Playing Checkers in Chinatown*

José-Antonio Espín-Sánchez and Santiago Truffa
Yale University Tulane University

VERY PRELIMINARY

Abstract

Between 1905-1935 the city of Los Angeles bought the water and land rights of the Owens Valley farmers and build and aqueduct to transfer the water. A map of the farmers plots sold in any given point in time would look like a checkerboard because the city is intentionally targeting specific farmers, or because the farmers are heterogeneous. We analyze the bargaining between the city and the farmers and the effects that farmers actions have on one another, and use that evidence to assess the checkerboarding claim. We estimate a dynamic structural model of the farmers decision on selling to the city. We found that there are large externalities when farmers sell, and those are larger when the selling farmer is closer to my plot, and when the selling farmer is closer to the river.

JEL Codes: N52, Q25, C73, L1

Keywords: Water Rights, War of Attrition

> "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)

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1 Introduction

Between 1905-1935 the city of Los Angeles bought the water and land rights of the Owens Valley farmers, build and aqueduct to transfer the water, and changed the history of the Valley and that of water transfers forever. The city grew form 100,000 people in 1900 to 1.2 million in 1930, becoming the largest city in California and the second largest in the U.S., a feat that would have been impossible without the water from the Owens river. Despite this achievement, the transfer has been immersed in controversy, exaggerated in the movie Chinatown, since its inception. The most onerous accusations made against the city was that they were checkerboarding their land purchases, i.e., that they were intentionally buying the land surrounding reluctant sellers, to drive down their demanded price.

In this article, we analyze the bargaining between the city and the farmers and the effects that farmers actions have on one another, and use that evidence to assess the checkerboarding claim. A map of the farmers plots sold in any given point in time would look like a checkerboard if the city is intentionally targeting specific farmers to physically isolate a reluctant seller. The problem is that the map would also look like a checkerboard if the city offers a fair price to each farmer, but some sell sooner than others. Moreover, even if the city is not checkerboarding, and isolated farmer would them have a lower reservation sale price, which created complicated dynamics due to the negative externalities generated by the sale of the farmer's neighbors.

There is extensive academic work on the Owens Valley controversy. The historical literature focuses on the characters of the story, and how their personal beliefs and personality traits affected the outcome (Hoffman, 1981; Kahrl, 1982; Davis, 1990). There has been some recent work in economics, most prominently by Gary Libecap (2005, 2007, 2009). He focuses on the prices that farmers received for their lands. He showed that although all farmers were paid more than their lands were worth, the surplus generated by the transfer was enormous and the city got most of it. He also shows, confirming Kahrl (1982) claims, that on average, farmers that sold later received a higher price.

We model the purchased made by the city as a war of attrition with externalities, which in practice resembles a Monopsonist strategy in the Coase conjecture (Coase, 1972). If the city could commit not to offer a larger price in the future, the city could extract all the surplus from the farmers. However, if the farmers could bargain as one, they might be able to extract most of the surplus from the transfer. The situation is complicated by the heterogeneity of the farmers of the negative externalities they exert on others, e.g., farmers whose plots are closer to the river, and where the canal that supply other farmers in the same ditch meet the river would produce a larger negative effect on the other farmers on the same ditch, than those farmers down the canal.

We use a novel and very detailed dataset, containing the exact date of each sale, the exact geo-location of each plot, as well as other characteristics: acreage, water rights, sale price, crops under cultivation. We use this new dataset to estimate the game that the between the city and the farmers, or more precisely the game between the farmers. We then to assess whether the city did indeed checkerboard their purchases. Finally, we use the estimated model to compute counterfactuals on what the prices paid would have been if the farmers had been able to bargain as one or bargain as one in each ditch.

2 Background and Data

2.1 Historical Background

By 1900 the officials of the city of LA realized that the water provided by the Los Angeles river would not be enough to meet the city's future water demand, given the projected population growth. Local leaders and business owners were interested in finding an external water supply to guarantee the city growth, and to compete with San Francisco for the main economic hub on California. The solution they devised was to bring the water from the Owens River, 300 miles north of LA, to the city. For this purpose they would need to build a large aqueduct, many dams and reservoirs and, more importantly, buy the water rights from their owners, the farmers at Owen's Valley.

The value of the water would be worth much more once it arrived to the city than at the valley. In order to keep these rents, the city officials devised a plan to get "enough" water rights from the farmers, before the project was made public. Because the water rights were tied to the land, the city had to buy the land in order to get the water rights. In 1904-1905, former mayor of LA Fred Eaton traveled through the valley buying options on the purchases of the land. At this stage, the intentions of the city were not public, and farmers sold their land at "normal" prices, that is, the value of the land plus the value of water, if the water was use for irrigation in the valley.

The Federal Reclamation Service was considering a reclamation project for the Owens Valley. The chief of the Reclamation Service in California was J.B. Lippincott, resident of Los Angeles and friend of Fred Eaton. The controversy begun here. Eaton was later accused of using his association with Lippincott to imply that the options would go to the reclamation project, not to the city. Although both men denied the accusations, many farmers claim that they would have ask for a higher price, had they known the land was not going to the Reclamation Service.

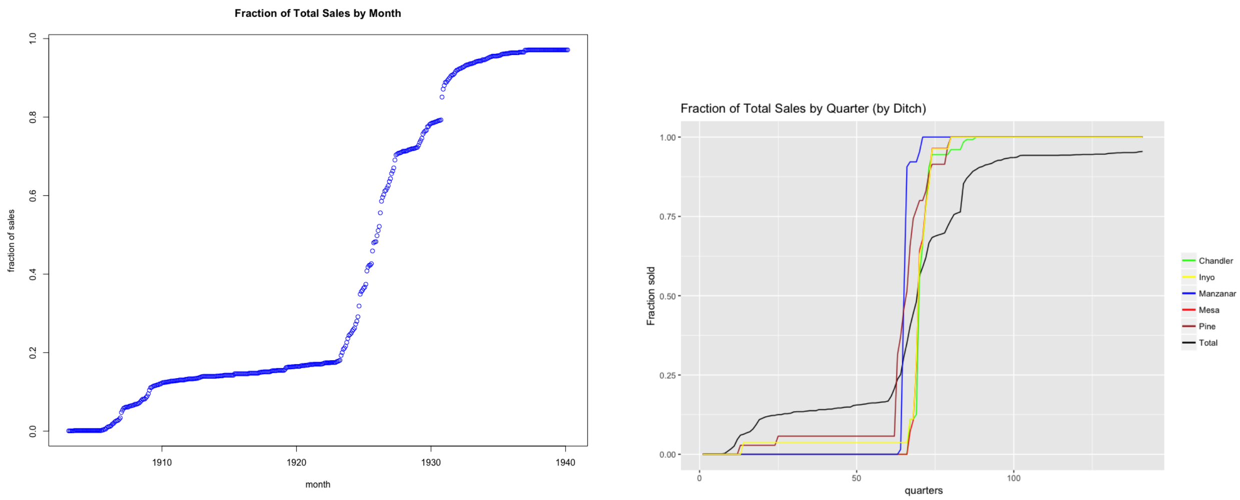
Fred Eaton returned to the city with all the options needed, and the plan was announced in the local newspapers. A \$1.5 million bond issue is approved by the voters for a wide margin, to finance a feasibility study and to purchase the land from Eaton's options. William Mulholland is then appointed Chief Engineer of the project and in 1907 another bond is put to the voters, for \$23 million, to finance the construction of the aqueduct. The aqueduct was completed in 1913. The policy in the city at the time prohibited to sell water for uses outside its limits. This meant that the nearby towns, which were also growing fast, had no option if the wanted to continue grow, but to apply for annexation to LA. The area of Los Angeles grew from 115 to 442 square miles in the following two decades, whereas the population increased from 533,535 in 1915 to more than 1,300,000 in 1930, and eventually LA became the second largest city in the US.

Notice that the options bought by Eaton in 1905 were just the beginning. The city's actual growth surpassed all projections and soon the city had to buy more land and water rights from the Owens Valley. After the project was announced, the farmers in the valley knew that the water would be used in LA, and demanded a higher price for their plots. The aqueduct is completed in 1913 and at the beginning, residual rights on water were enough to satisfy the City's demand. Due to the increase in population, a new bond is passed on 1922 for \$5 million. The drought in 1923 makes the city want to buy more water rights and in 1924 two more bonds passed for \$8 million each. Due to the controversy of the massive land purchase, the city is forced to buy the land and buildings on the towns within the valley, at pre Great Depression prices. In 1930 a new bond is issued for \$38.8 million, to acquire the town properties and to buy some land in the Mono Basin. Notice that, these purchases made the bulk of the total expenses although they contained no water rights. Subsequent bonds votes to buy more water rights happened in the following decades, and by 1934 the city own virtually all water rights in the valley, and over 90% of the land.

Within each bond, the same situation would arise. The city would have a fix amount of money to by land. The city would announce a committee that would evaluate the potential lands to be bought, and will make offers to each of the farmers individually. The farmers would then engage in a "war of attrition" among themselves. They knew that if they hold up, the city would offer them more money for their lands. However, when one a farmer sold their land this would create an externality on the other farmers. After a purchase the city would have less funds to continue buying up lands and will have less need for water. Moreover, for neighboring farmers, this externality would be larger. A farmer could get "isolated" from the river if the city buys all her neighbors. If the city buys most (usually two thirds) of the farms in a given ditch, it could then dissolve the ditch association and the remaining farmer would get no access to water. In this article we focus on this game between the farmers.

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.

These externalities were important are were recognized by all parties involved. Therefore, the farmers tried initially to negotiate as one, so that they would internalize the externalities and would get a better price. They form the Owens Valley Irrigation District (OVID). The city then bought out the main members of the OVID. The remaining farmers then created three smaller cartels, each with different levels of success. Each pool was a subset of the farmers owning water rights in the three major ditches. In 1927, following the collapse of the Watterson Brother's Bank, the Cashbought and the Watterson pool collapsed.

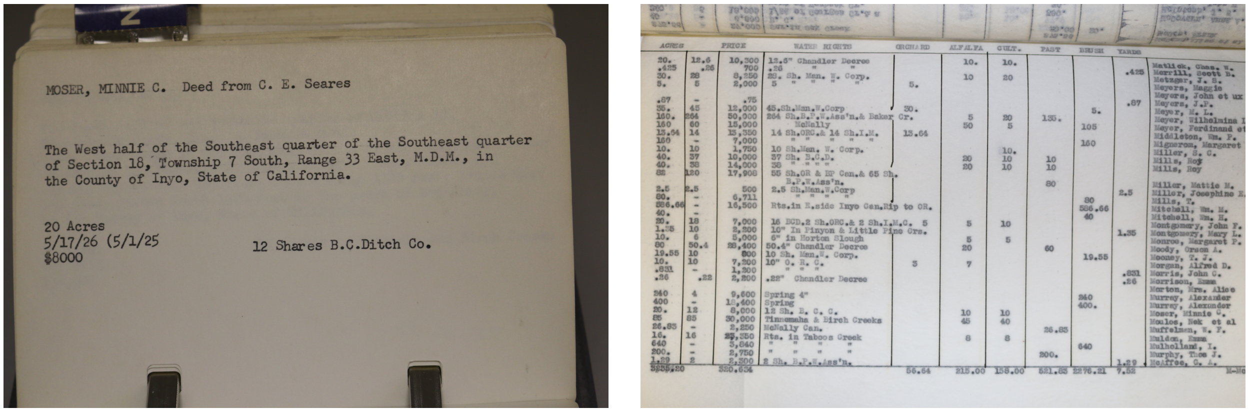
Although the city ended up buying all the land, when they where negotiating with the farmers, the farmers were unsure about how far they could sustain a hold up. Until the 1930s, there was uncertainty as to how much land and water the city of LA was going to buy and need. This uncertainty was driven by the recurrence of eventual droughts and by the increase in population in the city of LA. The ability of buying land was subject to availability of funds that came through sub sequential bonds. When the city run out of money, it was unclear whether they were going to be able to issue a new bond.

2.2 Sales Data

We created our main dataset from the transaction cards (deeds) stored at the Los Angeles Department of Water and Power (LADWP) archive in Bishop, Inyo county. In Figure 2.A

Figure 2: Sample Pictures from data collection.

A. Transaction Card. B. Survey.



Notes: Panel A: Caption of a transaction between Minnie C. Moser and the city of Los Angeles. Panel B: Caption of the survey conducted by the city of Los Angeles, where the plot owned by Minnie C. Moser is seventh from the bottom.

we can see a sample in that transaction card. Each transaction card makes a reference 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 correspond to a square of one mile times one mile, or 640 acres. Thus a quarter of a section correspond 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. This particular example is an easy one, but in some cases the same farmer has several plots, sometimes non-contiguous. In many cases the plots are not rectangular, and the Geo codification is more cumbersome. However, we were able to Geo code virtually all the plots. This is important not just to be able to create the maps, but also to create variables that are relevant to out analysis, as we explain below in subsection 2.3.

Table 1 shows summary statistics for the variables used in the analysis. As shown in Figure 2.A, we have not only the year of purchase but the exact date of purchase.[1] In the main analysis we only consider transactions between 1905 and 1935. The reason is that, as explained above in subsection 2.1, before 1905 farmers where unaware of the intentions of the city, and they sold their land to Fred Eaton. By 1935, the city owned all the water rights and virtually all the non-federal lands in the Owens Valley. There are some sporadic transactions in the 1970s and 1980s, but they are very different in nature to the land purchases of the

[1] 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.

beginning of the 20^{th} century.

In addition to the date of purchase, we have information regarding the size of the land and the amount paid for it, which we obtain directly from the cards. The cards do contain information regarding water rights, but in a format that is not directly comparable across farmers. In some cards the information is regarding the number of shares, sometimes it says a percentage of all rights in a particular creek, and some times it mentions first or second rights using miner's inches. All those measures are homogeneous and comparable within a ditch, but not across ditches. In order to get a comparable measure of water rights across all farmers, we merge our dataset with the data collected by Gary Libecap.[2] Gary Libecap's work cited above is based on the data available at the LADWP archive in Los Angeles. We merge our data with his data to obtain uniform measure of water rights.[3]

Table 1: Summary Statistics.

Variable	Mean	SD	Min	Max	Obs
Year	1,927	13.4	1,903	1,997	1,390
Acres	209.6	741.9	1	11,918	1,390
Price	26169	104594	1	2,000,000	1,250
Water Acres	257.3	882.45	0	17,850	1,381
Distance to the river	5,128	9,987.184	0	250,957	1,390
Distance to Mono lake	111,920	44,454.43	0	434,895	1,390
Distance to Owens lake	69,446	41,558.31	0	246,874	1,390

Notes: Summary statistics for selected variables. *Year* is a numeric variable that measures the year where the plot was sold. ...

In addition to the transaction cards, we complemented the data with the surveys conducted by the surveyors hired by LADWP. Figure 2.B shows a sample picture of the surveys summary. We merge the dataset created using the transaction cards with the survey data using the names of the farmers. In the survey we can also see how not only the name but also the acreage and the water rights data also match with the information in the cards. The

[2]We are very thankful to Gary Libecap for sharing his data with us.

[3]In Libecap's dataset there is a measure of annual water acres for each 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 contain fewer farmers than ours. Whereas we were able to find merge all farmers in his dataset in our dataset, there are about 600 farmers in our dataset that do not appear in his dataset. Thus, we do not have an exact measure of water acres for those farmers. However, most of those farmers have water rights in the same ditch as another farmer that appears in Libecap's dataset. We make the assumption 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.

survey, however, have an extra piece of information not present in the transaction cards, but that is an important determinant of the price paid: land use. In the survey, the land for each farmer is decomposed on how many acres are used for each of the following six categories: Orchard, Alfalfa, Cultivated, Pasture, Brush and Yards.

2.3 Geo-location data

As mentioned above, the transaction cards provide a detailed description of the exact location of each plot. We geo-located 2,750 plots. Figure 3.A shows the land holdings from the main sellers, i.e., those who received over $1 million for their lands.[4] Notice that the State of California was by far the largest seller. Fred Eaton appears as the second largest seller, despite not being a farmer or a land owner in the valley before 1905. He acted as an intermediary who bough land from the farmers and sold it to the city. Most of the land in in the lower part of the 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 correspond to the Rickey ranch, covering 11,190 acres and purchased for $425,000 after "a week of Italian work" by Eaton (cited by Reisner, 1986).

In addition to creating the maps, which are very useful to have a better understanding of the data, the goal of the geo-location is to create more variables. For each polygon geo-located, we can merge it with data available in GIS (Geographical Information Systems). After the merge we have important variables such as: altitude, roughness, slope, suitability and distance to the Owens river. All of which are important determinants of the quality of the land and thus the price received. We are specially interested on the distance to the river, because we conjecture that farmers, in a given ditch, whose plots are closer to the Owens river, thus at the beginning of the ditch, would create a larger externality in the other farmers, than farmers that farmers that are further away. Finally, geo-locating the plots for all farmers allow us to compute distances between farmers, and to perform a rigorous spatial analysis.

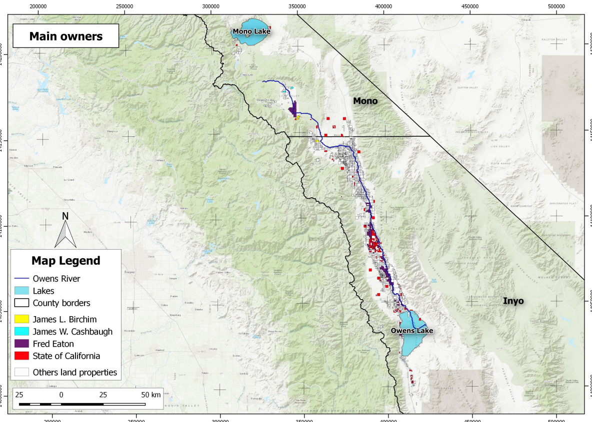
3 Preliminary Evidence

Table 2 shows the results for whether a sale will take place in a given month for each ditch (notice that as we calculated our variables at the ditch level, is as if we were adding a ditch fixed effect). The sale variable would be either zero if no sale took place that month or

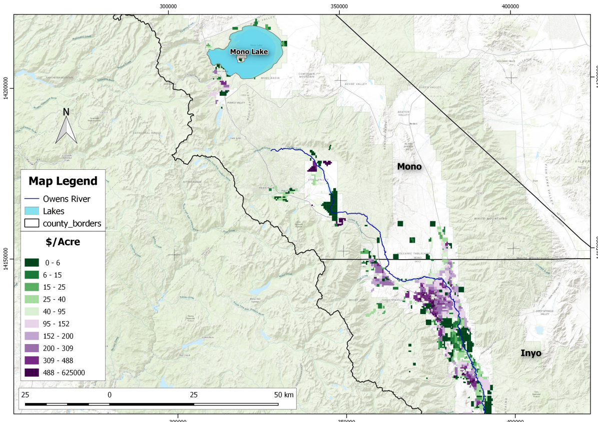
[4] James Birchim received $2 million in 1981 for 646.12 acres. James Cashbaugh received $1.4 million in 1985 for 636.66. Because these sale was so late, they are not included in our analysis.

Figure 3: Digitized maps in Owens Valley.

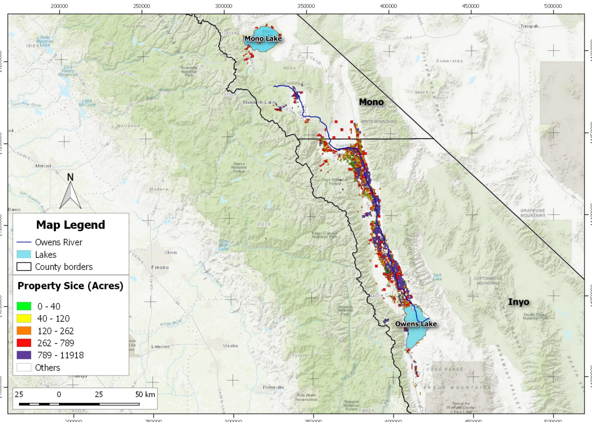
A. Main Owners of rights.



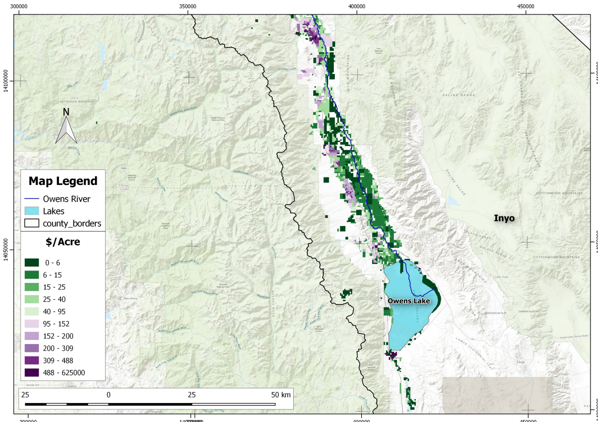
B. Dollars per acre paid in the North.



C. Land size.

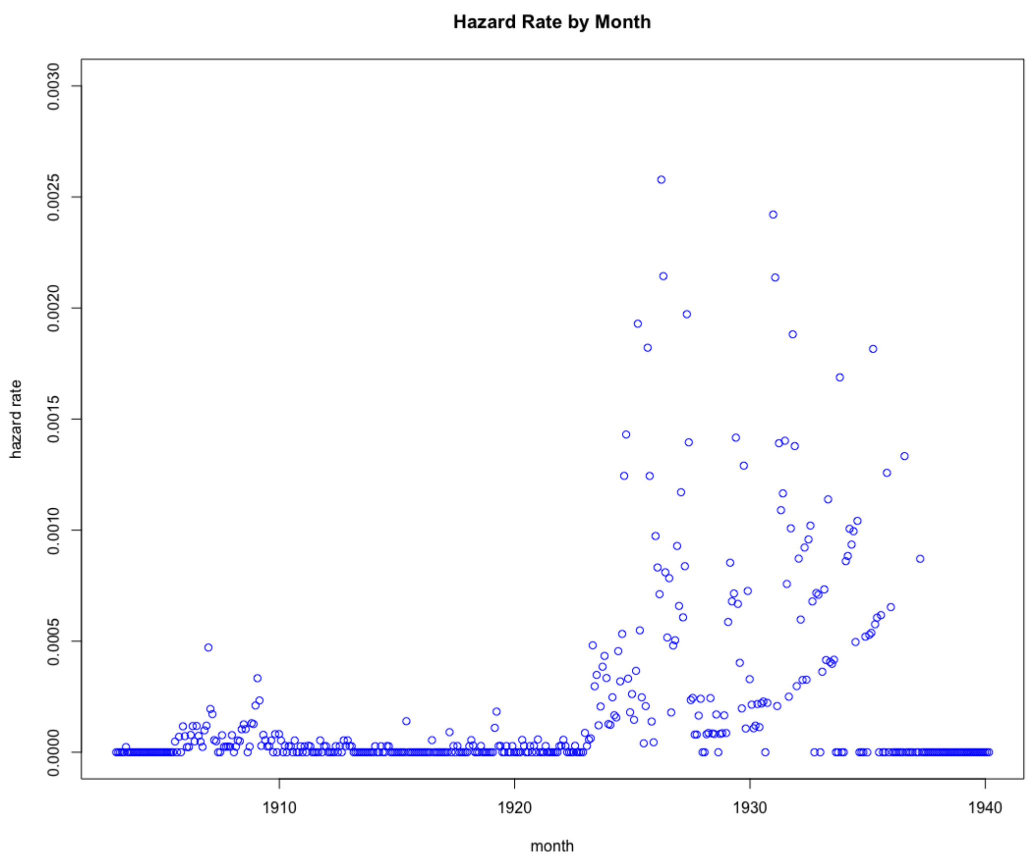


D. Dollars per acre paid in the South.



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 the dollars per acre paid for each plot in the north of the Owens Valley. Panel C: Map of the total area holding of each seller. . Panel D: Map of the dollars per acre paid for each plot in the south of the Owens Valley.

Figure 4: Empirical Hazard functions.



Notes: Hazard rates of selling times for all farmers.

Figure 5: Spatial Correlation.

Moran's I Test Results

Model	Observations	Moran I statistic	p-value
Sample P/A	1158	-1.21E-03	0.5139
Sample Timming	1158	0.333178241	2.20E-16
Timming (<1906)	38	0.38125082	0.0004194
Timming (1907-1912)	108	0.161978265	0.02568
Timming (1913-1921)	8	-0.12837051	0.4805
Timming (1922-1923)	90	0.265955734	0.000847
Timming (1924-1925)	135	0.278952641	4.11E-05
Timming (1926-1927)	154	0.504066624	1.42E-12
Timming (1927-1928)	188	0.062588665	0.1414
Timming (1928-1929)	178	0.367887174	2.16E-08
Timming (1930>)	259	0.503678295	2.20E-16

Notes: Results from a Moran 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.

one if at least one sale happened that month. We build state-level variables, which reflect how conditions are changing in time in each ditch. Sales to date represent the percentage of farmers that have sold to LADWP up to that month. Shares to date, on the other hand, represents the fraction of total shares that have been sold to the city until that moment in time. Price per acre represents the average price of the sales that have taken place up to that moment in time, and acres to date is the percentage of total acres in a given ditch that has been sold to the city. We control for year-month to absorb any unobserved time-varying changes.

Our results suggest that there is a significant interaction taking place at the ditch level, between farmers that have sold their land and farmers that have not. For instance, the lower the fraction of shares that have been sold and the higher dispersion on the remaining ownership of the shares, the higher the likelihood that a deal might take place in the future, which points out towards the city trying to get control of the decision rights in each ditch (recall that the LADWP needed 2/3 of the shares of a ditch to get the decision power). We find that the higher the average price the city paid in a ditch, the higher the chance it will buy land in the future (this might just be reflecting the fact that a particular ditch might be more attractive to the city). Finally, the higher fraction of land the city already controls, the lower the chances of observing a sale in the future. All of these results are suggestive of important co-dependence of sales among members of a given ditch.

In Table 3 we change our unit of analysis to look into the probability that any farmer

Table 2: Logistic regression at the Ditch Level.

	Dependent variable:						
	sale						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Time	0.0005***	0.0005***	0.0004***	0.0003***	0.0003***	0.0003**	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Sales to Date	−0.157	−0.483	−0.911	−0.680	−0.232	1.107	5.308***
	(0.437)	(1.207)	(1.267)	(1.223)	(1.439)	(1.559)	(1.876)
Shares to Date		0.307	−1.311	−1.437	−1.781	−2.101	−4.264***
		(1.061)	(1.229)	(1.165)	(1.302)	(1.315)	(1.542)
SD of Shares			2.148***	1.638***	1.759***	1.628***	1.234*
			(0.565)	(0.553)	(0.593)	(0.602)	(0.693)
Price per Acre				1.178***	1.380***	1.453***	2.234***
				(0.267)	(0.432)	(0.432)	(0.502)
SD of Price per Acre					−0.321	−0.222	−0.785
					(0.546)	(0.546)	(0.625)
Acres to Date						−1.049**	−2.502**
						(0.409)	(1.234)
Water to Date							0.739
							(0.996)
Constant	5.598***	5.601***	4.494**	2.727	2.314	1.717	−1.872
	(1.899)	(1.901)	(1.967)	(2.009)	(2.128)	(2.129)	(2.432)
Observations	1,094	1,094	1,094	1,090	1,090	1,090	1,007
Log Likelihood	−345.291	−345.249	−338.097	−323.786	−323.613	−320.396	−259.804
Akaike Inf. Crit.	696.581	698.498	686.194	659.572	661.226	656.792	537.608

*p<0.1; **p<0.05; ***p<0.01

Notes: Results from a Logistic regression computed at the ditch level. The dependent variable is whether any farmer in a given ditch sold in a given period. All independent variables measure a stock, unlike the dependent variable that is a flow. All independent variables are normalized so that they begin at 0 and end at 1. *Time* is the number of periods since the first sale. *Sales to Date* is the number of farmers that sold up to that period. *Shares to Date* is the number of shares in the same ditch that farmers that have sold up to that period. *SD of Shares* is the Standard Deviation of the shares in the same ditch that farmers that have sold up to that period. *Price per Acre* is the average price per acre paid to farmers in the same ditch. *SD of Price per Acre* is the Standard Deviation of the price per acre paid to farmers in the same ditch that have sold up to that period. *Acres to Date* is the total number of acres sold in that Ditch up to that period. *Water to Date* is the total number of water acres sold in that Ditch up to that period.

would sell to LADWP any given quarter. We do this analysis at the individual level to compute how the actions of the four spatially closer neighbors affect the probability of a farmer selling in the future. We control for ditch level, time-varying characteristics. From the table below we see that the higher the fraction of neighbors that have sold their land around a farmer, the lower the probability that the farmer will sell in the future. .

Table 3 is suggestive of the LADWP buying strategy. First, it could reflect the fact that LADWP was buying plots of lands around farmers that were either unwilling to sell or were aggressively bargaining (selection). It could also capture the fact that once the city bought the property around a given farmer, that farmers' land is less valuable to it, showing the presence of negative externalities (treatment). To separate selection from treatment effects, we will require a structural model.

4 Econometric Model

This section introduces the theoretical model. We model the game between the farmers as a game of perfect information, unlike Takahashi (2015), which estimates a model of imperfect information. Using the arguments in Harsanyi (1973), as we explain in more detail below in subsection 4.3, one can see that the two games are observationally equivalent. In other words, the data can be rationalize either by a game of perfect information, or by a game of imperfect information.[5] We choose to model the interaction as a game of perfect information because we think that it is realistic in the empirical setting studied here. The historical literature has pointed out how all farmers were informed both about the actions of other farmers selling their plots to the city, the amount they got offered and the characteristics of each plot.[6]

4.1 Theoretical Model

We model the interaction between the farmers as a War of Attrition (WoA) based on the results in Catepillan and Espín-Sánchez (2018), when they take as given the offer made by the city, and the contingent offers that the city would make over time. One can think of each game presented here as the game 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 a $t = 0$ and time is continuous. There $t = 0$ the city makes an offer to each

[5] Typically the game of imperfect information has a unique equilibrium, while the game of perfect information have many. We focus on the equilibria of the perfect information game where all farmers use mixed strategies, as this is the one that rationalized the data and the one that is observationally equivalent to the game of imperfect information.

[6] Pearce (2013) documents how close the community was in the small towns in the valley and how everyone knew even when their neighbor took the train to LA to sign the sale.

Table 3: Logistic regression at the Individual Level.

	Dependent variable:								
	first_sale								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Time	0.001***	0.0002***	0.0001**	0.0001**	0.0001*	0.0001	0.0001*	0.0001*	−0.00001
	(0.00003)	(0.00005)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Sale by Neighbours	−1.340***	−1.274***	−0.936***	−0.936***	−0.850***	−0.841***	−0.843***	−0.833***	−0.797***
	(0.100)	(0.099)	(0.100)	(0.100)	(0.100)	(0.101)	(0.101)	(0.101)	(0.128)
Price per Acre by Neighbours	0.00003*	0.00002*	0.00002	0.00002	0.00001	0.00002*	0.00002*	0.00002*	0.00003
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00002)
Water Acre by Neighbours	−0.0004	−0.0003	−0.0002	−0.0002	−0.0002	−0.0002	−0.0002	−0.0002	−0.0005
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.001)
Sales to Date		2.178***	−10.293***	−10.293***	−10.477***	−10.064***	−11.053***	−10.600***	−2.114
		(0.243)	(0.688)	(0.688)	(0.789)	(0.782)	(0.915)	(0.958)	(1.554)
Shares to Date			12.720***	12.720***	10.102***	8.849***	9.639***	9.659***	−1.718
			(0.706)	(0.706)	(0.926)	(0.974)	(1.046)	(1.041)	(1.539)
SD of Shares					2.797***	2.934***	2.673***	2.719***	6.342***
					(0.367)	(0.364)	(0.391)	(0.390)	(0.616)
Price per Acre						0.856***	0.297	0.048	0.839
						(0.229)	(0.376)	(0.417)	(0.521)
SD of Price per Acre							0.852**	0.973**	0.159
							(0.423)	(0.434)	(0.583)
Acres to Date								−0.531	0.415
								(0.330)	(0.778)
Water to Date									−0.807
									(0.751)
Constant	6.551***	−1.238	−4.089***	−4.089***	−4.776***	−5.084***	−4.656***	−4.433***	−6.726***
	(0.548)	(0.927)	(1.093)	(1.093)	(1.098)	(1.094)	(1.114)	(1.127)	(1.543)
Observations	43,928	43,928	43,928	43,928	43,928	43,928	43,928	43,928	26,656
Log Likelihood	−1,588.745	−1,541.913	−1,394.515	−1,394.515	−1,355.908	−1,348.143	−1,345.999	−1,344.724	−830.496
Akaike Inf. Crit.	3,187.490	3,095.826	2,803.030	2,803.030	2,727.815	2,714.285	2,711.998	2,711.449	1,684.992

*p<0.1; **p<0.05; ***p<0.01

Notes: Results from a Logistic regression computed at the individual level. The dependent variable is whether a farmer sold in a given period. All independent variables measure a stock, unlike the dependent variable that is a flow. All independent variables are normalized so that they begin at 0 and end at 1. *Time* is the number of periods since the first sale. *Sale by Neighbours* Dummy vairable that takes the value of 1 if a neighbour sold in the same period. *Water Acre by Neighbours* Number of water acres sold by neighbors. *Price per Acre by Neighbours* is the average price per acre paid to neighbouring farmers. *Sales to Date* is the number of farmers that sold up to that period. *Shares to Date* is the number of shares in the same ditch that farmers that have sold up to that period. *SD of Shares* is the Standard Deviation of the shares in the same ditch that farmers that have sold up to that period. *Price per Acre* is the average price per acre paid to farmers in the same ditch. *SD of Price per Acre* is the Standard Deviation of the price per acre paid to farmers in the same ditch that have sold up to that period. *Acres to Date* is the total number of acres sold in that Ditch up to that period. *Water to Date* is the total number of water acres sold in that Ditch up to that period.

farmer. The offer consists on a price $V_{i\cdot}(0)$ that the farmer would receive for their plot if she 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 the time since the game began, denoted by the scalar t; the number of farmers that have sold at a given point denoted by the scalar k; and in general in the identity of each of the farmers that have sold at a given point, denoted by the set $\mathcal{K}$. At each instant in time, a farmer decides whether to stay in the market or to sell his farm to the city. While staying, each farmer pays a monetary unitary instantaneous cost. The interpretation of this instantaneous cost in continuous time is that of discounting.

It is important to make a distinction between the whole game, that involves all the farmers in a ditch and their exit times, and each stage game, that involves only the subset of farmers that have not sold up to that point. We can focus on each stage game, when farmers take the continuation value after another farmer sells as given. In a stage game with n remaining farmers, the value of a given farmer of selling is just the offer made by the city for that case $V_{i\mathcal{K}}(t)$. Notice that the offer depends on the time, the identity of the farmer and the set of farmers that have sold already. If a farmer does not sell, his continuation value, that is the value of being active in the next stage game, would depend on the identity of the farmer who sold. The continuation value of the farmer is then $W^j_{i\mathcal{K}}(t)$ when farmer j sold his plot at time t. Because the farmer is deciding whether to sell or not, the important element is the difference between selling at time t, which involves and immediate reward $V_{i\mathcal{K}}(t)$, and not selling at time t, which involves a continuation value $W^j_{i\mathcal{K}}(t)$. We denote this difference by $\Delta^j_{i\mathcal{K}}(t) \equiv W^j_{i\mathcal{K}}(t) - V_{i\mathcal{K}}(t)$.

In order to solve the equilibrium, we make one assumption regarding the evolution of $\Delta^j_{i\mathcal{K}}(t)$ 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:

$$\Delta^j_{i\mathcal{K}}(t) = \Delta^j_{i\mathcal{K}} \cdot v(t)$$

Assumption A1 implies that the "shape" of $\Delta^j_{i\mathcal{K}}(t)$ over time is the same for all farmers. The intuition is that although the value is different for each farmer, and is changing over time, the "shape" of the change is common to all farmers. It is worth noticing that in the classical WoA models, the value of the "prizes" that the players get do not change over time, i.e., in the classical WoA $v(t) = 1$. This means that both the values of exiting and the continuation values are constant over time. A constant $\Delta^j_{i\mathcal{K}}(t)$, as we show below, implies a constant probability of exiting over time, which means that the distribution of exit times will have a constant hazard rate. Therefore, the assumption of constant values is equivalent to assuming that the distribution of exit times is exponential. Below we show how there is a direct relation between the shape of the valuations over time and the shape of the distribution of exit times, i.e., given a function of valuations over time, there is a unique distribution of exit times in equilibrium and given a distribution of exit times in the data, the is a unique function of valuations over time that rationalizes it. In Subsection 4.3 we show how our data allow us to non-parametrically identify the distribution of valuations. For simplicity and we chose a flexible parametric form for the estimation.

4.2 Equilibria

We now show how to solve for the unique equilibria where all farmers are using mixed strategies. See Catepillan and Espín-Sánchez (2018) for details and a broader discussion of equilibria. As defined above the value of staying until the next stage for farmer i when farmer j exits at time t in a stage game when the set $\mathcal{K}$ of farmers have already sold is $\Delta^j_{i\mathcal{K}}(t) = \Delta^j_{i\mathcal{K}} \cdot v(t)$. Since the cost of staying is unitary, the cost function over time is $C(t) = t$. We assume that $v(t)$ is differentiable. The utility for farmer i of staying until time t, given that farmer j is leaving at time s with probability $f_{j\mathcal{K}}(s)$ is:

$$U^j_{i\mathcal{K}}(t) \equiv \sum_{j\neq i} \int_0^t \left[\Delta^j_{i\mathcal{K}} \cdot v(s) - s\right] f_{j\mathcal{K}}(s) \prod_{k\neq i, k\neq j} \left[1 - F_k(s)\right] ds - t \left\{ \prod_{j\neq i} \left[1 - F_{j\mathcal{K}}(t)\right] \right\} \tag{1}$$

That is, farmer i gets $\left[\Delta^j_{i\mathcal{K}} \cdot v(s) - s\right]$ if farmer j is the first to sold, and does so at time $s < t$; and farmer i gets $-t$ if nobody sells before t. The derivative of the utility exists and we get the following expression

$$\begin{aligned}
\frac{dU^j_{i\mathcal{K}}(t)}{dt} \equiv & \sum_{j\neq i} \left[\Delta^j_{i\mathcal{K}} \cdot v(t) - t\right] f_{j\mathcal{K}}(t) \prod_{k\neq i, k\neq j} \left[1 - F_{k\mathcal{K}}(t)\right] - \left\{ \prod_{j\neq i} \left[1 - F_{j\mathcal{K}}(t)\right] \right\} \\
+ & \; t \sum_{j\neq i} f_{j\mathcal{K}}(t) \prod_{k\neq i, k\neq j} \left[1 - F_{k\mathcal{K}}(t)\right] \\
= & \left\{ \prod_{j\neq i} \left[1 - F_{j\mathcal{K}}(t)\right] \right\} \cdot \sum_{j\neq i} \left[\Delta^j_{i\mathcal{K}} \cdot v(t) \cdot f_{j\mathcal{K}}(t) - 1\right]
\end{aligned} \tag{2}$$

In equilibrium the expected utility of not selling for any farmer that is using a mixed strategy need to be constant. Otherwise the farmer would just sell (if his expected utility is negative) of not sell (if his expected utility is positive). Thus, in equilibrium, $\frac{dU^j_{i\mathcal{K}}(t)}{dt} = 0$ and the probability that farmer j sells at time t, $f_{j\mathcal{K}}(t)$, is the strategy followed by farmer j that makes all other farmers indifferent between selling or not, that is, $\lambda_{j\mathcal{K}}(t)$. This produces the following equilibrium condition for farmer i:

$$\sum_{j\neq i}\left[\Delta^{j}_{i\mathcal{K}}\cdot v(t)\cdot\lambda_{j\mathcal{K}}(t)\right]=1,\ \forall i \tag{3}$$

Notice that we have one equilibrium condition for each remaining farmer, n equations in total. The system of n equations will solve the strategies for each farmer $\lambda_{i\mathcal{K}}(t)$. We do so in two steps. The first step is to solve for $\phi_{i\mathcal{K}}$, such that

$$\sum_{j\neq i}\Delta^{j}_{i\mathcal{K}}\cdot\phi_{j\mathcal{K}}=1,\ \forall i$$

This is a linear system of equations and it is easy to solve. Subsection **??** in the appendix solves the case for three farmers to show the intuition behind the role of the values and the externalities on the probabilities of selling. 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 satisfy equilibrium condition 3:

$$\lambda_{i\mathcal{K}}(t)=1/\left[\phi_{i\mathcal{K}}\cdot v(t)\right] \tag{4}$$

Therefore, the distribution of exit times for farmer i in game $\mathcal{K}$ is

$$F_{i\mathcal{K}}(t)=1-c\cdot exp\left[-\int_{0}^{t}\frac{\phi_{i\mathcal{K}}}{v(s)}ds\right] \tag{5}$$

where c is the constant of integration that makes $F_{i\mathcal{K}}(t)$ a probability distribution. Notice that equation 8 is key to identify the shape of $v(t)$. In the model, using equation 5, for each $v(t)$ we can compute the exact shape of the distribution of selling times for each farmer in each game. When we look at the data, we can see the empirical distribution of selling times for each farmer for a given game, $\widehat{F_{i\mathcal{K}}(t)}$. With that distribution, we can compute the empirical hazard rate of selling times for each farmer for a given game, $\widehat{\lambda_{i\mathcal{K}}(t)}$. Then, using equation 8 we can compute the shape of $v(t)$ and estimate the externalities using the estimates on $\phi_{i\mathcal{K}}$.

4.3 Identification

The distributions of selling times are determined by the value of selling. Remember that the object of interest $\Delta_{i\mathcal{K}}^{j}(t)$ was defined as the difference between the continuation value when another farmer sells $W_{i\mathcal{K}}^{j}(t)$ and the value of selling $V_{i\mathcal{K}}(t)$. In the empirical application we only observe each farmer exiting once, so we will not be able to estimate all $\phi_{i\mathcal{K}}$. However, we can classify farmers depending on their observable characteristics, such that we will observe several selling times for a given configuration of the game. Therefore we can identify the function $v(t)$ non-parametrically. We will also observe all realizations of $V_{i\mathcal{K}}(t)$, which are the prices at which the farmers sold their plot. Therefore we are able to independently identify the functions $W_{i\mathcal{K}}(t)$ and $V_{i\mathcal{K}}(t)$. This means we could identify asymmetric values for each farmer, but not externalities. Finally, because we have information regarding the locations of the farmers' plots and their characteristics, we will be able to identify and estimate different functions $W_{i\mathcal{K}}(t)$, for different pairs of farmers i and j.

In other words, if we only have information on exit times, as is usually the case (see Takahashi, 2015), then we could only identify $v(t)$, that is the probability of selling for a farmer in a particular game, and we would have to restrict attention to symmetric games, estimating a single ϕ for a given number of farmers, identified up to a constant. In this case the function $\Delta(t)$ is just equal to the hazard rate of the distribution of selling 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.

If we also have information on the size of land and the value of the land for each farmer, then we could estimate an asymmetric WoA game and estimate $\Delta_i(t)$, thus identifying $v(t)$ and ϕ_i, up to a constant. If in addition, we have information on the prices received by the farmers, we could also estimate $W_i(t)$ from $V_i(t)$, thus identifying $v(t)$ and ϕ_i exactly. This is not trivial, and it is key in this case for both the estimation of the game and the counterfactuals. Moreover, it is rare to have such detailed data in an empirical estimation. Finally, if we have information regarding the locations of the farmers' plots and their characteristics, as well as the prices, we will be able to identify and estimate different functions $W_i^j(t)$, for different pairs of farmers, thus identifying $v(t)$ and $\phi_{i\mathcal{K}}$ exactly. Notice that this is the main innovation of the paper. We are estimating the externalities that a farmer exert on another farmer when she sells her land. Depending on the variability of the data, and how we define a market (game) we could be more or less flexible on the structure of $W_i^j(t)$. Summarizing, we can identify

- **Symmetric Game** — Data on exit times: $\Delta(t)$.
- **Asymmetric Game** — Data on exit times and individual characteristics: $\Delta_i(t)$.

- **Asymmetric Game** — Data on exit times, individual characteristics and sale prices: $W_i(t)$ and $V_i(t)$.
- **Asymmetric Game with Externalities** — Data on exit times, individual characteristics, sale prices and pair-specific information: $W_i^j(t)$ and $V_i(t)$.

5 Estimation Strategy

In the data there are events that would affect all farmers, not only farmers in the same ditch. The implicit assumption here is that we assume that sales by farmers outside the ditch affect all farmers in a given ditch in the same way. In particular, we will use the cumulative sales as a state variable in each game. In contrast, we believe that sales by farmers in the same ditch, will affect more farmers within the same ditch. Moreover, we think they could affect each farmer differently. Each stage game, as explained in Section 4, provides an exit time, which is the key variable. Each stage game also provides us with information regarding the farmer that sold, the farmers that were active but were not the first to sold, and the set of farmers that belonged to the same ditch, but have sold already.

The estimation consists on two steps. In the first step (Inner Loop), we get one pseudo parameter, θ^n from each game with a given number of farmers. In the second step (Outer Loop), we use *hedonic* regressions to get a set of parameters β from the pseudo-parameters in the first step. One contribution of this article is that we assume that the distribution of exit times follows an Exponentiated Gamma distribution. This allows us to estimate directly the first step, without having to use simulations.

5.1 Exponentiated Gamma

For the estimation, we assume that the "shape" of $\Delta_i(t)$ is that of the hazard function of a standard Exponentiated Gamma: $EG \sim (\theta)$.[7] Figure 4 shows the empirical hazard functions for exit times. Because the empirical hazard functions are not constant over time, we know that the distribution of exit times is not exponential. Thus we need to use a parametric form that is flexible enough to produce non-constant hazard functions, such as the EG. In addition to produce non-constant hazard functions, the EG is useful because, unlike most

[7] We could relax this assumption by generalizing if to be that of a Beta-Exponentiated Gamma ($BEG \sim (\theta, \lambda, a, b)$), if we restrict attention to the cases where the parameters λ, a and b are the same for all farmers and all games. That is, we could allow the "scale parameter" θ to vary across farmers and games, but fix the "shape" parameters to be the same across farmers and games. This way we can have a parametric function that is tractable at the same time that is very flexible in terms of variance, asymmetry and "thickness of the tails."

distributions, the order statistics of random variables generated by an EG have a closed form solution.[8] In particular, the density function of any order statistic from an EG is a weighted average of density function of EG, where the weights do not depend on the parameters to be estimated but only on the size of the sample n and the order statistic r.

A standard Exponentiated Gamma (EG) distribution ($EG(\theta)$) is characterized by a density function

$$f(x;\theta) = \theta x e^{-x}\left[1 - e^{-x}(x+1)\right]^{\theta-1} \tag{6}$$

and a cumulative distribution function

$$F(x;\theta) = \left[1 - e^{-x}(x+1)\right]^{\theta} \tag{7}$$

When the shape parameters $\theta = 1$ then the distribution is equivalent to a gamma distribution with shape parameter $\alpha = 2$ and scale parameter $\beta = 1$, i.e., $\Gamma(2,1)$.

The hazard function is

$$h(x;\theta) = \frac{f(x;\theta)}{1 - F(x;\theta)} = \frac{\theta x e^{-x}\left[1 - e^{-x}(x+1)\right]^{\theta-1}}{1 - \left[1 - e^{-x}(x+1)\right]^{\theta}} \tag{8}$$

For the estimation, we are interested on the distribution of the minimum of this random variable. For the *homogeneous* case, and following Shawky and Bakoban (2009) we get that the r^{th} order statistic is given by

$$f_{r:n}(x;\theta) = \sum_{i=0}^{n-r} d_i(n,r) f(x;\theta(r+i))$$

where

$$d_i(n,r) = (-1)^i n \frac{\begin{pmatrix} n-1 \\ r-1 \end{pmatrix}\begin{pmatrix} n-r \\ i \end{pmatrix}}{r+i}$$

Let $X_1, ..., X_n$ be a random sample of size n from an $EG \sim (\theta)$. If we are interested on the first order statistic (minimum) we get

[8]One exception is the Uniform distribution. Any order statistic from a Uniform distribution follows a Beta distribution. There are, however, two problems with using a Uniform distribution in this case. First, empirically, the distribution of exit times does not resemble a Uniform distribution. Second, in terms of estimation, estimating a Uniform or a Beta distribution is challenging because the support of the distribution depends on the parameters to be estimated.

$$f_{1:n}(x;\theta) = \sum_{i=0}^{n-1} d_i(n,r) f(x;\theta(1+i))$$

where

$$d_i(n,1) = (-1)^i n \frac{\begin{pmatrix} n-1 \\ i \end{pmatrix}}{1+i} = (-1)^i \frac{(n-1)!(n)}{(n-1-i)!(i!)(1+i)}$$

This means

$$f_{1:n}(x;\theta) = nf(x;\theta) - \left(\frac{n(n-1)}{2}\right) f(x;2\theta) + \left(\frac{n(n-1)(n-2)}{6}\right) f(x;3\theta) - ... + (-1)^{n-1} f(x;n\theta) \tag{9}$$

Building on the work by Shawky and Bakoban (2009) we have also developed the distribution of order statistics for a sample from *heterogeneous* distributions. Let $X_1, ..., X_n$ be a random sample of size n where each realization comes from an EG with different parameters belonging to the set $\Theta \equiv (\theta_1, ..., \theta_n)$. In particular, $X_i \sim EG(\theta_i)$ for $i = 1, 2, ..., n$, that is $X_1 \sim EG(\theta_1)$, $X_2 \sim EG(\theta_n)$,..., $X_n \sim EG(\theta_n)$. In this case we can compute the order statistics of the *heterogeneous* random sample. In particular, we are interested in the first *heterogeneous* order statistic (minimum) which has the form

$$f_{1:n}(x;\Theta) = \sum_{i=1}^{n} f(x;\theta_i) - \frac{1}{2}\sum_{i=1}^{n}\sum_{j\neq i} f(x;\theta_i+\theta_j) + ... + (-1)^{n-1} f\left(x; \sum_{i=1}^{n}\theta_i\right) \tag{10}$$

where $f(x;\theta)$ is the density function of an $EG(\theta)$. Notice that in the *homogeneous* case we have $\theta_i = \theta, \forall i$, equation 10 becomes equal to equation 9. In particular, the first term in equation 10 is just a sum of n identical terms. The second term is more complicated since it is the sum of all possible pairs. For example, when $n = 3$ the second term is made up of six terms: $f(x;\theta_1+\theta_2)+$ $f(x;\theta_1+\theta_3)+f(x;\theta_2+\theta_1)+$ $f(x;\theta_2+\theta_3)+f(x;\theta_3+\theta_1)+$ $f(x;\theta_3+\theta_2)$, but notice that it can be simplified as $2\left[f(x;\theta_1+\theta_2)+f(x;\theta_1+\theta_3)+f(x;\theta_2+\theta_3)\right]$, for the *homogeneous* case. Therefore when we divide by two, the term just include each density once. In the *homogeneous* case all three densities are identical, therefore the scalar multiplying the density is just 3, and the scalar inside the density is 2. The same logic applies to all terms, with alternating signs. The last term is again simple. Since it only includes one "permutation" that includes all densities. It is easy to check that the parameter inside the density is made up of the sum of n identical terms, so the scalar multiplying the density is

1 and the scalar inside the density is n.

5.2 First Step

In the first step of the estimation we need to recover a vector of θ for each exiting farmer. We will have heterogeneity as a function of the number of remaining farmers in a given ditch. To do so, we pool data from different ditches. We consider that each ditch is an independent game. We have twelve ditches that feature at least five exits (sells) or farmers in a ditch. For each ditch, we order farmers as a function of their exit time and we calculate the number of days (as a fraction of a year) between farmers' exits.

Next we pool data from games. For this part of the estimation, we only need to use data on the exit times of each game with n farmers. We calculate the probability that a given farmers exit in x days, when there are n remaining farmers in a game. In such game the strategy for each farmer is to exit at each point in time using an instantaneous probability of exiting of $\eta^n(t)$. This instantaneous probability of exiting correspond to the hazard function of an underlying distribution of exit times $\Phi^n(x;\theta^n)$. We are interested in $\Phi^n(x;\theta^n)$ because that is what we would use to create counterfactuals.

However, we do not observe all the realizations of exit times. We only observe the lowest among all realizations, that is the minimum or the first order statistic.[9] Therefore, the distribution of exit times would just follow the distribution of the exit times of 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 of $\Phi^n(t;\theta^n)$. In other words, each farmer will draw a time of exiting t_i from an $EG(\theta^n)$ but we will only observe the exit of the farmer with the lowest realization.

Based on the results above, in order to estimate a symmetric game with n farmers, we can use the following likelihood function

$$l\left(T_i^n, \theta^n\right) = \prod_{i=1} \psi^n(x_i^n;\theta^n) = \prod_{i=1} \left\{f_{1:n}(x_i^n;\theta^n)\right\} \tag{11}$$

where x_i is the realization of number of days until exit, since the beginning of the game, in a game with n remaining farmers, and $f_{1:n}(x_i^n;\theta^n)$ is the density of the minimum as defined in equation.

Notice that this likelihood will give us an estimate for θ^n but we are interested on $\Delta^n(t^n)$.

[9] 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 analog, the waiting time is the War of Attrition game is equivalent to the bid in the all pay auction.

For easy of estimation, we are restricting the shape that it can take. In particular, the assumption here is that $h\left(x^n, \theta^n\right) = \eta^n(x^n) = \frac{1}{(n-1)\Delta^n(x^n)}$, for all games. Therefore, $\Delta^n(x^n) = \frac{1}{(n-1)h(x^n,\theta^n)}$. The logic of the estimation is as follows. We observe a vector of exit times for each game with n farmers. Given this vector we estimate the parameter θ^n using the ML equation 11. With the estimated value $\hat{\theta}^n$we can compute the estimated hazard function $h\left(x, \hat{\theta}^n\right)$. Finally, with the estimated hazard function $h\left(x, \hat{\theta}^n\right)$ and using the equilibrium equation we can recover the distribution of valuations for each game $\Delta^n(x)$, which is then equal to

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

For example, for all games that had three remaining farmers, we pool the data from the twelve ditches, and we calculate what would be the probability of jointly see their exit times, when there are three farmers in a game. The advantage of using an Exponentiated Gamma distribution, is that we can compute what would be the probability of the minimum for different games. Thus, it is computationally feasible to represent the above likelihood function analytically. Although we do not have a close form solution for what the maximum likelihood estimator would look like, we can look for a vector of thetas, numerically. To do so, we partition the parameter space and we follow a grid search procedure. We compute the probability of all joint events, and we pick the combination of parameters that maximizes such probability.

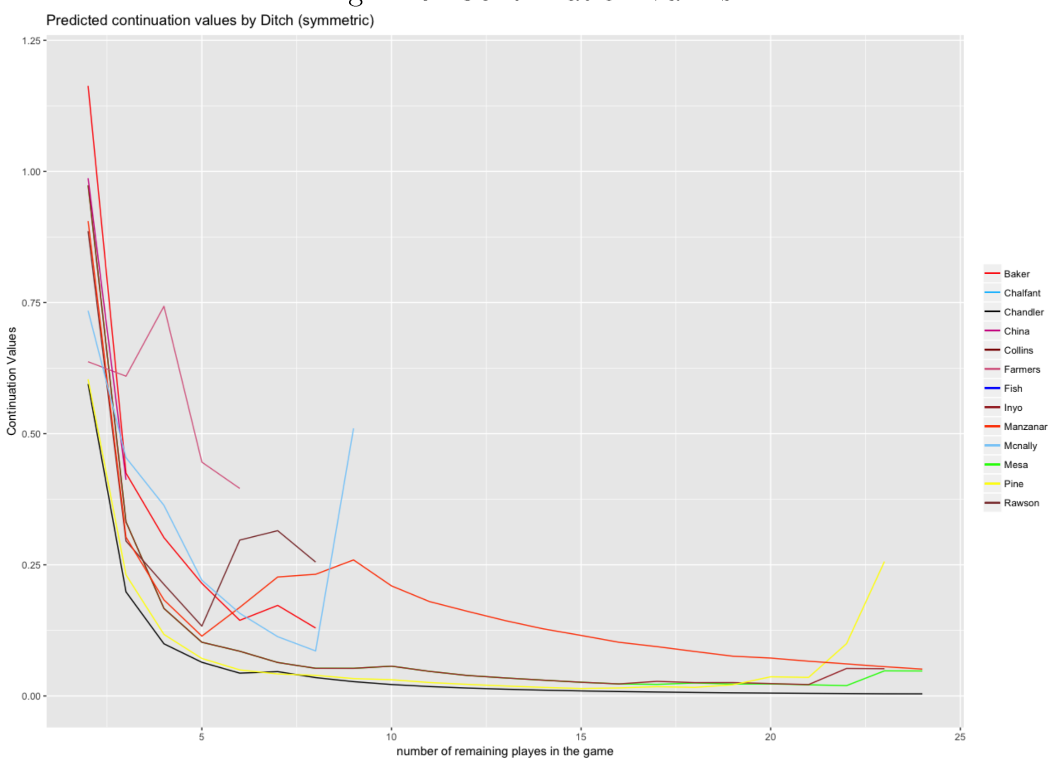
From our estimated vector of parameters, we can now project what would be the continuation value for each farmer in a given ditch.

5.3 Second Step

We have recovered from exit times $\Delta_i^n(x, n; \hat{\theta}) \equiv < \Delta_i^1(x_1, 1; \hat{\theta}), \Delta_i^2(x_2, 2; \hat{\theta}) ... \Delta_i^n(x_n, n; \hat{\theta}) >$, a vector of exit times for each farmer on a given ditch. Where x_j is the interval of time for farmer j to exit, when there are n farmers in the game. Thus, for each $j \epsilon \{1, 2..n\}$ farmer in a ditch i we can estimate this "value-cost" of waiting. Given that we assume that the value cost of waiting was equal to one, we will re-escalate this value. We assume that the cost of waiting for a year, can be approximated for each farmer as the annual interest rate it would receive by selling its plot of land. Thus $C_i = r * P_i$. This is true for the symmetric and asymmetric games. We can use these costs allow us to recover externalities. This is it is key to have data on final sales, not just the timing of the sales.

First, note that

Figure 6: Continuation Values.



Notes: Continuation values predicted by the model for each ditch, as a function of the number of remaining farmers in that ditch.

$$V_i^1(x) - V_i^2(x) = C_{i2}\Delta_i^2(x, 2 : \hat{\theta}) \tag{12}$$

$$V_i^1(x) - C_{i2}\Delta_i^2(x, 2 : \hat{\theta}) = V_i^2(x)$$

Since $V_i^1(x)$ is the continuation value of the last farmer to exit, then it has to be the case that $V_i^1(x) = P_i^1$, thus

$$P_i^1 - C_{i2}\Delta_i^2(x, 2 : \hat{\theta}) = V_i^2(x_2)$$

Now we can use this relation recursively:

$$V_i^2(x_2) - C_{i3}\Delta_i^3(x_3, 3 : \hat{\theta}) = V_i^3(x_3) \Leftrightarrow V_i^3(x_3) = P_i^1 - C_{i2}\Delta_i^2(x_2, 2 : \hat{\theta}) - C_{i3}\Delta_i^3(x_3, 3 : \hat{\theta})$$

Therefore

$$\hat{V}_i^n(x_n) = P_i^1 - \sum_{j=2}^{n} C_{ij}\Delta_i^j(x_j, j : \hat{\theta}) \tag{13}$$

Lets denote $\hat{V}_i \equiv < \hat{V}_i^1, ...\hat{V}_i^n >$ as the vector of all continuation values we can recover from exit times for ditch i.

On the other hand, recall that

$$\sum_{j \neq i} \hat{p}_j^i(x_i : \hat{\theta}) W_j^i(x_i) = \hat{V}^i(x_i)$$

where $\hat{p}_j^i(x_i : \hat{\theta})$ denotes the probability that farmer j exits the game at time x_i when there are i farmers remaining in the game. Note that from the asymmetric game, we can compute a probability of exiting that is different for each farmer in a given game. Finally, W_j^i is the continuation value of the game, where farmer j to exit.

Hedonic Assumption Given that the number of parameters we need to estimate is very big, and the fact that we only observe certain exits as each game is played only once, then we will need to assume a parametric function for the counterfactual estimation values. We will assume that we can decompose such value as the linear combination of relative observable characteristics between i and j.

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

Where we have K hedonic characteristics we will use, 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 (this could be the difference, yet we could also use a more flexible specification).

We are interested in recovering $\beta_{1\times K} \equiv < \beta_1 ... \beta_K >$. We can write the system of equations that we need as:

$$\begin{gathered}
\sum_{j<2} \hat{p}_j^2(x_2 : \hat{\theta}) W_j^2(x_2) = \hat{V}^2(x_2) \\
\sum_{j<3} \hat{p}_j^3(x_3 : \hat{\theta}) W_j^3(x_3) = \hat{V}^3(x_3) \\
.... \\
\sum_{j<N} \hat{p}_j^N(x_N : \hat{\theta}) W_j^N(x_N) = \hat{V}^N(x_N)
\end{gathered}$$

Where N is the maximum number of farmers in a given ditch (or as many as we need to use).

Note that this system can be r-written as:

$$\begin{gathered}
\sum_{j<2} \hat{p}_j^2(x_2 : \hat{\theta}) \beta_{1\times K} X_{K\times 1}^{2j} = \hat{V}^2(x_2) \\
\sum_{j<3} \hat{p}_j^3(x_3 : \hat{\theta}) \beta_{1\times K} X_{K\times 1}^{3j} = \hat{V}^3(x_3) \\
.... \\
\sum_{j<N} \hat{p}_j^n(x_N : \hat{\theta}) \beta_{1\times K} X_{K\times 1}^{nj} = \hat{V}^n(x_n)
\end{gathered}$$

Notice that we can re arrange terms here. Rearranging we get:

$$\sum_{j<2} \hat{p}_j^2(x_2 : \hat{\theta}) \beta_{1\times K} X_{K\times 1}^{2j} = \hat{p}_1^2(x_2 : \hat{\theta}) \left[\beta_1 X_{2j}^1(x_2) + \beta_2 X_{2j}^2(x_2) + .. + \beta_K X_{2j}^K(x_2) \right]$$

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

$$\sum_{j<3} \hat{p}_j^3(x_3 : \hat{\theta}) \beta_{1\times K} X_{K\times 1}^{3j} =$$

$$\hat{p}_1^3(x_3 : \hat{\theta}) [\beta_1 X_{3j}^1(x_3) + \beta_2 X_{3j}^2(x_3) + .. + \beta_K X_{3j}^K(x_3)] + \hat{p}_2^3(x_3 : \hat{\theta}) \left[\beta_1 X_{3j}^1(x_3) + \beta_2 X_{3j}^2(x_3) + .. + \beta_K X_{3j}^K(x_3) \right]$$

$$= \beta_{1\times K} \cdot \left[\sum_{j<3} \hat{p}_j^3 X_{3j}^1(x_3), .., \sum_{j<3} \hat{p}_j^3 X_{3j}^K(x_3) \right]_{K\times 1}$$

In general we will have that

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

Therefore we can re-write the system as:

$$\beta_{1\times K} \cdot \begin{matrix} \left[\hat{p}_1^2(x_2 : \hat{\theta}) X^1_{2j}(x_2), .., \hat{p}_1^2(x_2 : \hat{\theta}) X^K_{2j}(x_2) \right]_{K\times 1} \\ [...] \\ \beta_{1\times K} \cdot \left[\sum_{j<N} \hat{p}_j^N(x_N : \hat{\theta}) X^1_{Nj}(x_N), .., \sum_{j<N} \hat{p}_j^N(x_N : \hat{\theta}) X^K_{Nj}(x_N) \right]_{K\times 1} \end{matrix} = \hat{V}_{N\times 1}$$

Let denote

$$\hat{M}_{K\times N} = \begin{matrix} \left[\hat{p}_1^2(x_2 : \hat{\theta}) X^1_{2j}(x_2), .., \hat{p}_1^2(x_2 : \hat{\theta}) X^K_{2j}(x_2) \right]_{K\times 1} \\ [...] \\ \beta_{1\times K} \cdot \left[\sum_{j<N} \hat{p}_j^N(x_N : \hat{\theta}) X^1_{Nj}(x_N), .., \sum_{j<N} \hat{p}_j^N(x_N : \hat{\theta}) X^K_{Nj}(x_N) \right] K\times 1 \end{matrix}$$

$M_{K\times N}$ is a matrix that has as many columns as hedonic characteristics, and as many rows as farmers in a ditch. This matrix represents the weighted average (weighting by probability) of relative hedonic characteristics. What is crucial, is that we can compute this matrix, since we can compute the probabilities, and we observe relative characteristics. Then we have the following linear system:

$$\beta_{1\times K} \hat{M}_{K\times N} = \hat{V}_{N\times 1}$$

Hence, as long as we have as many characteristics as observations (or farmers in a game), we can recover $\hat{\beta}$. The main restriction that this part of the estimation imposes, is that the Matrix of weighted characteristics, must be invertible. For that to be the case it is crucial that we have the same number of hedonic features, as farmers in a game. We will then estimate, the hedonic parameters for each ditch. We will compute the following characteristics. First, what is the bilateral distance between farmers. Then, we will compute a time distance between farmers' sales. Finally, we compute what percentage of total ditch area, shares and crops a farmer has in each ditch. We do this in percentage to normalize across ditches.

Table **??** reports the estimated value, as the matrix we invert using the last six farmers in a given ditch. In order to have a sense of the sensibility of our point estimates, we perform a bootstrapping method where we calculate our parameters, changing one farmer randomly

Table 4: Structural Results.

	Dependent variable:				
	Distance	Days	Area	Shares	Crops+Water
Manzanar	−3.223584e-04	−9.381279e-02	1.055789e+03	5.339839e+02	1.121949e+02
	(1.244922e-03)	(3.913213e-02)	(1.599250e+03)	(2.474765e+03)	(3.378295e+03)
Chandler	−2.724007e-01	−8.838188e-01	5.579362e+03	1.047035e+05	1.412057e+06
	(2.323421)	(3.983956)	(6.801470e+04)	(4.567618e+05)	(5.942558e+06)
Baker	−9.955914e-02	−2.007032e-01	1.708856e+03	2.565922e+03	1.097686e+03
	(0.3331052)	(0.9408778)	(9432.15)	(4329.12)	(2936.54)
Inyo	−7.596677e-03	−1.008741e-01	4.856670e+02	1.992594e+03	5.338233e+02
	(0.01346477)	(0.08179139)	(723.83)	(827.86)	(559.74)
Pine	−1.677243e-03	−1.756256e-02	6.734066e+03	1.982493e+04	8.913564e+03
	(5.126984e-02)	(1.305122e-01)	(5.085023e+03)	(2.139731e+04)	(1.385493e+04)
Mcnally	−4.172011e-02	−1.946022e-01	8.000062e+03	4.319828e+03	1.629090e+04
	(1.324503e-01)	(4.713139e-01)	(1.597603e+04)	(7.317147e+03)	(3.938971e+04)
Rawson	−9.991557e-03	−2.897122e-01	4.142184e+02	1.085068e+03	1.203814e+03
	(4.793053e-04)	(1.478321e-02)	(1.562292e+01)	(4.743587e+01)	(5.316033e+01)
Farmers	−1.339126e-02	−1.379332e-02	1.412972e+04	1.056362e+04	7.988343e+02
	(0.1065179)	(0.0987675)	(5184.468)	(5291.69)	(5.428533e+02)
Collins	−3.343431e-02	−1.338889	1.666359e+03	1.122440e+02	
	(1.675754e-01)	(3.602116)	(1.771236e+03)	(2.716665e+03)	
Fish	−1.357456e-02	−1.620848	1.197909e+03		
	(2.040101e-02)	(1.118644)	(1.438405e+03)		

Notes: Results from the structural estimation

1000 times.

First we observe that there is a general consistency of the estimates across ditches. We find that the closer you are in space and in time, the higher the externality it would generate on a sell. On the pother hand, big sales, tend to be more important than small sales, yet this varies by ditch.

6 Conclusions

[TO COME]

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