of valuations using the standard model will be underestimated: $\mathbb{E}\left(\hat{v}_i\right)^{SM} < \mathbb{E}\left(v_i\right) = \mu_v$, where SM stands for standard model. Similarly, the estimation of the standard deviation of valuations will be overestimated: $\mathbb{V}\left(\hat{v}_i\right)^{SM} > \mathbb{V}\left(v_i\right) = \sigma_v$.[57] The same is true in the weak substitutes case.

Overestimation of the variance of the distribution is caused by attributing the variation in prices (among different units) to a relatively more dispersed underlying distribution. The farmer actually pays for the whole bundle in the first unit, thus deterring the entrance of other bidders in the remaining three auctions. The mean is underestimated when the common SC and DMR are not accounted for in the estimation. In the case of the exponential distribution used in our specifications, this failure translates into an underestimation of the parameter μ.

Columns 5 and 6 in Table 7 present the estimates from a standard English (button) auction. Aside from the mentioned bias in the parameter that characterizes the distribution, the results in these columns indicate that taking SC and DMR into account significantly contributes to the model's explanatory power. Figure 13 shows predicted prices from the standard (button) English auction model (specification 5 in Table 7), and compares them with actual prices and with those from our structural model (specification 3 in Table 7).[58] Consistent with these results, the *p-value* for the null hypothesis that $\hat{\alpha} = \hat{\beta}_0^C = \hat{\beta}_0^S = \hat{\beta}_1^C = \hat{\beta}_1^S = \hat{c} = 0$ is less than 10^{-4}.

An alternative approach is to ask how the incomplete model from Haile and Tamer (2003) can be adapted to the present case.[59] This alternative approach relies on two basic assumptions with intuitive appeal: (i) bidders do not bid more than they are willing to pay for a unit, and (ii) bidders do not allow an opponent to win at a price they are willing to beat. In our case, with SC and DMR, these two simple assumptions are violated. In the strict complements regime, bidders bid according to $b_i^1\left(v_i\right) = \left[4 - \alpha - 6\beta\right] v_i - 4c > v_i$, violating (i), and no bidder (except the highest type) participates in the second to fourth unit auctions, violating (ii). In the non weak substitutes regime, both assumptions are also violated, though the intuition is different. In this case, the equilibrium is only partially revealing: bidders' strategies are step functions, so the equilibrium is semi-pooling. When α is greater but close to β, bidders bid above their valuations to intimidate other bidders and deter entry

[57] In the strict complements case, and given a fixed number of potential bidders N, the (true) mean and variance of the $N-1$ order statistic will be greater than the estimated using the standard model because the (true) price paid will be $\left[4 - \alpha - 6\beta_{t,c}\right] v_{N-1:N} - 4c$ and not $4v_{N-1:N}$ (predicted by the standard model).

[58] See footnote 56.

[59] Larsen (2013) uses a similar approach to Haile and Tamer to obtain bounds about the primitives in an auction model followed by dynamic bargaining with two-sided incomplete information without solving for the equilibrium of the game.

in the second auction, thus (i) is violated. Additionally, the same argument as in Black and De Meza (1992) and Liu (2011) applies when goods are substitutes. The winner of the first auction imposes a negative externality on himself. His willingness to pay for the second unit is lower than it was for the first unit, making him a weaker bidder in such situations. Given that all bidders will internalize this effect, some will bid below their marginal utility for the object in the first auction. The greater are DMR, β, the greater this underbidding effect will be.

Applying these assumptions to the four-units bundle would not to produce informative bounds because marginal valuations of the units differ according to the regime and the number of different winners per four-unit auction. Bundling the four-unit or even applying Haile and Tamer's approach separately for each regime, requires the model in Section 4 as an interpretation of the underlying behavior.[60]

Complementarities are not Collusion. An alternative hypothesis of farmers' behavior in the strict complements regime is that bidders might be playing some collusive (non-competitive) strategy. As emphasized in Section 3, the demand side of this market for water is composed of as many as hundreds of farmers (Table 5). Even when farmers attend the auction and do not bid, the observed number of different winners is relatively high (Figure 12). (Note that all auctions were run in weeks similar to the one in Figure 12, so water for units 17-20 was available in the dam to sell.) Farmers compete for water that will ultimately determine the quality and quantity of their crop, and in some cases, even the survival of their trees (for example, drought years). It is unlikely that farmers can make credible collusive commitments in such a situation. Contemporaries emphasized the opposite situation: farmers competed aggressively for water,especially during droughts, while water owners were reluctant to lower the price of the water to meet the needs of the poorest farmers.[61]

The high number of non-collusive auctions provides evidence farmers did not collude. Farmers met every week, hence the discount rate from one week to the next one was close to 1. If we focus on two consecutive 4-unit auctions, the discount rate is virtually 1. Thus, any collusive agreement would be easy to sustain and we would observe no "price-wars", or deviations from collusive strategies. If the collusion hypothesis were true, all auctions would look collusive except, perhaps, during certain periods where we would observe price-wars. We observe in many cases, however, that both regimes are present during the same week. Unlike Baldwin, Marshall, and Richard (1997) this is not a formal test.[62]

Nevertheless, taking the analysis one step further, if the collusion hypothesis were true, we would expect more collusion in autumn-winter and less collusion in spring-summer. Incentives

[60] Note also that failure to consider the effect of the structural parameters (SC and DMR) explicitly introduces difficulties.

[61] These opinions, along with a qualitative analysis can be found in Vera Nicolás (2004).

[62] Collusion in repeated auctions has been analyzed conditional (Hopenhayn and Skrzypacz 2004) and unconditional (Porter and Zona 1999 and Pesendorfer 2000) on the history of the game. A discussion on how to detect collusion can be found in Porter (2005).

to deviate from the collusion strategy are higher in spring-summer because the value of the water is higher due to seasonalities (Figures 4 and 7). Punishment is about the same in any season. The maximum punishment would be to play the competitive equilibrium forever. Future discounted earnings in this case are similar in summer and in winter. Hence, deviating from the collusive strategy is more profitable in summer than in winter. However, the data show the opposite pattern. Figure 14 displays the distribution of auctions in the complementarities regime by month. Complementarities are more likely to be observed in summer than in winter, when water requirements (and hence equilibrium prices) soar. This is in line with our interpretation according to the model with sunk and entry costs.

A "competitive" collusion? We have implicitly assumed that farmers' plots were spaced sufficiently far apart from each other. Specifically, we assumed that no other farmer could use the same sub-channel just used by his neighbor. In reality, this assumption is not true for all cases. Because the cost of watering the sub-channel is sunk, if the plots of two farmers are located next to each other and they share the same sub-channel, then one farmer could free-ride and outbid the first winner in the second auction. Knowing this, the first winner would bid lower in the first auction. This situation would reduce the revenue of the auction and create inefficiencies. Since farmers might not internalize this free-riding effect, they would take into account the equilibrium outcome for the remaining auctions, and lower their bid in the first auction. They would then will try to outbid their neighbors in later auctions.

In a situation such as this, it would be relatively easy to sustain a collusive agreement among neighboring farmers. The number of members of the coalition would be small (say, three or four farmers), and because they are neighbors, they would know each other well and might even share animals or machinery for agricultural purposes. Each farmer in the coalition would compete in the auction for the first unit, but would not enter the remaining auctions if one member of the coalition won the first unit. With this agreement they would achieve efficiency by solving the free riding problem. With the resulting increase in efficiency, the revenue of the auction would also increase, and the auctioneer would not be opposed to the "collusion". This situation would not affect our results unless farmers coordinated bidding rings to not outbid neighboring farmers in the first auction.[63] [64]

[63] It will only affect the outcome when both the bidder with the highest valuation and the bidder with the second highest valuation belong to the same ring, but the bidder with the third highest valuation belongs to a different ring. In this case, our model predicts that the observed price is the valuation of the second highest bidder, but it actually corresponds to the valuation of the third highest bidder. This is unlikely in our empirical setting because the nearly 500 farmers would form around 150 rings (based on the geographical locations that we obtained from the census data). The probability that the two bidders with the highest valuation belong to the same ring is virtually zero. Moreover, the difference between the second highest and the third highest valuation will be small in any case.

[64] There is an extensive literature on the theory of bidding cartels (for example, Graham and Marshall 1987; Hendricks, Porter, and Guofu (2008); Hopenhayn and Skrzypacz (2004); and McAfee and McMillan 1992). For English auctions, Asker (2010) empirically investigates a bidding cartel of collectable stamps. See Harrington (2008) for a survey.

Efficiency. The model displayed in Section 4 assumes that it is costly for the bidders to enter the auction. In order to compare the sequential ascending price auction with other mechanisms, this entry cost has to be taken into account. In this context, and following Stegeman (1996), we interpret entry cost as the cost farmers incur when they send a message to the auctioneer, or to some other farmers. Here, the notions of *ex-ante* and *ex-post* efficiency are no longer equivalent. Although it may be *ex-ante* efficient that more than one player sends a message, it is always *ex-post* efficient that at most one player sends a message.

For this case where it is costly to send messages to the coordinator, Stegeman shows that the ascending price auction has an equilibrium that is *ex-ante* efficient. In contrast, the first-price auction may have no efficient equilibrium, and the author only considers the single-unit case. In our sequential unit case, we have shown that when goods are strict complements the analysis is identical to the single unit case. Hence, the result applies here as well. However, when goods are weak substitutes, the result only applies to the last auction. Although outside the scope of this paper, further work to investigate whether a sequential ascending price auction is *ex-post* efficient when the coordinator has to allocate several objects to players that face SC, DMR, and costly messages, would be a useful extension.

8 Conclusions.

By affecting bidders' behavior in sequential auctions, sunk costs and decreasing marginal returns in the presence of participation costs generate very different price dynamics within the same market. This difference in price dynamics is attributable to the varying extent to which the value of sequential goods complements or falls relative to previous units. The *deterrence* effect, whereby the same bidder pays a high price for the first unit (deterring others from entering subsequent auctions), and a low price for the remaining units, arises when sunk costs are relatively high compared to the decreasing marginal returns, thus creating complementarities among the goods. Substitutability arises due to decreasing returns when sunk costs are relatively small. In this case, equilibrium prices are similar in magnitude, regardless of whether the same or different bidders win the objects. Careful consideration of these features is fundamental to demand characterization, a cornerstone of many positive and normative questions in economics.

Using a novel data set from a decentralized market institution that operated privately for eight centuries in southern Spain, we document these price dynamics and develop a model to recover the underlying structural parameters and distribution of valuations. Although the bidders are better informed than the sellers in our model, the latter know that the sequential English auction allocates water (*ex-ante*) efficiently. Not requiring farmers to reveal their marginal valuations is an advantage of the mechanism, whose simplicity reduces costs associated with its implementation and helps explain its stability. We address three main questions. Are water units complements or substitutes, and why? Is the *deterrence* effect consistent with a competitive market structure or a consequence of collusive behavior among farmers? What would happen to the estimates in this setting if the researcher, by ignoring the importance of participation and sunk costs, failed to account for the complementarity feature of the sequential goods?

First we document that during the period under study both complementarities and substitutabilities are observed in the data, generating different price dynamics. Seasonality, related to the water requirements of the crops and the expected rainfall, affects the relative importance of sunk costs and decreasing returns, causing bidders to coordinate their actions in these regimes. Second, the apparent collusive behavior, when the same bidder wins all the goods, paying very low prices for all the units following the first unit, is actually competitive (or non-cooperative). Contrary to the collusion hypothesis, this behavior is caused by complementarities, and is observed when the value of water (as well as the average price paid per unit and, thus, the incentive to deviate from a collusion strategy) increases relative to the standard competitive pattern registered in the weak substitutes regime. This shows the importance of interpreting the data through the economic model. Finally, by estimating our model, we confirm the relevance of participation and sunk costs in our empirical environment. By testing the performance of our model relative to a standard English auction model without participation costs, we confirm that estimations using the latter are not accurate. Aside from the bias generated by ignoring sunk costs and decreasing returns, price dynamics play an important role, as it is not appropriate to attribute the variation in prices among sequential units (when the goods are complements) to a relatively more disperse underlying distribution of valuations.

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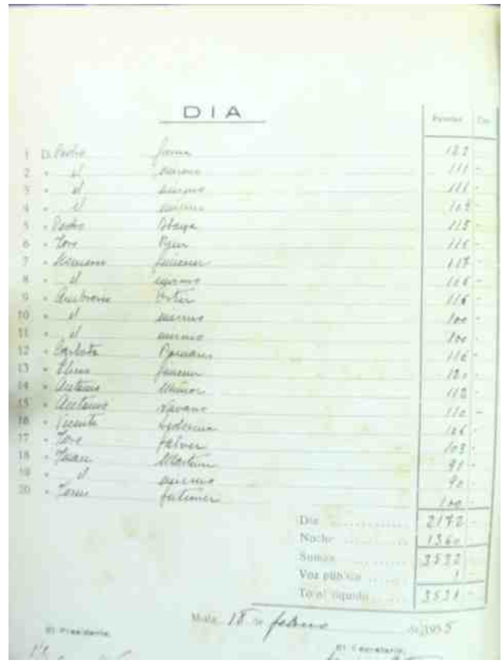
Figure 1: Auction Sample: Goods Are Substitutes

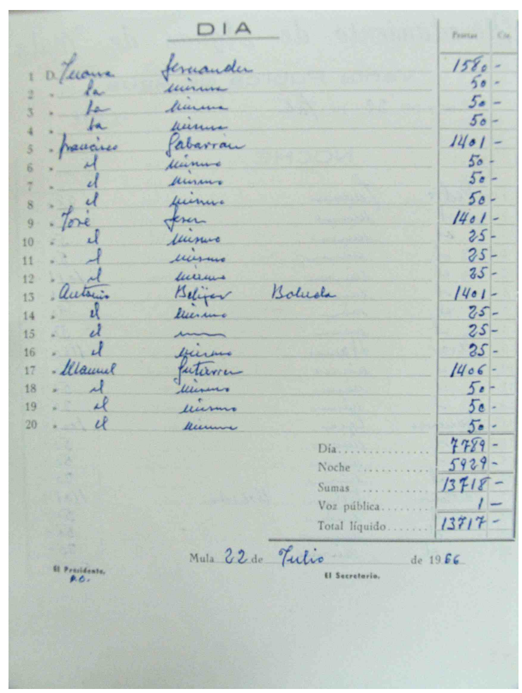
Auction #	Name	Price	Day
1	Pedro Fernández	123	Mo
2	Pedro Fernández	111	
3	Pedro Fernández	111	
4	Pedro Fernández	109	
5	Pedro Blaya	115	Tu
6	Jose Ruiz	116	
7	Mauricio Gutiérrez	117	
8	Mauricio Gutiérrez	106	
9	Ambrosio Ortíz	116	We
10	Ambrosio Ortíz	100	
11	Ambrosio Ortíz	100	
12	Carlota Pomares	116	
13	Eliseo Gutiérrez	120	Th
14	Antonio Muñoz	112	
15	Antonio Navarro	110	
16	Vicente Ledesma	106	
17	Jose Gálvez	103	Fr
18	Juan Martínez	91	
19	Juan Martínez	90	
20	Jesus Gutiérrez	100	



Sample from original data obtained from the historical archive: Goods Are Substitutes (Winter - February 18, 1955, Day). Units 1 to 4 are the units bought on Monday (Mo) during day (unit 1 corresponds to right to irrigate from 7AM to 10AM, unit 2 from 10AM to 1PM, unit 3 from 1PM to 4PM, and unit 4 from 4PM to 7PM). Similarly, units 5 to 8 are the units bought on Tuesday (Tu) during day; units 9 to 12 are the units on Wednesday (We) during day; units 13 to 16 are the units on Thursday (Th) during day; and units 17 to 20 are the units on Friday (Fr) during day.

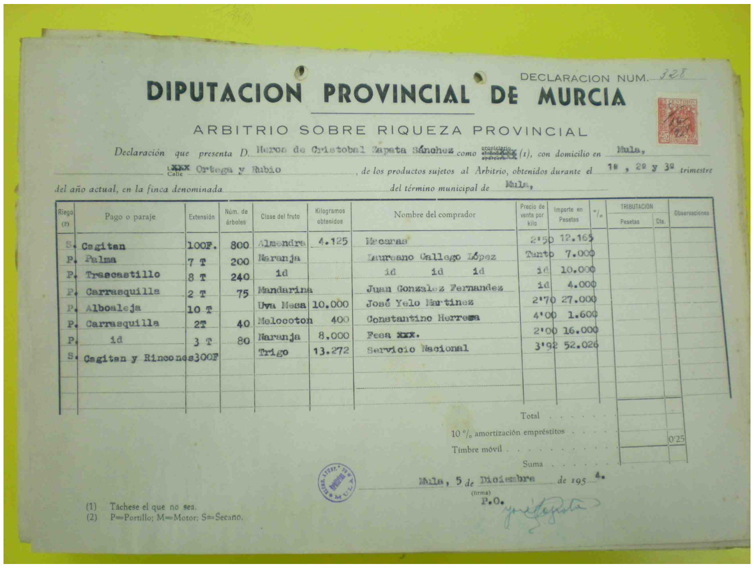
Figure 2: Auction Sample: Goods Are Complements

Auction #	Name	Price	Day
1	Juana Fernández	1580	Mo
2	Juana Fernández	50	
3	Juana Fernández	50	
4	Juana Fernández	50	
5	Francisco Gabarrón	1401	Tu
6	Francisco Gabarrón	50	
7	Francisco Gabarrón	50	
8	Francisco Gabarrón	50	
9	Jose Fernández	1401	We
10	Jose Fernández	25	
11	Jose Fernández	25	
12	Jose Fernández	25	
13	Antonio Belijar Boluda	1401	Th
14	Antonio Belijar Boluda	25	
15	Antonio Belijar Boluda	25	
16	Antonio Belijar Boluda	25	
17	Manuel Gutiérrez	1406	Fr
18	Manuel Gutiérrez	50	
19	Manuel Gutiérrez	50	
20	Manuel Gutiérrez	50	



Sample from original data obtained from the historical archive: Goods Are Complements (Summer - July 22, 1966, Day). See notes in Figure 1.

Figure 3: Sample of Individual Data Obtained from the Agricultural Census


DECLARACION NUM. 328

DIPUTACION PROVINCIAL DE MURCIA

ARBITRIO SOBRE RIQUEZA PROVINCIAL

Declaración que presenta D. Heros de Cristobal Zapata Sánchez como propietario (1), con domicilio en Mula, Calle Ortega y Rubio, de los productos sujetos al Arbitrio, obtenidos durante el 1º, 2º y 3º trimestre del año actual, en la finca denominada ______ del término municipal de Mula,

Riego (2)	Pago o paraje	Extensión	Núm. de árboles	Clase del fruto	Kilogramos obtenidos	Nombre del comprador	Precio de venta por kilo	Importe en Pesetas	°/o	Tributación Pesetas	Tributación Cts.	Observaciones
S.	Cagitan	100F.	800	Almendra	4.125	Mecaras	2'50	12.165				
P.	Palma	7 T	200	Naranja		Laureano Gallego López	Tanto	7.000				
P.	Trascastillo	8 T	240	id		id id id	id	10.000				
P.	Carrasquilla	2 T	75	Mandarina		Juan Gonzalez Fernandez	id	4.000				
P.	Alboaleja	10 T		Uva Mesa	10.000	José Yelo Martinez	2'70	27.000				
P.	Carrasquilla	2T	40	Melocoton	400	Constantino Herrera	4'00	1.600				
P.	id	3 T	80	Naranja	8.000	Fesa	2'00	16.000				
S.	Cagitan y Rincones	300F		Trigo	13.272	Servicio Nacional	3'92	52.026				

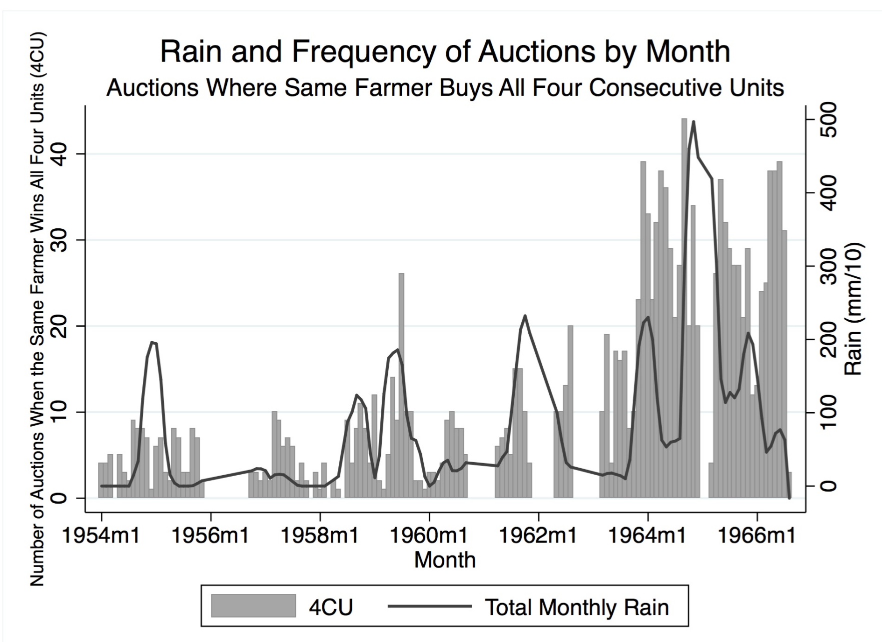
Total
10 °/o amortización empréstitos
Timbre móvil 0'25
Suma

Mula, 5 de Diciembre de 1954.
P.O.

(1) Táchese el que no sea.
(2) P=Portillo; M=Motor; S=Secano.

Sample Card from a Farmer Obtained from the Agricultural Census. Individual characteristics include: farmers' name (that we match to the names in the auctions), type of land and location, area, number of trees, production and the price at which this production was sold in the census year.

Figure 4: Rain and Frequency Distribution of 4CU Over the Sample Period



The figure displays for each month: i) the number of auctions where the same farmer wins all four consecutive units, and ii) total rain using a Nadaraya-Watson kernel regression (of 'total rain' on 'month of the year') with an Epanechnikov kernel with bandwidth selected by cross validation.

Figure 5: Winning Prices: by Number of Consecutive Units Bought by the Same Farmer and by Unit

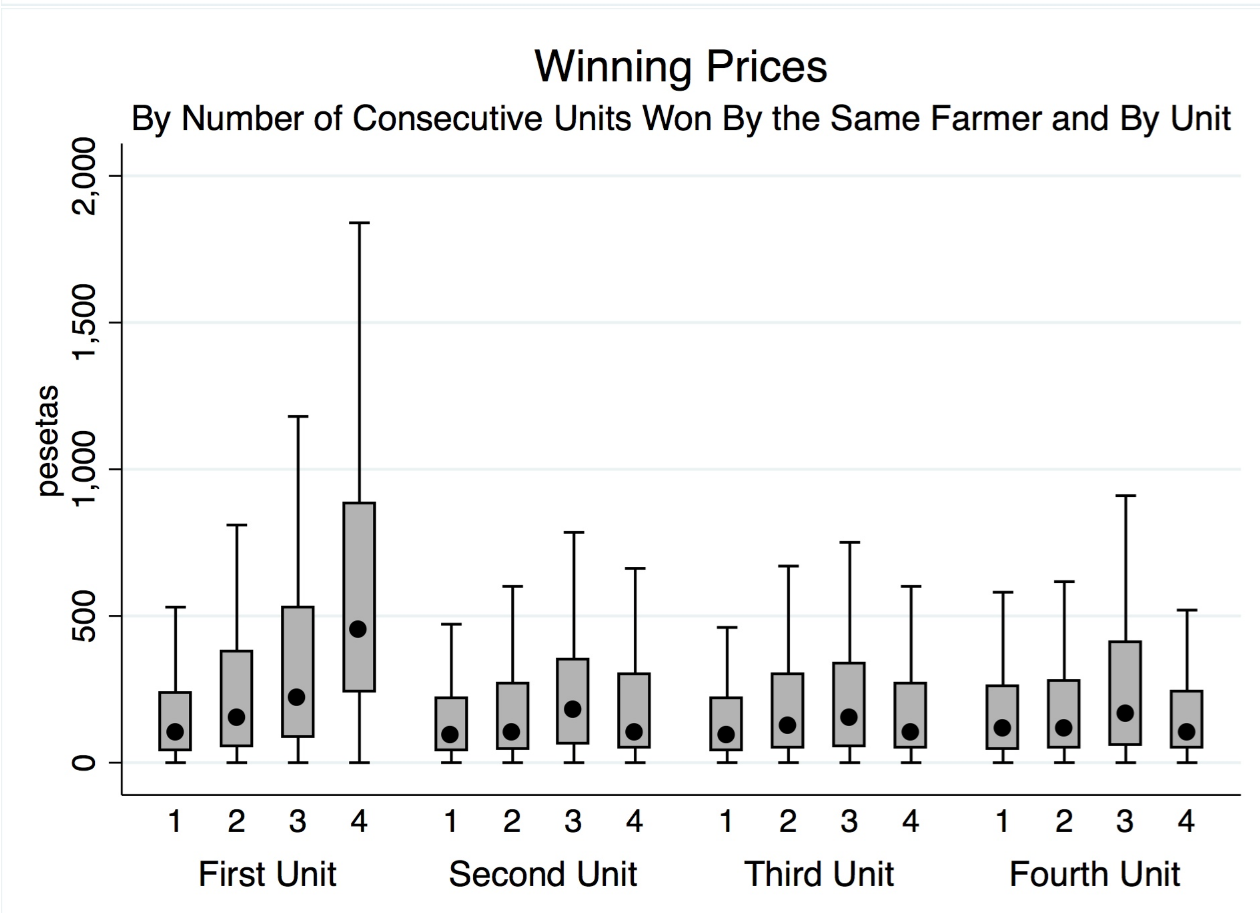
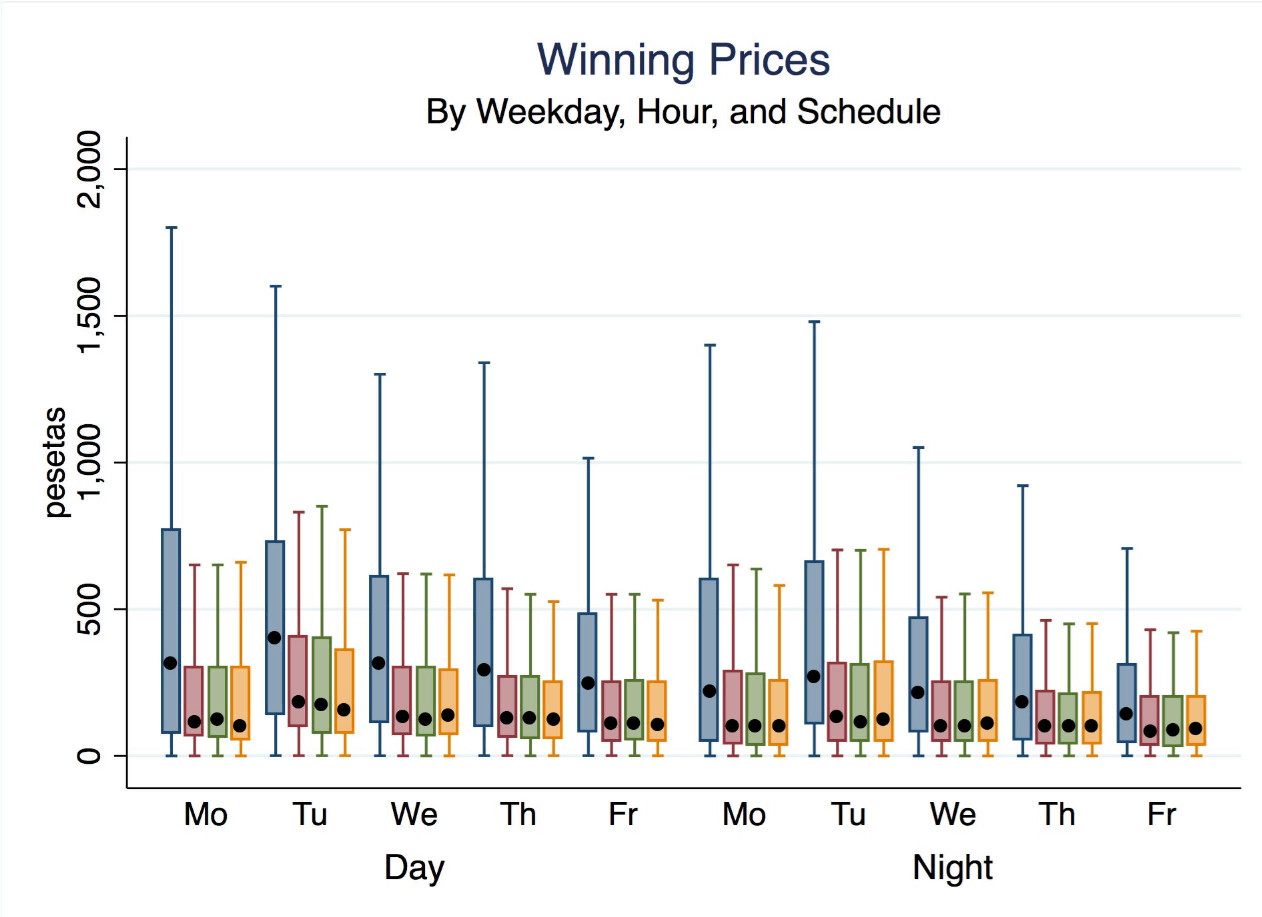
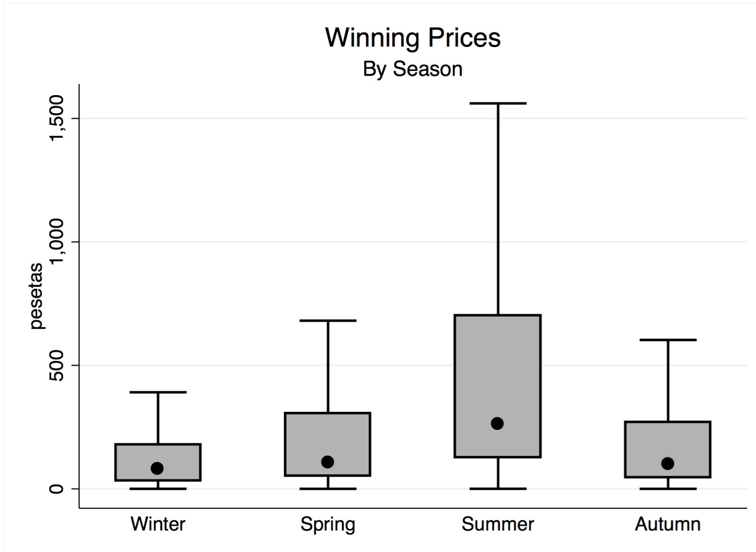


Figure 6: Winning Prices: by Weekday, Hour and Schedule



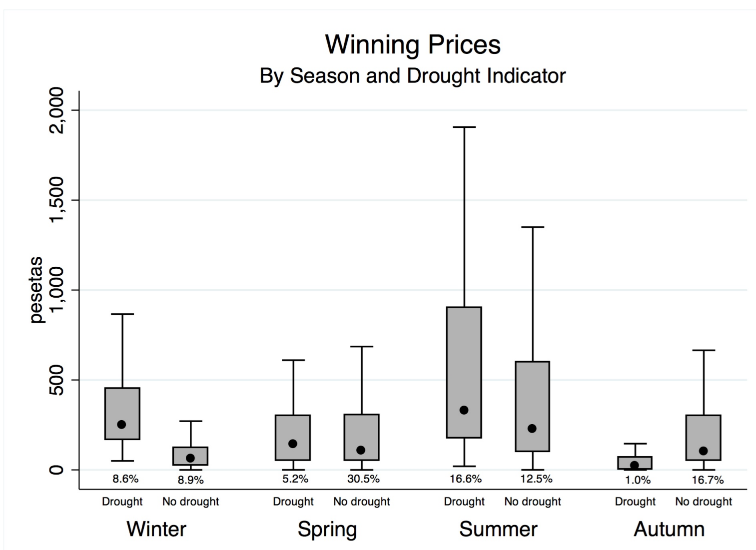
The figure displays the distribution of winning prices by: i) Unit (First Unit in Blue, Second Unit in Red, Third Unit in Green, and Fourth Unit in Orange); Weekday (Mo=Monday, Tu=Tuesday, We=Wednesday, Th=Thursday, and Fr=Friday); and Schedule (Day=Day-Time and Night=Night-Time). Thus, the figure displays the distribution of prices of each of the 40 units auctioned per week for the whole sample (disaggregated by Unit, Weekday, and Schedule). Each vertical box (unit) displays the maximum price (upper adjacent value), 75th percentile (upper hinge), median (black circle marker), 25th percentile (lower hinge), and minimum price (lower adjacent value).

Figure 7: Price and Seasonality



The figure displays the distribution of winning prices by season. Each vertical box displays the maximum price (upper adjacent value), 75th percentile (upper hinge), median (black circle marker), 25th percentile (lower hinge), and minimum price (lower adjacent value).

Figure 8: Winning Prices: by Season and Drought

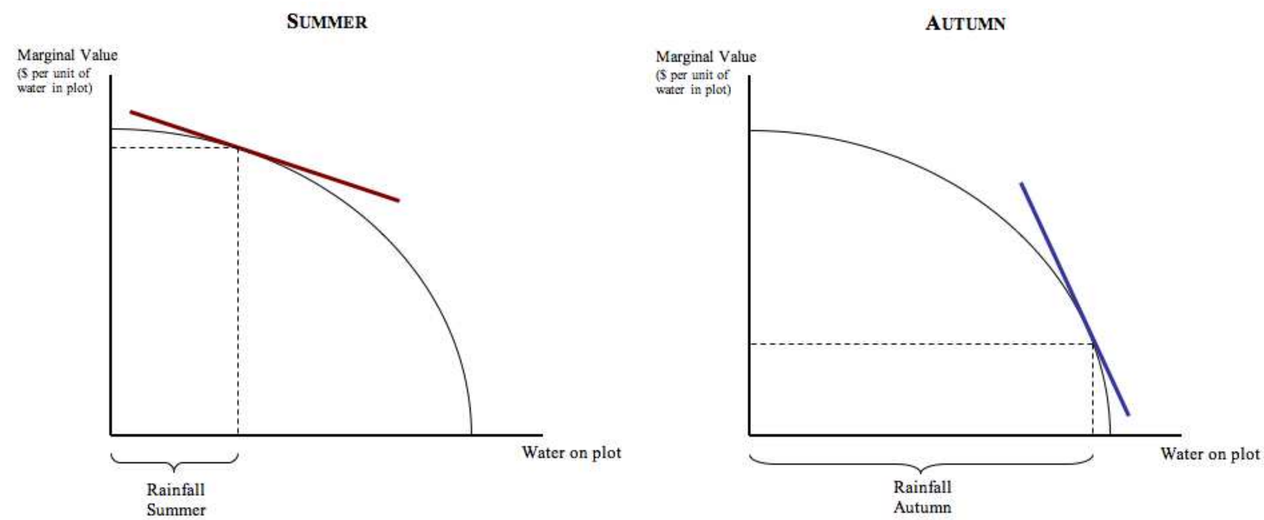


The figure displays the distribution of winning prices by: i) Season and Drought Indicator. Each vertical box displays the maximum price (upper adjacent value), 75th percentile (upper hinge), median, 25th percentile (lower hinge), and minimum price (lower adjacent value). We define a drought as an indicator that equals one when average monthly rain during the specific year is below a consensus threshold defined in the literature in terms of the historic annual average (following Gil Olcina 1994 we use a threshold of 40%). The numbers below each box correspond to the percentage (in terms of the whole sample) of observations in each box (*i.e.* al these numbers sum up to 100%).

Figure 9: The Channel System in Mula and the Sunk Cost of Initiating the Irrigation

The main canal (left panel) was made of concrete. The individual sub-channels (right panel) were dug into the ground. Thus, in these sub-channels, a water loss is incurred because water flows over a dry sub-channel (some water is absorbed by the ground).

Figure 10: Marginal Returns of Irrigation Water



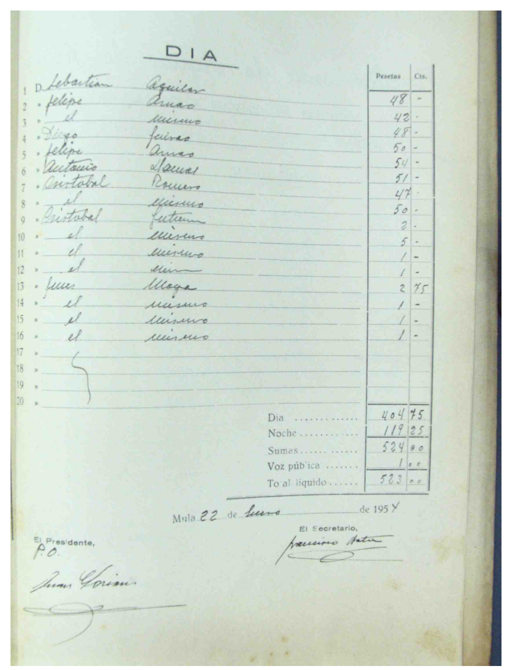
Marginal returns of water in summer (left) and autumn (right).

Figure 11: Within Price Distribution by Regime: First Price vs. Median Second to Fourth prices

Both figures display, for instances when the same farmer won all four units in a 4-unit auction, the normalized percentage change, Δ, of the first winning price against the median of the second to fourth winning prices: $\Delta = \frac{p_1 - m}{(p_1+m)/2}$, with $m = median\,(p_2, p_3, p_4)$. Note that $\Delta < 2$ and that $\Delta \to 2$ if, and only if, $p_1 \to \infty$, or $m \to 0$, or both; *i.e.* when the percentage change goes to infinity. In the figure on the left, Lower Bound is computed by assuming that all second, third, and fourth unit prices paid by the (same) farmer within the same four-unit auction display end-price preference for 0. In the figure on the right, Upper Bound is computed by assuming that only one among second, third, or fourth unit prices paid by the (same) farmer within the same four-unit auction display end-price preference for 0.

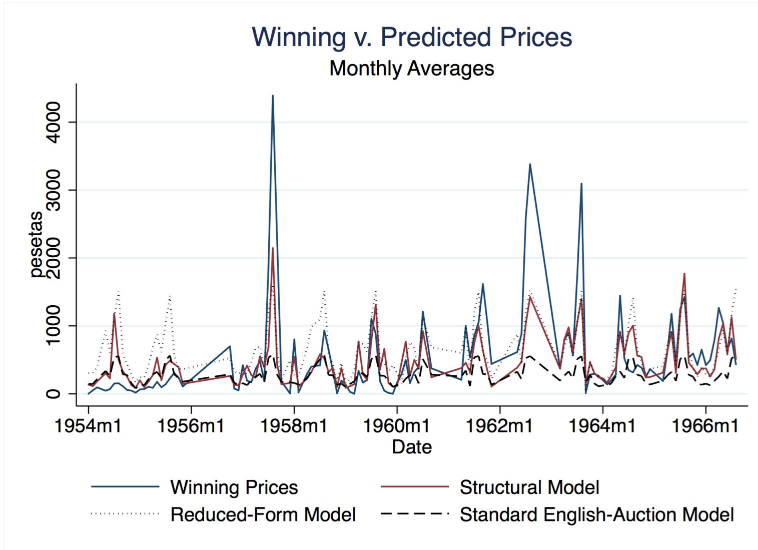
Figure 12: Auction Sample: Auction where Farmers Are Present and No Bids Are Placed

Auction #	Name	Price	Day
1	Sebastian Aguilar	48	Mo
2	Felipe Amaro	42	
3	Felipe Amaro	48	
4	Diego Guirao	50	
5	Felipe Amaro	54	Tu
6	Antonio Llamas	51	
7	Cristóbal Romero	47	
8	Cristóbal Romero	50	
9	Cristóbal Gutiérrez	2	We
10	Cristóbal Gutiérrez	5	
11	Cristóbal Gutiérrez	1	
12	Cristóbal Gutiérrez	1	
13	Luis Moya	2.75	Th
14	Luis Moya	1	
15	Luis Moya	1	
16	Luis Moya	1	
17			Fr
18			
19			
20			



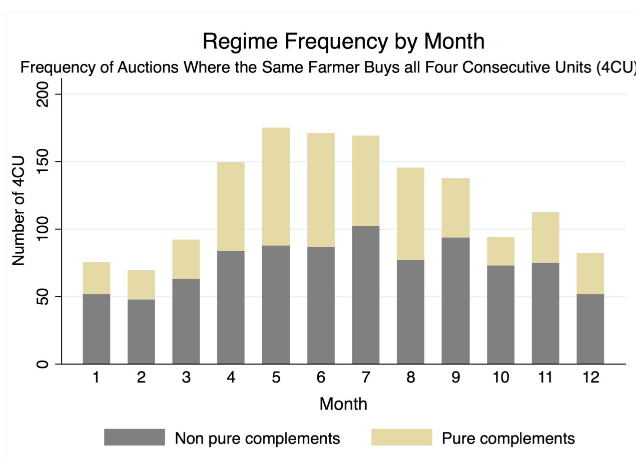
Sample from original data obtained from the historical archive: Auction where farmers are present and no bids are placed (Winter - January 22, 1954, Day).

Figure 13: Winning and Estimated Prices



The figure displays real prices against predicted prices using three different models: (i) our structural model (specification 3 in Table 7), (ii) a standard (button) English auction model (specification 5 in Table 7), and (iii) a reduced-form model for the sample using as regressors: *Past Rain*, unit (3 dummy variables), weekday (4 dummy variables), schedule (1 dummy variable), month (11 dummy variables), year (12 dummy variables), and individual fixed effects, in addition to a constant (for details about the reduced-form specification see Table 2 discussed in Subsection 3.3). The graph shows the mean monthly averages of the prices. Similar results are obtained using a spline (available in our earlier working paper Donna and Espin-Sanchez 2012). See Section C in the online appendix for a high definition version of this figure.

Figure 14: Regime Frequency Disaggregation by Month



The figure depicts the frequency of auctions where the same farmer buys all four consecutive units (4CU), by regime (see Section 3) and month. (Note that the sum of 4CU over months and regimes—the vertical lines in the graph—is equal to 1470 = 5880/4. See Table 1 in the paper and Table A1 in the online appendix.) It can be seen that complementarities are more likely to be observed in summer than in winter, where water requirements (and, hence, equilibrium prices) soar. We interpret this as evidence in favor of the competition hypothesis (according to our model with entry and sunk costs) and against the collusion hypothesis.

Table 1: Distribution of Winning Prices: by Number of CU and Sequential Auction

Panel 1: Price distribution by number of consecutive bids: All Auctions

	Median	Mean	SD	Max	Min	Obs
1CU	101	218.2	327.9	3000	0.05	3530
2CU	123	256.7	364.6	2700	0.05	2866
3CU	190	320.0	415.5	4050	0.05	1716
4CU	182	339.9	470.2	4830	0.05	5880

Panel 2: Price distribution by number of consecutive bids: First Auction

	Median	Mean	SD	Max	Min	Obs
1CU	100	211.1	304.1	2921	0.05	977
2CU	150	305.0	427.8	2700	0.05	673
3CU	220.5	410.0	512.5	4050	0.05	382
4CU	451	677.6	689.5	4830	0.05	1470

Panel 3: Price distribution by number of consecutive bids: Second Auction

	Median	Mean	SD	Max	Min	Obs
1CU	93.25	219.8	373.0	3000	0.10	624
2CU	103.5	230.2	328.0	2685	0.05	867
3CU	181	294.9	364.7	2850	0.05	539
4CU	101	242.7	309.3	2605	0.05	1470

Panel 4: Price distribution by number of consecutive bids: Third Auction

	Median	Mean	SD	Max	Min	Obs
1CU	94	200.8	312.3	2357	0.10	715
2CU	126.5	256.5	353.9	2601	0.10	778
3CU	151.5	285.55	379.0	2801	0.05	536
4CU	100	229.2	294.2	2701	0.05	1470

Panel 5: Price distribution by number of consecutive bids: Fourth Auction

	Median	Mean	SD	Max	Min	Obs
1CU	114.5	233.4	330.2	2601	0.05	1214
2CU	113.5	239.6	344.8	2601	0.10	548
3CU	167	311.6	411.6	2630	0.05	259
4CU	100	210.1	272.6	2935	0.05	1470

Panel 6: Price distribution for 4CU

Auction	Median	Mean	SD	Max	Min	Obs
1st to 4th	182	339.9	470.2	4830	0.05	5880
1st	451	677.6	689.5	4830	0.05	1470
2nd	101	242.7	309.3	2605	0.05	1470
3rd	100	229.2	294.2	2701	0.05	1470
4th	100	210.1	272.6	2935	0.05	1470
1st and 2nd	253	460.2	576.9	4830	0.05	2940
2nd and 3rd	101.0	235.9	301.9	3001	0.05	2940
3rd and 4th	100.0	219.7	283.7	2935	0.05	2940
1st to 3rd	200.0	383.2	512.4	4830	0.05	4410
2nd to 4th	100.0	227.3	292.7	3001	0.05	4410

The table displays the Distribution of Winning Prices. Panels 1 to 5 presents the Distribution of Prices disaggregated by cases where the same farmer buys one, two, three, or four consecutive units (1CU, 2CU, 3CU, or 4CU, respectively). Panel 1 presents the Distribution of Prices for All Auctions (*i.e.* First, Second, Third, and Fourth Auctions). Panel 2 presents the Distribution of Prices for First Auctions. Panel 3 presents the Distribution of Prices for Second Auctions. Panel 4 presents the Distribution of Prices for Third Auctions. Panel 5 presents the Distribution of Prices for Fourth Auctions. Finally, Panel 6 presents Distribution of Prices just for 4CU (*i.e.* for the subsample of 5880 auctions where the same farmer won all four consecutive units). Note that the first line in Panel 6 (1st to 4th) displays the same information as the last line in Panel 1 (4CU). The second line in Panel 6 (1st) displays the same information as the last line in Panel 2 (4CU). The third line in Panel 6 (2nd) displays the same information as the last line in Panel 3 (4CU). The fourth line in Panel 6 (3rd) displays the same information as the last line in Panel 4 (4CU). The fifth line in Panel 6 (4th) displays the same information as the last line in Panel 5 (4CU).

Table 2: Correlation Between Winning Prices and Covariates

Variables	(1)	(2)	(3)	(4)
Rain MA7	-4.0543***	-4.1117***	-2.9911***	-3.1741***
	(0.6742)	(0.6894)	(0.5580)	(0.6227)
Rain Day Bought	-0.2346	-0.1853	0.0519	0.1779
	(0.1434)	(0.1416)	(0.1558)	(0.1531)
Unit 2 Day		-167.9547***	-167.8286***	-180.6172***
		(19.4659)	(19.4542)	(21.8896)
Unit 3 Day		-173.0328***	-172.9066***	-188.0507***
		(19.9287)	(19.9165)	(22.7544)
Unit 4 Day		-176.5446***	-176.5451***	-190.8276***
		(20.4404)	(20.4387)	(23.0968)
Unit 2 Night		-237.5795***	-237.8597***	-249.3275***
		(24.9031)	(24.9367)	(27.3493)
Unit 3 Night		-243.3244***	-243.5220***	-257.6533***
		(25.4507)	(25.4838)	(28.3077)
Unit 4 Night		-254.8376***	-255.1867***	-266.4109***
		(25.7254)	(25.7817)	(28.9070)
Tuesday		26.0232***	32.1906***	10.0596
		(7.4927)	(8.2359)	(12.4758)
Wednesday		-34.5756***	-29.3838**	-31.7270**
		(10.6269)	(11.9714)	(15.4702)
Thursday		-59.6530***	-55.4057***	-42.9164***
		(10.7704)	(12.3518)	(15.0439)
Friday		-94.9538***	-95.5421***	-76.3654***
		(12.7055)	(14.4995)	(17.2939)
Night		-110.0908***	-111.0406***	-102.6780***
		(11.3642)	(10.9544)	(13.4322)
Unit FE	No	Yes	Yes	Yes
Weekday FE	No	Yes	Yes	Yes
Schedule FE	No	Yes	Yes	Yes
Month FE	No	No	Yes	Yes
Individual FE	No	No	No	Yes
R^2	0.016	0.083	0.230	0.359
Observations	13,801	13,801	13,801	13,801

All columns are OLS regressions. Dependent variable is the winning price in each auction (one *cuarta*). Robust standard errors in parentheses. FE stands for *Fixed Effects*. *Individual FE* refers to a set of dummy variables identifying different winners (names) in our sample. We obtain similar results including *Week FE* (a set of dummy variables identifying 52 or 53 weeks of the corresponding year). *** $p<0.01$, ** $p<0.05$, * $p<0.1$. Sample restricted to auctions with positive bids during the period January 1954 to August 1966.

Table 3: End-Price Preferences

	All units (1)		First Unit (2)		Non First Unit (3)		Second Unit (4)		Third Unit (5)		Fourth Unit (6)	
Last Digit	Freq	%	Freq	%	Freq	%	Freq	%	Freq	%	Freq	%
0	2,905	49.9	468	32.1	2,437	55.8	809	55.5	811	55.7	817	56.1
1	1,541	26.4	469	32.2	1,072	24.5	370	25.4	369	25.3	333	22.9
2	201	3.5	116	8.0	85	1.9	32	2.2	24	1.7	29	2.0
3	138	2.4	59	4.0	79	1.8	29	2.0	23	1.6	27	1.9
4	68	1.2	40	2.7	28	0.6	10	0.7	9	0.6	9	0.6
5	531	9.1	123	8.4	408	9.3	114	7.8	144	9.9	150	10.3
6	218	3.7	91	6.2	127	2.9	43	3.0	37	2.5	47	3.2
7	71	1.2	33	2.3	38	0.9	19	1.3	12	0.8	7	0.5
8	61	1.0	24	1.6	37	0.9	8	0.6	12	0.8	17	1.2
9	48	0.8	24	1.6	24	0.6	12	0.8	5	0.3	7	0.5
Total	5,828	100	1,457	100	4,371	100	1,457	100	1,457	100	1,457	100

Sample restricted to 4CU auctions (*i.e.* instances when the same farmer won all four units in a 4-unit auction). *Last Digit* refers to the end-digit winning price. Non integer winning prices are excluded.

Table 4: End-Price Preferences by Regime

	First Unit				Fourth Unit			
	Strict Compl (1)		Weak Substitutes (2)		Strict Compl (3)		Weak Substitutes (4)	
Last Digit	Freq	%	Freq	%	Freq	%	Freq	%
0	220	38.3	236	29.0	575	100	240	29.5
1	185	32.2	264	32.5	0	0	323	39.7
2	42	7.3	69	8.5	0	0	24	2.9
3	17	3.0	41	5.0	0	0	26	3.2
4	16	2.8	22	2.7	0	0	6	0.7
5	45	7.8	76	9.4	0	0	125	15.4
6	34	5.9	50	6.2	0	0	43	5.3
7	8	1.4	22	2.7	0	0	6	0.7
8	6	1.0	14	1.7	0	0	13	1.6
9	2	0.4	19	2.3	0	0	7	0.9
Total	575	100	813	100	575	100	813	100

Sample restricted to 4CU auctions. *Last Digit* refers to the end-digit winning price. Non integer winning prices are excluded. Regime is determined by assuming all second, third, and four unit prices paid by the same winner within the same four-unit auction display end-price preference for 0.

Table 5: Timing Structure of Different Winners: Estimation Sample

Month	1954	1955	1956	1957	1958	1959	1960	1961	1962	1963	1964	1965	1966	Total
1	4	6	0	3	1	11	3	0	0	0	28	0	11	61
2	4	4	0	2	4	2	3	0	0	0	19	0	21	57
3	5	3	0	9	0	1	2	0	0	10	29	8	23	79
4	0	2	0	6	2	5	4	6	0	17	28	38	28	121
5	5	7	0	6	1	13	9	6	9	4	32	30	31	130
6	3	7	0	7	0	8	10	7	10	14	23	25	29	119
7	2	3	0	6	9	26	8	5	13	15	17	21	23	117
8	9	3	0	3	4	10	7	14	18	15	21	16	3	102
9	8	8	0	3	8	10	5	13	0	8	35	19	0	97
10	8	7	3	2	11	2	0	9	0	10	16	19	0	78
11	7	2	3	0	8	2	0	4	0	21	29	23	0	82
12	1	0	2	2	3	1	0	0	0	36	18	12	0	69
Total	48	43	8	43	48	80	47	54	44	106	179	147	128	537

Total, in the last row, refers to the total number of *different winners* for the *specific year* (column). Given that, within a year, the same bidders win multiple units in several months, this number is below the sum over months, by year. Similarly for the last column, where *Total* is the number of *different bidders* for the *specific month* (row) during the 13-year sample. Finally, 537, refers to the total number of different bidders in the whole sample. The monthly average of different bidders who bought water in the sample (years 1954 to 1966) is 8.31.

Table 6: Rain Expectations and Regime Coordination

Variables	(1)	(2)	(3)
Future Rain	-0.0030***	-0.0030***	-0.0034***
	(0.0013)	(0.0013)	(0.0013)
Weekday FE	NO	YES	YES
Schedule FE	NO	YES	YES
Month FE	NO	NO	YES

Sample restricted to the one used in the structural estimation in Table 7. Almost identical results are obtained using the whole sample. All specifications are probit regressions. Marginal effects are reported. Robust standard errors in parenthesis. Dependent variable is a dummy variable equal to one if the regime is strict complements (see Section 5). *Future Rain* is a moving average of rain in Mula for seven days after the corresponding date of the auction (*Future Rain* is a proxy variable for farmers' rain expectations for the day where they are buying water). *Past Rain* (a moving average of rain in Mula for seven days before the corresponding date of the auction) and *Actual Rain* (the amount of rain in Mula in the day of the auction) are not statistically significant in any of the above regressions. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 7: Structural Estimation

Structural parameters	Sequential Auction Model (1)	(2)	(3)	(4)	Standard Model (5)	(6)
Mean Valuation $[\mathbb{E}(\hat{V})]$	148.25	127.11	152.93	138.94	166.99	142.73
	(10.129)	(8.153)	(70.832)	(61.847)	(87.373)	(81.648)
Sunk Cost ($\hat{\alpha}$)	0.0301	0.0300	0.0301	0.0303		
	(8.2e-04)	(9.7e-04)	(3.0e-03)	(9.1e-03)		
$\hat{\beta}_0^c$	0.0101	0.0103	0.0102	0.0105		
	(1.2e-05)	(1.3e-04)	(4.9e-03)	(1.3e-03)		
$\hat{\beta}_0^s$	0.0100	0.0110	0.0101	0.0112		
	(0.0024)	(0.0020)	(4.9e-03)	(1.3e-03)		
Future Rain						
$\hat{\beta}_1^c$	5.99e-10	1.54e-10	5.29e-10	5.94e-10		
	(1.6e-04)	(1.5e-04)	(1.1e-10)	(3.2e-10)		
$\hat{\beta}_1^s$	0.21279	0.18280	0.21278	0.18282		
	(0.0059)	(0.0037)	(0.0267)	(0.0775)		
Mean $\hat{\rho}$						
- *Strict Complements*	0.3801	0.2456	0.6811	0.4239		
- *Weak Substitutes*	-0.3056	-0.2655	-0.3085	-0.2637		
N	8	10	8	10	8	10
Past Rain Polynomial	No	No	Yes	Yes	Yes	Yes
Schedule Dummy	No	No	Yes	Yes	Yes	Yes
Weekday Dummy Variables	No	No	Yes	Yes	Yes	Yes
Month Dummy Variables	No	No	Yes	Yes	Yes	Yes
Pseudo R^2	0.2832	0.2751	0.5303	0.4842	0.1414	0.1333
Log likelihood	-12,870	-13,940	-11,423	-12,375	-50,930	-54,956
# of Auctions	5,951	5,951	5,951	5,951	5,951	5,951

Bootstrapped standard errors ($B = 1,000$) are reported in parenthesis (for the Mean Valuation it corresponds to the bootstrapped standard error corresponding to $Z_t'\gamma$). Estimates in columns 1 to 4 (sequential auction model) are obtained using the estimation procedure described in Subsection 6.1 using KNITRO, a solver for nonlinear optimization, with tolerance level of 1.0e-12 (see Sections D and E in the online appendix for details). For the distribution of private values and inclusion of covariates, we use an exponential distribution. Estimates in specifications 5 and 6 (standard model) are MLE obtained by maximizing the likelihood function from a standard English auction model allowing the mean of the distribution of valuations depend on the same characteristics as in the other specifications as indicated in equation 7, without fixed costs nor decreasing marginal returns (the sample is the same as the one in columns 1 to 4, including in this case all sequential prices in the estimation). Number of years in the sample is 13. Number of months in the sample is 119. The number of different winners (across all 13 years) is 537. The complementarity parameter, ρ, is computed as detailed in the in Section 4. When the goods are strict complements is given by $\rho_t^C = \frac{\alpha - 3\beta_t^C}{1-\alpha} = \frac{\alpha - 3(\beta_0^C + \beta_1^C R_t^F)}{1-\alpha}$. The table reports, for each specification of the sequential auction model in columns 1 to 4: $\hat{\bar{\rho}}^C = \frac{\hat{\alpha} - 3\left(\hat{\beta_0^C} + \hat{\beta_1^C}\frac{1}{T}\left(\sum_{t=1}^T D_{a,t}R_t^F\right)\right)}{1-\hat{\alpha}}$. Similarly, when the goods are weak substitutes, the table reports, for each specification: $\hat{\bar{\rho}}^S = \frac{\hat{\alpha} - 3\left(\hat{\beta_0^S} + \hat{\beta_1^S}\frac{1}{T}\left(\sum_{t=1}^T \left(D_{b,t}R_t^F + D_{c,t}R_t^F\right)\right)\right)}{1-\hat{\alpha}}$.

Table 8: Structural Estimation (continued)

Structural parameters	Specifications					
	Sequential Auction Model				Standard Model	
	(1)	(2)	(3)	(4)	(5)	(6)
Covariates						
Past Rain ($\hat{\gamma}_1$)			-1.668	-2.076	-1.416	-1.2422
			(0.301)	(0.547)	(0.379)	(0.664)
(Past Rain)^2 ($\hat{\gamma}_2$)			0.0076	0.0126	0.0034	0.0032
			(0.0448)	(0.0958)	(0.1496)	(0.1520)
Night ($\hat{\gamma}_3$)			-27.230	-23.56	-30.003	-25.916
			(7.556)	(9.649)	(5.039)	(3.629)
Tuesday ($\hat{\gamma}_4$)			-0.2873	-10.985	-2.7134	-2.4331
			(0.6449)	(9.7063)	(7.1630)	(2.6197)
Wednesday ($\hat{\gamma}_5$)			-2.4616	-2.1883	-5.8751	-5.0944
			(0.5406)	(0.9572)	(2.5602)	(6.0395)
Thursday ($\hat{\gamma}_6$)			-8.8423	-8.366	-15.755	-13.502
			(0.6169)	(0.8544)	(4.7014)	(2.5863)
Friday ($\hat{\gamma}_7$)			-17.805	-9.795	-28.154	-24.271
			(5.016)	(3.418)	(12.903)	(2.118)
Feb. ($\hat{\gamma}_8$)			-11.373	-41.023	-4.8293	-5.0584
			(23.299)	(35.705)	(2.330)	(4.949)
Mar. ($\hat{\gamma}_9$)			27.356	18.067	34.954	30.126
			(12.386)	(8.491)	(5.218)	(1.676)
Apr. ($\hat{\gamma}_8$)			82.481	53.902	78.799	67.396
			(23.456)	(17.127)	(3.426)	(11.579)
May. ($\hat{\gamma}_{10}$)			115.140	81.751	114.483	96.142
			(24.822)	(30.187)	(4.366)	(15.015)
Jun. ($\hat{\gamma}_{11}$)			49.771	40.248	57.478	48.341
			(23.112)	(18.698)	(8.429)	(15.16)
Jul. ($\hat{\gamma}_{12}$)			195.980	115.752	225.337	191.341
			(26.035)	(48.982)	(216.025)	(102.962)
Aug. ($\hat{\gamma}_{13}$)			233.750	183.06	247.57	210.08
			(28.562)	(27.608)	(195.347)	(87.953)
Sep. ($\hat{\gamma}_{14}$)			74.494	160.78	88.173	74.259
			(23.684)	(34.040)	(39.318)	(12.133)
Oct. ($\hat{\gamma}_{15}$)			77.623	62.664	81.093	69.953
			(14.532)	(22.385)	(30.165)	(10.558)
Nov. ($\hat{\gamma}_{16}$)			3.3622	-13.302	13.2099	10.6131
			(2.3941)	(7.513)	(16.725)	(9.6974)
Dec. ($\hat{\gamma}_{17}$)			7.4696	-0.9495	2.8462	2.2106
			(2.2226)	(2.5513)	(3.6735)	(4.0308)
Intercept ($\hat{\gamma}_0$)	148.253	127.117	90.885	96.131	101.717	87.978
	(10.121)	(8.153)	(32.274)	(25.754)	(179.285)	(74.073)
N	8	10	8	10	8	10
Pseudo R^2	0.2832	0.2751	0.5303	0.4842	0.1414	0.1333
Log likelihood	-12,870	-13,940	-11,423	-12,375	-50,930	-54,956
# of Auctions	5,951	5,951	5,951	5,951	5,951	5,951

See notes in Table 7.