Playing Checkers in Chinatown*  
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[VERY PRELIMINARY, PLEASE DO NOT CITE]  

Abstract  
From 1905 to 1935, the city of Los Angeles bought rights to water and land from Owens Valley farmers and built an aqueduct to transfer the water to its residents. The dark version of the story is that Los Angeles bullied and isolated reluctant farmers in order to get cheap water. A map of the plots farmers sold at any given point in time, however, could look like a checkerboard either because the city intentionally targeted specific farmers, whose land sales would create negative externalities for the remaining farmers, or because farmers were heterogeneous. To assess the checkerboarding claim, we analyze bargaining between the city and farmers and evaluate effects farmers’ actions had on one another. We estimate a dynamic structural model of farmers’ decisions to sell to the city. We find large externalities when farmers sold which are larger for neighboring farmers when the seller was closer to the river.  

JEL Codes: N52, Q25, C73, L1  
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“The only reason they were ‘checkerboarding’ was because this fellow wanted to sell out and the next one didn’t.”

A. A. Brierly (Owens Valley farmer), cited in Delameter (1977)

“Their efforts were focused on the key properties which controlled the points of access to the river, so that the less favorably situated ranchers inland could be cut off from their water supply if they refused to negotiate.”


1 Introduction

While urbanization is viewed as a critical engine of development, urban population growth creates both opportunities and challenges. As developing countries urbanize over the next forty years, the United Nations predicts an unprecedented increase in the number of people—3.5 billion—moving into cities: “Urban areas are expected to absorb virtually all the future growth of the world’s population,” This presents a challenge to make new cities sustainable, including guaranteeing a safe supply of water (United Nations, 2019). The movement of people from rural to urban environments presents a challenge that will require the reallocation of natural resources like water. Evenly distributing transfer benefits among urban and rural dwellers is an important concern for economists and policymakers.

To study this distributional question, we revisit probably the most famous episode of water transfer in American history. Between 1905 and 1935, the city of Los Angeles (LA) purchased water and land rights from Owens Valley farmers, built an aqueduct to divert water to city dwellers, and changed the Valley’s history forever. Hydrated by Owens River water, the city grew from a population of 100,000 in 1900 to 1.2 million in 1930, becoming the largest city in California and the second largest in the U.S. Despite this achievement, the water transfer was controversial, dramatized in popular culture by the movie Chinatown and investigated by journalists and scholars ever since. The most serious accusation leveled against the city was that officials checkerboarded their land purchases, i.e., that they intentionally bought land surrounding reluctant sellers to drive down prices. In this paper, we first address the historical question of whether the city was checkerboarding and explore to what extent it might have behaved strategically in its purchases of land and water.
rights. We then study bargaining between the city and farmers to assess how externalities might have affected the distribution of rents between the two parties.

Due to the limitations of historical data, and the nature of water as an economic good, this has been a challenging question to answer. First of all, the current literature does not use geo-coded transaction or dated plot sale data. Secondly, water is a very peculiar good that imposes externalities on private owners and public users alike. Therefore, we cannot study transactions between farmers and the city in isolation but must use a collective decision perspective, in which LA could strategically buy out different farmers to influence the selling value for the remaining farmers. Ultimately, our reduced form analysis cannot capture the rich endogenous interactions between farmers deciding to sell, and at what price, which would require a model that can flesh out the dynamic incentives farmers faced in a bargaining game.

We built a novel and very detailed dataset containing the exact date of each sale, the precise geo-location of each plot, and other property characteristics including acreage, water rights, sale price, and crops under cultivation. We use this new dataset to assess whether the city purchased land in a checkerboard pattern. To do so, we first show that there is a spatial correlation on the date of sale within the whole valley. We then estimate reduced form regressions to explain in a dynamic setting whether a farmer sold or not and at what price. Our results suggest that there is a significant interaction taking place at the irrigation ditch level, driven by externalities from neighbors who were sellers, between farmers who sold their land and farmers who did not.

We model the purchases made by the city as a dynamic game with externalities, which in practice resembles a Monopsonist strategy in the Coase conjecture (Coase, 1972). If the city could commit not to offer a higher price in the future, the city could extract all of the farmers’ surplus from the transfer. However, if farmers could bargain as one group, they might have been able to obtain most of the surplus. The situation is complicated by farmers’ heterogeneity and the negative externalities they exert on others, e.g., farmers whose plots were closer to the river at its juncture with an irrigation ditch would produce a larger negative effect on other farmers on the same ditch than those farmers located further along the ditch. We exploit the detailed sale time data to show that the shape of the hazard rate is not constant, which requires a model with valuations that change over time. Our focus is not on the interaction of the city vis-à-vis farmers as a group, but rather, the interaction between individual farmers, given the behavior of the city. We estimate the model in two steps. In the first step, we recover a vector of pseudo parameters using only sale times. In the second step, we use the estimated pseudo parameters and the probabilities they imply to estimate hedonic regressions to obtain a set of parameters for
each fundamental farmer characteristic.

Unlike the previous literature on the topic, we locate each plot sold to the city and can thus answer broader questions. First, we can assess externalities each farmer imposes on other farmers, i.e., their probability of selling and the price they take. We find evidence that externalities depend on fundamental farmer characteristics including total water rights and proximity to the Owens River. Second, given the externalities, we can test the city’s checkerboarding, i.e., whether the city offered more money to farmers who created higher externalities in order to drive down prices for the remaining farmers. We do not find conclusive evidence that the city was checkerboarding. This is not surprising given that the offers were made by a committee intended to give each farmer a fair price for their land rather than to minimize overall negotiation time.

Estimating a dynamic game with externalities and time variable valuations is challenging on multiple dimensions. In the presence of externalities, each farmer’s payoff is affected by their own decisions and by those of other farmers. If a farmer sold land at a given price, it could mean his value of waiting was low given the high price offered by the city. With negative externalities, this behavior is also consistent with the price offered by the city being low, but the farmer expected one of his neighbors to sell soon, which would lower his continuation value, and the price the city would offer him in the future. Moreover, because farmers’ continuation values and probabilities of selling change over time, separately identifying all parameters places high demands on the data. We adapt the War of Attrition game in Catepillan and Espín-Sánchez (2019) to our empirical setting and show that under general assumptions we can identify the parameters. Moreover, in equilibrium, our dynamic game resembles a Proportional Hazard Rate Model, in which the “shape” of the continuation value over time is a function of sale probability. We estimate each variable’s externalities and direct effects using simple linear regressions in a second stage. Finally, we use the estimated model to compute counterfactual sale prices if farmers had been able to bargain as one group, or bargain irrigation ditch by irrigation ditch.

This paper relates to a rich political economy literature on coordination problems associated with the overuse and depletion of natural resources like water (Ostrom, 1962). Within this literature, there is a long tradition of analyzing common-pool resources (Ostrom, 2010) and institutional management of negative externalities for goods like water that are both subtractable and difficult to exclude. In Los Angeles, we study how the city strategically exploited these features of water markets to maximize the rents it could extract from farmers. In the presence of externalities, private decisions by farmers can take the form of collective decisions. Literature on vote buying (Dal Bo, 2007) has shown that
a principal can influence agents’ collective decisions to induce inefficient outcomes at almost no cost, as long as the principal can reward decisive players differently and agents face high coordination costs. We find evidence consistent with the prediction that the city targeted key players strategically, and thus purchased farmer’s water rights for a price very close to their marginal cost.

Historians and economists have extensively researched the Owens Valley controversy. The historical literature tells a story focused on how characters’ beliefs and personalities affected land sales and water transfers (Hoffman, 1981; Kahrl, 1982; Davis, 1990). However, historians differ on whether LA was a villain, or just as a rational business-minded agent. Whereas Kahrl (1982) and Reisner (1987) portray valley citizens as innocent victims, Hoffman (1981) takes a more neutral view of the inevitability of conflict given LA’s early 20th century population growth. Owens Valley farmers, such as Delameter (1977) and Pearce (2013), instead tell a story of farmers willing to sell their failing farms while townspeople, with the help of the Watterson brothers and the local newspaper, bullied both farmers and city agents until they received compensation for their urban properties in 1925. In economics, the most prominent recent work by Libecap (2005, 2007, 2009) considers land prices. Although all farmers were paid more than their land was worth, the transfer of property rights generated an enormous surplus, most of which the city got. Confirming claims by Kahrl (1982), the researcher found that on average, farmers who sold later received a higher price. Our model can account for this time feature of the data. However, our focus is not on the interaction of the city vis-à-vis the farmers as a group, but rather, interaction among farmers, given the behavior of the city.

Our paper contributes to the literature on the procurement and privatization of public services. There are at least two accounts of government privatization decisions. One view, focuses on transaction costs (Williamson, 1985; Hart et al., 1997) and an alternative view (Boycko et al., 1996) emphasizes politicians’ private benefits. We study a unique case, in which a public actor strategically centralizes the provision of a public good to secure its availability. We also contribute to the literature on the impact of access to water infrastructure like mains and pipes in urban areas. If urban environments expand, without building out this infrastructure, unconnected households may suffer negative welfare effects and impose negative externalities on their neighbors (Ashraf et al., 2017). By contrast, there is plenty of evidence that large investments in water systems led to significant welfare gains in the US (Cutler and Miller, 2005) as life expectancy drastically improved (Ferrie and Troesken, 2008) and infant mortality declined (Alsan and Goldin, forthcoming). These near miraculous results also hold for the city of Paris (Kesztenbaum and Rosenthal, 2017). We analyze arguably the most important water infrastructure project in the history
of modern America, focusing on how a city acquired water from farmers to guarantee access for urban dwellers. Our results also relate to the rich development economics literature about the health impacts of water access in rural environments (Ashraf et al., 2017; Kremer et al., 2011; Shanti et al., 2010; Devoto et al., 2012). Merrick (1985) and Galiani et al. (2005) find that the access to piped water infrastructure reduces the incidence of disease.

In terms of modeling and methodology, our paper contributes to the literature in industrial organization. Takahashi (2015) studies a WoA with symmetric players and without externalities. The classic article on offshore oil drilling by Hendricks and Porter (1996) consider a simpler WoA with information externalities. More recently, Hodgson (2018) studies oil drilling in the North Sea using a framework and solving for an equilibrium by restricting the behavior of firms. Our results extend to information externalities in R&D as in Bolton and Harris (1999).

2 Background and Data

2.1 Historical Background

By 1900, LA city officials had realized that Los Angeles River water could not meet the growing city’s future water demand. Political leaders and business owners wanted to find an external water supply to compete with San Francisco for economic primacy in the state. To transport water from the Owens River 300 miles to the north, these civic leaders needed to build a large aqueduct in addition to many dams and reservoirs and, most importantly, buy water rights from Owens Valley farmers. Since the value of the water would be higher in the city than the valley, city officials devised a plan to keep these rents: buy “enough” water rights from farmers before the project went public. Because water rights were tied to land ownership, the city first had to buy land. In 1904 and 1905, former LA mayor Fred Eaton traveled through the valley buying options to purchase land. At this stage, the city’s intentions were still private and farmers sold their land for “normal” prices, that is, the value of the land plus the value of water, used for irrigation in the valley.

At the same time, the Federal Reclamation Service (FRS) considered a reclamation project for the Owens Valley. The chief of the FRS in California, J.B. Lippincott, was a Los Angeles resident and friend of Fred Eaton. This relationship later proved controversial when Eaton was accused of using his association with Lippincott to imply that he was purchasing options for the reclamation project, not the city. Although both men denied the accusations, many farmers claimed that they would have asked for a higher price if they had known the land was not going to the FRS. Fred Eaton returned to the city with
all the necessary options and announced the plan in local newspapers. Voters approved a $1.5 million bond issue by a wide margin, financing a feasibility study and raising funds to purchase the land on Eaton’s options. After William Mulholland was appointed Chief Engineer of the project, voters approved a $23 million bond in 1907 to finance construction of the aqueduct. When the aqueduct was completed in 1913, city policy prohibited water sales outside municipal boundaries. This meant that fast-growing nearby towns needed to apply for annexation to LA. Indeed, Los Angeles grew from 115 to 442 square miles in the following two decades.

This growth surpassed all projections, and soon the city had to buy more land and water rights from the Owens Valley. Now, valley farmers knew their water would be used in LA and demanded a higher price for their plots. In the beginning, residual water rights satisfied the City’s demand but population increases soon put pressure on these supplies. In quick succession, voters passed a new $5 million bond in 1922, and after the drought of 1923, two $8 million bonds in 1924. Due to the controversy over the initial massive land purchase, the city was forced to buy land and buildings from the townspeople at pre-Great Depression prices. Still, when the California legislature permitted reparations for water loss in 1925, it limited the city’s liability for damage from “construction or operation of the aqueduct.” (Kahrl, 1982, p. 296). In 1930, Los Angeles issued a new bond for $38.8 million to acquire land without water rights: town properties and plots in the Mono Basin.1 Over the following decades, Los Angeles voters approved additional bonds to purchase water rights. By 1934, the city owned virtually all of the valley’s water rights, over 95% of its farmland and 85% of its towns.

Each bond set in motion the same pattern of bargaining. With its investment fund fixed, the city announced a committee to evaluate potential purchases, and made individual offers to farmers. The farmers then played a “war of attrition” among themselves. Each farmer knew that if they held out, the city would offer more money for their land. However, when one farmer sold their land, this decision imposed an externality on other farmers since the city had less money to buy land and lower demand for water.

The closer the farmers, the bigger the externality. Farmers could be “isolated” or cut off from the river if the city bought all of their neighbors’ lands. If the city bought most (usually two thirds) farms on each irrigation ditch, it could dissolve the ditch association and deprive remaining farmers of access to water. In this article, we focus on the strategic game between farmers. These externalities were important and acknowledged by all parties involved. Therefore, farmers initially tried to negotiate together in order to internalize

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1 According to (Kahrl, 1982), the city paid a total of $5,798,780 for the town properties: Bishop $2,975,833; Big Pine $722,635; Independence $730,306; Laws $102,446; and Lone Pine $1,217,560.
externalities and raise prices. In 1923, farmers formed the Owens Valley Irrigation District (OVID). Then, the city bought out the OVID’s leaders. Next, the city began buying land adjacent to “the oldest canal on the river [McNally Ditch] before its property owners joined the irrigation district” (Hoffman, 1981, p. 179). In a retaliatory cycle, farmers stole water from the McNally Ditch, and the city “adopted a policy of indiscriminate land and water purchases in the Bishop area, infuriating valley people, who accused the city of ‘checkerboarding.’” (Hoffman, 1981, p. 179). The city then began to buy into canal companies operating on the Owen and Big Pine rivers and Bishop Creek, starting with “key properties which controlled the points of access to the river, so that the less favorably situated ranchers inland could be cut off from their water supply if they refused to negotiate.” (Kahrl, 1982, p. 279, emphasis added). One scholar judges this “strategy of division and attrition” as “especially cruel, [...] because it placed an even larger burden of responsibility on the farmers and ranchers who held out” (Reisner, 1987, p. 93, emphasis added). The remaining farmers who owned water rights on the three major ditches created three smaller associations but two, the Cashbrought and the Watterson, collapsed following the failure of the Watterson Brother’s Bank.

Although the city eventually bought all the land in the valley, during negotiations, farmers were unsure how long they could hold out. The city indiscriminately purchased property, “leaving farmers uncertain of their neighbors’ intentions.” (Hoffman, 1981, p. 180). This observation motivates our modeling a game of perfect information because since farmers knew each other, and each other’s plot valuations, any uncertainty was due farmers’ reactions to the city’s offers. Until the 1930s, there was uncertainty as to how much land and water the city of LA needed and would buy. This uncertainty was driven by the recurrence of drought and by LA’s population increase. Further, the city’s ability to purchase land was subject to the availability of funds from sequential bonds. When the city ran out of money, it was unclear whether a new bond could be issued.

2.2 Water Law in the West

We now briefly discuss water rights in the Owens Valley. As mentioned in Libecap (2007), farmers held both appropriative and riparian surface water rights in the Owens Valley. Whereas appropriative rights can be separated from the land and sold, riparian rights are inseparable and unsellable. Appropriative rights are based on first appropriation and measured in miner’s inches or as a percentage of all water in each irrigation ditch. These rights could be senior or junior. During a dry season, all the senior rights have to be fulfilled before any junior rights claimants receive water.
Figure 1: Sales over time.

A. Fraction of Total Sales by Month.  
B. Fraction of Total Sales by Ditch.

Notes: Panel A: Fraction of total sales in the data with monthly frequency. Panel B: Fraction of total sales in each ditch with quarterly frequency.

rights are senior or junior, and we transform either miner’s inches or a percentage of flow in the ditch into a measure of capacity. We compute the amount of water in acres for each plot. When waters rights were riparian, LA typically bought all the land surrounding the irrigation ditch, e.g., “all rights in Sanger Ditch” or “all rights in Baker Creek.” In those cases, we cannot measure water rights because there is no explicit mention of the land’s water carrying capacity.

2.3 Sales Data

We created our main dataset from the transaction cards of deeds stored at the Los Angeles Department of Water and Power (LADWP) archive in Bishop, Inyo County. In Figure 2.A we show a sample transaction card. Each transaction card refers to a particular Section, in a particular Township and a particular Range, all of them in Mount Diablo Meridian (M.D.M.). Typically, one section corresponds to a square of one-mile times one-mile, or 640 acres. Thus, a quarter of a section corresponds to 160 acres; a quarter of a quarter corresponds to 40 acres; and half of a quarter of a quarter corresponds to 20 acres, as in Figure 2.A. Two features make the deed data cumbersome to process: in some cases the same farmer owned several, sometimes non-contiguous, plots and in many cases, the plots were not rectangular. We were nonetheless able to geo-code all plots, enabling us to
create the maps and variables we need for the estimation. For our baseline analysis, we merge all continuous plots owned by the same farmer, and treated the merged plot as a single plot.

Table 1 shows summary statistics for the variables used in the analysis. As shown in Figure 2.A, we have the exact date of purchase. We only consider transactions between 1905 and 1935 for reasons explained above in subsection 2.1: before 1905, farmers were unaware of the city’s intentions and their land to Fred Eaton but by 1935, the city owned all water rights and virtually all non-federal lands in Owens Valley. There are some sporadic transactions in the 1970s and 1980s, but they are very different in nature from early 20th century land purchases.

In addition to the purchase date, we obtain plot size and sale price directly from the transaction cards. Water rights are recorded as number of shares, percentage of all rights in a particular creek, and first or second rights using miner’s inches. These measures are homogeneous and comparable within a ditch, but not across ditches. To construct a uniform measure of water rights across all farmers, we merged our dataset with data collected
Table 1: Summary Statistics.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</th>
<th>Obs</th>
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<tbody>
<tr>
<td>Year</td>
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<td>1,903</td>
<td>1,997</td>
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<td>Acres</td>
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<td>Price</td>
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<td>104594</td>
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<td>2,000,000</td>
<td>1,250</td>
</tr>
<tr>
<td>Water Acres</td>
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<td>882.45</td>
<td>0</td>
<td>17,850</td>
<td>1,381</td>
</tr>
<tr>
<td>Distance to the river</td>
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<td>9,987.184</td>
<td>0</td>
<td>250,957</td>
<td>1,390</td>
</tr>
<tr>
<td>Distance to Mono lake</td>
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<tr>
<td>Distance to Owens lake</td>
<td>69,446</td>
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<td>246,874</td>
<td>1,390</td>
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</tbody>
</table>

Notes: Summary statistics for selected variables. Year is a numeric variable that measures the year where the plot was sold. Acres is the number of acres of the property sold. Price is the final price that the farmer received for her plot. The lower number of observations with prices is due to some farmers exchanging their land for another piece of land owned by the city. Water Acres represents the amount of water rights, measured in water acres per year, that each farmer owns.

by Gary Libecap from the LADWP archive in Los Angeles. 4

We supplemented the dataset with surveys conducted by LADWP surveyors. Figure 2.B, shows a sample picture of the survey summary. We merge the transaction cards data with survey data on farmer names. In the survey data, we observe that acreage size and water rights also match the transaction card data. The survey contains an extra piece of information that is an essential determinant of sale price: land use categorized as Orchard, Alfalfa, Cultivated, Pasture, Brush and Yards.

We distinguish three generations of academic work on LA water by data source. The first generation includes historians such as Hoffman (1981) and Kahrl (1982) who used summary data, most commonly compiled by Thomas H. Means, to draw their conclusions. Given the lack of detailed or individual data they determine the total amount that the city spent but reach no definite conclusions regarding the evolution of prices or the size and distribution of the surplus. The second generation includes Gary Libecap’s conclusions

\[3\text{For many of the cards, we do see two dates. We know that the later date, or the only date when there is only one, was the date when the land was sold. We believe that the first date is the date when the offer was made.}\]

\[4\text{In Libecap’s data set, there is a measure of annual water acres per farmer. Hence, for the farmers in his dataset, we have an exact measure of water acres. For reasons that are not clear to us, his dataset contains fewer farmers than ours. Whereas we were able to match all farmers in his dataset to our dataset, there are about 600 farmers in our dataset who do not appear in Libecap’s dataset. However, most of these missing farmers have water rights in the same ditch as another farmer who appears in Libecap’s dataset. We assume that all shares and all miner inches in a given ditch convey the same number of water acres, and we use Libecap’s data to extrapolate the water acres for those farmers.}\]
that as prices increased, the city extracted most of the surplus and farmers who would later received better prices on average (Libecap, 2005, 2007, 2009). Gary Libecap, however, compiled individual but not geographical data and thus omitted variables that affected plot value. This paper is a third generation analysis using geo-coded variables that help explain plot heterogeneity. Our crucial innovation is using geographical information to test and compute spatial externalities, which allow us to evaluate the efficiency and checkerboarding of city purchases.

2.4 Geo-location data

As mentioned above, the transaction cards describe each plot’s exact location. We geo-coded 2,750 plots. Figure 3.A shows land held by main sellers who received over $1 million for their land. Notice that the State of California was by far the largest seller. Despite not being a farmer or landowner in the valley before 1905, Fred Eaton was the second largest seller because he acted as an intermediary who bought land from farmers and sold it to the city. Most land was located in the southern valley, close to Owens Lake. However, it is worth noticing the large plot of land sold by Eaton in Mono County. This plot of land, corresponding to the 11,190 acre Rickey ranch, had the best natural spot for a reservoir (Long Valley). After “a week of Italian work,” Eaton purchased the ranch for 425,000 and sold it to the city, thereby destroying his friendship with Los Angeles engineer Mulholland (cited by Reisner, 1987).

Geo-located data is useful both for mapping and creating variables. We can merge each geo-coded polygon with data available in GIS (Geographical Information Systems) software. We construct important variables such as altitude, roughness, slope, suitability and distance to the Owens River, which are important determinants of land quality and thus sale price. We are especially interested in distance to the river based on our conjecture that within a ditch, farmers whose plots are closer to Owens River impose a larger externality than farmers further away. Finally, geo-coding all farmers’ plots allows us to calculate distances between farmers, and thus the magnitude of externalities, and to perform a rigorous spatial analysis.

3 Preliminary Evidence

In this section, we present descriptive statistics and reduced-form analysis that, to-

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5) James Birchim received $2 million in 1981 for 646.12 acres. James Cashbaugh received $1.4 million in 1985 for 636.66. Because these sales happened so late, they are not included in our analysis.

6) (Reisner, 1987) also implies that Lippincott favored the application of the Nevada Power Mining and Milling Company, founded by Thomas B. Rickey, over that of the Owens River company, for the building of a power plant in the valley. Lippincott recommendation was then key to convince Rickey to sell the ranch.
Figure 3: Digitized maps in Owens Valley.

A. Main Owners of rights.  
B. Dollars per acre paid in the North.

C. Land size.  
D. Dollars per acre paid in the South.

Notes: Panel A: Map with the main water rights owners, i.e., those who received over $1 million. Notice that Fred Eaton is listed although he was an intermediary. Panel B: Map of dollars paid per acre paid for each plot in northern Owens Valley. Panel C: Map of the total land area held by each seller. Panel D: Map of the dollars paid per acre for each plot in southern Owens Valley.
gether with the historical evidence presented in Subsection 2.1, motivates our design of the theoretical model and structural estimation. We first run a Moran test of spatial correlation. Table 2 shows that there is spatial correlation on the date of sale within the whole valley, suggesting the presence of spatial externalities and the importance of geo-coded data. We also compute the unconditional hazard rates of sale time by ditch. Figure 4 demonstrates that the shape of the hazard rate of sale time varies over time, which means that a standard linear regression cannot capture the variation in our data. Finally, we show several reduced-form regressions to explain in a dynamic setting whether or not a farmer sold land, and at what price. First, we estimate a Cox model, which can capture both time variation and farmer-specific variation. Table 5 displays results from the Cox regression. We also run a linear regression including variables related to spatial externalities. Table 6 shows externalities that affect individuals differently over time. Therefore, a Cox model should not be used because it cannot capture individual-time variation, i.e., a Cox model requires no individual-time variation. The individual-time variation shown in Table 6 is, however, constant between two consecutive exits, i.e., constant within a sub-game. This means that we should model farmers’ behavior as an exit game with a time-variant hazard rate that resets every time a farmer in the same ditch sells. All of the above observations motivate our choice of a War of Attrition model with externalities and time-variant valuations.

3.1 Spatial Correlation

In Table 2, we present the results of a Moran’s I test of spacial correlation. The Moran’s I is a non-parametric test that measures the spacial correlation of a particular value. Consider an example where half of the farmers sell at one time while the other half sell at another time. If all those who sold first are clustered together on one side, and all those who sold later are clustered together on another side, then the Moran’s I statistic would be equal to 1. Instead, if farmers who sold first do not neighbor any other farmer who sold first—a checkerboard pattern—then the Moran’s I statistic would be equal to -1. Finally, if farmers sold their land at random times, the Moran’s I statistic would be equal to 0.

The first row in Table 2 shows the results of a Moran’s I test for the variable of interest Price per Acre. The test shows no spacial correlation on Price per Acre for the whole sample. This finding seemingly contradicts the hypothesis proposed by Kahrl (1982) that farmers who “clustered” along the river received higher prices per acre for their plots. Notice, however, that this is a strong weak test because it considers linear relations and

\[ ^7 \text{In Appendix ??, we show robustness results that confirm these patterns are due to externalities imposed by a neighbor’s land sale and not other hypotheses.} \]
imposes the same relationship across the whole map. Kahrl hypothesizes a strong spatial relationship, presumably only for farmers on the main ditches, between location on the river or far away from the river, but a zero relation between any other pair of plots. Therefore, zero spatial correlation for the whole map does not necessarily contradict Kahrl (1982).

The second row in Table 2 shows the results of a Moran’s I test for the variable of interest sale date. The test shows a strong and significant positive spatial correlation on sale dates consistent with our motivation of spacial externalities across neighboring farmers. In other words, when a farmer sold his plot, his neighbors were more likely to sell. Notice that this correlation could also be spurious. Given the nature of the city’s land purchases, the began making offers to farmers in the southern Valley, and as water demands increased, moved north. In other to control for this change, we decompose the sample into several time windows and run the test within those windows. Before 1906, Fred Eaton purchased plots farmers did not know would be sold to the city. Sales from 1907 to 1912 correspond to sales after the city announced but had not finished the aqueduct construction, Here too we see a positive spacial correlation. After the aqueduct was built, but before the city passed a new bond to buy more water (1913-1921), eight reluctant farmers who sold at random times for idiosyncratic reasons drove the lack of spatial correlation. Since the city decided to raise funds to buy more water in 1922, this is our period of interest, which contains most water and land sales and most of the conflict Dividing the sample into two year windows, we see that the spacial correlation is very high and significant. This implies that the high spacial correlation in the second row is not an artifact of the city first buying the southern part of the valley, but rather results from strong spacial correlation across farmers whose lands were within the same part of the valley.

3.2 Hazard Rates

Figure 4 shows the unconditional hazard rates of farmers exiting by quarter. We compute hazard rates following a similar approach as Hendricks and Porter (1996). We restrict attention to farmers who belonged to a ditch with more than five farmers. We set the first period for each ditch to be the quarter when the first farmer in that ditch sold his land to the city. During the first 30 quarters, the hazard rate is erratic but trends downward. As we show later in Section 4, a downward sloping hazard rate is consistent with an upward value of waiting. After 30 quarters, most of the farmers sold while a handful of outliers explain the positive hazard rate after 50 periods.

The hazard rate’s variation from high to low suggests that the baseline rate is not con-
3.3 Reduced Form Analysis

In Table 3 we regress several covariates on the price paid by LA. We include variables from archival records that affect price such as Acres and Water Acres. The results are unsurprising, and the sign and size of effects are reasonable. In addition to these variables, we linked each individual plot with climatic and geophysical information. The climatic and geophysical variables affect productivity and are usual inputs to compute land productivity. The additional climatic variables are annual precipitation, snow and humidity. The additional geophysical variables are mean elevation, slope and roughness. Below we use all of these variables as controls when estimating the effects of externalities.

We included climatic and geophysical variables to address concerns that plots of land were heterogeneously on productive and thus the results driven by unobserved differences. We do find differences in climate and physical characteristics across the valley. Moreover, as the results in Table 3 show, these differences affected the price that farmers

Table 2: Spacial Correlation.

<table>
<thead>
<tr>
<th>Model</th>
<th>Observations</th>
<th>Moran I statistic</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample P/A</td>
<td>1158</td>
<td>-1.21E-03</td>
<td>0.5139</td>
</tr>
<tr>
<td>Sample Timming</td>
<td>1158</td>
<td>0.333178241</td>
<td>2.20E-16</td>
</tr>
<tr>
<td>Timming (&lt;1906)</td>
<td>38</td>
<td>0.38125082</td>
<td>0.0004194</td>
</tr>
<tr>
<td>Timming (1907-1912)</td>
<td>108</td>
<td>0.161978265</td>
<td>0.02568</td>
</tr>
<tr>
<td>Timming (1913-1921)</td>
<td>8</td>
<td>-0.12837051</td>
<td>0.4805</td>
</tr>
<tr>
<td>Timming (1922-1923)</td>
<td>90</td>
<td>0.265955734</td>
<td>0.000847</td>
</tr>
<tr>
<td>Timming (1924-1925)</td>
<td>135</td>
<td>0.278952641</td>
<td>4.11E-05</td>
</tr>
<tr>
<td>Timming (1926-1927)</td>
<td>154</td>
<td>0.50406624</td>
<td>1.42E-12</td>
</tr>
<tr>
<td>Timming (1927-1928)</td>
<td>188</td>
<td>0.062588665</td>
<td>0.1414</td>
</tr>
<tr>
<td>Timming (1928-1929)</td>
<td>178</td>
<td>0.367887174</td>
<td>2.16E-08</td>
</tr>
<tr>
<td>Timming (1930+)</td>
<td>259</td>
<td>0.503678295</td>
<td>2.20E-16</td>
</tr>
</tbody>
</table>

Notes: Results from a Moran’s I test of spatial correlation on the year that each farmer sold their plot. Sample P/A corresponds to the spatial correlation of price per acre. Sample Trimming corresponds to the spatial correlation of year of sale, taking all the observations between 1906 and 1935. Timing (X) corresponds to the spatial correlation of year of sale, taking all the observations included in X.
Figure 4: Unconditional Hazard Rates.

Notes: Unconditional hazard rate for farmers who belong to a ditch with 5 or more farmers.
received, *i.e.*, farmers with more productive lands received a higher price per acre for their land.

Table 4 uses the same variables as Table 3 above but the explanatory variable is Sale Date, *i.e.*, days since January 1, 1900. The negative coefficient on the variable Acres means that farmers who owned larger plots, typically big landowners or ranchers, sold sooner than smaller farmers. The large negative and significant coefficient on Mean roughness means that farmers with poor quality land also sold earlier.

The econometric specification in Table 4 implicitly assumes that the probability of selling is constant over time. Based on the estimated hazard rate in Figure 4, the hazard rate is not constant. Hence, we also estimate a Cox model. Table 5 shows the results of the Cox model. Notice that the negative coefficient on the variable Acres means that farmers who owned larger plots had a higher probability of selling and, thus, sold earlier than smaller farmers. Overall, the coefficients are similar, but with opposite signs, than those in Table 4.

The advantage of the Cox model is that it does not restrict how probability of selling changes over time. The Cox model is a particular case of Proportional Hazard Rate Models (PHRM). In a PHRM, the hazard rate, or the individual instantaneous probability of selling, can be decomposed into two multiplicative terms: one term (baseline hazard) that depends only on time and one term that depends only on individual characteristics. Therefore, the Cox model does not impose any restriction on how the probability of selling changes over time, except that the baseline hazard is the same for all farmers beginning at time zero, regardless of the actions of any farmer. We are interested in estimating spatial externalities, *i.e.*, the effect that a farmer’s sale has on neighboring farmers. However, the Cox model is not flexible enough to estimate such a model. To illustrate this point and to share evidence of spacial externalities, we extend the cross-sectional dataset and transform it into a panel dataset. In the panel dataset, we create variables that relate to actions by other farmers in the same ditch.\footnote{In the appendix, we also show similar results for neighboring farmers, defined as the four farmers with the closest plots to a given farmer.} The variables are: Distance to Owens river (m), Percentage of Sales to date (percentage of farmers on the same ditch who have sold), Percentage of Shares to date (percentage of water rights in the ditch that have been sold), SD-Percentage shares to date (the standard deviation of the percentage of water rights in the ditch that have been sold), Mean-price/acre to date (the average across farmers on the same ditch on the price per acre received for their plots), SD-price-acre to date (the standard deviation across farmers on the same ditch on the price per acre received for their plots), Percentage acres to date (percentage of land rights in the ditch that have been sold).
# Table 3: Price Determinants.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Price per acre</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Acres</td>
<td>−0.06</td>
</tr>
<tr>
<td></td>
<td>(0.08)</td>
</tr>
<tr>
<td>Water acres</td>
<td>−0.07</td>
</tr>
<tr>
<td></td>
<td>(0.28)</td>
</tr>
<tr>
<td>Annual precip.</td>
<td>241.05</td>
</tr>
<tr>
<td></td>
<td>(1,028.14)</td>
</tr>
<tr>
<td>Annual snow</td>
<td>−102.30</td>
</tr>
<tr>
<td></td>
<td>(381.30)</td>
</tr>
<tr>
<td>Annual humidity</td>
<td>271.05</td>
</tr>
<tr>
<td></td>
<td>(857.80)</td>
</tr>
<tr>
<td>Mean elev.</td>
<td>−0.73</td>
</tr>
<tr>
<td></td>
<td>(0.84)</td>
</tr>
<tr>
<td>Mean slope</td>
<td>0.002**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>Mean roughness</td>
<td>−682.68**</td>
</tr>
<tr>
<td></td>
<td>(321.48)</td>
</tr>
<tr>
<td>Constant</td>
<td>498.16***</td>
</tr>
<tr>
<td></td>
<td>(119.79)</td>
</tr>
<tr>
<td></td>
<td>−11,158.75</td>
</tr>
<tr>
<td></td>
<td>−8,514.23</td>
</tr>
<tr>
<td>Observations</td>
<td>972</td>
</tr>
<tr>
<td>R²</td>
<td>0.001</td>
</tr>
</tbody>
</table>

*Note:* $^*$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

*Notes:*
Table 4: Time of Sale Determinants.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Days between 01/01/1900 and sale</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acres</td>
<td>−0.53***</td>
<td>−0.53***</td>
<td>−0.48***</td>
<td>−0.50***</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Water acres</td>
<td>0.34*</td>
<td>0.19</td>
<td>0.26</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.19)</td>
<td>(0.19)</td>
<td>(0.18)</td>
<td></td>
</tr>
<tr>
<td>Annual precip.</td>
<td>−893.81</td>
<td>−980.76</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(677.80)</td>
<td>(660.63)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual snow</td>
<td>344.38</td>
<td>345.66</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(251.37)</td>
<td>(245.18)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual humidity</td>
<td>−723.63</td>
<td>−714.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(565.50)</td>
<td>(552.07)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean elev.</td>
<td>3.06***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.52)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean slope</td>
<td>0.001**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean roughness</td>
<td>−378.33*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(203.83)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>9,192.13***</td>
<td>9,141.71***</td>
<td>40,707.15</td>
<td>37,404.84</td>
</tr>
<tr>
<td></td>
<td>(80.63)</td>
<td>(86.39)</td>
<td>(25,091.66)</td>
<td>(24,492.89)</td>
</tr>
<tr>
<td>Observations</td>
<td>990</td>
<td>988</td>
<td>988</td>
<td>986</td>
</tr>
<tr>
<td>R²</td>
<td>0.09</td>
<td>0.10</td>
<td>0.15</td>
<td>0.20</td>
</tr>
</tbody>
</table>

*Note:* p<0.1; **p<0.05; ***p<0.01

Notes:
Table 5: Cox Regressions.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Days between 01/01/1900 and sale</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acres</td>
<td>0.0001***</td>
<td>0.0001***</td>
<td>0.0001***</td>
<td>0.0002***</td>
</tr>
<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0002)</td>
<td>(0.0002)</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>Water acres</td>
<td>0.0002***</td>
<td>0.0002***</td>
<td>0.0001**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0001)</td>
<td>(0.0001)</td>
<td>(0.0001)</td>
<td></td>
</tr>
<tr>
<td>Annual precip.</td>
<td>−0.023***</td>
<td></td>
<td>0.257</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td></td>
<td>(0.297)</td>
<td></td>
</tr>
<tr>
<td>Annual snow</td>
<td></td>
<td>−0.087</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.110)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Annual humidity</td>
<td></td>
<td>0.194</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.248)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean elev.</td>
<td></td>
<td>−0.002***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0002)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean slope</td>
<td></td>
<td>−0.00000***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00000)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean roughness</td>
<td></td>
<td>0.245**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.096)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>990</td>
<td>988</td>
<td>988</td>
<td>986</td>
</tr>
<tr>
<td>R²</td>
<td>0.016</td>
<td>0.023</td>
<td>0.042</td>
<td>0.146</td>
</tr>
</tbody>
</table>

**Note:** *p<0.1; **p<0.05; ***p<0.01

**Notes:**
and SD-Percentage acres to date (the standard deviation of the percentage of land rights in the ditch that have been sold).

Table 6 shows the results from a Logit regression of the panel dataset on the set of controls that determine price and externality one variable at a time. Notice how Distance to the Owens River does not seem to have an effect on whether a farmer sold or not. The variables representing mean characteristics (their number, their water rights and their land rights) of farmers who sold are all positive and significant. This observation is consistent with positive spatial externalities, and with externalities growing for farmers with larger plots and more water rights, i.e., key farmers. Moreover, measures of those characteristics’ standard deviations are also positive and significant, which suggest convex effects, i.e., farmers with more land who sell have more than proportional effects on their neighbors. In summary, the results in Table 6 are consistent with spatial externalities. The econometric specification in Table 6, however, implicitly assumes that hazard rates are constant between two farmers exits.

The evidence presented in this section can be summarized as follows: hazard rates of selling are not constant over time, thus, a linear regression is not adequate; the probability of selling depends on action by other farmers (spatial externalities), thus a Cox model is not flexible enough. Therefore, we need an econometric model that allows for spatial (farmer to farmer) externalities and allows sale probabilities to change over time and between farmers’ sales. In the next section, we present such a model and solve for its equilibrium.

4 Econometric Model

This section introduces the theoretical model. Unlike (Takahashi, 2015)’s model of imperfect information, we assume farmers have perfect information. Using the arguments in Harsanyi (1973), as we explain below in subsection 4.4, the two games are observationally equivalent. In other words, the data can be rationalized either by a game of perfect or imperfect information.9 We choose to model interaction between farmers as a game of perfect information because we think that it is realistic in the empirical setting studied here. The historical literature notes that all farmers were informed about sales, prices, and characteristics of other farmers’ plots.10

9 Typically, while a game of imperfect information has a unique equilibrium, a game of perfect information has multiple. The perfect information game equilibria in which all farmers used mixed strategies rationalized the data and is observationally equivalent to the game of imperfect information.

10 Pearce (2013) documents how close the community was in the valley’s small towns and how everyone knew when their neighbor took the train to LA to sign sale papers.
Table 6: Externalities Effects.

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Sale in quarter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Dist. to Owens River (m)</td>
<td>−0.00002 (0.00003)</td>
</tr>
<tr>
<td>Prct. sales to date</td>
<td>7.153*** (0.235)</td>
</tr>
<tr>
<td>Prct. shares to date</td>
<td>6.254*** (0.187)</td>
</tr>
<tr>
<td>SD-Prct. shares to date</td>
<td>18.242*** (1.070)</td>
</tr>
<tr>
<td>Mean-price/acre to date</td>
<td>0.005*** (0.0001)</td>
</tr>
<tr>
<td>SD-price/acre to date</td>
<td>0.003*** (0.0001)</td>
</tr>
<tr>
<td>Prct. acres to date</td>
<td>6.807*** (0.197)</td>
</tr>
<tr>
<td>SD-Prct. acres to date</td>
<td>−1.939 (1.874)</td>
</tr>
<tr>
<td>Constant</td>
<td>−4.152*** (1.165)</td>
</tr>
<tr>
<td></td>
<td>−5.908*** (1.546)</td>
</tr>
<tr>
<td></td>
<td>−2.077 (1.778)</td>
</tr>
<tr>
<td></td>
<td>−5.398*** (1.078)</td>
</tr>
<tr>
<td></td>
<td>−0.056 (1.973)</td>
</tr>
<tr>
<td></td>
<td>−1.450 (1.638)</td>
</tr>
<tr>
<td></td>
<td>−4.416*** (1.487)</td>
</tr>
<tr>
<td></td>
<td>1.555 (1.648)</td>
</tr>
</tbody>
</table>

| Controls? | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Observations | 23,827 | 23,827 | 23,827 | 23,827 | 23,827 | 23,827 | 23,827 | 23,827 | 997 | Log Likelihood | −1,570.760 | −745.600 | −822.786 | −1,437.158 | −1,078.121 | −1,211.416 | −822.166 | −563.115 |
| Akaike Inf. Crit.            | 3,159.519 | 1,509.200 | 1,663.572 | 2,892.315 | 2,174.242 | 2,440.832 | 1,662.331 | 1,144.230 |

Note: *p<0.1; **p<0.05; ***p<0.01

Notes:
4.1 Theoretical Model

We model the interaction between farmers as a War of Attrition (WoA) game based on the results in Catepillan and Espín-Sánchez (2019), taking as given the city’s offers. One can think of each game as one played between farmers in the same ditch. There are $N$ farmers with each farmer (he) indexed by $i = 1, ..., N$ and the city of LA (she) as $i = 0$. The game begins at $t = 0$ and time is continuous. When $t = 0$ the city makes an offer to each farmer. The offer consists of a price $V_i(0)$ that the farmer would receive for their plot if he sold at $t = 0$. There is perfect information and we assume that the city can commit to a stream of future offers to each farmer. Future offers are then common knowledge and may depend on time since the game began, indicated by the scalar $t$; the number of farmers that have sold at a given point denoted by the scalar $k$; and in general on the identity of each of the farmers who sold at a given point, denoted by the set $K$. At each moment in time, a farmer decides whether to stay in the market or to sell his farm to the city. If staying, each farmer pays a monetary unitary instantaneous cost. This instantaneous cost can be interpreted in continuous time as discounting.

It is important to distinguish between the whole game played by all farmers in a ditch and each stage game between the subset of farmers who have not sold up to that point. In each stage game, farmers take the continuation value—that is, the value of being active in the next stage game—after another farmer sells as given. In a stage game with $n$ remaining farmers, the value of selling for a given farmer is the city’s offer $V_{iK}(t)$. Notice that the offer depends on time, the farmer’s identity, and the set of farmers who have already sold. If a farmer does not sell, his continuation value, depends on the identity of the farmer who did sell. The continuation value of the farmer is $W_{iK}^j(t)$ if farmer $j$ sold his plot at time $t$. As the farmer decides whether to sell or not, he considers the difference between selling at time $t$, which involves an immediate reward $V_{iK}(t)$, and not selling at time $t$, which involves a continuation value $W_{iK}^j(t)$. We denote this difference by $\Delta_{iK}^j(t) \equiv W_{iK}^j(t) - V_{iK}(t)$. Finally, we define $\Delta_{iK}(t)$ as the expected difference between selling or not at time $t$. In particular

$$\Delta_{iK}(t) \equiv \sum_{j \neq i} f_{jK}(t) W_{iK}^j(t) - V_{iK}(t) = W_{iK}(t) - V_{iK}(t) \tag{1}$$

where $f_{jK}(t)$ is the instantaneous probability that farmer $j$ sells at time $t$. Notice that the expected difference is not a fundamental element of the whole game or the stage game because it depends on each other farmer’s probability of selling $f_{jK}(t)$, which are equilibrium objects.

To solve the equilibrium, we make one assumption regarding the evolution of $\Delta_{iK}^j(t)$ over time.
**Assumption A1:** The difference in valuation between selling or not for each farmer is separable in time, and all farmers have a common time component

\[ \Delta_{jk}^i (t) = \Delta_{jk}^i \cdot v(t) \]

Assumption A1 implies that the “shape” of \( \Delta_{jk}^i (t) \) over time is the same for all farmers. The intuition is that although the value differs for each farmer and changes over time, the “shape” of the change is common to all farmers. In the classical WoA models, the value of the “prizes” players receive does not change over time, i.e., in the classical WoA \( v(t) = 1 \).

Thus, both sale values and continuation values are constant over time. A constant \( \Delta_{jk}^i (t) \), as we show below, implies a constant probability of selling over time, which means that the distribution of sale times will have a constant hazard rate. Therefore, assuming constant values is equivalent to assuming that the distribution of selling times is exponential.

Below, we show how there is a direct relationship between the shape of valuations over time and the shape of sale time distributions, i.e., given a function of valuations over time \( v(t) \), there is a unique distribution of sale times in equilibrium and given a distribution of sale times in the data, there is a unique function of valuations over time that rationalizes it. In Subsection 4.4 we show how our data allow us to non-parametrically identify the distribution of valuations. For simplicity, we choose a flexible parametric form for the estimation.

### 4.2 Equilibria

We now show how to solve for the unique equilibria where all farmers use mixed strategies.\(^{11}\) As defined above, farmer \( i \)'s value of waiting until the next stage when farmer \( j \) sells at time \( t \) in a stage game when the set \( K \) of farmers have already sold is \( \Delta_{jk}^i (t) = \Delta_{jk}^i \cdot v(t) \). Since the cost of waiting is unitary, the cost function over time is \( C(t) = t \). We assume that \( v(t) \) is differentiable. Farmer \( i \)'s utility of waiting until time \( t \), given that farmer \( j \) leaves at time \( s \) with probability \( f_{jk}(s) \) is

\[
U_{ik}^j(t) \equiv \sum_{j \neq i} \int_0^t \left[ \Delta_{jk}^i \cdot v(s) - s \right] f_{jk}(s) \prod_{k \neq i, k \neq j} [1 - F_k(s)] ds - t \left\{ \prod_{j \neq i} [1 - F_{jk}(t)] \right\} \tag{2}
\]

That is, farmer \( i \) gets \( \left[ \Delta_{jk}^i \cdot v(s) - s \right] \) if farmer \( j \) is the first to sell, and at time \( s < t \); and farmer \( i \) gets \(-t\) if no one sells before \( t \). The derivative of the utility exists and we obtain the following expression

\(^{11}\)See Catepillan and Espín-Sánchez (2019) for details and a broader discussion of equilibria.
In equilibrium, the expected utility of not selling for any farmer using a mixed strategy needs to be constant. Otherwise, the farmer would sell (if his expected utility is negative) or not sell (if his expected utility is positive). Thus, in equilibrium, \( \frac{dU_i}{dt} = 0 \) and the probability that farmer \( j \) sells at time \( t \), \( f_{jK}(t) \). Farmer \( j \)'s strategy that makes all other farmers indifferent between selling or not is, \( \lambda_{iK}(t) \). This produces the following equilibrium condition for farmer \( i \)

\[
\sum_{j \neq i} \left[ \Delta_{ijK} \cdot v(t) \cdot \lambda_{jK}(t) \right] = 1, \forall i
\]  

(4)

Notice that we have one equilibrium condition for each remaining farmer. The system of \( n \) total equations solves strategies for each farmer \( \lambda_{iK}(t) \) in two steps. The first step is to solve for \( \varphi_{iK} \), such that

\[
\sum_{j \neq i} \Delta_{ijK} \cdot \varphi_{jK} = 1, \forall i
\]

This system of equations is linear and easy to solve. Appendix ?? solves the case for three farmers in order to show the intuition behind values and externalities in sale probabilities. The intuition extends to more than three farmers but the algebra is cumbersome. Then, the strategy for farmer \( i \), that is the probability distribution of selling over time, must follow a hazard rate that satisfies equilibrium condition 4

\[
\lambda_{iK}(t) = \frac{1}{\varphi_{iK} \cdot v(t)}
\]  

(5)

Therefore, the distribution of selling times for farmer \( i \) in game \( K \) is

\[
F_{iK}(t) = 1 - c \cdot \exp \left[ - \int_0^t \frac{\varphi_{iK}}{v(s)} ds \right]
\]  

(6)

where \( c \) is the constant of integration that makes \( F_{iK}(t) \) a probability distribution. No-
tice that equation 5 is key to identify the shape of $v(t)$. In the model, using equation 6, for each $v(t)$ we can compute the exact shape of the distribution of each farmer’s sale time in each game. When we look at the data, we see the empirical distribution of each farmer’s sale time for a given game, $\hat{F}_{iK}(t)$. With that distribution, we can compute the empirical hazard rate of sale times for each farmer for a given game, $\hat{\lambda}_{iK}(t)$. Then, using equation 5 we can compute the shape of $v(t)$ and estimate the externalities using the estimates on $\phi_{iK}$.

4.3 Linear value function

The model presented above computes equilibria for any value function $v(t)$. We next show results from a linear value function, now.

$$v(t) = \alpha + \beta t \quad (7)$$

Following equation 5 and equation 7 we can write the hazard rate of sale times for farmer $i$ as

$$\lambda_{iK}(t) = \frac{1}{\phi_{iK}(\alpha + \beta t)} = \frac{1}{\alpha_i + \beta_i \cdot t} \quad (8)$$

The hazard rate in equation 8 corresponds to the hazard rate of a Generalized Pareto Distribution (GPD) with scale parameter $\alpha_i$ and shape parameter $\beta_i$. In other words, when $v(t)$ is linear, the equilibrium distribution of each farmer’s sale times follows a GPD.\footnote{The Generalized Pareto Distribution has a cumulative distribution function $F(t) = 1 + \left(1 + \frac{\beta_i t}{\alpha}ight)^{\frac{1}{\beta_i}}$ and a probability density function $f(t) = \alpha^{-1} \left(1 + \frac{\beta_i t}{\alpha}\right)^{-1/\beta_i - 1}$.}

Notice that this example also includes the Exponential distribution as a particular case, i.e., when $\beta = 0$ the value function is constant, the hazard rate is constant and the distribution of sale times is Exponential.

The GPD has the nice property that if a random variable $t$ has a GPD, then the conditional distribution of $t - \tau$ given $t > \tau$ is also a GPD with the same shape parameter $\beta_i$ and a scale parameter equal to $\alpha'_i = \alpha_i + \tau \beta_i$. For each farmer in every stage game, the distribution of sale times since the last sale follows a GPD. The intuition is simple. When one farmer sells the game is similar than the original game. In the original game we have a set of $\phi_{iK}$ characteristic of each game with one element for each farmer. In that game, looking at the future each farmer is playing a game where there is an immediate value of selling of $\alpha_i = \phi_{iK}\alpha$ and a slope of $\beta_i = \phi_{iK}\beta$, where $K$ is the original set of farmers. If another farmer sells at time $t = \tau$, then each farmer plays a game with an immediate value of selling of $\alpha'_i = \phi_{iK'}(\alpha + \beta \tau)$ and a slope of $\beta_i = \phi_{iK'}\beta$, where $K'$ is the original set of farmers.\footnote{The Generalized Pareto Distribution has a cumulative distribution function $F(t) = 1 + \left(1 + \frac{\beta_i t}{\alpha}ight)^{\frac{1}{\beta_i}}$ and a probability density function $f(t) = \alpha^{-1} \left(1 + \frac{\beta_i t}{\alpha}\right)^{-1/\beta_i - 1}$.}
farmers minus the farmer who sold. In other words, when a stage game ends linearly affects the scale parameter but not the shape of the distribution of subsequent stage games’ sale times. Given this structure, we only need to estimate two parameters $\alpha$ and $\beta$ that determine the value function’s shape and original scale for the city’s offer to farmers. We could estimate one pair for each ditch.

### 4.4 Identification

For simplicity, we drop the sub-index denoting that in a given game, the remaining player belongs to the set $\mathcal{K}$. From the previous section, we know that in a WoA game the distribution of sale times is determined by the value of selling. Equation 1 defined the object of interest $\Delta_i(t)$ as the difference between the continuation value when another farmer sells $W_j(t)$ and the value of selling $V_i(t)$. In the empirical application, we only observe each farmer selling once, so we cannot estimate all $\phi_i$. However, we can classify farmers depending on their observable characteristics such that we observe several sale times for a given configuration of the game. Therefore we can identify the function $v(t)$ non-parametrically. We also observe all realizations of $V_i(t)$, which are the prices farmers sold their plots for. Therefore, we independently identify the functions $W_i(t)$ and $V_i(t)$. This means we could identify asymmetric values but not externalities for each farmer. Finally, because we have information regarding the location of farmers’ plots and their characteristics, we identify and estimate different functions $W_i(t)$ for different pairs of farmers $i$ and $j$.

In other words, if we only have information on sale times, as is usually the case (see Takahashi, 2015), then we could only identify a farmer’s probability of selling in a particular game $v(t)$. Thus, we would restrict our attention to symmetric games, estimating a single $\phi$ for a given number of farmers identified up to a constant. In this case, the function $\Delta(t)$ equals the hazard rate of the distribution of sale times for each game with the same number of farmers. That is, we could estimate a function for games with two farmers, another function for games with three farmers and so on.

Knowing land size and value for each farmer, we could model an asymmetric WoA game and estimate $\Delta_i(t)$, thus identifying $v(t)$ and $\phi_i$, up to a constant. If in addition, we have information on the prices farmers received, we could also estimate $W_i(t)$ from $V_i(t)$, thus identifying $v(t)$ and $\phi_i$ exactly. It is rare to have such detailed data in an empirical estimation, and its availability crucially allows us to estimate both the game and the counterfactuals. Finally, if we have information regarding the locations, characteristics, and prices of farmers’ plots, we will be able to identify and estimate different functions
\( W^j_i(t) \) for different pairs of farmers, thus identifying \( \nu(t) \) and \( \phi_i \) exactly. Notice that this is the main innovation of the paper: we estimate the externalities a farmer exerts on another farmer when he sells land. Depending on data variability and market definition, we could be more or less flexible with the structure of \( W^j_i(t) \). Summarizing, we can identify

- **Symmetric Game** — Data on sale times: \( \Delta(t) \).
- **Asymmetric Game** — Data on sale times and individual characteristics: \( \Delta_i(t) \).
- **Asymmetric Game** — Data on sale times, individual characteristics and sale prices: \( W_i(t) \) and \( V_i(t) \).
- **Asymmetric Game with Externalities** — Data on sale times, individual characteristics, sale prices and pair-specific information: \( W^j_i(t) \) and \( V_i(t) \).

5 Estimation Strategy

In the data, some events affect all farmers, regardless of their irrigation ditch. We implicitly assume that sales by farmers outside their ditch affect all farmers in their given ditch the same way. In particular, we use cumulative sales as a state variable in each game. By contrast, we believe that farmers’ sales affect other farmers within their same ditch. Moreover, we think the effect differs for each farmer. Each stage game, as explained in Section 4, contains the key variable of sale time and information on farmers who sold, who were active but not the first to sell, and who belonged to the same ditch but already sold.

The key econometric innovation concerning previous work relates to spatial externalities and time-varying values. As mentioned above, we have information regarding the location of each farmer’s plot and the exact date they sold land. This information is essential to estimate the spacial externalities and, therefore, test the checkerboarding claim. Moreover, preliminary evidence shows two relevant empirical facts: the hazard rate of sale time varied over time and sales by farmers on the same ditch influenced remaining farmers’ behavior. The former means that we need to model the dynamics of the farmer’s behavior. The latter means that we need to model the externalities among farmers. Our econometric model can account for both facts.

We focus on a type of model with a unique equilibrium that account for these data features. This model falls within the class of proportional hazard rate models (PHRM)
but is more general than the usual application of PHRM as we allow the baseline hazard, \( i.e. \), the component of the hazard rate that depends on time only, to vary by game. In other words, we allow the baseline hazard rate to reset each time a farmer in the same ditch sells property. Therefore, our model encompasses the Cox model in terms of the generality of the data generating process, being the Cox model a particular case of our model when the hazard rate does not reset. In the main estimation, we assume value functions to be linear over time. Thus, exit times follow a Generalized Pareto distribution.

The estimation proceeds in two steps. In the first step (Inner Loop), we get one vector \( \theta^n \) of pseudo parameter for each game, with as many elements as farmers in the game. In the second step (Outer Loop), we use hedonic regressions to obtain a set of parameters \( \beta \) using the pseudo-parameters we estimated in the first step. This allows us to separate both parts and estimate hedonic parameters without having to use simulations.

5.1 Proportional Hazard Rate Models

In Section 4 we solved the model with Assumption A1, which implies that for the empirical distribution of each farmer’s sale times, hazard rates \( \lambda_{ik}(t) \) are proportional to each other. Thus, we need to estimate a Proportional Hazard Rate Model (PHRM). The CDF of a PHRM is defined by

\[
1 - F(t; \Omega; \theta) = [1 - G(t; \Omega)]^\theta, \theta > 0, \tag{9}
\]

and we write the PDF as

\[
f(t; \Omega; \theta) = \theta g(t; \Omega) [1 - G(t; \Omega)]^{\theta - 1}, \theta > 0, \tag{10}
\]

where \( G(t; \Omega) \) is a CDF, \( \theta \) is a positive shape parameter and \( \Omega \) is a parameter vector that characterizes the source distribution. The hazard rate of a PHRM distribution is

\[
\frac{f}{1-F} = \frac{\theta g [1-G]^{\theta - 1}}{[1-G]^\theta} = \theta \frac{g}{1-G}, \]

which implies that the hazard rate of \( F \) is proportional to that of \( G \) and the scalar of proportionality is the shape parameter \( \theta \). In both cases, we call \( G(x; \Omega) \) the source CDF, due to the generation process. This class of models is interesting because, as shown above, a WoA with changing values will generate this statistical process. Each farmer’s equilibrium strategy will be to choose a sale time. In a given stage game, the probability distribution of sale times for a given farmer follows a PHRM distribution. All farmers will have the same source distribution, which is also determined by \( v(t) \) but has a different shape parameter \( 1/\phi_{ik} \).
There is, however, one issue in linking the model to the data. Even when each farmer’s equilibrium strategy is to choose a sale time in each stage game, we only observe sale time for the farmer who sells, *i.e.*, the farmer whose with the quickest sale time. In other words, we have a censored problem. We can only infer that other farmers’ sale times were later. This issue is similar to estimating the distribution of valuations in a second price auction (SPA) when the econometrician only observes the winning bid. In a SPA, observed behavior (winning bid) is the second order statistic of the underlying distribution of valuations. In the WoA, observed behavior (sale time) is the minimum of the underlying distribution of sale times. Moreover, in our case, it is the minimum of asymmetric random variables because farmers have different valuations for holding or selling in a given stage game. Properties of the PHRM are useful when dealing with this issue.

Following Espín-Sánchez and Wu (2019) we have also developed the distribution of order statistics for an asymmetric sample. Let $T_1, \ldots, T_n$ be a random sample of size $n$ where each realization comes from a PHRM with different parameters $\Theta \equiv (\theta_1, \ldots, \theta_n)$. In particular, $T_i \sim G(\theta_i)$ for $i = 1, 2, \ldots, n$, that is $T_1 \sim PHRM(\theta_1)$, $T_2 \sim PHRM(\theta_2)$, ..., $T_n \sim PHRM(\theta_n)$. In this case, we compute order statistics for the asymmetric random sample. In particular, we are interested in the first asymmetric order statistic (minimum) which has the form

$$ f_1(t) = f(t; \Omega; \bar{\theta}) , \quad (11) $$

where $f(t; \Omega; \theta)$ is the density function of a PHRM and $\bar{\theta} = \sum_{k=1}^{n} \theta_k$. Notice that in the symmetric case when $\theta_i = \theta$, equation 11 becomes simpler. For the symmetric case, the distribution of the minimum is the same as that of a PHRM with parameter $n\theta$.

In our baseline case, as shown above in subsection 4.3, we assume that the value function is linear over time and, thus, the distribution of sale times follows a Generalized Pareto Distribution (GPD), where $\Omega \equiv (\alpha, \beta)$. A PHRM with GPD is characterized by

$$ f(t; \alpha, \beta; \theta) = \frac{\theta}{\alpha} \left(1 + \beta t / \alpha\right)^{(\theta-\beta)/\beta} \quad (12) $$

and a cumulative distribution function

$$ 1 - F(t; \alpha, \beta; \theta) = \left(1 + \beta t / \alpha\right)^{\theta/\beta} \quad (13) $$

The hazard function is then

$$ h(t; \alpha, \beta; \theta) = \frac{f(t; \alpha, \beta; \theta)}{1 - F(t; \alpha, \beta; \theta)} = \frac{\theta}{\alpha} \frac{\left(1 + \beta t / \alpha\right)^{(\theta-\beta)/\beta}}{(1 + \beta t / \alpha)^{\theta/\beta}} = \theta \frac{1}{\alpha + \beta \cdot t} \quad (14) $$
We can then characterize equation 11 in the case where the source distribution follows a GPD as

\[ f_1(t; \alpha, \beta; \theta) = \frac{\bar{\theta}}{\alpha} (1 + \beta t/\alpha)^{(\theta-\beta)/\beta} \]  

(15)

A PHRM is empirically characterized by a separability assumption, \textit{i.e.}, we can decompose the hazard rate into two independent components: a baseline hazard rate that depends on time but is shared across individuals and an idiosyncratic component that does not change over time. Therefore, we write the empirical hazard function as

\[ h(t, x) = h_0(t) \cdot \theta(X_i, \beta) \]  

(16)

where \( h_0(t) \) is the baseline hazard rate and \( \theta(X_i, \beta) \) is the idiosyncratic component. The vector \( X_i \) should not change over time. However, in our case each observation is a particular stage game that begins when one farmer sells and ends when the next farmer sells. Therefore, we can include variables in \( X_i \) that change over time as long as they do not change during the stage game, \textit{i.e.}, we can include time variable state variables such as percentage of farmers in a ditch that have already sold, or the fraction of water rights remaining in by ditch.

5.2 First Step

In the first step of the estimation, we recover a \( \theta \) for each farmer. We allow farmers to be heterogeneous on their “shape” parameter. To do so, we treat each ditch as an independent game and thus independently estimate a vector of shape parameters for each game. We have thirteen ditches with at least six sales by farmers in that ditch. For each ditch, we order farmers as a function of their selling time and calculate the number of days between farmers’ sales.

Using only sale times, we calculate the probability that a given farmer sells in \( x \) days when there are \( n \) remaining farmers in a game. In such a game, each farmer’s strategy is to sell at each point in time using an instantaneous probability \( \eta^n(t) \). However, we do not observe all sales, only the lowest among all realizations—that is the minimum or the first order statistic.\(^{13}\) Therefore, the distribution of sale times would follow the distribution of sale times in the first order statistic. We can also define \( \Psi^n(x; \theta^n) \), with density \( \psi^n(x; \theta^n) \), as the distribution of the first order statistic (minimum) or \( n \) draws from \( \Psi^n(t; \theta^n) \). In

\(^{13}\)Remember that a War of Attrition can be modeled as a particular all-pay auction, where all \( n \) farmers pay the lowest bid, and the \( n-1 \) farmers with the highest bids get the prize—that is, they get to stay in the game. In that analogy, the waiting time for the War of Attrition game is equivalent to the bid in the all-pay auction.
other words, each farmer draws a sale time $t_i$ from an $EG(\theta^n)$ but we only observe the sale of the farmer with the lowest realization.

To estimate an asymmetric game with $n$ farmers, we use the following likelihood function

$$l(T^n_i, \theta^n) = \prod_{i=1}^n \psi^n(x^n_i; \theta^n) = \prod_{i=1}^n \left\{ f_{1:n}(x^n_i; \theta^n) \right\}$$

(17)

where $x_i$ is the realization of number of days until the sale since the beginning of the game in a game with $n$ remaining farmers and $f_{1:n}(x^n_i; \theta^n)$ is the density of the minimum as defined in equation 10. We estimate our vector of parameters running a Maximum Likelihood Estimator (MLE) for each game.

Given the functional forms derived from the theory, we build continuation values using our estimated hazard rates.

In particular, the theoretical results imply that $h(x^n, \theta^n) = \eta^n(x^n) = \frac{1}{(n-1)\Delta^n(x^n)}$ for all games. Therefore, since $\Delta^n(x^n) = \frac{1}{(n-1)h(x^n, \theta^n)}$ with the estimated value $\hat{\theta}^n$ we can compute the estimated hazard function $h(x, \hat{\theta}^n)$ and thus recover the distribution of valuations for each game $\Delta^n(x)$, which is equal to

$$\Delta^n(x) = \frac{1}{(n-1)h(x, \hat{\theta}^n)}$$

The advantage of using a PHRM is that we can compute the probability of the minimum for each game. Thus, the likelihood estimation is computationally feasible.

5.3 Second Step

From the previous section we know that in a WoA game, the distribution of sale times is determined by the value of selling. Moreover, in equilibrium, the hazard function of the sale distribution for a particular game with a set of $n$ farmers is identical to the difference in continuation values $\Delta_i(t)$, where

$$\Delta_i(t) \equiv \sum_{j \neq i} p_j(t)W^j_i(t) - V_i(t) = W_i(t) - V_i(t)$$

(18)

where $p_j(t)$ is the instantaneous probability that farmer $j$ sells at time $t$, $W^j_i(t)$ is the continuation value of a game where farmer $j$ has just sold and $V_i(t)$ is the value that farmer $i$ gets from selling. Since valuations must be positive, we define $V_i(t) = ln(P_i(t))$. This way
prices are the exponential of the intrinsic valuation. Notice that while $W_j(t)$ and $V_i(t)$ are fundamentals of the model, $p_j$ is an equilibrium outcome determined for other farmers using $\Delta_j(t)$. Notice that as we observe several sale times for a given configuration of the game, we have already identified the function $\Delta_i(t)$ non-parametrically. We also observe several realizations of $V_i(t)$ which are the natural log of the price at which the farmers sold their plot. Therefore we can independently identify the functions $W_i(t)$ and $V_i(t)$. Finally, since we have information regarding locations and characteristics of farmers’ plots, we will be able to identify and estimate different functions $W_j^i(t)$ for different pairs of farmers. We can thus re-write the equation as

$$V_i(t) = \sum_{j \neq i} p_j(t) W_j^i(t) - \Delta_i(t)$$

(19)

Here we can observe prices, and since we already have an estimate for the probability of any farmer selling, their continuation values as well. We need to make one further assumption in order to identify potential externalities.

Given that we need to estimate a vast number of parameters but can only observe some sales since each game is only played once, we need to assume a parametric function for the counterfactual estimation values. We assume that we can decompose this value as the linear combination of relative observable characteristics between $i$ and $j$.

$$W_j^i = \beta_1 X_{ij}^1(x_i) + \beta_2 X_{ij}^2(x_i) + .. + \beta_K X_{ij}^K(x_i) = \beta_{1\times K} X_{ij}^{1\times K}$$

Where we have $K$ hedonic characteristics and $< X_{ij}^1 = g(X_i^1, X_j^1, x_i), X_{ij}^K = g(X_i^K, X_j^K, x_i) >$ is some function of time-varying attributes $J$, or the attribute in time $x_i$ for $i$ and $j$. We could also use a more flexible specification. We are interested in recovering $\beta_{1\times K} \equiv < \beta_1, ..., \beta_K >$. In Appendix A.1 we show that we can write the above system as

$$\beta_{1\times K} \cdot \left[ \hat{p}_1^2 \left( x_2 : \hat{\theta} \right) X_2^1(x_2), ..., \hat{p}_2^2 \left( x_2 : \hat{\theta} \right) X_2^K(x_2) \right]_{K\times 1} - \Delta_{N\times 1} = V_{N\times 1}\left[ \sum_{j<N} \hat{p}_j^N \left( x_N : \hat{\theta} \right) X_{Nj}^1(x_N), ..., \sum_{j<N} \hat{p}_j^N \left( x_N : \hat{\theta} \right) X_{Nj}^K(x_N) \right]_{K\times 1}$$

We define
\[
\hat{M}_{K \times N} = \begin{bmatrix}
p^2_1 \left( x_2 : \hat{\theta} \right) X^1_{2j}(x_2), & \ldots, & p^2_1 \left( x_2 : \hat{\theta} \right) X^K_{2j}(x_2)
\end{bmatrix}_{K \times 1}
\]

\[
\beta_{1 \times K} \cdot \left[ \sum_{j < N} \hat{p}^N_j \left( x_N : \hat{\theta} \right) X^1_{Nj}(x_N), \ldots, \sum_{j < N} \hat{p}^N_j \left( x_N : \hat{\theta} \right) X^K_{Nj}(x_N) \right]_{K \times 1}
\]

\[M_{K \times N}\] is a matrix with as many columns as hedonic characteristics and as many rows as farmers in a ditch. This matrix represents the weighted average of relative hedonic characteristics, with weights calculated by probability. Since we can compute the probabilities and we observe relative characteristics, the crucial step is estimating the matrix. Then we have the following linear system

\[V_{N \times 1} = \beta_{1 \times K} \hat{M}_{K \times N} - \Delta_{N \times 1}\]

Hence from this expression, we recover the fundamental structural parameters of the game \(\hat{\beta}\) by running a simple linear regression of the form

\[V_{N \times 1} = \beta_{1 \times K} \hat{M}_{K \times N} - \Delta_{N \times 1} + \epsilon\]

Notice that the above expression is very flexible. We can estimate the same regression with a random coefficients model, which allows the hedonic parameters to be ditch dependent.

Table 7 reports the estimated value of the linear specification that allows us to recover the game’s structural parameters. Crucially in the hedonic model, there are many degrees of freedom regarding the econometric specification of the linear regression. To establish inclusion and exclusion criteria, we use a machine learning method (Random Forest, RF). In the RF we attempt to predict prices as a function of all possible observable variables, including plot characteristics and the externality variables defined above. We then evaluate variables’ explanatory power and include only those with high explanatory power in the final hedonic specification.

In Table 7, we show results from both an OLS regression and a random coefficients model with betas that vary by ditch. “Days” counts days since first sale and captures any time variant trend. “Min distance” measures distance to the river. Assuming an asymmetric probability distribution, “value asymmetric” is the idiosyncratic component of the continuation value of a farmer who does not sell. “Crop_p” represents each farmer’s area under cultivation as a percentage of the total area cultivated in a given ditch. This calculation allows us to pool ditches and compare farmers across games. “Area acres_p” and
Table 7: Structural Estimates.

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<th>linear mixed-effects</th>
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<td>(182,223.700)</td>
<td>(121,374.900)</td>
<td></td>
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<tr>
<td>water_acre_p</td>
<td>209,889.000**</td>
<td>2,416.525</td>
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<tr>
<td></td>
<td>(87,075.660)</td>
<td>(57,286.500)</td>
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<tr>
<td>crops_p</td>
<td>−447,093.200***</td>
<td>−86,807.920</td>
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<tr>
<td></td>
<td>(166,911.600)</td>
<td>(116,811.900)</td>
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<tr>
<td>distance_other</td>
<td>−0.589**</td>
<td>−0.765</td>
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<td></td>
<td>(0.293)</td>
<td>(8.883)</td>
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<tr>
<td>days_since_other</td>
<td>27.521***</td>
<td>5.147</td>
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<tr>
<td></td>
<td>(6.895)</td>
<td>(888.192)</td>
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<tr>
<td>acres_other</td>
<td>−428,665.800***</td>
<td>−67,330.990</td>
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<tr>
<td></td>
<td>(105,160.400)</td>
<td>(75,834.610)</td>
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</tr>
<tr>
<td>Constant</td>
<td>246,543.300***</td>
<td>7,777.345</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(59,837.140)</td>
<td>(39,745.890)</td>
<td></td>
</tr>
</tbody>
</table>

Observations | 328 | 328  |
R²            | 0.385 | 0.367  |
Adjusted R²   | 0.367 |      |
Log Likelihood |      | −3,851.471 |
Akaike Inf. Crit. |      | 7,766.942 |
Bayesian Inf. Crit. |      | 7,888.318 |
Residual Std. Error | 63,071.120 (df = 318) | |
F Statistic   | 22.075*** (df = 9; 318) |

Note: *p<0.1; **p<0.05; ***p<0.01
“water acres _p” are respectively percentage of total acres and percentage of total water acres per ditch. We find that distance to the river plays a crucial role in the price farmers received. The closer to the river their land, the higher the price farmers could charge. On the other hand, the more acres of land and water farmers had, the more they charged for their property.

For each player, variables termed “others” are the weighted average using the MLE probabilities of the characteristics of other farmers who share an irrigation ditch. These variables aim to capture externalities that other farmers imposed on sale price in each game. The closer a farmer was to another potential seller, the higher the externalities they imposed on sale prices by selling property. Farmers with more land also tended to impose larger price externalities on those farmers who did not sell.

6 Counterfactuals

Once we estimate the structural model above, for any potential specification of the model, we can compute the price for all farmers using the following expression for expected prices

\[ P_{N \times 1} = e^{\hat{\beta}_{1 \times K} K_{K \times N} - \Delta_{N \times 1}} \quad (20) \]

Notice that in equation 20, regardless of the estimated parameters, prices are bounded below by zero. Therefore, we can estimate the distribution of prices the city would have paid in the absence of externalities. In a counterfactual exercise, we compute expected prices in the presence of externalities in relationship to expected prices when the coefficients associated with sales by other farmers in the ditch are equal to zero. We find that on average, the city paid 7.6 percent less because of externalities. On the other hand, the very presence of externalities compressed prices, increasing their standard deviation by 7.2 percent.

We then compute the difference between the price a farmer received with and without externalities. We call this difference “gains from externalities,” and plot the difference for each farmer against farmers’ characteristics in Figure 6 below. In Figure 6.A we show gains from externalities on the y-axis versus the amount of cultivated land each farmer had n the x-axis. We see that there is a non-monotonic relationship between gains form externalities and acres of cultivated land. Farmers who cultivated more land were exposed to higher financial loses given externalities in the bargaining process. Figure 6.B shows a similar scatter plot with gains from externalities and total acres, and a very similar non-
monotonic relationship between the two variables. This suggests that whether or not a farmer cultivated more land played little role in the externalities received. Measuring in water acres farmers, Figure 6.C shows similar results. That these three relationships look similar should come at no surprise as the three variables are positively correlated. Finally, Figure 6.D shows a scatter plot with gains from externalities versus distance to the river. Farmers who gained the most in terms of sale price, from externalities were closest to the river. We see a significant negative relationship up to a about one kilometer, where this relationship flattens out.

7 Conclusions

In this article, we explore the most famous and controversial water transfer, from the Owens Valley to Los Angeles, in U.S. history. Ever since, the city has been accused of checkerboarding, i.e., targeting particular farmers to increase other farmers’ willingness to sell, and to decrease their price. In economic terms, the accusation implies the existence of spatial externalities farmers whose plots were contiguous or on the same irrigation ditch. This raises several questions. Were there spatial externalities in the Owens Valley? If so,
Figure 6: Gains from externalities.

A. Cultivated Land.  

B. Acres.  

C. Water Acres.  

D. Distance to the River.  

Notes: The solid line follows a linear fit whereas the dotted line specifies a non-parametric estimate of the mean or median function of the vertical axis variable given the horizontal axis variable and, optionally, a non-parametric estimate of the conditional variance. The mean function and the variance functions are drawn for ungrouped data.  
how important were those externalities to prices the city paid? And, did the city, knowing of these externalities, act strategically to target key farmers?

To address these questions, we collect new data including the price, date, and location of each land sale. Our key contribution to the literature is to precisely locate each farmer’s plot and determine its exact date of sale. This information is essential to estimate spatial externalities and, therefore, test the checkerboarding accusation. Moreover, preliminary evidence reveals two relevant empirical facts: the hazard rate of sale time varied over time and farmers’ sales the selling behavior of other farmers with land on the same irrigation ditch. From these the former means that we need to model farmer’s behavioral dynamics. The latter means that we need to model externalities among farmers. We present a new econometric model that accounts for both facts and produces a unique equilibrium consistent with the data. The model falls within the class of proportional hazard rate models (PHRM) but is more general data generating process than the Cox model. In particular, whereas Cox requires the baseline hazard rate to be common to all farmers, our model allows the hazard rate to “reset” every time a farmer exits. The Cox model is thus a particular case of our model when the hazard rate does not reset. Moreover, when we assume that value functions are linear concerning time, we show that the distribution of exit times follows a Generalized Pareto distribution.

In addition to the new econometric model, we present an original estimation method. The estimator proceeds in two stages which simplifies and quickens the estimation, making the estimator transparent and very flexible in terms of variables and specifications. In the first stage, we estimate pseudo-parameters that are consistent with behavior observed in the data. These pseudo-parameters are consistent with any specification of the relationship between farmers’ individual characteristics and externalities, and are only a function of exit times. Therefore, the pseudo-parameters only need to be estimated once, and it is easy to do so. due to a key result derived from the closed-form solution of the asymmetric order statistic in PHRM models. In the second stage, we use the estimated pseudo-parameters and estimate the relationship between farmers’ and neighbors’ characteristics and prices. The specification in the second stage is unrestricted and produces easy-to-interpret and transparent results. The intuition behind these results is more general than the case studied here and could be applied to other settings including environments with information externalities or where PHRM are suitable.

Our results show there were critical spatial externalities, but that the city generally based offers on the fundamental value of land, not farmers’ potential externalities. The city, however, targeted particular farmers in 1922, which did create significant externalities and effectively broke the coordination problem by disrupting the farmers’ sale association.
In this sense, the city did not systematically checkerboard farmers because after buying out key farmers on central irrigation ditches, the threat of farmers coordinating threat was effectively over. We obtain this important insight from the combination of detailed historical research—by identifying historians’ claims about the past and looking closely at historical data—and rigorous analytical economic analysis—by collecting comprehensive data and developing new models and estimation techniques. We think these dual research strategies would be useful in many other historical settings.
References


Davis, Mike, City of Quartz: Excavating the Future in Los Angeles, Verso, 1990.


A Structural Estimation

A.1 Derivation of Linear Regression for the Structural Model

We can write the system of equations that we need as

\[
\sum_{j<2} \hat{p}_j^2 (x_2 : \hat{\theta}) W_j^2(x_2) - \Delta^2_i(t) = V^2(x_2)
\]

\[
\sum_{j<3} \hat{p}_j^3 (x_3 : \hat{\theta}) W_j^3(x_3) - \Delta^3_i(t) = V^3(x_3)
\]

\[
\sum_{j<N} \hat{p}_j^N (x_N : \hat{\theta}) W_j^N(x_N) - \Delta^N_i(t) = V^N(x_N)
\]

Where \(N\) is the maximum number of farmers in a given ditch.

Note that this system can be re-written as

\[
\sum_{j<2} \hat{p}_j^2 (x_2 : \hat{\theta}) \beta_{1xK}X^{2j}_{Kx1} - \Delta^2_i(t) = V^2(x_2)
\]

\[
\sum_{j<3} \hat{p}_j^3 (x_3 : \hat{\theta}) \beta_{1xK}X^{3j}_{Kx1} - \Delta^3_i(t) = V^3(x_3)
\]

\[
\sum_{j<N} \hat{p}_j^n (x_N : \hat{\theta}) \beta_{1xK}X^{nj}_{Kx1} - \Delta^N_i(t) = V^N(x_N)
\]

Notice that we can rearrange terms here. Rearranging we get

\[
\sum_{j<2} \hat{p}_j^2 (x_2 : \hat{\theta}) \beta_{1xK}X^{2j}_{Kx1} = \hat{p}_1^2 (x_2 : \hat{\theta}) [\beta_1X^{1j}_{2j}(x_2) + \beta_2X^{2j}_{2j}(x_2) + \ldots + \beta_KX^{Kj}_{2j}(x_2)]
\]

\[
= \beta_{1xK} \cdot \left[ \hat{p}_1^2 (x_2 : \hat{\theta}) X^{1j}_{2j}(x_2), \ldots, \hat{p}_1^2 (x_2 : \hat{\theta}) X^{Kj}_{2j}(x_2) \right]_{Kx1}
\]

\[
\sum_{j<3} \hat{p}_j^3 (x_3 : \hat{\theta}) \beta_{1xK}X^{3j}_{Kx1} = \hat{p}_1^3 (x_3 : \hat{\theta}) [\beta_1X^{1j}_{3j}(x_3) + \beta_2X^{2j}_{3j}(x_3) + \ldots + \beta_KX^{Kj}_{3j}(x_3)] + \hat{p}_2^3 (x_3 : \hat{\theta}) [\beta_1X^{1j}_{3j}(x_3) + \beta_2X^{2j}_{3j}(x_3) + \ldots + \beta_KX^{Kj}_{3j}(x_3)]
\]

\[
= \beta_{1xK} \cdot \left[ \sum_{j<3} \hat{p}_j^3 X^{1j}_{3j}(x_3), \ldots, \sum_{j<3} \hat{p}_j^3 X^{Kj}_{3j}(x_3) \right]_{Kx1}
\]

In general we will have that
\[
\sum_{j < N} \hat{p}_j^N (x_N : \hat{\theta}) \beta_{1 \times K} X_{Nj}^{Nj} = \beta_{1 \times K} \cdot \left[ \sum_{j < N} \hat{p}_j^N X_{Nj}^1 (x_N) , ..., \sum_{j < N} \hat{p}_j^N X_{Nj}^K (x_N) \right]_{K \times 1}
\]

Therefore we can rewrite the system as

\[
\beta_{1 \times K} \cdot \left[ \hat{p}_1^2 (x_2 : \hat{\theta}) X_{2j}^1 (x_2) , ..., \hat{p}_1^2 (x_2 : \hat{\theta}) X_{2j}^K (x_2) \right]_{K \times 1} - \Delta_{N \times 1} = V_{N \times 1}
\]

**B Identification and Externalities**

In this section, we discuss in details the identification in symmetric and asymmetric games, as well as in games with externalities. We show that games without externalities are always identified, whereas games with externalities are only identified with restrictions in the parameter space.

**B.1 Symmetric Game**

For simplicity and easy of exposition we will first layout out how to estimate the symmetric game first. The results will also help us as a benchmark to compare with the results with an asymmetric and a game with externalities. Let consider a game with \( n \) identical players without externalities. In the first stage of the game, the players face the following trade-off

\[
\sum_{j \neq i} \eta_j^n (t) dt \prod_{l \neq i, l \neq j} (1 - p_l) \Delta^n (t) = \prod_{l \neq i} (1 - p_l) dt
\]

Therefore, the solution is given by

\[
\sum_{j \neq i} \eta_j^n (t) \Delta^n (t) = 1
\]

Since \( \Delta^n (t) \equiv W^{n-1} (t) - V^n (t) \) is the same for all players, we have \( \eta_j^n (t) = \eta^n (t) \). Moreover, the equilibrium here is determined by
\[
\sum_{j \neq i} \eta_j^n(t) \Delta^n(t) = (n-1) \eta^n(t) \Delta^n(t) = 1
\]

Thus,

\[
\eta^n(t) = \frac{1}{(n-1) \Delta^n(t)}
\]  \hspace{1cm} (21)

\[
\Delta^n(t) = \frac{1}{(n-1) \eta^n(t)}
\]  \hspace{1cm} (22)

Where equation 21 defines the equilibrium strategies as a function of the fundamentals of the game, and equation 22 defines the parameters to be estimated as a function of the observed behavior. Notice that although we could estimate \(\Delta^n(t)\) for each game with \(n\) players, \(\Delta^n(t)\) is not a function of the fundamentals of the game only, since it contains \(W^{n-1}(t)\) which is the continuation value of a symmetric game with \(n-1\) players. However, in a game with \(n = 2\) players, since the game ends when one of the players exit, the value of \(W^{n-1}(t)\) is just the value of getting the last “prize” that is the price the city pays to the last farmer. In other words, \(W^1(t) = V^1(t)\). Therefore, in the last game we can recover \(\Delta^2(t) \equiv V^1(t) - V^2(t)\), which is a function of the fundamentals of the game. Once we estimate this, we can compute the expected value of playing a game with two players, and put this value into the continuation value of a game with three players and so on. Notice that without information on the prices the city paid to the farmers, we cannot identify \(V^1(t)\) and \(V^2(t)\) independently. We could identify \(V^3(t), V^4(t)\) and so on, but not the first two because after the \((n-1)^{th}\) player exits, the \(n^{th}\) exits immediately after.

### B.1.1 Example: Symmetric game with three players

In this example there are only three players and the game is fully characterized by the three parameters \(V^1, V^2, V^3\) and \(v(t)\). Moreover, because of symmetry, the games with two players are all identical. Thus, for each game, we will have two exit observations: one corresponding to a symmetric game with two players and another one corresponding to a symmetric game with three players. For this case, equation 22 corresponds to

\[
\Delta^3 \equiv (V^2 - V^3) = \frac{1}{2 \eta^3} \quad \text{and} \quad \Delta^2 \equiv (V^1 - V^2) = \frac{1}{\eta^2}
\]

That is, in a symmetric game, players are identical and we only have one hazard rate of exit in each game. Thus, with two games, we can recover one parameter from each of the
two games. If we have many games in the data, but only have information on exit times, we can recover \( \Delta^3 \equiv V^2 - V^3 \) and \( \Delta^2 \equiv V^2 - V^3 \), and the shape of \( v(t) \) given parametric assumptions. Because the game is symmetric, there is no need to discuss other variables or additional data to estimate parameters.

B.2 Asymmetric Game

Although the symmetric game is easy to estimate and it only requires data on exit times, most settings would require the game to be asymmetric. We now consider a game with \( n \) asymmetric players without externalities. In the first stage of the game, the players face the following trade off

\[
\sum_{j \neq i} \eta^a_n(t) dt \prod_{l \neq i, l \neq j} (1 - p_l) \Delta^a_i(t) = \prod_{l \neq i} (1 - p_l) dt
\]

Therefore, the solution is given by

\[
\sum_{j \neq i} \eta^a_n(t) \Delta^a_i(t) = 1
\]

Notice that now \( \eta^a_n(t) \) is not the same across players. Moreover, with the assumption that \( \Delta^a_i(t) = \Delta^a_j \cdot v(t) \), we can solve the system and get

\[
\eta^a_n(t) = \frac{1}{v(t)} \left[ -\frac{1}{\Delta^a_i \left( \frac{n - 2}{n - 1} \right)} + \frac{1}{n - 1} \sum_{j \neq i} \frac{1}{\Delta^a_j} \right]
\]

(23)

\[
\Delta^a_i = \frac{1}{v(t) \left[ \sum_{j \neq i} \eta^a_j(t) \right]}
\]

(24)

Where equation 23 defines the equilibrium strategies as a function of the fundamentals of the game, and equation 24 defines the parameters to be estimated as a function of the observed behavior. Notice that the symmetric case is a particular case of the asymmetric case because when \( \Delta^a_i = \Delta^a_j \) for all farmers, then equation 23 above simplifies to equation 21. Also, it is worth noticing that whereas the behavior of each player depends on the valuations of all players in a non-linear way, as shown in equation 23, to recover the valuation of a given player, we just need to add up the instantaneous probability of exiting of all the other players, as shown in equation 24. Moreover, because the shape of \( \Delta^a_j(t) \) is the inverse of the shape of \( \eta^a_j(t) \), we can define \( \eta^a_j(t) \equiv \eta^a_j / v(t) \), and get
\[
\Delta_i^n = \frac{1}{\sum_{j \neq i} \eta_j^n}
\]  

(25)

Although we could estimate \(\Delta_i^n(t)\) for each farmer for each game with \(n\) players, \(\Delta_i^n(t)\) is not a function of the fundamentals of the game only, since it contains \(W_i^{n-1}(t)\) which is the continuation value of an asymmetric game with \(n - 1\) players. However, following the same argument as before, in a game without externalities we have that \(W_i^1(t) = V_i^1(t)\). Therefore, we could identify all \(V_i^n(t)\) except the first two because after the \((n - 1)^{th}\) player exits, the \(n^{th}\) exits immediately after.

B.2.1 Example: Asymmetric game with three players

In this example there are only three asymmetric players, and the game is characterized by nine parameters: \(V_i^3 < V_i^2 < V_i^1\), for \(i = 1, 2, 3\). Where \(V_i^l\) is the value that player \(i\) gets from getting the \(l^{th}\) prize. Because of the asymmetry, there are three different games with two players. Equation 24 corresponds to three equations when there are three players

\[
\Delta_1^3 \equiv (V_1^2 - V_1^3) = \frac{1}{\eta_2 + \eta_3} \quad \text{and} \quad \Delta_2^3 = \frac{1}{\eta_1 + \eta_3} \equiv (V_2^2 - V_2^3) \quad \text{and} \quad \Delta_3^3 = \frac{1}{\eta_2 + \eta_1} \equiv (V_3^2 - V_3^3);
\]

two equations when player one exits first

\[
\Delta_{2,1}^2 \equiv (V_2^1 - V_2^2) = \frac{1}{\eta_3} \quad \text{and} \quad \Delta_{3,1}^2 \equiv (V_3^1 - V_3^2) = \frac{1}{\eta_2};
\]

two equations when player two exits first

\[
\Delta_{1,2}^1 \equiv (V_1^1 - V_1^2) = \frac{1}{\eta_3} \quad \text{and} \quad \Delta_{3,2}^1 \equiv (V_3^1 - V_3^2) = \frac{1}{\eta_1};
\]

and two equations when player three exits first

\[
\Delta_{1,3}^2 \equiv (V_1^1 - V_1^2) = \frac{1}{\eta_3} \quad \text{and} \quad \Delta_{2,3}^1 \equiv (V_2^1 - V_2^2) = \frac{1}{\eta_1};
\]

Where \(\eta_i^3\) is the hazard rate of player \(i\) when there are three players in the game and \(\eta_i^{2,j}\) is the hazard rate of player \(i\) when there are two players in the game and player \(j\) has already exited. Two important things to remark here. First, looking at the equations for the game with three players, is clear that we cannot recover \(V_i^2\) from \(V_i^3\) for any of the players, without additional information. Thus we need a normalization, typically we normalize
\( V_1^3 = V_2^3 = V_3^3 = 0 \). Second, looking at the six equations for the three games with two players, we can see that there are only three independent equations. For example, we have that \( \Delta_{2,1}^2 = (V_1^1 - V_2^1) = \Delta_{2,3}^2 \). This is because, in a game without externalities the differences in valuations between staying and exiting is independent of the identities of the players who already exited. In terms of identification, this implies that \( \eta_{3,1}^2 = \eta_{1,3}^2 \). That is, the hazard rate of player 3, when playing against player 2 (because player 1 exited), is the same as the hazard rate of player 1, when playing against player 2 (because player 3 exited). This is important because it means that an asymmetric game without externalities is over-identified, but also that we can compute these hazard rates empirically and use them as a test for externalities.

In contrast to the symmetric game, when players are asymmetric, we can recover a hazard rate from each player in each game. That means we can recover three hazard rates from the game with three players and two hazard rates from each of the three asymmetric games. This is a total of nine hazard rates. However, as mentioned above, three of the hazard rates in the two-player games as redundant, so we end up with only six independent equations, and we need to normalize three parameters, one for each player. If we normalize \( V_1^3 = V_2^3 = V_3^3 = 0 \), then we can identify \( V_i^2 < V_i^1 \), for \( i = 1, 2, 3 \).

### B.3 Game with externalities

We now consider a game with \( n \) players with externalities. In a given stage of the game, when there are \( n \) players in the game, the players face the following trade-off

\[
\sum_{j \neq i} \eta_{ij}^n(t) dt \prod_{l \neq i, l \neq j} (1 - p_l) \Delta_{n,j,i}^n(t) = \prod_{l \neq i} (1 - p_l) dt
\]

Therefore, the solution is given by

\[
\sum_{j \neq i} \eta_{ij}^n(t) \Delta_{n,j,i}^n(t) = 1
\]

Notice that now \( \eta_{ij}^n(t) \) is not the same across players. Moreover, because of the externalities, the continuation value for player \( i \) after player \( j \) exits, depends on the identity of player \( j \). Notice that \( \Delta_{n,j,i}^n(t) \) is the difference between staying and exiting for player \( i \), when staying means that player \( j \) would quit, in a game with \( n \) players at time \( t \). With the assumption that \( \Delta_{n,j,i}^n(t) = \Delta_{n,j}^n \cdot v(t) \), we can see that, as in the asymmetric case, the shape of \( \eta_{ij}^n(t) \) would be equal to the inverse of \( v(t) \). However, in general we might not have a
closed-form solution for \( \eta_i^n \), but we know it is the solution to a linear system of equations. We can get

\[
\sum_{j \neq i} \eta_i^n(t) \Delta_i^{n,j}(t) = 1
\]  

(26)

\[
\Delta_i^n = \frac{1}{v(t) \left[ \sum_{j \neq i} \eta_i^n(t) \right]}
\]  

(27)

Where equation 26 defines the equilibrium strategies as a function of the fundamentals of the game (implicitly), and equation 27 defines the parameters to be estimated as a function of the observed behavior. It is worth noticing that whereas the behavior of each player depends on the valuations of all players in a non-linear way, as shown in equation 26, to recover the valuation of a given player, we just need to add up the instantaneous probability of exiting of all the other players, as shown in equation 27. Moreover, because the shape of \( \Delta_i^{n,j}(t) \) is the inverse of the shape of \( \eta_i^n(t) \) we can define \( \eta_i^n(t) \equiv \eta_i^n / v(t) \), and get

\[
\Delta_i^n \equiv \sum_j \Delta_i^{n,j} = \frac{1}{\sum_{j \neq i} \eta_i^n}
\]  

(28)

In general, as we illustrate with the example below we cannot estimate \( \Delta_i^{n,j}(t) \) for each farmer for each game with \( n \) players, because there are more elements \( \Delta_i^{n,j}(t) \) than observations in the data. \( \Delta_i^{n,j}(t) \) is not a function of the fundamentals of the game only, since it contains \( W_i^{n-1,j}(t) \) which is the continuation value for player \( i \) of a game with externalities with \( n - 1 \) players, when player \( j \) exited first. In this case, in a game without externalities, we cannot identify all the parameters. Nonetheless, in practice, externalities will have a particular form, which means that there are restrictions on the values of \( \Delta_i^{n,j} \), with enough restrictions, we could identify all the parameters in the game.

### B.3.1 Example: Game with externalities with three players

In this example there are only three players, and the game is characterized by eighteen parameters, six for each player: \( V_i^{123}, V_i^{132}, V_i^{213}, V_i^{231}, V_i^{312}, V_i^{321} \), for \( i = 1, 2, 3 \). Where \( V_i^{xyz} \) is the value that player \( i \) gets when the allocation of prizes is such that player \( x \) gets the first prize, player \( y \) gets the second prize and player \( z \) gets the third prize. In the case we are considering here. However, we can restrict the number of parameters by having some
restrictions on the vector of preferences for each player. Because of the asymmetry, there are three different games with two players.

Before we show the equations, notice that in the first game, with three players, no player has exited yet. However, in the second round, one player would have already exited and, because of the externalities, the continuation value of player $i$ of staying would depend on the identity of the player that exited. We can define $V^2_i$ as the expected value for player $i$ of playing a game with two players. Taking as given the strategies for the players, we can compute this “average” value. Conditional on player $i$ not exiting in the first round, she will face player $j$ with probability $\frac{\eta^3_j}{\eta^3_j + \eta^3_k}$ and face player $k$ with probability $\frac{\eta^3_k}{\eta^3_j + \eta^3_k}$. If player $k$ exits, then player $i$ faces player $j$ then her valuation would be $V^{kij}_i$, and if player $j$ exits, then player $i$ faces player $k$ and her valuation would be $V^{jik}_i$. Then, we can define

$$V^2_i \equiv \eta^3_k \frac{V^{kij}_i}{\eta^3_j + \eta^3_k} + \eta^3_j \frac{V^{jik}_i}{\eta^3_j + \eta^3_k}. \quad (29)$$

Using a similar argument, we can define $V^3_i$ as the expected value for player $i$ of exiting first in a game with three players as

$$V^3_i \equiv \left( \frac{\eta^{2,i}_j}{\eta^{2,i}_j + \eta^{2,i}_k} V^{ijk}_i + \frac{\eta^{2,i}_k}{\eta^{2,i}_j + \eta^{2,i}_k} V^{ikj}_i \right). \quad (30)$$

We have expressed the expected values as functions of the valuations and the hazard rates, but as we show below, all the hazard rates can be written as a function of the valuations, so the expected valuations can be written as a function of the valuations only. We can now write the corresponding equations: three equations when there are three players

$$\Delta^3_1 \equiv (V^2_1 - V^3_1) = \frac{1}{\eta^3_2 + \eta^3_3} \quad \text{and} \quad \Delta^3_2 = \frac{1}{\eta^3_j + \eta^3_k} \equiv (V^2_2 - V^3_2) \quad \text{and} \quad \Delta^3_3 = \frac{1}{\eta^3_2 + \eta^3_1} \equiv (V^2_3 - V^3_3);$$

two equations when player one exits first

$$\Delta^2_{2,1} \equiv (V^{132}_2 - V^{123}_2) = \frac{1}{\eta^2_3} \quad \text{and} \quad \Delta^2_{3,1} \equiv (V^{123}_3 - V^{132}_3) = \frac{1}{\eta^2_2};$$

two equations when player two exits first

$^{14}$Even in a game with externalities, when there are only two players left, there are only two possible valuations for each player. In other words, conditional on a particular exit history, externalities play no role when there are only two players left. In a game with externalities when player $k$ has exited, player $i$ would get a value of $V^{kij}_i$ if she exits, or $V^{jki}_i$ if player $j$ exits, with $V^{jki}_i > V^{kij}_i$. Playing this 2-player game has an expected value of $V^{kij}_i$ for player $i$. 

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\[ \Delta_{2,2}^1 \equiv (V_1^{231} - V_1^{213}) = \frac{1}{\eta_3^2} \quad \text{and} \quad \Delta_{3,2}^1 \equiv (V_3^{213} - V_3^{231}) = \frac{1}{\eta_1^2}; \]

and two equations when player three exits first

\[ \Delta_{2,3}^3 \equiv (V_3^{321} - V_3^{312}) = \frac{1}{\eta_2^3} \quad \text{and} \quad \Delta_{2,3}^2 \equiv (V_2^{312} - V_2^{321}) = \frac{1}{\eta_1^2}; \]

Where \( \eta_i^3 \) is the hazard rate of player \( i \) when there are three players in the game and \( \eta_i^{2,j} \) is the hazard rate of player \( i \) when there are two players in the game and player \( j \) has already exited. Two important things to remark here. First, looking at the equations for the game with three players, is clear that we cannot recover \( V_i^2 \) from \( V_i^3 \) for any of the players, without additional information. Thus we need a normalization. In the case without externalities, typically we normalize \( V_i^3 = V_i^2 = V_3^3 = 0 \). Notice that, because of the externalities, \( V_i^2 \) and \( V_i^3 \) are not fundamentals, but functions of the fundamentals, so one normalization for each player, would just reduce the parameters to be estimated by three from eighteen to fifteen. In many cases, however, we can assume that after one player exits, his valuation is not affected by the subsequent exit order. This assumption implies that \( V_i^{i,j,k} = V_i^{i,k,j} \) for each player, which reduces the number of parameters by three. The two normalizations mentioned above means that \( V_1^{123} = V_1^{132} = V_2^{231} = V_2^{213} = V_3^{312} = V_3^{321} = 0 \), that is, whenever any player exit first, her value is zero, regardless of what the other players do. Second, looking at the six equations for the three games with two players, we can see that now all six equations are independent, unlike in the case without externalities. For example, we have that \( \Delta_2^{2,1} = (V_2^{132} - V_2^{123}) \neq (V_2^{312} - V_2^{321}) = \Delta_2^{2,3} \). In other words, the value of playing a game with two players for player 2 is different depending on the identity of the other player.

Without any normalization we have nine independent equations and eighteen parameters, so we cannot identify all the parameters. With the two normalizations mentioned above, we can identify the three expected values \( V_i^2 \), \( V_2^2 \) and \( V_3^2 \). In fact, we can identify all three just with the first three equations for the game with three players. However, each expected values is a function of two of the eighteen valuations, which are not independently identified, without further restrictions. For example, with the normalizations we know that \( V_i^2 = \frac{1}{\eta_i^2 + \eta_i^3} \). However, we know that \( V_i^2 \equiv \frac{\eta_i^3}{\eta_i^2 + \eta_i^3} V_1^{312} + \frac{\eta_i^2}{\eta_i^2 + \eta_i^3} V_1^{213} \), and \( V_1^{312} \) and \( V_1^{213} \) are not identified in general, because we have nine equations and twelve remaining parameters to be identified.