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Abstract

We investigate the efficiency of a market relative to a non-market institution—an auction relative to a quota—as allocation mechanisms in the presence of frictions. We use data from water markets in southeastern Spain and explore a specific change in the institutions to allocate water. On the one hand, frictions arose because poor farmers were liquidity constrained. On the other hand, wealthy farmers who were part of the wealthy elite were not liquidity constrained. We estimate a structural dynamic demand model under the market by taking advantage that water demand for *both* types of farmers is determined by the technological constraint imposed by the crop's production function. This approach allows us to differentiate liquidity constraints from unobserved heterogeneity. We use the estimated model to compute welfare under market and non-market institutions. We show that the institutional change from markets to quotas increased efficiency for the farmers considered.

JEL Codes: D02, G14, L11, L13, L42, L50.

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1 Introduction

Market efficiency has always been central to economics. In the absence of frictions a market is efficient because it allocates goods according to the valuation of consumers. When *frictions* are present, however, a non-market institution may be more efficient. We study the efficiency of a market relative to a non-market institution in the presence of a specific type of market friction: liquidity constraints. Mainstream economics has long recognized the role frictions on market efficiency. Yet no empirical study has investigated the efficiency of a market relative to a non-market institution in the presence of liquidity constraints to our knowledge. Furthermore, the relative efficiency is not ranked. We develop a structural dynamic demand model under the market, estimate the model using individual-level data about water markets in Spain, and use the estimated model to compute efficiency under both institutions. We show that the institutional change from markets to quotas increased water allocation efficiency for the farmers considered.

Water allocation is a central concern of policy discussions around the world. Water scarcity is extremely acute in places such as India, Latin America, and the U.S. (Vörösmarty *et al.*, 2010). Seventy percent of fresh water usage worldwide is for irrigation. Water markets have emerged as the preferred institution to allocate irrigation water used by farmers in the developed world, particularly in dry regions of the U.S. and Australia (Grafton *et al.*, 2011). Yet markets may not be efficient when some of these farmers are poor. Consider the friction that arises when poor farmers do not have enough cash to pay for water in the market; that is, some farmers are liquidity constrained. A market allocates water to the farmer who has the highest valuation and is not liquidity constrained. A market failure occurs if some of the farmers who are liquidity constrained have higher valuations than farmers who are not liquidity constrained. In this case a simple quota, a non-market institution, may allocate water more efficiently than a market.

We investigate the efficiency of a market relative to a non-market institution—a quota described below—as water allocation mechanisms in the presence of frictions. We use data from water markets in southeastern Spain to perform the empirical analysis. Frictions arose in this setting because some farmers did not have enough cash during the summer to purchase water in the market. As the price of water increased substantially during southeastern Spain's dry season, the region's rapidly-growing fruit trees required more water. These price and demand conditions made summer the *critical* or dry season.

In the leading article of the first volume of the *American Economic Review,* Coman (1911) refers to the problem of liquidity constraints during the critical season: "In southern Spain, where this system obtains and water is sold at auction, the water rates mount in a dry season to an all but prohibitive point." During the critical season, only wealthy farmers could afford to buy water. However, poor farmers with the same production technology (*i.e.,* who grew the same agricultural products) would also benefit from water purchases during the critical season. Indeed, we find that poor farmers bought less water during the critical season than wealthy farmers who grew the same crop mix and number of trees.[1,2]

We exploit four unique features of the setting in southeastern Spain to evaluate efficiency. First, for over 700 years from 1244 until 1966, farmers in the city of Mula used an unregulated market to allocate river water for irrigation.[3] This scenario is unusual because water markets are typically regulated when used (Grafton *et al.*, 2011; Libecap, 2011). Changes in regulation over time or across geographic markets preclude to infer gains from trade using price differences. Recovering demand in such cases requires strong assumptions about market participants. Second, water in this setting is an intermediate good used to produce crops, the final products. Water demand is determined by the technological constraint imposed by the crop's production function, which in turn determines the seasonal water need of the trees, as we explain below. Thus, demand for water is independent of the wealth of the farmer, provided that the farmer has enough cash to pay for water. We focus on farmers who only grew apricot trees and, thus, have the same production function. Third, some Mula farmers were part of the wealthy elite. We identify these wealthy farmers by merging urban real estate tax records with water auction data.[4] We use that wealthy farmers were not liquidity constrained as argued in Section 2 and the previous feature—that water is an intermediate good—to estimate the transformation rate of the production function that characterizes the demand system for *all* apricot farmers. This approach allows us to use the empirical context of Mula to differentiate liquidity constraints from unobserved heterogeneity, as discussed in Section 7. Finally, in 1966 the market was replaced by a quota, a non-market institution.[5]

[1] In the context of agricultural irrigation in this paper, we define a farmer as *wealthy* if the farmer owned urban real estate and as *poor* otherwise. See next section for details.

[2] Problems associated with high market prices for water during the critical season are common in dry regions. For California water market, for example, futures on a water price index are traded at the Chicago Mercantile Exchange to reduce price fluctuations and increase allocation efficiency by allowing "water users [to] hedge future price risk" (CME, 2020).

[3] The market institution was an auction. See Donna and Espín-Sánchez (2018) for details.

[4] In Donna and Espín-Sánchez (2021) we use a different criterion to identify wealthy farmers, whether a farmer used the *don* honorific title. In the article we show that the behavior of poor and wealthy farmers thus defined is also consistent with the presence of liquidity constraints.

[5] Most towns in the region had used quotas to allocate water to farmers since the *Reconquista* in the 13^{th} century. The system of quotas provided insurance to farmers who were guaranteed to obtain enough water to prevent their trees from withering during a drought. The towns of Mula and Lorca, which had used auctions to allocate water since the 13^{th} century, were the only exceptions. The origin of this institutional diversity in the area is accidental as we explain in Subsection 2.2. The auction persisted in Mula until 1966, when the farmers' association obtained a credit line to buy water property rights and switched to the system of quotas.

Under quotas farmers who owned a plot of fertile land were entitled to a fixed amount of irrigation water—proportional to the size of their plot— and paid only a small annual fee for maintenance costs. A natural question arises: How did the institutional change from markets to quotas affect welfare in the presence of liquidity constraints?

We empirically investigate how this institutional change affected efficiency as a measure of welfare. With output data before and after the institutional change, computing welfare would be straightforward. However, no output data is available. We build a structural econometric model that allows us to compute output under markets and quotas. The econometric model uses detailed input data and farmers' plot characteristics during the market, along with a crop production function that transforms these inputs into output, to compute the *counterfactual* production before and after the institutional change. In the model, irrigation water has diminishing returns and farmers are heterogeneous on two dimensions: their willingness to pay (productivity) and their ability to pay for the water (cash holdings). On the one hand, markets are efficient in the absence of liquidity constraints. On the other hand, a system of fixed quotas is efficient in the absence of heterogeneity in productivity due to decreasing marginal returns to water.[6]

In our empirical setting farmers are *ex-post* heterogeneous in productivity because they receive a productivity shock. In addition, some farmers are liquidity constrained. In this general case, the efficiency of markets relative to quotas is ambiguous as explained in Section 6. It is then an empirical question to assess which institution is more efficient. To the best of our knowledge, we are the first to empirically investigate the efficiency of a market relative to a quota in the presence of liquidity constraints.

We begin our analysis by estimating demand for water under the market system. To estimate demand, we account for three features of the empirical setting. First, irrigation increases the soil moisture level, thus reducing future demand for water. Irrigation creates an intertemporal substitution effect where water today is an imperfect substitute for water tomorrow due to evaporation. Second, some farmers are liquidity constrained. Wealthy, unconstrained farmers strategically delay their purchases until the critical season when fruit trees need water the most. Poor farmers, who may be liquidity constrained, buy water before the critical season in anticipation of a price increase. Finally, weather seasonality increases water demand during the critical season when fruit grows most rapidly. Seasonality shifts the demand system conditional on intertemporal substitution and liquidity constraints.

The farmer's utility has three components in our econometric model. First, the crop

[6]In a static setting, markets are efficient if farmers are sufficiently wealthy and quotas are efficient if farmers are homogeneous. If all farmers are homogeneous and sufficiently wealthy, both markets and quotas are efficient. In a dynamic setting with discrete units, such as the one studied in this paper, the characterization of efficiency is more complex as described next.

production function that transforms water into fruit. Second, the cost of producing the fruit, measured as the total amount spent on water plus an irrigation cost. Finally, a farmer-specific idiosyncratic productivity shock. Conditional on soil moisture, type of agricultural product, and number of trees, the productivity of the farmers is assumed to be homogeneous up to the idiosyncratic shock.[7] This specification allows to identify the other source of heterogeneity: liquidity constraints. To estimate the econometric model, we construct a conditional choice probability estimator described in Section 4. For the estimation, we only use data on wealthy farmers who were not liquidity constrained.

We use the estimated dynamic demand system to compute welfare under markets and quotas. We show that a quota, where each farmer is allocated a fixed amount of water every three weeks, increased welfare relative to markets. Such a quota is similar to the quota implemented in Mula. When farmers irrigate often, they pay more irrigation costs. Crops may wither if irrigation is seldom performed. The frequency of irrigation thus affects welfare. Markets are inefficient in comparison to a simple quota because: (i) farmers are relatively homogeneous; (ii) liquidity constraints are present, and (iii) farmers' utility is concave in the amount of water used for irrigation. This fundamental result shows the importance of choosing appropriate institutions to allocate goods in the presence of frictions.

In summary, we make three main contributions: (1) we build a unique data set that includes detailed financial information and individual characteristics, and a novel econometric approach to estimate demand in the presence of storability, liquidity constraints, and seasonality; (2) we investigate the efficiency of markets relative to quotas in the presence of liquidity constraints by exploring a specific institutional change; and (3) from an efficiency perspective, we conclude that the institutional change improved welfare for the farmers studied because quotas more often allocated water units according to farmers' valuations than did markets.

Related Literature

Scholars propose two competing hypotheses to explain the coexistence of markets and quotas in Spanish irrigation communities. On the one hand, Maass and Anderson (1978) claimed that, absent operational costs, markets are more efficient than quotas but both systems coexisted because the less efficient system of quotas was simpler and easier to maintain. Once operational costs are taken into account, quotas are more efficient than markets where

[7] We construct an individual measure of soil moisture for each farmer. To do that, we use farmers' water purchase decisions, the amount of rainfall, and the crop production function taken from the agricultural engineering literature as described in Section 3. The constructed measure of soil moisture is used as an observable variable in the empirical analysis.

water is abundant. This hypothesis is supported by evidence from markets where water was extremely scarce (Musso y Fontes, 1847; Pérez Picazo and Lemeunier, 1985). On the other hand, Garrido (2011) and González Castaño and Llamas Ruiz (1991) argued that owners of water rights had political power and were more concerned about their revenue than the system's efficiency.

The theoretical literature on markets with liquidity constraints is relatively recent (*e.g.,* Che and Gale, 1998). Our model is closest to that of Che *et al.* (2013). The authors assume that agents consume at most one unit of a good with linear utility in their type. They conclude that while markets are always more efficient than quotas, some non-market mechanisms outperform markets when resale is allowed. In our model, we allow agents to consume multiple, discrete units with a concave utility function and incorporate dynamics by allowing intertemporal substitution between units. In our setting, the efficiency of markets and quotas is not strictly ranked. However, non-market mechanisms with resale outperform both markets and quotas as in Che *et al.* (2013).

Auctions with liquidity constraints can be seen as a particular case of asymmetric auctions. Athey *et al.* (2013) and Krasnokutskaya and Seim (2013) conclude that preferential auctions decrease efficiency if they reallocate from high-bid bidders to low-bid bidders. If some bidders face liquidity constraints, however, giving them preferential treatment could increase efficiency as in Marion (2007). For example, if liquidity-constrained bidders have higher valuations than unconstrained bidders, reallocation would increase efficiency. Identifying valuations from liquidity constraints is necessary to estimate efficiency gains in preferential auctions. Ignoring the presence of liquidity constraints in preferential auctions may bias the estimated distribution of valuations. This logic applies to firms as well as individuals. If firms face capacity constraints, as in Jofre-Bonet and Pesendorfer (2003), small firms are more efficient than large, low-capacity firms. Capacity constraints may bias the analysis against small firms because they are more likely to face liquidity constraints. A normative implication is that efficiency is increased by treating small firms' bids favorably. A positive implication is that small firms' productivity will be underestimated if one incorrectly assumes they are unconstrained when they are in fact constrained.

Our historical setting is also related to the economic development literature. Rosenzweig and Wolpin (1993) estimate a structural model of agricultural investment in the presence of credit constraints. Udry (1994) studies how rural Nigerian farmers use government loans to insure against output variability. Jayachandran (2013) shows that liquidity-constrained Ugandan land owners prefer upfront payment in cash over promised future payments. Bubb *et al.* (2018) study rural India, where liquidity constraints in water markets reduce efficiency, as in our case.

We estimate a dynamic demand model with seasonality and storability. While there is a large empirical industrial organization literature on dynamic demand (*e.g.,* Boizot *et al.,* 2001; Pesendorfer, 2002; Hendel and Nevo, 2006; Gowrisankaran and Rysman, 2012; Donna, *forthcoming*), none of these articles examine how liquidity constraints affect demand.[8] To the best of our knowledge, this paper is the first to propose and estimate a demand model with storability, seasonality, and liquidity constraints. Timmins (2002) studies dynamic demand for water and is closest to our paper. He estimates demand for urban consumption rather than demand for irrigation. While Timmins (2002) uses parameters from the civil engineering literature to estimate the supply of water, we use parameters from the agricultural engineering literature to determine both demand structure and soil moisture. To estimate the parameters that characterize demand, we exclude data from poor farmers who may be liquidity constrained, and use data from wealthy farmers, who are not. We project inferred preferences from these *trusted choices* onto the welfare of poor farmers. Using trusted choices for welfare analysis is an approach similar to that of, *e.g.*, Handel and Kolstad (2015) and Ketcham *et al.* (2016), who use informed consumers' choices or revealed preferences to identify risk preferences or to proxy for misinformed consumers' concealed preferences, respectively.[9]

2 Environment, Institutions, and Data

2.1 Environment

Southeastern Spain is among the most arid regions in Europe. The aridity arises because of its location to the east of the Prebaetic system and due to the *foehn* effect.[10] Rivers flowing down the Prebaetic system mountains provide irrigation water for the whole region. Summers are dry. Rainfall occurs most often during fall and spring. Most years are dryer than the average. There are only a few days of high-intensity rain per year.[11]

Figure 1.A maps Mula's location in the southeastern Spain. Figure 1.B displays a satellite image of Mula (located at the bottom of the map), the *De la Cierva* dam (top), and the main locations of farmers' plots (numbered circles to the left/bottom of the city/dam). Green circles denote subareas containing both poor and wealthy apricot farmers (1, 2, 4, and 7). Orange (3 and 6) and yellow circles (5) denote subareas containing only wealthy or poor

[8] See Aguirregabiria and Nevo (2013) for a survey.

[9] A related approach is to investigate choices of trusted experts in the industry as in, *e.g.*, Bronnenberg *et al.* (2015) and Johnson and Rehavi (2016).

[10] The Prebaetic system includes the *Mulhacén*, which is the highest mountain in the Iberian Peninsula.

[11] For example, on October 10, 1943, a total of 681 millimeters of rain fell in Mula. The yearly average was 326 millimeters.

farmers, respectively. Two patterns emerge. First, all farmers' plots are near the main canal. Second, wealthy and poor farmers are not sorted into specific locations based on their wealth.

With volatile water prices and rainfall, farmers also find it difficult to predict how much cash they need to purchase water in the market. Seasonal water demand peaks during the pre-harvest weeks when fruit grows quickly. Farmers sell their output once per year, after the harvest, and thus collect cash, or revenue, only once per year. The weeks when farmers most need cash to purchase water for thirsty trees in the market are the weeks furthest away from the prior year's harvest payment. As a consequence, poor farmers without other sources of revenue may be liquidity constrained.

Farmers take into account the joint dynamics of water demand and water price when making purchasing decisions. Water today is an imperfect substitute for water tomorrow. Farmers consider current prices of water and form expectations about their future evolution. A farmer who expects to be liquidity constrained during the critical season—when demand is highest—may decide to buy water several weeks before the critical season when the price of water is lower.

Farmers are *hand-to-mouth* consumers in that they have only enough money for basic necessities (González Castaño and Llamas Ruiz, 1991). A farmer who expects to be liquidity constrained in the future would attempt to borrow money. However, poor farmers in Mula did not have access to credit markets.[12] Even if a credit market had existed, lenders may not have loaned to poor farmers. In the presence of limited liability (poor farmers) and non-enforceable contracts (poor institutions), endogenous borrowing constraints emerge.[13] Hence, non-enforceable contracts would have prevented farmers from holding cash when they needed it most.[14]

2.2 History and Origins

The Kingdom of Murcia enjoyed prosperity and stability under the reign of Ibn Hud, from 1228 until his murder in 1238. That year Jaime I, King of Aragon, conquered Valencia and prepared to march south to Murcia. The Kingdom of Castile was also expanding its territory to the south. By 1242 Castile had conquered most of Murcia. Ibn Hud's son, Ahmed

[12] Interviews with surviving farmers confirm that some farmers were liquidity constrained—they did not have enough cash to buy the amount of water they desired—yet they did not borrow money from others. A summary of the interviews is available here.

[13] See Albuquerque and Hopenhayn (2004) for a model of endogenous liquidity constraints.

[14] In contrast to members of the German credit cooperatives in Guinnane (2001), farmers in southeastern Spain were unable to create an efficient credit market. Spanish farmers were poorer than German farmers, and weather shocks were greater in magnitude and aggregate, rather than idiosyncratic, shocks. Hence, to reduce risk, Spanish farmers should have resorted to external financing. However, external financing had problems like monitoring costs and information acquisition that credit cooperatives did not have.

traveled to Alcaraz (Toledo) to meet its prince Alfonso and begin peace talks. The Christian kingdom of Castile and the Muslim kingdom of Murcia signed the treaty of Alcaraz. Castile would have political control over its protectorate Murcia but Muslims would keep their assets and customs. The governors of the cities of Mula and Lorca rejected this agreement. Castile's army conquered both cities by force and expropriated citizens' assets, including water property rights.[15] The conquerors created a shareholder-owned corporation, a cartel, to hold water property rights in each city. The original corporation owners were the Order of the Temple in Lorca and the Order of Santiago in Mula. Each city's corporation ran periodic auctions to sell water usage rights, and paid dividends to share owners at the end of the year. All other towns and cities in the region kept their pre–*Reconquista* system of quotas.

After seven centuries of operation the Mula auction ended in 1966 when the farmers' union (*Sindicato de Regantes*) reached an agreement with the corporation (*Heredamiento de Aguas*) for a system of fixed quotas. In 1966 the *Sindicato* secured a credit line for the express purpose of buying water property rights, which it began purchasing share by share from the original owners.[16] During this transition period, the *Sindicato* paid a fixed price for each unit of river water and allocated it among farmers using quotas.

2.3 Institutions

Markets. Since the thirteenth century, Mula farmers had used a sequential outcry ascending price (or English) auction to allocate water. The basic structure of the sequential English auction remained unchanged until 1966, when the last auction was run. The auctioneer sold each unit sequentially and independently of the others. The auctioneer tracked the buyer's name and price paid for each unit of water. Farmers had to pay in cash on auction day.[17]

Water was sold by the *cuarta* (quarter), a unit that denoted the right to use water flowing through the main channel for three hours beginning at a specific date and time. Property rights to water and land were independent of each other. Some individuals, not necessarily farmers, were waterlords. Waterlords owned the right to use water flowing through the channel. Farmers who participated in auctions owned only land. Water was stored at the main dam, the *De la Cierva* dam, and delivered to a farmer's plot by a system of channels. Water flowed from the dam through the channels at approximately 40 liters per second,

[15] The initial shock is similar to that in Chaney and Hornbeck (2016).

[16] See Espín-Sánchez (2017) for more details about the transition to quotas.

[17] Allowing farmers to pay after the critical season would have helped to mitigate problems created by liquidity constraints and would have increased auction revenue. However, the corporation's bylaws stipulated that payment had to be in cash. This requirement suggests that water owners were concerned about repayment after the critical season due to non-enforceable contracts (poor Spanish institutions).

meaning each unit of water sold at auction (*i.e.,* the right to use water from the canal for three hours) carried approximately 432,000 liters of water. During the period under analysis, auctions were held once a week, every Friday. During each session, 40 units were auctioned: four units for irrigation during the day (from 7:00 AM to 7:00 PM), and four units for irrigation during the night (from 7:00 PM to 7:00 AM) on each weekday (Monday to Friday). Our sample consists of all water auctions in Mula from January 1955 until July 1966.

Quotas. On August 1, 1966 the water allocation system switched from a market to a fixed quota system, as explained above. Under quotas, water rights were tied to land ownership. Each plot of land was assigned a fixed amount of water every three weeks, called a *tanda.* The amount allocated to each farmer was proportional to the size of their plot. Every December, a lottery assigned a farmer's order within each round of irrigation for the whole year. At the end of the year, farmers paid a fee to the *Sindicato* proportional to the size of their plot. Importantly, farmers paid after the critical season and were thus not liquidity constrained.[18] In the counterfactual analysis we compare welfare under this quota system, a non-market institution, and under markets.

2.4 Data

We built a unique panel data set using four main data sources. The first source is the weekly auction data from Mula's municipal archive. For the period from January 1955 until the last auction in July 1966, we observe purchase price, number of units purchased, purchase date, and irrigation date. We compute real prices using the price index by the INE (*Instituto Nacional de Estadística*) from Uriel *et al.* (2000).[19] The second source is rainfall data from the Spanish National Meteorological Agency. The third source is a cross-sectional agricultural census data set from 1955. The census data contain information regarding farmers' plots, including type of agricultural products grown, number of trees, total production, and output sale price. The final source is urban real estate tax records from 1955. We use this information to identify farmers who were not liquidity constrained. Below we provide a brief description of these sources. In the final constructed dataset, each period represents one week and each individual represents one farmer. The unit of observation is a farmer-week.[20]

[18]Farmers owned the water rights under the quota system and paid for the average cost of system operation. The fee covered yearly maintenance costs, including guards' salaries and dam maintenance costs. This fee was substantially lower than the per-unit average price of water under the market system.

[19]See Appendix A.1.5 for details.

[20]See Appendix A.1 for additional details and summary statistics.

Auction Data. Auction data encompass 602 weeks divided into three categories based on bidding behavior and water availability: (i) normal periods (300 weeks), when for each auction transaction the winner's name, purchase price, irrigation date and time were recorded; (ii) no-supply periods (295 weeks), when due to water shortage in the river or damage to the dam or channel—usually after intense rain—no auction was carried out; and (iii) no-demand periods (7 weeks), when some units were not sold due to lack of demand because of recent rain and the price dropped to zero. For the empirical analysis we use data for the period 1955 to 1966.

Rainfall Data. We link auction data to daily rainfall data for Mula, which we obtain from the Spanish National Meteorological Agency. In regions with a Mediterranean climate, rainfall occurs mainly during spring and fall. Agricultural products cultivated in the region require the most water in spring and summer, between April and August. The coefficient of variation of rainfall is 450 percent ($^{37.08}/_{8.29}\times 100$), indicating that rainfall varies substantially.

Agricultural Census Data. We also link auction data to the 1954/55 agricultural census data from Spain. The agricultural census data provide information on individual characteristics of farmers' land. The census recorded the following individual characteristics: type of land and location, area, number of trees, production, and production sale price during the census year. We match the name of the farmer on each census card with the name of the winner of each auction.

Urban Real Estate Tax Data. We link the above data to the urban real estate tax registry from 1955. To identify the source of financial constraints, we need a variable related to farmers' wealth that is unrelated to their demand for water. We use urban real estate taxes to identify wealthy farmers, as explained in the next section.

2.5 Preliminary Analysis

Four main types of fruit tree grow in the region: orange, lemon, peach, and apricot. Oranges are harvested in winter, when water prices are low; thus farmers are unlikely to face liquidity constraints. The other three fruits are harvested in the summer. We focus on apricots because they are the most common summer crop.

Wealthy Farmers. We define a farmer as *wealthy* if the value of urban real estate of the farmer obtained from the urban real estate tax data is positive and *poor* otherwise.[21] Because farmers grow agricultural products in rural areas, urban real estate constitutes non-agricultural wealth. In the empirical analysis we use this set of wealthy farmers and exploit that they were never liquidity constrained. We make two observations. First, the value

[21] We obtained similar results using median wealth as a threshold to define wealthy farmers.

of farmers' urban real estate should not affect their production function (*i.e.,* the farmer's willingness to pay for water), conditional on type of agricultural product, size of plot, and number of trees. That is, after accounting for these variables, the value of the urban real estate should not be correlated with a farmer's demand for water because the latter is determined by the crop production function, apricots in the case studied in this paper. Second, we argue that wealthy Mula farmers were never liquidity constrained. Wealthy farmers each owned several urban properties. While wealthy farmers' average annual urban real estate rental income was 5,702 pesetas, their average annual irrigation water expenditure was 500 pesetas. In 1963, the sample year when water expenditures were highest, farmers' average annual water expenditure was 1,619 pesetas. No poor farmer owned any urban property.

Water Demand and Apricot Trees. Table 1 displays the growth cycle of the typical apricot tree cultivated in Mula, the *búlida* apricot. These trees most need water during the late fruit growth stages II and III, and the Early Post-Harvest (EPH).[22] Stage III corresponds to the period when the tree transforms water into fruit at the most rapid rate. The *critical season* corresponds to fruit growth stage III and the EPH period. The latter is important due to the *hydric stress* that the tree suffers during harvest.[23]

Unconstrained farmers' demand for water is determined by their apricot trees' need for water. That is, consider two farmers who grow only apricots, have the same number of trees, and are not liquidity constrained. Water demand is determined by the tree's water need according to the apricot production function in Table 1. These two farmers should have the same demand for water up to an idiosyncratic shock. For unconstrained farmers, there should be no relationship between water demand and monetary value of urban real estate. The next figure and table show that this relationship only holds for wealthy farmers under the market institution, thus indicating that some of the poor farmers are liquidity constrained.

The top panel in Figure 2 shows the effect of weather seasonality on water price during the market period. The figure displays average weekly water prices and average weekly rainfall in Mula. The shaded area corresponds to the critical season as defined above. Fruit growth stage III goes from week 18 (early May) to week 24 (early June). The EPH goes from week 24 (early June) to week 32 (early August). The price of water increases substantially during

[22]The beginning of the post-harvest period coincides with week 24. In the model in Section 3 we assume that all harvesting takes place during week 24. In practice, the harvest would take several weeks. The tree is vulnerable during the EPH weeks, when the tree's moisture level would affect the current year's harvest.

[23]Hydric stress refers to a situation when the tree is unable to absorb water from the soil (see Appendix A.2).

the critical season.[24] The bottom panel in Figure 2 shows purchasing patterns by wealthy and poor apricot farmers, displaying average liters of water per tree purchased by each type of farmer during the market. Wealthy farmers—who are not liquidity constrained—demand water as predicted by Table 1. Wealthy farmers strategically delay their purchases and buy water during the critical season, when the apricot trees need water the most. Poor farmers—who may be liquidity constrained—display a bimodal purchasing pattern for water inconsistent with Table 1. The first peak occurs before the critical season, when water prices are relatively low. Poor farmers buy water before the critical season because they anticipate being unable to afford water during the critical season, when prices are high. A fraction of the purchased water will evaporate, but the rest remains as soil moisture. The second peak occurs after the critical season, when water prices are again relatively low. After the critical season, poor farmers' plots have a low moisture level if they were unable to buy sufficient water during the critical season. Poor farmers buy water after the critical season to prevent their trees from withering. Poor farmers' purchasing patterns—frequent purchases before and after the critical season, and fewer during the critical season—is explained by the model presented in Section 3, which includes seasonality, storability, and liquidity constraints.[25]

Table 2 shows similar evidence to the one presented in Figure 2 using OLS regressions. As in Figure 2, in Table 2 we restrict attention to farmers who grow only apricot trees. We regress the number of units per tree purchased by each farmer in a given week on several covariates. We use the number of units per tree to account for farmers' plot size.[26] Column 1 shows that wealthy farmers purchase more water overall. The coefficient is not statistically different from zero in column 2 when we include the covariates. This finding is consistent with wealthy and poor farmers purchasing the same amount of water throughout the year. In columns 3 and 4 we include an interaction between *wealthy* and *critical season*. The interaction term is positive and statistically different from zero. Wealthy farmers demand more water per tree during the critical season than poor farmers who have the same agricultural products. That is, wealthy farmers demand more water per tree during the critical season than do poor farmers who grow the same, identical type of tree: *búlida* apricot. The effect of liquidity constraints on the demand for water is evident during the critical season due to the large increase in the price for water during the market. For robustness, in columns 5

[24]See description above and Appendix A for details.

[25]Table 2, discussed next, shows that differences in purchases between poor and wealthy farmers are only significant during the critical season. Our model has clear predictions for the difference in purchasing patterns during the critical season. Outside the critical season the predictions are ambiguous and depend on the severity of liquidity constraints. Poor farmers buy less water than wealthy farmers outside the critical season only when liquidity constraints are severe.

[26]Wealthy farmers own larger plots. Because farmers can only buy whole units of water, there may be economies of scale in water purchases only available to wealthy farmers.

and 6 we also include the interaction between *wealthy* and an indicator of water purchases during the first 10 weeks of the year. The coefficient of this interaction is not statistically different from zero as expected.[27]

3 Structural Model

We now present the model used to compute efficiency under markets and quotas. Measuring efficiency would be straightforward with output data; that is, with data about apricot production before and after the institutional change. However, such output data is not available. We instead compute output using the apricot production function and detailed input data including water units purchased, rainfall amount, and farmers' plot characteristics. We proceed in three steps. First, we present the structural model, which uses the mentioned production function and three features from the setting studied: storability, liquidity constraints, and seasonality.[28] Second, we estimate the model using input data for wealthy farmers under the market institution. Finally, we use the estimated model to compute the counterfactual apricot output for *all* farmers, both under markets and quotas; that is, before and after the institutional change. We use total apricot production as a measure of efficiency as described below.

We focus on the demand system for farmers who only grew apricot trees. This group of 24 farmers was the largest single-crop group. There were, however, more than 500 farmers who could participate in the market. Hence, we assume that the distribution of the highest valuation among the other 500 farmers is exogenous to the valuation of a given farmer conditional on week of the year, price, and rain during the previous week. This assumption is sensible in our setting because it is unlikely that any individual farmer could affect the market price as discussed in Donna and Espín-Sánchez (2018). We estimate a different price distribution for each week of the year that depends on rainfall during the previous week.[29]

The economy consists of N rational and forward-looking farmers indexed by i. Water increases soil moisture in the farmer's plot. From the farmer's point of view there are two goods in the economy: moisture denoted by M and measured in liters per square meter, and money denoted by μ and measured in real pesetas (henceforth, pesetas). Time is denoted by

[27] Appendices A.3 and C.5 present additional evidence and estimates about poor farmers' liquidity constraints..

[28] In contrast to Donna and Espín-Sánchez (2018), we do not model the auction game here. Thus, we abstract from the within-week variation in prices which is very low as shown in Donna and Espín-Sánchez (2018). We translate the auction mechanism into a simpler dynamic demand system, whereby individual farmers take prices as exogenous, as explained in the next paragraph. This approach allows us to focus on the dynamic behavior of farmers across weeks.

[29] See Appendix B for details.

t. The horizon is infinite and the discount between periods is $\beta \in (0,1)$. Demand is seasonal. We denote the season by $w_t \in \{1,2,...,52\}$, representing each of the 52 weeks in a given year. In each period, the supply of water in the economy is exogenous. Farmers only receive utility for water consumed during the critical season. Water is an intermediate good. Hence, utility refers to farmers' profits and is measured in pesetas, *not* in utils. Water purchased in any period can be carried forward to the next period, but it *evaporates* as indicated by the evolution of soil moisture in equation 2 described below. Farmers' preferences are represented by:

$$u\left(j_{it}, M_{it}, w_t, p_t, \varepsilon_{ijt}; \gamma, \zeta\right) = h\left(j_{it}, M_{it}, w_t; \gamma\right) - \zeta\,\mathbf{1}\{j_{it} > 0\} - p_t j_{it} + \varepsilon_{ijt}, \tag{1}$$

where $j_{it} \in \{0,1,...,J\}$ indicates the number of units that farmer i purchases in period t; $h(\cdot)$, is the apricot production function common to all farmers, strictly increasing in the plot moisture level, M_{it}; p_t is the price of water in period t; $\mathbf{1}\{\cdot\}$ is an indicator function; ε_{ijt} is an additive productivity shock to farmer i in period t given that the farmer bought j_{it} units of water; and γ and ζ are parameters. We describe these objects below.

The parameter ζ represents farmers' irrigation costs. A disutility could result, *e.g.*, if the farmer hires a laborer. We restrict attention to the case of farmers who do not incur irrigation costs when they do not irrigate and irrigation costs are constant across units. A farmer's optimization problem is subject to the constraints described in the explanation of equation 6. The function $u(\cdot)$ depends implicitly on the amount of rainfall, r_t, which affects moisture, and the parameter that characterizes the distribution of the productivity shocks, σ_ε, described below.

Following the literature on irrigation communities in southeastern Spain we assume that farmers are *hand-to-mouth* consumers;[30] that is, we require that $(\mu_{it} - p_t j_{it}) \geq 0$, $\forall j_{it} > 0$ (limited liability). We further assume that wealthy farmers obtain cash flow from their non-agricultural wealth. Wealthy farmers always have enough cash and the limited liability constraint is never binding. The constraint, however, could be binding for poor farmers. Poor farmers might buy water before the critical season when water prices are low in anticipation of the binding constraint during the critical season. Farmers differ from each other in two ways. First, they differ in their productivity shock, ε_{ijt}. Second, they differ in their wealth μ_{it}. Both, ε_{ijt} and μ_{it}, are private information. We describe the evolution of wealth below.

State Variables and Value Function

Farmer i has the following state variables.

Moisture. Moisture, M_{it}, measures the amount of water accumulated in a farmer's plot.

[30] See González Castaño and Llamas Ruiz (1991) and the references therein.

The moisture level is obtained by applying the procedure from the agricultural engineering literature.[31] We construct an individual moisture level variable for each farmer. For the estimation we treat moisture as an observable state variable similar to inventory in Hendel and Nevo (2006).[32] Trees on a farmer's plot wither and die if soil moisture falls below the permanent wilting point, denoted by the scalar PW obtained from the agricultural engineering literature. Each farmer i must satisfy the constraint $M_{it} \geq PW$ for all t. This inequality constrains the objective function. The farmer's utility is zero if the inequality is not satisfied. The evolution of M_{it} is given by Allen *et al.* (2000):[33]

$$M_{it} = min \left\{ M_{i,t-1} + r_{t-1} + \frac{j_{it-1} \cdot 432,000}{area_i} - ET\left(M_{it-1}, w_{t-1}\right), FC \right\}, \tag{2}$$

where r_t is the amount of rainfall measured in liters per square meter in period t; $432,000$ is the number of liters contained in each unit of water; $area_i$ is the farmer's plot area measured in square meters; $ET\left(M_{it}, w_t\right)$ is the adjusted *evapotranspiration* in period t;[34] and FC is the full capacity of the farmer's plot. Moisture and seasonality are the main determinants of water demand. The moisture level increases with rain and irrigation, and decreases over time as water accumulated in soil evaporates. We use equation 2 to compute the moisture level. This equation accounts for decreasing marginal returns of water in two ways. First, because a farmer's plot has a maximum capacity represented by FC, farmers *waste* water if the soil moisture level increases above FC. Second, water evaporation is greater for higher levels of moisture. Thus, farmers with high levels of moisture in their plots waste more water. In sum, there are declining returns to units purchased for irrigation, even when the production function is linear in moisture.

Weekly Seasonal Effect. The week of the year, w_t, is the weekly seasonal effect. This is a deterministic variable with support on $\{1, 2, ..., 52\}$ that evolves as follows: $w_t = w_{t-1} + 1$ if $w_{t-1} < 52$, and $w_t = 1$ otherwise. Farming is a seasonal activity, with a different water requirement for each crop depending on the season. Apricot trees' water requirements are captured by the production function, $h\left(j_{it}, M_{it}, w_t; \gamma\right)$. Because the water auction occurred once a week, we include a state variable with a different value for each week.

Price of Water and Rainfall. For each week t, the price of each unit of water, p_t,

[31] See Appendix A.2 for details.

[32] We assume that errors in measurements do not systematically differ between wealthy and poor farmers. We believe this assumption is reasonable in the empirical context analyzed because all farmers' plots are located in a small, relatively flat area spanning less than two times four kilometers, and wealthy and poor farmers are not sorted into specific locations as can be seen in Figure 1.A.

[33] The variable moisture accounts for the decreasing marginal returns of water on area because larger plots receive smaller increase in moisture after purchasing a unit of water. See equation 2.

[34] Evapotranspiration refers to the process by which water in plants is transferred into the atmosphere. It is the sum of evaporation from soil and transpiration through leaves. See Appendix A.2.

and the amount of rainfall in the town, r_t, are random variables whose joint probability distribution is described next. We model the joint probability distribution of prices and rainfall to capture three main empirical regularities from our setting. First, the major determinant of water price is weather seasonality, captured by the week of the year. Second, the variation of prices and rainfall across years is low conditional on the week of the year.[35] Third, there are weeks when no auction was run (no-supply weeks) as explained in Subsection 2.4. The data in this paper cover a sample of 11 years. We model the joint evolution of water price in period t and rainfall in period $t-1$ assuming that, holding fixed the week of the year, farmers jointly draw a price-rain pair, (p_t, r_{t-1}), *i.i.d.* among the 11 pairs available with equal probability; that is, the 11 years of the same week.[36] The water for each week was sold on the Friday of the previous week. When a farmer jointly draws a pair price-rain, the rain corresponds to the rain during the week prior to the irrigation. Thus, prices for the irrigation week are drawn conditional on the week of the year, and rainfall during the previous week. Rain during the previous week captures the dynamic of droughts; that is, that prices are systematically higher when there is no rain. We model weeks with no supply as weeks with *infinite* prices to reflect the impossibility of purchasing water during those weeks. We allow for the distribution of weekly prices to have a positive probability mass at infinity. Farmers know the probability of an infinite price given the week of the year and the prior week's rain, and behave accordingly.[37]

Productivity Shock. The productivity shock, $\epsilon_{it} \equiv (\epsilon_{i0t}, ..., \epsilon_{iJt})$, is a choice-specific component of the utility function.[38] We assume that the productivity shocks, ε_{ijt}, are drawn *i.i.d.* across individuals and over time from a Gumbel distribution with CDF $F(\varepsilon_{it}; \sigma_\varepsilon) = e^{-e^{-\varepsilon_{it}/\sigma_\varepsilon}}$, where σ_ε is a parameter to be estimated. The variance of this distribution is given by $\sigma_\varepsilon^2\pi^2/6$. The higher the value of the parameter σ_ε, the more heterogeneous the distribution of productivity. In addition, productivity shocks are drawn *i.i.d.* across the choice of not buying, $j = 0$, and buying, $j > 0$. Every farmer receives one shock, but the shock is the same for all $j > 0$. Formally, let $\hat{j} \in \{0, 1\}$, where $\hat{j} = 0$ if $j = 0$ and $\hat{j} = 1$ if $j > 0$. Then the productivity shocks $\varepsilon_{i\hat{j}t}$ are drawn *i.i.d.* across $\hat{j} \in \{0, 1\}$, so $\varepsilon_{ijt} = \varepsilon_{i\hat{j}t}$ for $j = 0$ and $\varepsilon_{ijt} = \varepsilon_{i\hat{j}t}$ for $j > 0$. We present closed-form expressions for the conditional choice probabilities using this specification in Appendix B.3.[39]

[35]See Appendix A.1.

[36]We obtained similar results by estimating the joint distribution of prices and rain non-parametrically conditional on the week of the year, and then drawing price-rain pairs from this distribution conditional on the week of the year.

[37]See Appendix B for details.

[38]Alternatively, one could refer to these shocks as a component of irrigation costs. These shocks have no impact on the marginal productivity of moisture. See Section 6 for a discussion of their impact on welfare.

[39]The choice is not binary; that is, $j_{it} \in \{0, 1, ..., J\}$. In Appendix B.3, we describe two specifications

Cash Holdings. The cash holdings, μ_{it}, measure the amount of cash that farmer i has in period t. The cash variable μ_{it} is measured in pesetas and evolves according to:

$$\mu_{it} = \mu_{i,t-1} - p_{t-1} j_{i,t-1} + \phi_{i0} + R_{it} + \nu_{it}, \tag{3}$$

where ϕ_{i0} captures the weekly consumption of individual i that is constant over time; R_{it} is the revenue that farmer i obtains in period t from selling their harvest discussed in equation 8; and ν_{it} are idiosyncratic financial shocks that are drawn *i.i.d.* across individuals and over time from a normal distribution.[40] The farmer collects revenue after the harvest in week 24. The yearly revenue, R_{it}, is:

$$R_{it} = \begin{cases} 0 & \{t : w_t \neq 24\} \\ Rev_{it} & \{t : w_t = 24\} \end{cases}, \tag{4}$$

where the farmer's collected revenue in harvest, Rev_{it}, is:[41]

$$Rev_{it} = \sum_{w_t=1}^{52} h\left(j_{it}, M_{it}, w_t; \gamma\right). \tag{5}$$

The value function is given by:

$$\begin{aligned} V\left(M_{it}, w_t, p_t, r_t, \mu_{it}, \epsilon_{ijt}\right) \equiv \max_{j_{it} \in \{0,1,\ldots,J\}} &\left\{h\left(j_{it}, M_{it}, w_t; \gamma\right) - \zeta\, \mathbf{1}\{j_{it} > 0\} - p_t j_{it} + \varepsilon_{ijt} + \right. \\ &\left. + \beta \mathbb{E}\left[V\left(M_{i,t+1}, w_{t+1}, p_{t+1}, r_{t+1}, \mu_{i,t+1}, \epsilon_{i,t+1}\right) | M_{it}, w_t, p_t, r_t, \mu_{it}, \epsilon_{i,t}, j_{it}\right]\right\}, \\ &\text{s.t. } M_{it} \geq PW, \quad j_{it} p_t \leq \mu_{it}, \quad \forall j_{it} > 0, \end{aligned} \tag{6}$$

subject to the evolution of the state variables as described above. The expectation is taken over r_t, p_t, ε_{ijt}, and ν_{it}. For wealthy farmers we assume that the constraint $j_{it} p_t \leq \mu_{it}$ is not

for productivity shocks. First, for the case of *i.i.d.* shocks across choice alternatives, where each choice alternative involves the purchase of a different number of units. Second, the one presented above, where the productivity shocks are drawn *i.i.d.* across the choice of not buying, and buying. In terms of the estimation, we obtained similar results using a binary variable for the decision whether to buy water with *i.i.d.* shocks across these choice alternatives, indicating that the extensive margin is what matters (see Appendix C.2).

[40] As mentioned, we assume that wealthy farmers are never liquidity constrained. Therefore we do not include equation 3 in the demand estimation. Equation 3 is only used to estimate liquidity constraints in Appendix C.5.

[41] The production function measures production in pesetas. The actual price at which production was sold was determined in the international output market and was the same for all farmers. We do not have data about that price. Hence, we recover farmers' revenue up to this constant (the common price at which all farmers' production was sold in the international apricot market). This price only shifts the revenue function of all (wealthy and poor) farmers and does not affect the welfare analysis.

binding.

The Apricot Production Function

The production function of the apricot tree is given by Torrecillas *et al.* (2000):

$$h\left(j_{it}, M_t, w_t; \gamma\right) = \left[\gamma \cdot \left(M_t - PW\right) \cdot KS\left(M_t\right) \cdot Z\left(w_t\right)\right], \tag{7}$$

where $h\left(j_{it}, M_t, w_t; \gamma\right)$ is the harvest at period t; γ is a parameter that measures the transformation rate of water into apricots during the fruit's growth season and the EPH period; $KS\left(M_t\right)$ is the *hydric stress* coefficient, which is a weakly increasing function of moisture; $Z\left(w_t\right)$ is a dummy variable that equals 1 during weeks 18 to 32 and 0 otherwise, which captures the seasonal stages of the *búlida* apricot tree explained above.[42] Substituting in the production function, the farmer's revenue in a given year is:

$$Rev_{it} = \sum_{w_t=18}^{32} \gamma \cdot \left(M_t - PW\right) \cdot KS\left(M_t\right). \tag{8}$$

4 Estimation

We estimate the parameters that characterize demand, $\Theta \equiv \left(\gamma, \sigma_{\varepsilon}, \zeta\right)$, using data from wealthy farmers. For the estimation we exclude data from poor farmers who may be liquidity constrained. We assume that there is no persistent unobserved heterogeneity that affects the production function of wealthy and poor farmers differently; that is, we assume no dynamic sample selection on unobservables. We also assume that wealthy farmers are never liquidity constrained. Although these assumptions are not necessary to identify the model, they simplify the estimation and are motivated by the empirical context.[43]

Demand Estimates

We construct a two-step conditional choice probability (CCP) estimator to estimate the parameters that characterize demand.

Step 1. We compute transition probability matrices for the following observable state variables: moisture, week, price, and rain. The productivity shocks, ε_{ijt}, can be integrated analytically as shown in the appendix. The evolution of moisture depends on both farmers' decisions to buy water and on rainfall. Certain values of moistness are therefore never reached in the sample, even when their probability of occurrence is nonzero. To estimate demand,

[42] See Appendix A.2 for details.

[43] For discussions and robustness analyses see Section 2, and Appendices A.3 and C.

however, we need to integrate the value function over certain combinations of state-space variables not reached in the sample but simulated in step 2. Thus, we first estimate the CCP using the values of the state space reached in the sample. Then we use the CCP estimator to predict the CCP on the values of the state space unreached in the sample as described in Appendix B.1.[44]

Step 2. We build an estimator similar to the one proposed by Hotz *et al.* (1994). We use transition matrices to forward simulate the value function from equation 6.[45] This procedure gives us the predicted CCP by the model as a function of the parameter vector, Θ. We estimate Θ using a GMM estimator based on the moment conditions proposed by Hotz *et al.* (1994).

Identification. We assume that wealthy farmers are not liquidity constrained. Under this assumption, the identification of Θ follows the standard arguments (*e.g.,* Rust, 1996; Magnac and Thesmar, 2002; and Aguirregabiria, 2005). In our case the transformation rate, γ, is identified from variation in purchasing patterns across seasons and variation in moisture across farmers within the same season. The irrigation cost, ζ, which is constant across units and independent of the moisture level, is identified from variation in price levels and farmers' decisions to buy or not, holding constant the moisture level.

The parameter σ_ε is identified because our specification for the utility function in equation 1 does not include a parameter that multiplies the price of water. Such parameter is typically called α in the industrial organization literature (*e.g.*, Hendel and Nevo, 2006). In the industrial organization literature econometricians usually assume $\sigma_\varepsilon = 1$ and estimate α with the utility function in *utils*. In such cases, α is not identified from $1/\sigma_\varepsilon$. In our case the utility function is in pesetas, not in *utils* as explained above.

In Appendix B, we provide additional details regarding: (i) the estimation procedure; (ii) the properties of the estimator; (iii) the specification of the productivity shocks; and (iv) the specification used for the law of motion for prices and water.

5 Estimation Results

Table 3 displays estimation results from the demand model in equation 6 using the procedure described above. We present two sets of estimates. In columns 1 and 2, we perform the

[44] We estimate the CCP using a logistic distribution; that is, a multinomial logit regression described in Appendix B.1. We obtained similar results estimating the CCP non-parametrically using kernel methods to smooth both discrete and continuous variables. See Appendix C.1.

[45] For the initial condition of the moisture we follow Hendel and Nevo (2006, p. 1,647) and use the estimated distribution of moisture to generate its initial distribution. See Appendix B.1.

estimation with only one type of farmer who has the median number of trees in the sample ("Area heterogeneity: No"). This means that when we forward simulate the value function we use the median area for all individual farmers i. In column 1, we use the apricot production function as outlined in equation 7. The estimated transformation rate is $\hat{\gamma}_L = 0.09$. For robustness, in column 2, we add a quadratic term for moisture, γ_Q, to the specification in column 1 to explicitly incorporate potential increasing or decreasing marginal returns.[46] The estimated coefficient on the quadratic term of the transformation rate is small in magnitude, $\hat{\gamma}_Q = 2.91e - 05$. The marginal effects at the average moisture level are similar across specifications. In columns 3 and 4, we repeat the estimation from the previous two columns using farmers' actual plot area ("Area heterogeneity: Yes"). We report the mean $\Theta \equiv (\gamma, \sigma_\varepsilon, \zeta)$ across types. The estimated scale parameter of the distribution of idiosyncratic productivity, $\hat{\sigma}_\varepsilon$, is similar in magnitude across specifications. The higher the parameter σ_ε, the higher the variance of the distribution of idiosyncratic productivity. When $\sigma_\varepsilon = 1$, the distribution of idiosyncratic productivity is a standard Gumbel. The estimated irrigation cost has the expected sign and a sensible magnitude.[47]

For the welfare analysis we use estimates from specification 3, with estimated transformation rate $\hat{\gamma}_L = 0.09$. This coefficient measures the transformation rate from excess moisture to pesetas during the critical season. The average moisture per tree, taking into account the hydric stress coefficient, during the critical season is 873.93. On an average year, a farmer obtains 27.97 pesetas per tree per week during the critical season which translates to 391.59 pesetas per tree per year.

Ignoring the presence of liquidity constraints biases the estimated demand elasticity. To see this, consider the decrease in demand due to an increase in price during the critical season. When farmers are liquidity constrained, their decrease in demand has two components: (1) the decrease in demand due to the price being greater than the valuation of certain farmers; and (2) the decrease in demand due to some farmers being liquidity constrained, even when their valuation is above the prevailing price. Not accounting for the second component of demand would attribute this decrease to greater price sensitivity. One would thus incorrectly interpret liquidity constraints as a more elastic demand, thereby biasing the absolute value of the estimated demand elasticity upwards.

[46] The production function with the quadratic term is: $h(j_{it}, M_t, w_t; \gamma_L, \gamma_Q) = \left[\gamma_L (M_t - PW) + \gamma_Q (M_t - PW)^2\right] KS(M_t) Z(w_t)$.

[47] In Appendix C.2, we present additional estimates from the model using a binary variable for the decision to buy water. Similar results are obtained. We also obtained similar results using: (i) a specification that allows for different transformation rates for pre-season ($18 \leq week \leq 23$) and in-season ($24 \leq week \leq 32$); and (ii) an autoregressive specification for the productivity error term.

In Appendix C, we provide robustness analyses and additional results regarding: (i) nonparametric CCP; (ii) estimates of additional specifications of the model; (iii) goodness of fit; (iv) alternative estimation methods; and (v) estimates of lower bounds on the probability of being liquidity constrained.

6 The Welfare Effects of Market *vs.* Non-Market Institutions

We use the estimated demand system to compare welfare under markets, quotas, and the highest-valuation allocation.[48]

6.1 Gains from Trade and Inefficiency

There are two potential sources of inefficiency in water allocation. First, allocation could be inefficient if some farmers receive water at a time when they are relatively unproductive. This inefficiency arises because farmers are *ex post* heterogeneous in productivity. Let us call this *inefficiency due to heterogeneity.* Second, the allocation could be inefficient if some farmers receive water when their soil moisture level is relatively high. This inefficiency arises because the production function is concave in water. Let us call this *inefficiency due to concavity.* Quotas allocate water units uniformly. They always create inefficiency due to heterogeneity, but never inefficiency due to concavity. Markets would correct both inefficiencies if there were no liquidity constraints, but would create both inefficiencies if liquidity constraints are present. If farmers are heterogeneous and the production function is linear in the number of units purchased, markets are always more efficient than quotas. Quotas are more efficient than markets when there is large heterogeneity in wealth, and small heterogeneity in productivity. Markets are more efficient in the opposite case. In the general case where there is heterogeneity in both wealth and productivity, the efficiency of markets relative to quotas is ambiguous.

In our empirical setting, large heterogeneities in wealth create liquidity constraints. Under the dynamics generated by soil moisture, liquidity constraints create inefficiency due to concavity by allocating water to wealthy farmers with relatively high soil moisture levels. Heterogeneity in productivity is captured by the productivity shocks, ε_{ijt}. Although these shocks are drawn *i.i.d.* across individuals and over time, the estimated value of σ_ε

[48] The HV corresponds to the static first-best allocation. Due to dynamics and the possibility of strategic delaying in water purchase decisions it may not coincide with the dynamic first-best allocation, which is a complex problem outside the scope of this paper.

measures the degree of such heterogeneity. The higher the value of the parameter σ_ε, the more heterogeneous the distribution of productivity. Because ours is a discrete choice model and the error term ϵ_{ijt} is choice-specific, the relevant measure for efficiency is the difference in ϵ_{ijt} across choices conditional on the choice, not the ϵ_{ijt} by itself, nor the unconditional difference. For example, in the case in which $J = 1$ the farmer chooses whether to buy one unit or not to buy. The farmer balances the difference in utility between buying or not considering both the observable and unobservable components. The probability of a farmer buying water increases with the conditional expectation of difference in ϵ_{ijt}. The expectation of this difference conditional on buying is positive. It is negative conditional on not buying. That is: $\mathbb{E}\left[\epsilon_{i1t} - \epsilon_{i0t}|j = 1\right] > \mathbb{E}\left[\epsilon_{i1t} - \epsilon_{i0t}\right] = 0 > \mathbb{E}\left[\epsilon_{i1t} - \epsilon_{i0t}|j = 0\right]$. By construction, the unconditional mean of the differences in the error term is zero. Hence, in the quota system, because farmers cannot choose when to irrigate, the conditional (on irrigation) and unconditional expectations of the difference in the error terms are zero: $\mathbb{E}\left[\epsilon_{i1t} - \epsilon_{i0t}\right]= \mathbb{E}\left[\epsilon_{i1t} - \epsilon_{i0t}|j = 1\right]=\mathbb{E}\left[\epsilon_{i0t} - \epsilon_{i1t}|j = 0\right]=0$. However, in the market system farmers *do* choose when to irrigate. The conditional expectation is always positive under the market. Farmers are more likely to irrigate when their unobserved utility of irrigation is positive, $\epsilon_{i1t} > \epsilon_{i0t}$. They are more likely not to irrigate when their unobserved utility for no irrigation is positive, $\epsilon_{i0t} > \epsilon_{i1t}$. Thus, under the market system: $\mathbb{E}\left[\epsilon_{i1t} - \epsilon_{i0t}|j = 1\right] > 0$ and $\mathbb{E}\left[\epsilon_{i0t} - \epsilon_{i1t}|j = 0\right] > 0$. In other words, gains from trade are realized under the market system. The greater the parameter σ_ε, the greater are the gains from trade. In our empirical setting gains from trade are translated into irrigation timing. Farmers trade with each other based on their preferred irrigation weeks. There are no gains from trade under the quota system.

6.2 Welfare Measures

We compute two welfare measures, revenue and welfare, both as the yearly mean per tree and per farmer net of the irrigation cost. We do not take into account water expenses because they represent transfers and we are interested in welfare as a measure of efficiency. The only difference between revenue and welfare is due to the choice specific unobservable component ϵ_{ijt} explained above.[49] We compute welfare measures for the following allocation mechanisms: (1) markets using complete units, M, wherein complete water units are assigned to the farmer who bought them as observed in the data; (2) quotas with random assignment of complete units, Q, wherein every time we observe a farmer purchasing a unit of water under the

[49]Welfare is always greater than revenue under the market system because the former accounts for the differences in the choice specific unobservable component. Not accounting for these differences would underestimate welfare under the market. See previous subsection.

market system, the complete unit of water is assigned uniformly at random, proportional to their amount of land, among all farmers; (3) quotas with sequential assignment of complete units, Q-X%, wherein every time we observe a farmer purchasing a unit of water under the market system, the complete unit of water is assigned uniformly at random, proportional to their amount of land, among the X% of farmers who did not receive irrigation for the longest period of time; and (4) the highest-valuation allocation using complete units, HV, wherein every time we observe a farmer purchasing a unit of water under the market system, the complete unit of water is assigned to the farmer who values the water the most.[50] In all cases, M, Q, Q-X%, and HV, we compute the welfare measures using the actual water allocation from the data under the market system; that is, the total amount of water allocated by all mechanisms is the same.[51] Beginning in 1966, Mula's quota allocated units in sequential rounds of three weeks. The quota in Q-25% is therefore closest to this system. Next, we describe how we compute the welfare measures.[52]

Market using Complete Units (M)

We use the moisture level in poor and wealthy farmers' soil resulting from their actual purchase decisions under the market.

Quotas (Q and Q-X%)

Revenue and welfare coincide because farmers do not choose when to irrigate. We only report one measure called welfare. The farmers bought 637 units of water under the market system in the setting studied. Under the quota system, we allocate the same number of units of water, 637, in the same week when these units were bought under the market.

Highest Valuation using Complete Units (HV)

We compute the highest-valuation allocation using complete units (HV) as follows. Every time we observe that a farmer purchased a unit of water during the market on a particular date, the complete unit of water is assigned to the farmer who has the lowest moisture level on that date. It corresponds to the farmer who has been the longest without irrigation.

[50]The quota Q is *naive* in that it does not account for obvious observables that affect allocation efficiency. In our case, the quota Q does not account for recent irrigation. Allocating frequent units of water to the same farmer who recently irrigated is both inefficient and easy to account in the quota. The quota implemented in Mula used a *tanda* (fixed amount of water every three weeks) to condition on this issue. In the next subsection, we provide an example regarding the importance of the timing for irrigation, the obvious covariate used to condition the quota in the Mula setting.

[51]We obtain similar results simulating purchase decisions under the market system and then using the resulting allocation to compute welfare under quotas and HVc.

[52]See Appendix D for details.

6.3 Welfare Results

Table 4 displays welfare results under markets, quotas, and the HV allocation. We report mean welfare per farmer, per tree, and per year. The bottom part of the table shows the mean number of units per farmer during the whole period under analysis for each mechanism. The total amount of water is the same in all mechanisms. Differences in welfare across columns result from differences in soil moisture levels across farmers.

Under the market system poor farmers had a lower welfare than wealthy farmers. The quota system increased poor farmers' welfare partially at the expense of wealthy farmers' welfare. The quota Q-25% increases total efficiency relative to the market by 7.3 percent ($^{648.14}/_{604.11} - 1$). Table 4 shows that the following ranking holds in terms of efficiency: HV $>$ Q-25% $>$ Q-50% $\cong$ M, where the symbols "$>$" and "$\cong$" indicate, respectively, *greater welfare than* and *welfare is not statistically different from*. Randomly allocating units of water, in proportion to land area, results in decreased efficiency compared to markets. In Q-50%, complete units of water are allocated among the 50 percent of farmers who received less water in the past, in proportion to their land holdings. Welfare under Q-50% is not statistically different from welfare under markets.

Market, Quotas, and Highest Valuation. Figure 3 shows the welfare comparison among the market M, the HV allocation, and quotas Q-X% for different values of X. The figure shows mean welfare per farmer per tree per year. The main difference between HV and M is that poor farmers do not buy many water units during the critical season under M. Randomly allocating complete units of water decreases efficiency relative to markets due to decreasing marginal returns of water in the apricot production function. Although all farmers receive the same amount of water per tree, timing is important. For example, consider the case of two identical farmers A and B. Suppose that there are four units of water allocated in four consecutive weeks, 1, 2, 3, and 4. Allocating the first two units during weeks 1 and 2 to farmer A, and the second two units during weeks 3 and 4 to farmer B, results in a lower welfare than allocating the first unit to A, the second unit to B, the third unit to A, and the fourth to B. As X decreases, the quota system allocates units among the farmers who irrigated the least in the past. This assignment is similar to the HV allocation, where water flows to the farmer who values it most. At the limit, as X decreases, welfare under the quota is similar to welfare under HV. In our empirical setting, varying X is equivalent to varying the duration of the round. Long rounds indicate that farmers do not irrigate frequently. Short rounds indicate that farmers often incur irrigation costs.

Yearly Results. Figure 4 shows welfare results by year and by allocation mechanism. There is substantial variation across years due to variation in rainfall. Revenue is lowest for both poor and wealthy farmers during 1962 and 1963, the driest years in our sample.

The top two panels in Figure 4 display welfare disaggregated for poor and wealthy farmers. Although the performance of M is similar to that of Q-50%, the distribution is different. Wealthy farmers perform better under M than under Q-50%. Poor farmers perform better under Q-50% than under M. During dry years, such as 1963 or 1964, poor farmers perform better under Q than under M. The difference between M and HV is the highest for the harvest of 1964. The year 1963 was the year with the lowest rain in the sample.[53] Drought increased the price of water relative to other years in the sample. The drought's negative impact on poor farmers under M was larger than its positive impact on wealthy farmers.[54]

7 Discussion

7.1 Vertical Mergers

The institutional change from markets to quotas can be interpreted as a vertical merger. Under the market system, an upstream firm—the *Heredamiento de Aguas,* an effective cartel—owned water rights. The upstream firm sold water to the *Sindicato de Regantes*, the farmers' association downstream. Farmers purchased irrigation water and used it as an intermediate input to produce agricultural products sold in the output market. Farmers can thus be interpreted as firms in the competitive market downstream. Under quotas, farmers became owners of the water rights. Upstream and downstream firms consolidated into a single entity. In others words, the cartel and the farmers vertically integrated.[55]

Since Coase (1937), economists have argued that vertical integration could be more efficient than a vertical market if transaction costs between upstream and downstream firms are present. Williamson (1975, 1985) and the literature that followed showed that vertical integration improves efficiency when uncertainty in the intermediate input market exists. Liquidity constraints can be viewed as a type of transaction cost that makes vertical markets inefficient. A system of quotas, interpreted as a vertical integration, ameliorates such transaction costs along the lines of Coase, Williamson, and the literature that followed, thus increasing efficiency.

[53]The harvest season here refers to a full year beginning in August. Thus, the 1964 output is produced with the rainfall between August 1963 and July 1964.

[54]We analyzed the welfare implications of the institutional change from markets to quotas for farmers who grew only apricots. These welfare results do not necessarily apply to farmers who grew other crops, or to farmers who had a mix of several crops. For example, farmers who grew a summer (*e.g.,* apricot) and a winter (*e.g.,* oranges) crop may smooth spending throughout the year and may not benefit as much from quotas. See Subsection 7.4 and Appendix E.2.

[55]Under quotas, the farmers' association bought water property rights and dissolved the cartel.

7.2 Horizontal Mergers and Sharecropping

A natural question arises: why did wealthy farmers not buy poor farmers' land? Following the merger discussion in the previous subsection, if wealthy farmers consolidated their land with that of poor farmers, the combined entity would also ameliorate frictions from liquidity constraints. In other words, a horizontal merger downstream between wealthy and poor farmers could address the inefficiency caused by liquidity constraints.

Downstream consolidation did not occur in the setting studied due to diseconomies of scale. Fruit trees exhibit decreasing marginal returns in the number of grown trees (Hoffman, 1996). The optimal exploitation size is relatively small. Table 5 shows that the average number of trees was 73 for the farmers studied. It was extremely rare for a farmer to have more than 200 trees. A large plot cannot be worked by the farmer alone. The farmer would have to hire/supervise workers. In the setting studied 90 percent of farm plots were smaller than one hectare. In terms of the legal arrangement, 97 percent of farmers were owners, 2.6 percent were tenants, and 0.4 percent were sharecroppers; that is, the great majority of farmers were owners. There was only one sharecropper where the owner of the land was a recent widow. All farmers were land owners among those who grew only apricots.

7.3 Strategic Supply

The president of the *Heredamiento de Aguas* decided whether to run the auction each week. There is no evidence whether this decision was strategic. If there was sufficient water in the dam, the auction was held. However, the president could stop the auction at any time, and did so if the price fell considerably, usually to less than 1 peseta. This uncommon situation happened only after an extraordinarily rainy season.

7.4 Unobserved Heterogeneity

The production differences in Table 4 are attributable to differences in soil moisture levels. All farmers are equally productive up to the productivity shock. Some farmers irrigate more than others, thus translating into output differences. The productivity shocks are week- and farmer-specific, and depend on whether the farmers irrigate. We interpret them as an opportunity cost of irrigation. During a particular week, irrigation may be costly for idiosyncratic reasons. Markets help to efficiently allocate idiosyncratic shocks by allowing farmers to choose when to irrigate. Gains from trade are realized in the market system. By contrast, quotas require a rigid schedule, forcing farmers to irrigate during specific weeks regardless of their idiosyncratic preference.[56]

An alternative explanation would be that the production differences are due to unobserved differences in productivity. For example, it could be that wealthy farmers used additional productive inputs, such as manure, in greater quantities than did poor farmers. Thus, poor farmers' production would be lower than wealthy farmers' production due both to differences in soil moisture levels and additional productive inputs.

The previous argument cannot be rule out explicitly due to data limitations. There is no data about the relative use of these additional productive inputs. However, it does not affect the main counterfactual result from Table 4. Artificial fertilizers were not introduced in Mula until the 1970s (González Castaño and Llamas Ruiz, 1991). Farmers used manure and mules when farming the land (López Fernández and Gómez Espín, 2008; Garrido and Calatayud, 2011). If poor farmers faced liquidity constraints buying water, it is possible that they also faced liquidity constraints buying additional inputs. Therefore, if wealthy farmers used additional productive inputs in greater quantities than did poor farmers under the market system, the transition from markets to quotas would increase poor farmers' production more than the amount predicted in Table 4. Under quotas farmers do not have to make large payments for water, leaving them extra cash to buy additional productive inputs. In other words, poor farmers are less likely to be liquidity constrained to buy additional inputs under quotas. Thus, even if poor farmers were less productive than wealthy farmers under the market, they would likely be as productive as wealthy farmers under quotas.[57] We elaborate about this issue next.

Correlation Between Wealth and Productivity in Mula

The hypothesis that there are no persistent differences in productivity between wealthy and poor farmers is untestable. Yet we believe it is reasonable in the empirical context analyzed. All farmers' plots are located in a small, relatively flat area spanning less than

[56] Although our model does not allow for persistent unobserved heterogeneity, we estimate the parameter σ_ϵ^2, which determines the variance of the idiosyncratic shock, $\sigma_\epsilon^2\pi^2/6$. The higher the value of σ_ϵ^2, the more heterogeneous the distribution of productivity. If σ_ϵ^2 is large enough, markets are more efficient than quotas because, under quotas, there is no decision nor gains from trade. See Subsection 6.1.

[57] This argument assumes that, under quotas, poor farmers are not liquidity constrained to buy other inputs. On the one hand, we believe this is a reasonable assumption in Mula because under quotas farmers were not liquidity constrained (Garrido and Calatayud, 2011). On the other hand, if poor farmers were still liquidity constrained under quotas, they would be less constrained than they were under markers because they do no have to pay for their main input, water. Therefore, even if the productivity gap caused by input differences does not close completely, it would close partially.

In terms of the model, this discussion can be interpreted as a weaker assumption required for the welfare results to hold. The welfare analysis only requires that poor farmers are as productive as wealthy farmers under quotas, which we believe is a credible assumption in the historical context of Mula as explained in this subsection.

two times four kilometers. Weather and soil conditions are thus the same. To the best of our knowledge, there are no historical sources mentioning explicitly or implicitly differences in productivity among farmers, or between wealthy and poor farmers. Table 6.A shows that although wealthy farmers have larger plots (column 1), there are no differences in revenue per tree between poor and wealthy farmers when considering all agricultural products (column 5).[58] Interviews with surviving farmers confirm this information.[59] The differences between poor and wealthy farmers (columns 2, 3, and 4) are attributable to the larger plots owned by wealthy farmers.[60]

Table 6.B shows that the only group for whom there are substantial differences in revenue per tree between poor and wealthy are apricot-only farmers. These differences are explained by moisture differences between poor and wealthy during the 1954 critical season. If farmers grew other agricultural products in addition to apricot trees (*e.g.*, orange trees), there are no substantial differences between wealthy and poor farmers. Revenue for oranges is not correlated with the wealth of the farmer. Oranges are harvested in winter, unlike apricots which are harvested in the summer. Water prices are low during the winter and liquidity constraints play no role. Farmers who grew both apricots and oranges could use the cash obtained in the winter (from the orange harvest) to buy water for apricots in the summer. Similarly, farmers could use the cash obtained from the apricot harvest to buy water for oranges in winter. Polycrop farmers are thus not affected by liquidity constraints. Farmers who only grew apricots did not have access to such a cash-smoothing mechanism. Results for other agricultural products harvested in the summer, such as lemons and peaches, are similar to those for apricots, but smaller in magnitude (columns 6 and 7). The results in Table 6.B confirm our previous discussion. They provide evidence about liquidity constraints and low-productivity heterogeneity. Column 1 shows that poor apricot-only farmers have substantially lower average revenue per apricot tree than wealthy apricot-only farmers. Column 2 shows that the revenue per orange tree is similar for poor and wealthy farmers who grew orange and other trees. Columns 3 through 5 display similar results to the ones in column 2 for farmers who grew other trees together with apricot, lemon, and peach, respectively. Output differences among the farmers who only grew apricots are due to differences in water input utilization used by wealthy and poor farmers, not due to differences in their production function.[61]

[58] The table uses the data from the agricultural census. This is the only year when revenues are observed.

[59] A summary of the interviews is available here.

[60] The year responsible for the revenue reported in Table 6 was particularly dry. Water prices were substantially higher than other years in the sample. We would therefore expect large differences in revenue per tree if differences in productivity were large.

[61] That is, our model properly explains such output differences using differences in purchased water and the same production function. When looking at the revenue per tree for wealthy farmers, farmers growing

The evidence presented above suggests that the correlation between wealth and productivity is small. The correlation coefficient between urban real estate and revenue per tree in 1954 is -0.06. Nonetheless we performed a sensitivity analysis to examine how large the correlation should be to revert the welfare results in Table 4.

Correlation Between Wealth and Productivity in the Model

One way to perform such analysis is to allow the apricot production function, $h(j_{it}, M_t, w_t; \gamma)$, to shift with wealth. Let Φ_i be a factor multiplying the apricot production function of farmer i and be given by:

$$\Phi_i \equiv 1 + \rho_{w,p}\mathrm{NW}_i + (1-\rho_{w,p})\vartheta_i \qquad \forall t, \tag{9}$$

where $\rho_{w,p} \in [0,1]$ is the correlation between wealth and productivity, NW_i is the normalized wealth of farmer i such that $\mathbb{E}(\mathrm{NW}_i) = 0$ and $\mathbb{V}(\mathrm{NW}_i) = 1$, and ϑ_i is an *i.i.d.* random shock to farmer i such that $\mathbb{E}(\vartheta_i) = 0$ and $\mathbb{V}(\vartheta_i) = 1$.[62]

Data about the use of additional inputs are not available. It is thus not possible to pin down the correlation parameter $\rho_{w,p}$ in the empirical setting studied. To perform the sensitivity analysis we simulate the model for different values of $\rho_{w,p}$ using equation 9 as follows. In each simulation $s \in S = 1,000$, each farmer $i \in \{1,\ldots,24\}$ has always the *same* normalized wealth, NW_i, obtained from the data. We let ϑ_i to be a random draw from the normalized empirical wealth distribution, *i.e.,* a random draw from NW_i.[63] Thus, in each simulation s, each farmer i has a *different* random draw, ϑ_i. The resulting simulation noise vanishes progressively as $\rho_{w,p} \to 1$. For each simulation s, first, we obtain Φ_i^s for farmer i. Then, we use the same procedure as in the baseline model to compute welfare.

Figure 5 displays the average (across simulations) welfare results. It shows the sensitivity of the welfare results from Table 4 to the correlation between wealth and productivity for $\rho_{w,p} \in [0,1]$. The figure displays the welfare difference between quotas minus markets as a function of $\rho_{w,p}$ and as percentage of the welfare under markets with $\rho_{w,p} = 0$ (the baseline in Table 4). The top panel displays the welfare of quotas Q-25% minus the welfare of markets M. In our baseline case in Table 4 there is no correlation between wealth and productivity,

only apricot trees have a greater revenue than farmers growing also other crops. The reason behind this result is that wealthy farmers growing only apricot trees have a lower average number of trees (73 trees) than farmers growing also other crops (109 trees). This feature is due to the disseconomies of scale discussed in Subsection 7.2.

[62] Two comments are in turn. First, $\mathbb{E}(\Phi_i) = 1$. Second, if $\rho_{w,p} = 0$, there is no correlation between wealth and productivity, but there is permanent heterogeneity unlike the original model. We are back to the original model when, in addition, the variance of the random shocks goes to zero.

[63] This procedure avoids to arbitrarily choose the distribution of the white noise. Results are almost identical using other distributions such as a standard normal.

$\rho_{w,p} = 0$, and the quotas Q-25% produce 7.3 percent more per tree than markets M. As the correlation increases, quotas are relatively less efficient than markets. (When $\rho_{w,p} \in [-1, 0]$ the welfare difference of quotas minus markets is obviously larger.) In the extreme case where $\rho_{w,p} = 1$ (*i.e.,* wealthy farmers are always more productive than poor farmers with the same soil moisture level), the welfare difference between quotas Q-25% and markets M is minimal because under markets wealthy farmers buy more water during the critical season than do poor farmers (Figure 2).

The top panel in Figure 5 shows that quotas Q-25% are more efficient than markets M even when wealth and productivity are perfectly correlated; that is, even when $\rho_{w,p} = 1$. This may seem counter-intuitive because by moving from quotas Q-25% to markets M there is a transfer of water from wealthy more productive to poor less productive farmers according to equation 9. However, equation 9 defines a shift in productivity (*i.e.,* wealthy farmers are more productive than poor farmers) for farmers with the *same* soil moisture level. Under markets M, wealthy farmers have substantially higher levels of moisture than do poor farmers. The top panel in the figure shows that wealthy farmers are thus less productive than poor farmers even when $\rho_{w,p} = 1$. This result is due to the concavity of the apricot production function. A redistribution of water from wealthy to poor farmers under quotas Q-25% results in a net increase in efficiency: the efficiency increase due to the concavity of the production function more than compensates the efficiency decrease due to poor farmers being less productive (as defined by equation 9).

The bottom panel in Figure 5 displays the welfare of quotas Q-40% minus the welfare of markets M. In Table 4 the correlation is $\rho_{w,p} = 0$ and the welfare difference of quotas Q-40% minus markets M is approximately 3.5 percent.[64] As $\rho_{w,p}$ increases, quotas Q-40% are less productive than markets M in contrast to the top panel, where quotas Q-25% are always more efficient than markets. Both panels in Figure 5 show that markets are relatively more efficient than quotas as $\rho_{w,p}$ increases (downward slope). This result is because the mechanisms to allocate water are fixed in each panel (Q-25% and M in the top panel, and Q-40% and M in the bottom panel). Therefore, there is no increase in efficiency due to concavity in the production function as $\rho_{w,p}$ varies. The increase in efficiency due to the concavity can be seen in Figure 4 for a given value of correlation between wealth and productivity, $\rho_{w,p} = 0$.[65]

[64] Figure 5 shows Q-40% instead of Q-50% because the welfare difference between Q-50% and markets M is not statistically different when the productivity is not correlated with wealth as discussed in Subsection 6.3. In Figure 5 we want to show a quota such that: (i) the welfare difference is statistically significant and positive for $\rho_{w,p} = 0$; (ii) intersects the benchmark zero horizontal line; and (iii) the welfare difference is statistically significant and negative for $\rho_{w,p} = 1$. Such quota is Q-40%.

[65] In principle, one could argue that the shifter in productivity from equation 9 may be large enough such that the slope of the lines in Figure 5 were steeper and, hence, markets M outperformed quotas Q-25% for large values of $\rho_{w,p}$. This is not the case in the empirical setting studied as discussed above. If the production

7.5 Liquidity Constraints *vs.* Risk Aversion or Impatience

One concern when identifying liquidity constraints is that risk aversion has similar empirical implications for agents' behavior. If poor farmers are more risk averse than wealthy farmers, their water purchase before the critical season (*i.e.,* before uncertainty about rain is realized) is consistent with both liquidity constraints and risk aversion. Farmers that might be liquidity constrained in the summer would buy more water in the spring, anticipating that high prices in the summer may prevent them from buying water. Risk averse farmers would reduce the expected variation of their expenses in the summer by buying more water in the spring and, thus, reducing their summer water demand. The main difference in farmers' behavior under liquidity constraints and risk aversion occurs during the summer, when prices are high and uncertainty is realized. On the one hand, if poor farmers face liquidity constraints, they would not be able to buy summer water when the price is high, even if the moisture level in their plots is low. On the other hand, if poor farmers are unconstrained but risk averse, they would have the same demand for water as wealthy farmers during the summer (*i.e.,* after uncertainty about rain is realized), conditional on soil moisture levels. In Table 2 column 4 we show that holding the moisture level fixed, poor farmers buy less water than wealthy farmers during the critical season. Following the results in this table, along with the opinions presented above, we conclude that poor farmers faced liquidity constraints. Our argument and analysis cannot rule out that farmers may also be risk averse, but risk aversion alone cannot explain the behavior in Table 2.[66]

In Appendix E, we provide additional discussions regarding: (i) the strategic unit size and sunk costs of irrigation; (ii) the optimal crop mix; (iii) trees, droughts, and insurance; (iv) collusion; and (v) attrition.

8 Concluding Remarks

In the absence of frictions a market is efficient because it allocates goods according to the valuation of consumers. When frictions are present, however, markets may not be efficient. We study the efficiency of a market relative to a quota in the presence of specific type of market friction: liquidity constraints. In this case, the efficiency of markets relative to quotas is theoretically ambiguous. We use data from water markets in southeastern Spain

function is linear, and wealth and productivity are perfectly correlated, markets are always more efficient than any mechanism of quotas.

[66]The same argument rules out the possibility that the results are driven by poor farmers being more impatient (lower discount factor) than wealthy farmers.

and explore a specific change in the institutions to allocate water that switched from a market to a quota. Frictions arose in this setting because the consumers were farmers who had to pay in cash for the purchased water. Poor farmers did not always have such cash during the critical season when their crops needed water the most. Wealthy farmers who were part of the wealthy elite were not liquidity constrained. We estimate a structural dynamic demand model under the market by taking advantage of the fact that water demand for *both* types of farmers is determined by the technological constraint imposed by the crop production function. This approach allows us to differentiate liquidity constraints from unobserved heterogeneity. We use the estimated model to compute efficiency as a measure of welfare under both institutions. We show that the institutional change from markets to quotas increased efficiency for the farmers considered.

The contributions of this paper are twofold. First, from a historical perspective, we provide empirical evidence of a source of inefficiency in water markets. Second, from an industrial organization perspective, we propose a dynamic demand model that includes storability, seasonality, and liquidity constraints. Ignoring the presence of liquidity constraints one would incorrectly interpret their effect as a more elastic demand, thereby biasing the absolute value of the estimated demand elasticity upwards. To perform the estimation we use only the choices of farmers who were not liquidity constrained. Then we use the model to infer the conduct of *all* farmers in a counterfactual setting in which no one was liquidity constrained.

One important insight from our paper is that the change from a market to a non-market institution was intended to increase total production, despite that it would also be more egalitarian. That is, the institutional change aimed at efficiency, not equality. Our analysis exploits the small degree of heterogeneity across neighboring farmers and the presence of liquidity constraints in the setting studied. This efficiency approach could also be relevant in other settings where goods are allocated using non-market mechanisms. Examples include fisheries, forests, and other common-pool resources that are typically managed locally, without internal prices. Mooring slots in harbors are usually non-tradable. Public housing projects in many cities allocate apartments and houses following non-market considerations. In each case, the nature of the friction might be different: overexploitation, negative externalities, or spatial spillovers. Our methodology to evaluate relative efficiency may also be applied in such cases.

Since the work by Coase (1937) and Williamson (1975, 1985) economists have long argued that vertical integration could be more efficient than a vertical market in the presence of transaction costs in the input market. Liquidity constraints can be viewed as a type of transaction cost. A system of quotas, interpreted as a vertical integration, ameliorates such transaction costs along the lines of Coase, Williamson, and the literature that followed, thus increasing efficiency.

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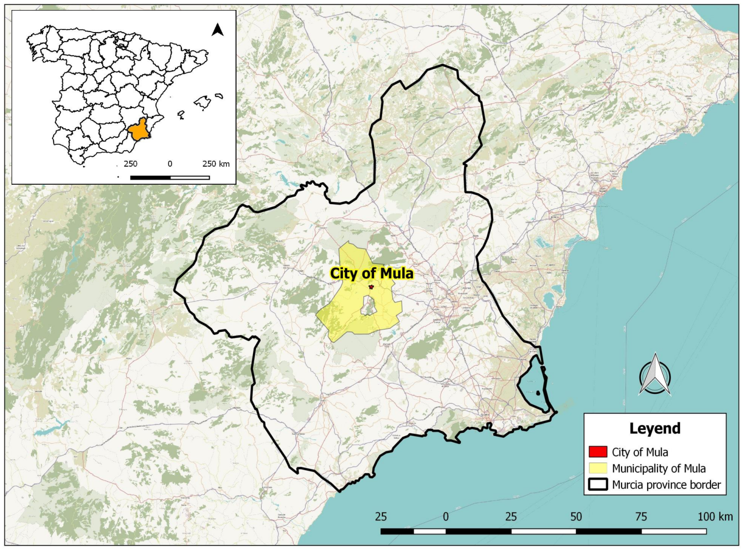
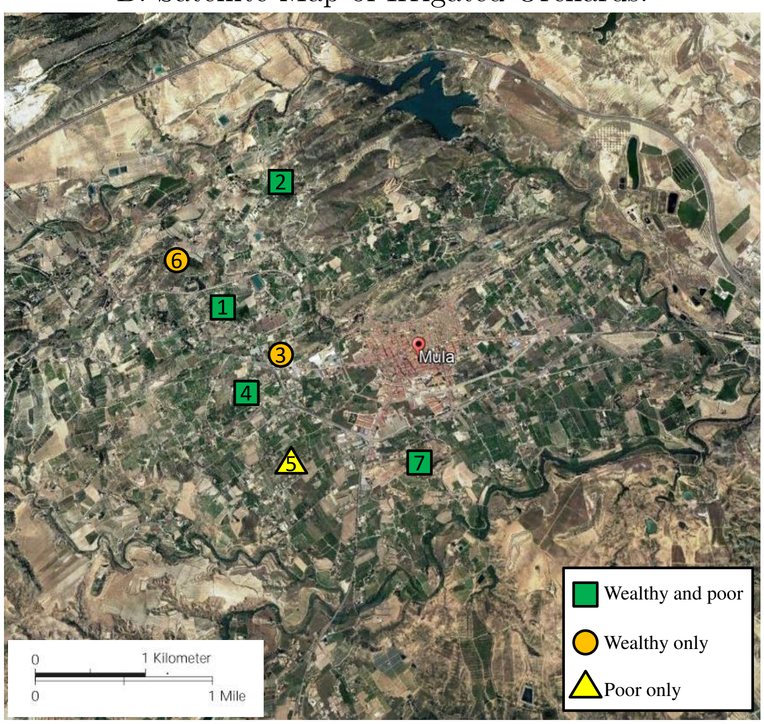
Figure 1: Mula and the Irrigated Plots.
A. Map of Spain, Murcia and Mula.

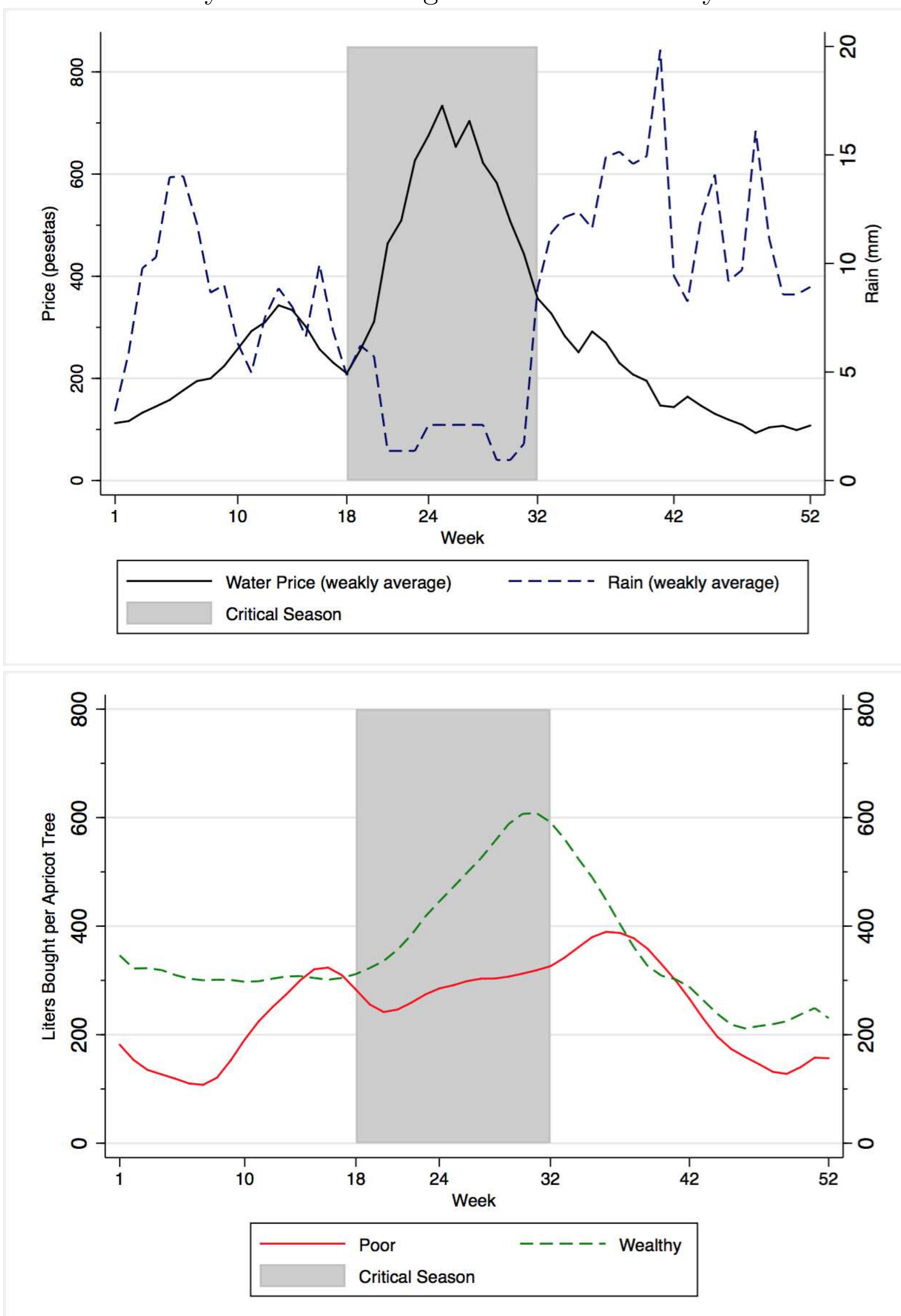


B. Satellite Map of Irrigated Orchards.



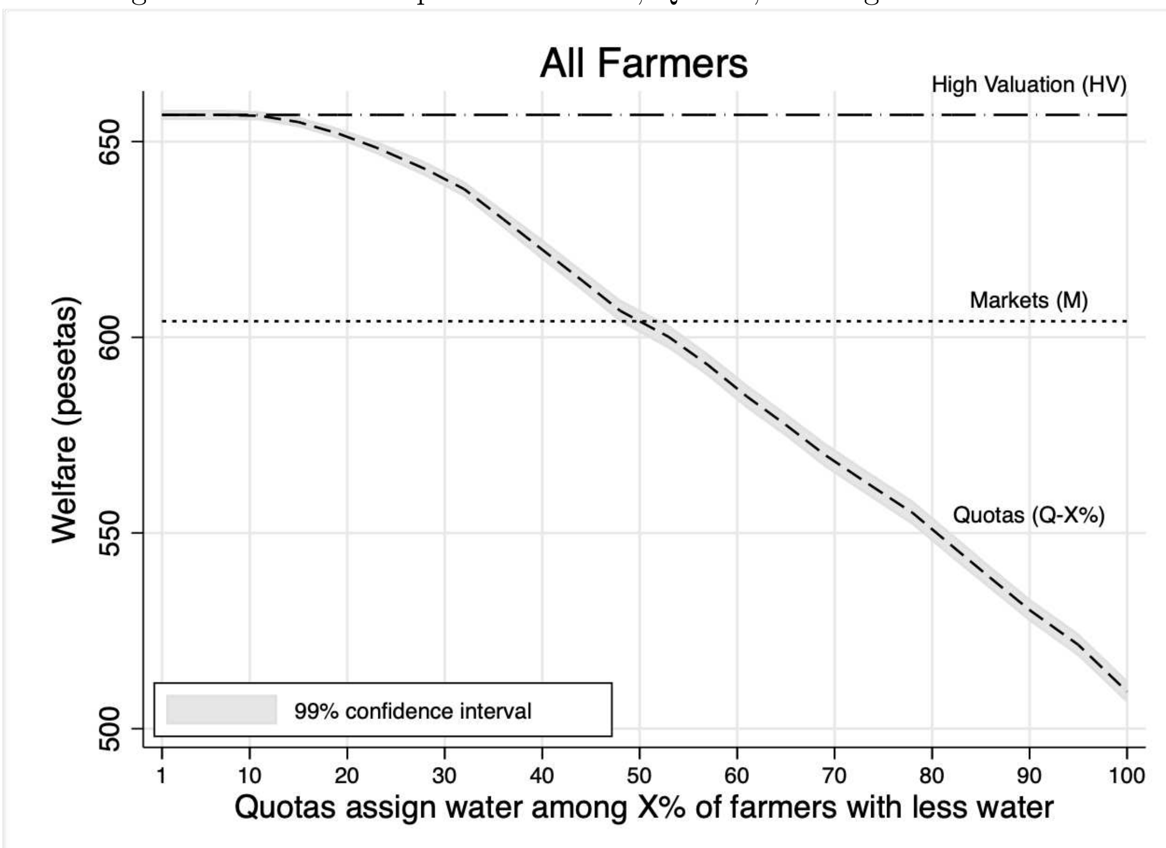
Notes: Panel A. Physical map of the region of Murcia. The Municipality of Mula is in yellow and the urban area in red. Panel B. Satellite map depicting the main subareas with more than one apricot farmer, 5km by 6km. Subareas ordered according to the number of plots, denoted by n: (1) *Trascastillo,* $n = 9$; (2) *Herrero,* $n = 9$; (3) *Peñuelas,* $n = 4$; (4) *Palma,* $n = 3$; (5); *Carrasquilla,* $n = 3$; (6*) El Niño,* $n = 3$; (7) *San Sebastian,* $n = 2$. Some farmers owned several plots in different subareas. Agricultural census data contain only information about subareas' names and number of plots. It is therefore not possible a more detailed disaggregation/location of the farmers' plots. The percentage of poor (wealthy) farmers who owned plots in more than one subarea is 27.3 (28.6) percent. Green/square: subareas with both wealthy and poor farmers. Orange/circle: subareas with only wealthy farmers. Yellow/triangle: subareas with only poor farmers.

Figure 2: Seasonality and Purchasing Patterns of Wealthy and Poor Farmers.



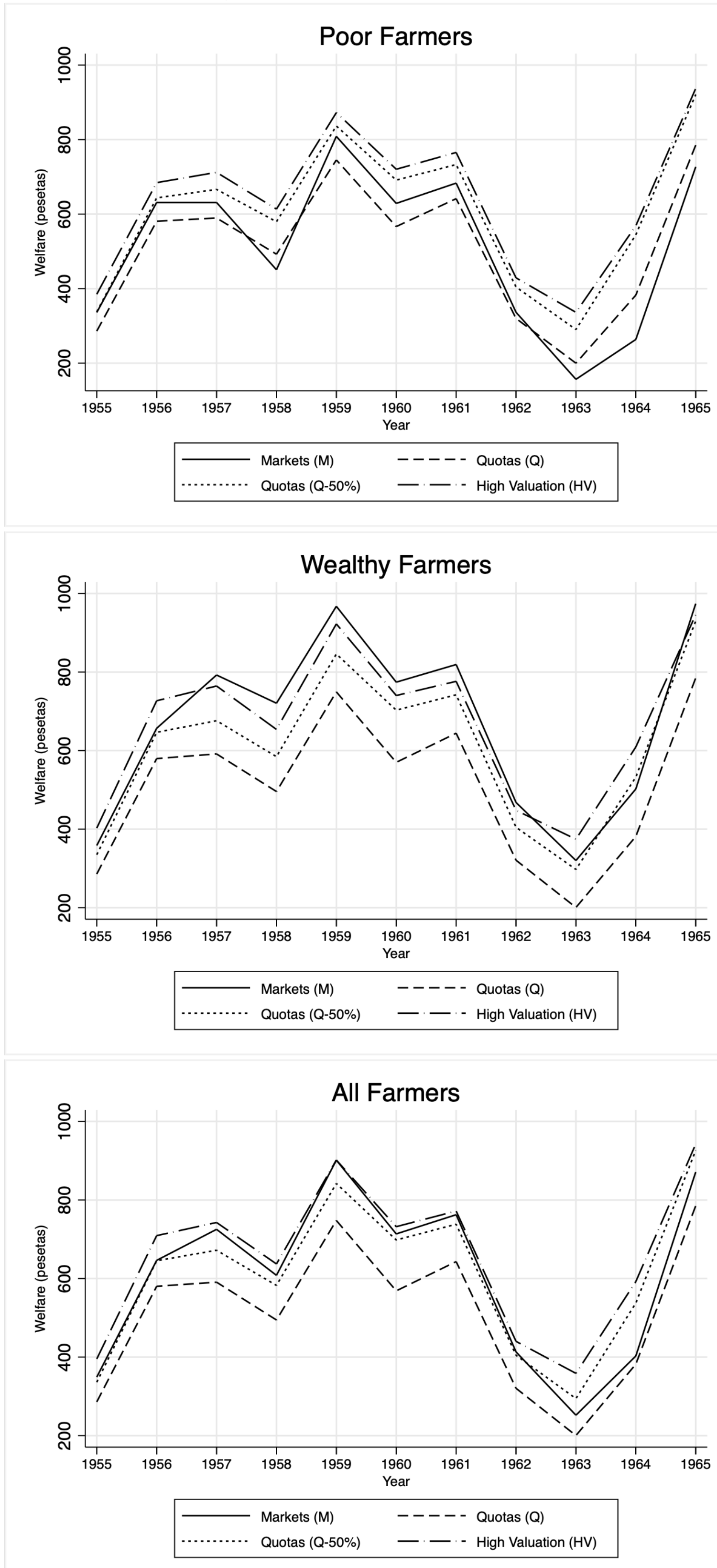
Notes: The top panel displays the average weekly prices of water paid in the market (left vertical axis) and the average weekly rain in Mula (right vertical axis) together with a shaded area for the critical season of apricots trees as defined in Table 1. The bottom panel displays the average liters bought per farmer and per tree disaggregated by wealthy and poor farmers together with a shaded area for the critical season of apricots trees. A farmer is defined as *wealthy* if the farmer owns urban real estate, and poor otherwise.

Figure 3: Welfare Comparison: Market, Quotas, and Highest Valuation



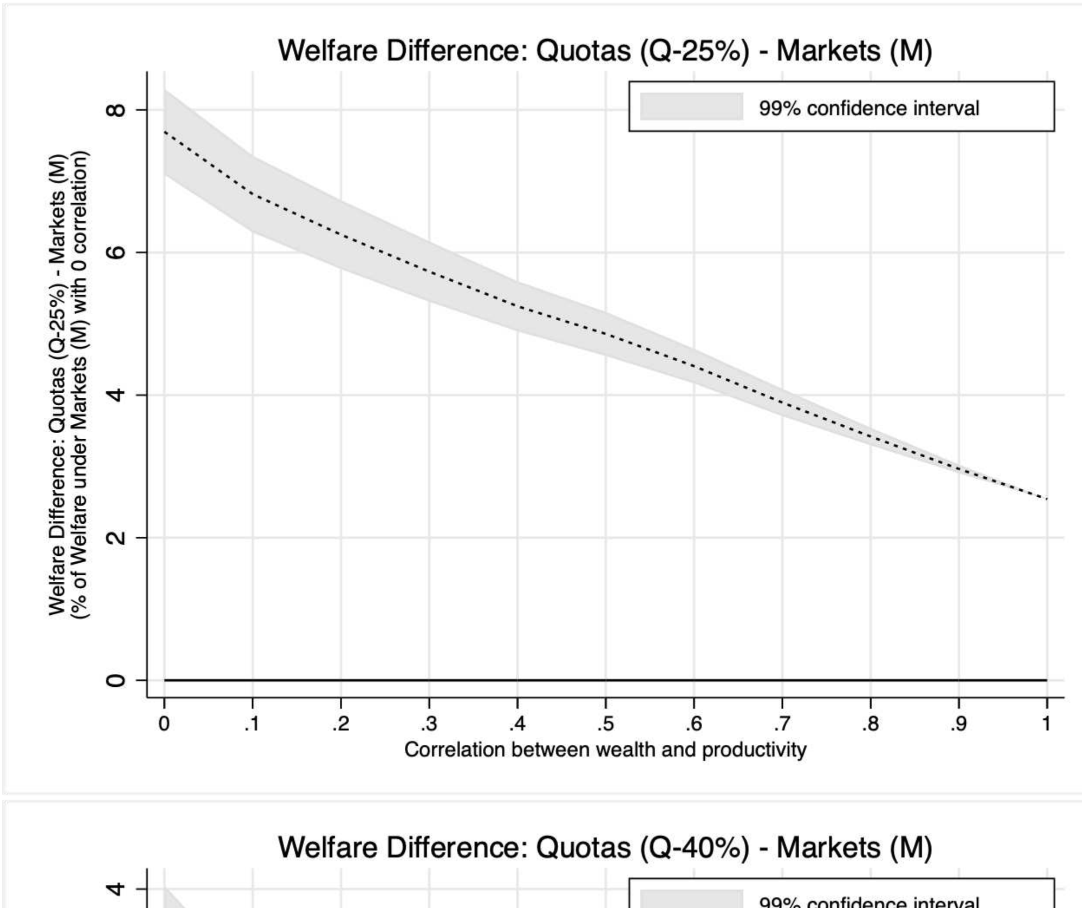
Notes: See Appendix D for a discussion about the computation of the welfare measures. Confidence intervals account for uncertainty about the estimated parameters (by drawing from the asymptotic distribution) and across simulations.

Figure 4: Welfare by Year.



Notes: See Appendix D for a discussion about the computation of the welfare measures.

Figure 5: Efficiency gains as a function of the correlation between wealth and productivity.



Notes: See Appendix D for a discussion about the computation of the welfare measures in this figure. Confidence intervals account for uncertainty about the estimated parameters (by drawing from the asymptotic distribution) and across simulations.

Table 1: Seasonal Stages for *Búlida* Apricot Trees.

<table>
<tr><td>JAN</td><td>FEB</td><td>MAR</td><td>APR</td><td>MAY</td><td>JUN</td><td>JUL</td><td>AUG</td><td>SEP</td><td>OCT</td><td>NOV</td><td>DEC</td></tr>
<tr><td>DORM</td><td>FLOW</td><td colspan="3">FRUIT GROWTH</td><td colspan="6">POST-HARVEST</td><td>DORM</td></tr>
<tr><td colspan="2"></td><td>I</td><td>II</td><td>III</td><td colspan="2">EARLY</td><td colspan="4">LATE</td><td></td></tr>
</table>

Notes: Obtained from Pérez-Pastor *et al.* (2009). DOR refers to Dormancy. FLOW refers to Flowering. The critical season corresponds to Fruit Growth III and Early Post-harvest.

Table 2: Demand for Water per tree and Urban Real Estate.

# units bought per tree	(1)	(2)	(3)	(4)	(5)	(6)
Wealthy	0.0146***	0.0087**	0.0104***	0.0054	0.0101	0.001
	(0.0036)	(0.0041)	(0.0039)	(0.0043)	(0.0053)	(0.0057)
(Wealthy)			0.0243***	0.0192***	0.0246***	0.0226***
× (Critical Season)			(0.0076)	(0.0079)	(0.0084)	(0.0084)
(Wealthy)					0.0005	0.0083
× (Winter Season)					(0.0092)	(0.0070)
Covariates	No	Yes	No	Yes	No	Yes
Number of observations	14,448	14,448	14,448	14,448	14,448	14,448

Notes: All regressions are OLS specifications. The sample is restricted to farmers who grow only apricots. The dependent variable is the number of units bought per tree by each individual farmer during a given week. *Wealthy* is a dummy variable that equals 1 if the value of urban real estate of the farmer is positive, and 0 otherwise. *Critical season* is a dummy variable that equals 1 if the observation belongs to a week during the critical season, and 0 otherwise. *Winter Season* is a dummy that equals 1 if the observation belongs to weeks 42-52 or 1-15, and 0 otherwise. *Covariates* are the price paid by farmers in the market, the amount of rainfall during the week of the irrigation, and the farmer's soil moisture level. Standard errors in parentheses. * $p<0.10$; ** $p<0.05$; *** $p<0.01$.

Table 3: Structural Estimates

	(1)	(2)	(3)	(4)
Transformation rate ($18 \leq week \leq 32$):				
– Linear term: $\hat{\gamma}_L$	0.0895 (0.0085)	0.0588 (0.0136)	0.0888 (0.0082)	0.1214 (0.0140)
– Quadratic term: $\hat{\gamma}_Q$	–	2.91e-05 (3.01e-06)	–	2.71e-05 (1.61e-06)
Irrigating cost: $\hat{\zeta}$	20.3078 (1.0168)	198.3030 (17.5353)	19.4981 (0.6370)	318.7562 (26.4049)
Scale parameter of Gumbel distribution: $\hat{\sigma}_\varepsilon$	6.2097 (0.4794)	8.3579 (0.1354)	6.1719 (0.4704)	8.4373 (1.3331)
Marginal effect	0.0895	0.1100	0.0888	0.1690
Area heterogeneity	No	No	Yes	Yes
Number of Observations	8,008	8,008	8,008	8,008

Notes: Standard errors are computed using 200 bootstrap replications where we reestimate the demand transitions and conditional choice probabilities, and then minimize the GMM criterion function to find $\hat{\Theta}$. We bootstrap by individual farmer resampling an individual farmer's history for the whole period under analysis. The computed standard errors thus account for the history and serial correlation within farmers. Marginal effects reported at the mean moisture. See Section 4 for details.

Table 4: Welfare Results

	Markets complete units (Welfare and revenue)		Quotas complete units (Welfare)				High Valuation complete units (Welfare)
	M (Revenue)	M (Welfare)	Q	Q-75%	Q-50%	Q-25%	HV
Welfare measures: (mean per farmer, per tree, per year)							
- All farmers pre-season (24 farmers)	391.5922	393.7679	333.6184	364.4124	391.6846	417.4138	422.9042
- All farmers on-season (24 farmers)	208.2992	210.3393	175.3770	197.0761	215.3261	230.7296	233.7367
- Poor farmers whole season (10 farmers)	509.9335	513.9817	508.2111	562.0366	604.3807	635.2081	638.6265
- Wealthy farmers whole season (14 farmers)	664.1471	668.4826	509.5555	561.0969	608.8892	657.3830	669.5083
- All farmers whole season (24 farmers)	599.8914	604.1072	508.9953	561.4885	607.0107	648.1435	656.6409
Amount of water allocated: (mean number of units per farmer)							
- Poor farmers whole season (10 farmers)	19.6000	19.6000	27.0783	27.4090	27.1927	26.5408	26.5337
- Wealthy farmers whole season (14 farmers)	31.5000	31.5000	26.1584	25.9221	26.0766	26.54.23	26.5474
- Total units allocated whole season (24 farmers)	637	637	637	637	637	637	637

Notes: See Appendix D for a discussion about the computation of the welfare measures.

Table 5: Number of Trees in 1954. By Type of Crop and Farmer Type

		Apricot (only) (1)	Orange (other) (2)	Apricot (other) (3)	Lemon (other) (4)	Peach (other) (5)	Lemon (only) (6)	Peach (only) (7)
All Farmers	# trees	73.0	152.0	90.0	102.4	93.1	68.4	97.5
Poor	# trees	80.6	137.1	72.1	85.8	83.8	56.5	.
Wealthy	# trees	66.6	163.0	106.0	113.2	99.9	84.3	97.5
Number farmers		24	322	239	64	45	7	6

Notes: Own elaboration from the 1954 Agricultural census. *Crop (only)* refers to the farmers who only grow *crop* trees. *Crop (other)* refers to the farmers who grow *crop* and other trees. *Crop* refers to apricot, orange, lemon, and peach. We define a farmer as *wealthy* if the farmer owns urban real estate and as *poor* otherwise. See Section 2 for details.

Table 6: Farmers characteristics and wealth.

Panel A: Size and Composition of Plots and Wealth for all agricultural products.

	Area Total (Ha) (1)	Area with trees (Ha) (2)	Fraction with trees (3)	Revenue (pesetas) (4)	Revenue/ area (pesetas/m^2) (5)
Urban real estate	34,023***	22,069***	-0.0355	23,894***	-0.1797
	(9,747)	(7,031)	(0.0320)	(4,024)	(0.7543)
Number of observations	388	388	388	388	388

Notes: All regressions are OLS specifications. The dependent variable is the variable in each column. *Urban real estate* measures the value of a farmer's urban real estate in pesetas. Standard errors in parentheses. * p<0.10; ** p<0.05; *** p<0.01.

Panel B: Revenue per tree in 1954 for each agricultural products.

		Apricot (only) (1)	Orange (other) (2)	Apricot (other) (3)	Lemon (other) (4)	Peach (other) (5)	Lemon (only) (6)	Peach (only) (7)
Total	Rev. per tree	134.2	125.1	124.7	112.9	51.8	85.7	72.8
Poor	Rev. per tree	95.3	131.9	126.2	123.9	47.2	73.1	.
Wealthy	Rev. per tree	167.1	120.2	123.2	104.9	55.2	98.3	72.8
# farmers		24	322	239	64	45	7	6

Notes: Own elaboration from the 1954 Agricultural census. *CROP (only)* refers to the revenue generated by CROP trees for farmers that only grow CROP trees. *CROP (other)* refers to the revenue generated by CROP trees for farmers who grow CROP and other trees. (CROP represents Apricot, Orange, Lemon, and Peach.) *Wealthy* is a dummy variable that equals 1 if the value of urban real estate of the farmer is positive, and 0 otherwise.

Appendix to: The Illiquidity of Water Markets*

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Contents

Appendix

This is the appendix for "The Illiquidity of Water Markets," by Javier D. Donna and José-Antonio Espín-Sánchez.

A Additional Description of the Data, Moisture, and Preliminary Analysis

A.1 Additional Description of the Data

Table A1 shows the summary statistics of selected variables used in the empirical analysis.

Table A1: Summary Statistics of Selected Variables.

Variable	Mean	St. Dev.	Min	Med	Max	No. obs.
Weekly rain (*mm*)	8.29	37.08	0	0	423.00	602
Water price (pesetas)[a]	326.16	328.45	0.005	217.9	2,007	307
Real estate tax (pesetas)	482.10	1,053.6	0	48	8,715	496
Area (*ha*)	2.52	5.89	0.024	1.22	100.1	496
Number of trees[b]	311.3	726.72	3	150	12,360	496
Units bought	0.0295	0.3020	0	0	4	145,684

Notes: The sample refers to all farmers. There are 496 census cards in the archive. We matched 242 individuals to the auction data. The agricultural census include farmers who have only *secano,* or dry, lands and thus, are not in our sample. The sample after the matching process consists of 602 weeks and 242 individuals for a total of 145,684 observations.
[a] Water price is the weekly average price in the auction. [b] Number of trees includes vines.

A.1.1 Auction Data

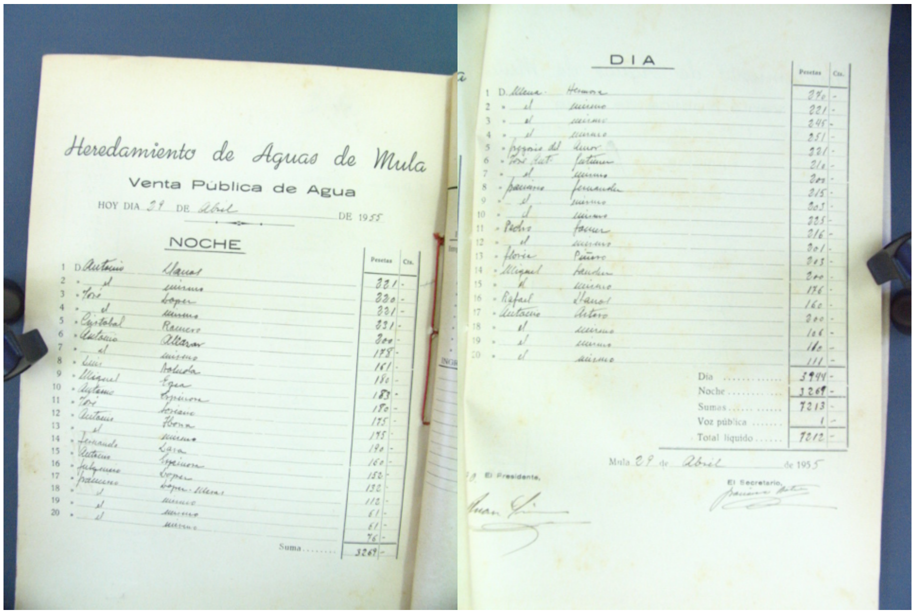
The mechanism to allocate water to farmers was a sequential outcry ascending price (or English) auction. The auctioneer sold each unit sequentially and independently of each other. The auctioneer recorded the buyer's name and the price they paid for every unit. The farmers could not store water in their plots. Reselling water was forbidden.

The basic selling unit was a *cuarta* (quarter), the right to use water that flowed through the main irrigation channel for three hours. Water was stored at the *De La Cierva* dam and flowed from the dam through the channels at approximately 40 liters per second. As a result, one *cuarta* carried approximately 432,000 liters of water. During our sample period, auctions were carried out every Friday. Each week, 40 *cuartas* were auctioned: four *cuartas* for irrigation during the day (from 7:00 AM to 7:00 PM) and four *cuartas* for irrigation during the night (from 7:00 PM to 7:00 AM), for each weekday (Monday to Friday). The auctioneer first sold the 20 *cuartas* corresponding to night times, and then the 20 *cuartas* corresponding to day times. Within each day and night group, units were sold beginning with Monday's four *cuartas* and finishing with Friday's.

We have auction data for 602 weeks, which can be divided into three categories based on bidding behavior and water availability: (i) normal periods (300 weeks), when the winner's name, purchase price, and date and time of irrigation were registered for each auction transaction; (ii) no-supply periods (295 weeks), when due to water shortage in the river or damage to the dam or channel—usually because of intense rain—no auction was held; and (iii) no-demand periods (7 weeks), when some units went unsold due to lack of demand after recent rainfall, and the price dropped to zero. Our sample for the empirical analysis focuses on the period from 1955 until 1966.

Figure A1 shows a sample from the original auction record of May 17, 1963. Units 1 to 4 are the units purchased for Monday during day (unit 1 corresponds to the right to irrigate from 7AM to 10AM, unit 2 from 10AM to 1PM, unit 3 from 1PM to 4PM, and unit 4 from 4PM to 7PM). Similarly, units 5 to 8 are the units purchased for Tuesday during day; units 9 to 12 for Wednesday during day; units 13 to 16 for Thursday during day; and units 17 to 20 for Friday during day. We observe the name of the farmer who won each auction and the price they paid for water.

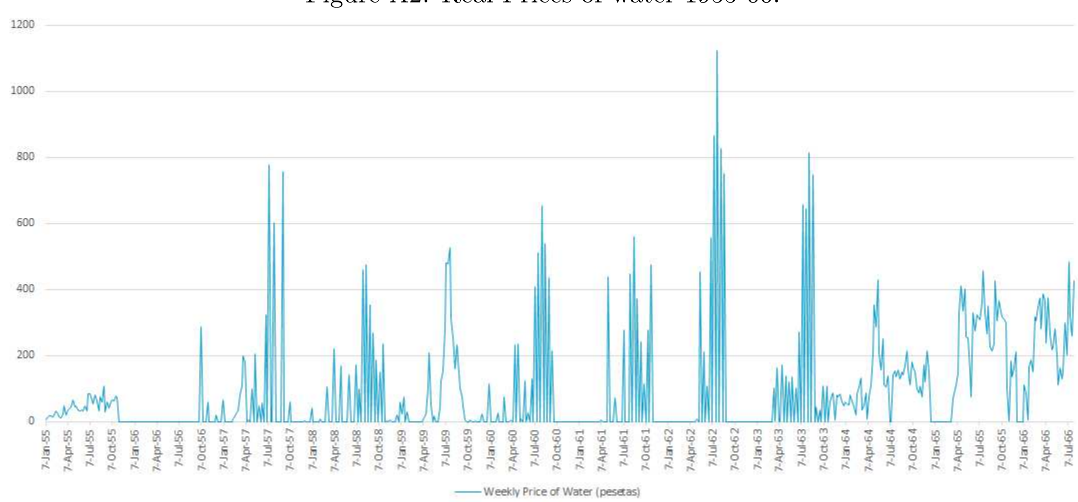
Figure A1: Sample of Auction Sheet.



Notes: Sample pictures of the data from the Municipal Archive in Mula, Section *Heredamiento de Aguas*. These pictures correspond to the same card containing the information of the winners and price paid for the 40 units sold on April 29, 1955.

Figure A2 shows the weekly average price paid by farmers during the sample period. Prices varied substantially ranging from 0.0025 to 1122 in real pesetas. In the fall of 1955 a large flood damaged the dam for several months and auctions were not run until the next fall. In some dry years, like 1961-63, auctions were not run in winter, causing prices to soar in spring and summer. The distribution of prices was relatively stable, except during dry years, like 1962, when prices were substantially higher.

Figure A2: Real Prices of water 1955-66.

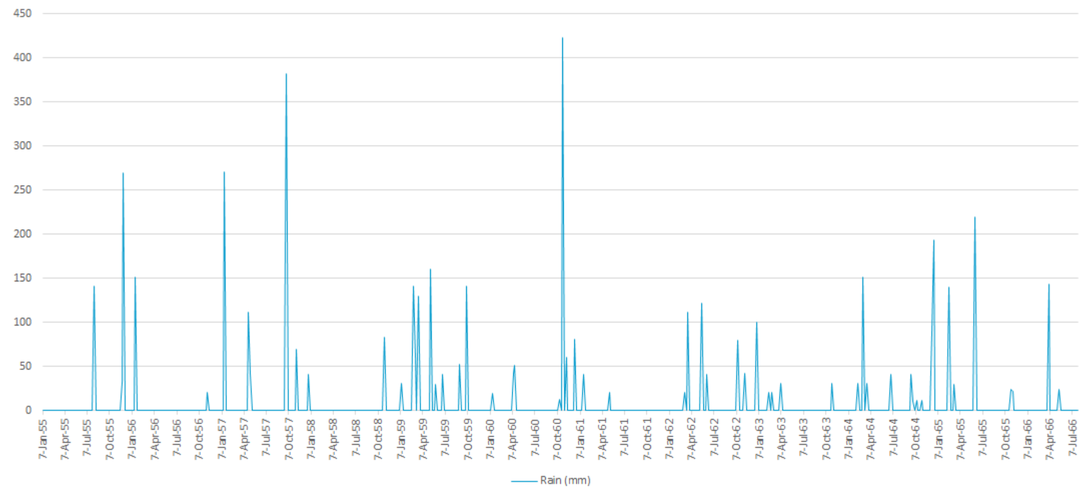


Notes: Weekly average real price of the water sold at auction in Mula, from January 1955 until July 1966, when the last auction was run. We use the price index from Uriel *et al.* (2000). The base year is 1970. We transform annual inflation rates into weekly inflation rates using the geometric average across weeks for each year.

A.1.2 Rainfall Data

We also link auction data to daily rainfall data for Mula, which we obtain from the *Agencia Estatal de Metereología*, AEMET (the National Meteorological Agency). Mediterranean climate rainfall occurs mainly in spring and fall while peak water requirements for products cultivated in the region are reached in spring and summer. From April to August, more frequent irrigation is recommended when the tree's production quality is most sensitive to water availability. Figure A3 shows that only few weeks had positive rainfall. In our sample the weekly rainfall exceeded the yearly average on two occasions, in September 1957 and in October 1960.

Figure A3: Weekly Rainfall in Mula (*mm*).



Notes: Weekly rainfall in Mula from date from the AEMET.

A.1.3 Agricultural Census Data

We also link auction data to Spain's 1954/55 agricultural census, which provides information on individual characteristics of farmers' land. The Spanish government enumerated all cultivated plots, production crops, and agricultural assets available in the country. Individual characteristics include the type of land and location, area, number of trees, production, and the price at which this production was sold in the census year. There are approximately 500 different bidders in our sample.

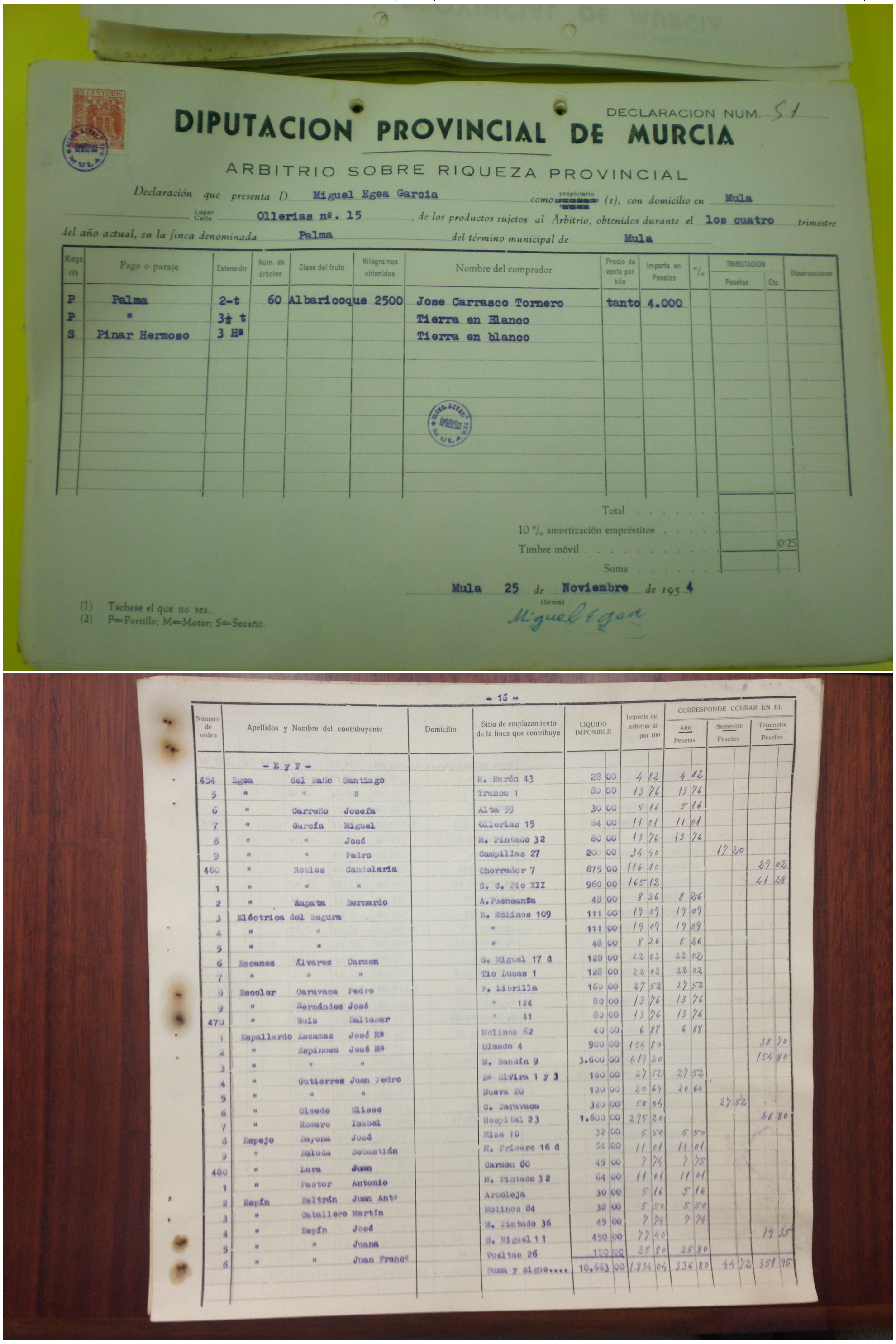
Panel A in Figure A4 shows a sample card of a farmer in the agricultural census data. *Area* and *the number of trees* vary considerably across farmers. On average, each farmer who grew only apricots had 73 trees.

Mula farmers most commonly planted orange trees (33 percent), followed by apricots (29 percent), lemons (12 percent), and peaches (5 percent). These farmers also grew a wide variety of vegetables including tomatoes, red peppers, cucumbers, and potatoes. Vegetables were complementary to fruit trees. Trees yielded greater returns on investment but required irrigation at specific times of the year and up to five years to reach maturity. Vegetables can be harvested a few months after planting but have lower returns. In the arid conditions of the empirical setting studied, vegetables can produce high output during a rainy year and cost less during drought because they mature annually.

A.1.4 Real Estate Tax Data

Panel B in Figure A4 shows a sample card from the Urban Real Estate Taxes Registry. The name and address provide a unique identification, and match the entries in the auction data and the agricultural census. The public records of annual real estate income taxes paid by each individual urban property owner in the town of Mula are stored in the General Section of Mula's Municipal Archive. We first link names in the auction data to those in the agricultural census data. Then, we link matched names to those in the Urban Real Estate Taxes Registry. Farmers had to pay an annual tax equal to 17 percent of the taxable income from their urban real estate. That is, 17 percent of the rental value of the properties, not the stock value of the properties. Rural real estate holdings were subject to different taxes.

Figure A4: Sample of Agricultural Census (top) and Urban Real Estate Taxes registry (bottom).



DECLARACION NUM. 51

DIPUTACION PROVINCIAL DE MURCIA

ARBITRIO SOBRE RIQUEZA PROVINCIAL

Declaración que presenta D. Miguel Egea Garcia como propietario (1), con domicilio en Mula Lugar Calle Ollerias nº. 15, de los productos sujetos al Arbitrio, obtenidos durante el los cuatro trimestre del año actual, en la finca denominada Palma del término municipal de Mula

Riego (2)	Pago o paraje	Extensión	Núm. de árboles	Clase del fruto	Kilogramos obtenidos	Nombre del comprador	Precio de venta por kilo	Importe en Pesetas	%	TRIBUTACION Pesetas	Cts.	Observaciones
P	Palma	2-t	60	Albaricoque	2500	Jose Carrasco Tornero	tanto	4.000				
P	"	3½ t				Tierra en Blanco						
S	Pinar Hermoso	3 Hª				Tierra en blanco						

Total

10 %, amortización empréstitos

Timbre móvil 0'25

Suma

Mula 25 de Noviembre de 1954

(firma)

Miguel Egea

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

- 16 -

Número de orden	Apellidos y Nombre del contribuyente	Domicilio	Sitio de emplazamiento de la finca que contribuye	LIQUIDO IMPONIBLE	Importe del arbitrio al por 100	CORRESPONDE COBRAR EN EL Año Pesetas	Semestre Pesetas	Trimestre Pesetas
	- E y F -							
454	Egea del Baño Santiago		H. Hurón 43	28 00	4 82	4 82		
5	" " "		Tranca 1	80 00	13 76	13 76		
6	" Carreño Josefa		Alta 59	30 00	5 16	5 16		
7	" García Miguel		Ollerías 15	64 00	11 01	11 01		
8	" " José		M. Pintado 32	80 00	13 76	13 76		
9	" " Pedro		Campillas 27	200 00	34 40		17 20	
460	" Robles Candelaria		Chorrador 7	675 00	116 10			29 02
1	" " "		S. S. Pio XII	960 00	165 12			41 28
2	" Zapata Bernardo		A. Fuensanta	48 00	8 26	8 26		
3	Eléctrica del Segura		R. Molinos 109	111 00	19 09	19 09		
4	" "		"	111 00	19 09	19 09		
5	" "		"	48 00	8 26	8 26		
6	Escamez Álvarez Carmen		S. Miguel 17 d	128 00	22 02	22 02		
7	" " "		Tio Lucas 1	128 00	22 02	22 02		
8	Escolar Caravaca Pedro		F. Librilla	160 00	27 52	27 52		
9	" Hernández José		" 124	80 00	13 76	13 76		
470	" Ruiz Baltasar		" 41	80 00	13 76	13 76		
1	Espallardo Escamez José Mª		Molinos 62	40 00	6 88	6 88		38 70
2	" Espinosa José Mª		Olmedo 4	900 00	154 80			154 80
3	" " "		M. Bandín 9	3.600 00	619 20			
4	" Gutierrez Juan Pedro		Dª Elvira 1 y 3	160 00	27 52	27 52		
5	" " "		Nueva 20	120 00	20 64	20 64		
6	" Olmedo Eliseo		C. Caravaca	320 00	55 04		27 52	
7	" Romero Isabel		Hospital 23	1.600 00	275 20			68 80
8	Espejo Bayona José		Miza 10	32 00	5 50	5 50		
9	" Boluda Sebastián		M. Primero 16 d	64 00	11 01	11 01		
480	" Lara Juan		Carmen 60	45 00	7 74	7 75		
1	" Pastor Antonio		M. Pintado 32	64 00	11 01	11 01		
2	Espín Beltrán Juan Antº		Arboleja	30 00	5 16	5 16		
3	" Caballero Martín		Molinos 84	32 00	5 50	5 50		
4	" Espín José		M. Pintado 36	45 00	7 74	7 74		
5	" " Juana		S. Miguel 11	450 00	77 40			19 35
6	" " Juan Francº		Vueltas 26	150 00	25 80	25 80		
			Suma y sigue....	10.663 00	1.834 04	336 80	44 72	351 95

Notes: Sample cards from the Municipal Archive in Mula. Panel A: card from the Agricultural Census in 1955. Miguel Egea García lived in Mula at 15 Calle Ollerías, and owned three plots, one uncultivated, two *Tahúllas* containing 60 apricot trees. In 1954, he harvested 2,500 kg of apricots that he sold in bulk for 4,000 pesetas. Panel B: card from the Urban Real Estate Taxes Registry, corresponding to 1954. The same person, Miguel Egea García in registry number 457, paid 64 pesetas in taxes on his house at 15 Calle Ollerías.

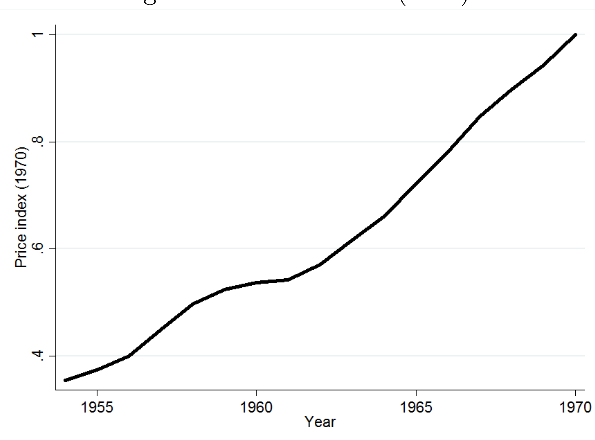
The urban tax base is useful for comparisons because it uses the same formula for all properties. For the 24 farmers who grew only apricots, the taxable base is a clear indicator of wealth differences. Ten of these farmers owned no urban real estate. These are the farmers categorized as poor. The conversion from tax base to actual value is not straightforward. The tax base is equivalent to estimated annual rent (net of the maintenance costs) that the owner collected on their property. The average value of the tax base of an urban house was about 40 pesetas.

For wealthy farmers who owned multiple properties, mansions, and palaces, the value (tax base) is substantially higher.

A.1.5 Price Index

We use the price index by the INE (*Instituto Nacional the Estadística*), the Spanish National Institute of Statistics, to compute real prices. In particular, we use the price index from Uriel *et al.* (2000). Because our period of observation is a week, rather than a year, we transform annual inflation rates into weekly inflation rates using the geometric average across weeks for each year. Figure A5 displays the price index. It can be seen that it doubled between 1955 and 1966.

Figure A5: Price Index (1970).



Notes: The graph represents the annual price index from Uriel *et al.* (2000) during the period of study.

A.2 Additional Description of the Soil Moisture and Apricot Production Functions

This section closely follows Allen *et al.* (2006). Trees are traditionally planted in a square grid, with each trunk 9 meters (m) apart. Hence, on average, there is one tree for every 81 m^2. This density corresponds to our data for apricot trees with an average ratio of trees per m^2 of 79.96 and a ratio between total number of trees and total area of 78.25 trees per m^2. These numbers are slightly smaller than the predicted 81 trees per m^2 because some farmers placed their trees very close to the edge of their plots.

Evapotranspiration (ET, henceforth) is the loss of water suffered by trees due to both evaporation (E) of water stored in soil and transpiration (T) of water stored in leaves. We use tthe Food and Agriculture Organization's recommended method to compute the evolution of moisture loss due to ET in Allen *et al.* (2006):

$$ET_{cb,t} = K_{cb,t} \cdot ET_0.$$

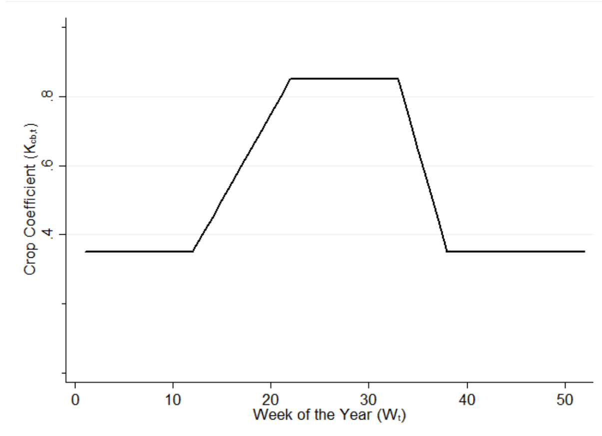
where $ET_{cb,t}$ is the weekly ET of crop c, ET_0 is the weekly reference ET and $K_{cb,t}$ is the weekly base crop coefficient.[1] Both $ET_{cb,t}$ and ET_0 are measured as millimeters per week. ET is affected by climatic factors including radiation, air temperature, atmospheric humidity, and wind speed. The effect of those parameters is summarized in ET_0. We use the estimations of ET_0 in Franco *et al.* (2000), which are independent of the crop.

We can distinguish four phases: initial, development, median, and final of the growing season. Following (Allen *et al.*, 2006, p. 107) we have $L_{ini} = 20$, $L_{dev} = 70$, $L_{med} = 120$, and $L_{fin} = 60$ a total of 270 days, before the critical season. The coefficient $K_{cb,t}$ is flat during the initial period (with $K_{cb,ini} = 0.35$)., linearly increasing from the development period until the median period, flat during the median period (with $K_{cb,med} = 0.85$), and linearly decreasing during the final period (with $K_{cb,fin} = 0.60$ on average). During the no-growth period until it reaches the

[1]We follow the notation in Allen *et al.* (2006), where the subscript b is not a subindex. Allen *et al.* (2006) differentiate between the crop coefficient K_c and the base crop coefficient K_{cb}. The crop coefficient is an average. We use the base crop coefficient K_{cb} because we allow ET to vary with the moisture.

next year's initial period at $K_{cb,ini}$, the coefficient $K_{cb,t}$ is linear. [2] Figure A6 displays the evolution of coefficient $K_{cb,t}$ over a year.

Figure A6: Evolution of the base crop coefficient $K_{cb,t}$ over a year.



Notes: The figure represents the relationship between the base crop coefficient $K_{cb,t}$ for apricot trees in southeastern Spain and the weekly calendar taken from Allen *et al.* (Figure 37, 2006).

A.2.1 Evapotranspiration Under Hydric Stress

ET_c refers to the ET of crop c under standard conditions. One should adjust the value of ET_c ($ET_{c,adj}$) when standard conditions do not hold. When the soil is wet, water has high potential energy, meaning that it can be easily absorbed by tree roots. When the soil is dry, water is not as easily absorbed. When a plot's soil moisture falls below a certain threshold, we say that a crop is under Hydric Stress (HS, henceforth). The effects of HS are incorporated by multiplying K_{cb} by the HS coefficient KS:

$$ET_{c,adj} = KS \cdot K_{cb} \cdot ET_0.$$

Water availability refers to soil's ability to keep water available for plants. After a heavy rain or irrigation, the soil absorbs water until full capacity is reached. Soil's Full Capacity (FC, henceforth) represents moisture that absorbent soil retains against gravitational forces, *i.e.*, soil moisture when downward vertical drainage has decreased substantially. In our case:

$$FC = 1000 \cdot \theta_{FC} \cdot Z_r,$$

where θ_{FC} is the moisture content of the soil at FC in cubic meters per cubic meters (that is, how many cubit meters of water can be contained in one cubic meter of soil); and Z_r is the depth of the tree's roots in meters.

In the absence of a water source, soil moisture decreases due to trees' water consumption. As this consumption increases, the moisture level decreases, making it harder for trees to absorb the remaining water. Eventually, a point is reached beyond which the tree can no longer absorb any water: the Permanent Wilting (PW, henceforth) point. The PW point is the soil moisture level at which the tree dies. In our case:

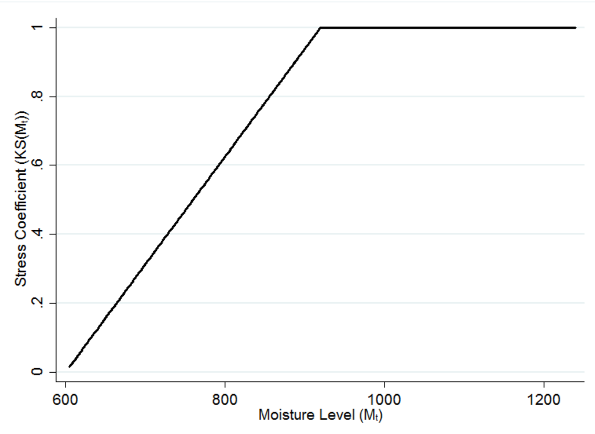
$$PW = 1000 \cdot \theta_{PW} \cdot Z_r,$$

where θ_{WP} is the moisture content of the soil at the Permanent Wilting Point (PW, henceforth), measured in cubic meters per cubic meters; and Z_r is the depth of the tree's roots in meters.

Moisture levels above FC cannot be sustained given the effect of gravity. Moisture levels below PW cannot be extracted by the roots of the trees. Hence, the Total Available Water (TAW, henceforth) is the difference:

[2] Equation 66 in Allen *et al.* (2006). It corresponds to coefficients for apricot trees without soil cover and with potential frosts, Table 17 (p. 140).

Figure A7: Relationship between the HS coefficient KS and the soil moisture level for apricots.



Notes: This figure represents the relationship between the HS coefficient, KS, and the level of moisture in the soil for apricot trees in southeastern Spain. The parameters are taken from Allen *et al.* (Figure 42, 2006).

$$TAW = FC - PW,$$

where $Z_r = 4m$ in the case of apricot trees irrigated with traditional flooding methods. The soil in Murcia is limestone, hence $(\theta_{FC} - \theta_{PW}) \in [0.13, 0.19]$ and $\theta_{PW} \in [0.09, 0.21]$. For our estimation we take the middle point: $FC = 1240$, $PW = 600$, and $TAW = 640$.

In practice, a tree absorbs water from soil at a slower rate, even before reaching the PW point. When a tree is under HS, it does not absorb water at the proper rate. The fraction of water that a tree can absorb without suffering HS is the Easily Absorbed Water (EAW, henceforth):

$$EAW = p_c TAW,$$

where $p_c \in [0, 1]$. For the case of the apricot tree $p_c = 0.5$, thus $EAW = 320$. The HS coefficient $KS \equiv KS(M_t)$ is a function of the moistness of the plot M_t:

$$KS(M_t) = \begin{cases} 1 & \text{if} \quad M_t > FC - TAW(1 - p_c) \\ \frac{M_t - PW}{EAW} & \text{if} \quad FC - TAW(1 - p_c) \geq M_t > PW \\ 0 & \text{if} \quad M_t \leq PW \end{cases} . \tag{A.1}$$

Figure A7 shows the evolution of the coefficient of HS for apricot trees, according to equation A.1. When soil moisture level is below the PW point (600 millimeters), the tree dies and there is no transpiration. When the moisture level is sufficiently high (920 millimeters), the tree does not suffer from HS and therefore transpiration is maximal. When soil has enough moisture for the tree to survive ($M_t > PW$), but not enough for the tree to function normally ($M_t < FC - TAW(1 - p_c)$), the tree suffers from HS. HS makes the tree transpire less that it would otherwise.

Adding the subscripts for the periods:

$$ET_{c,adj,t}(M_t) = KS(M_t) \cdot K_{cb,t} \cdot ET_0. \tag{A.2}$$

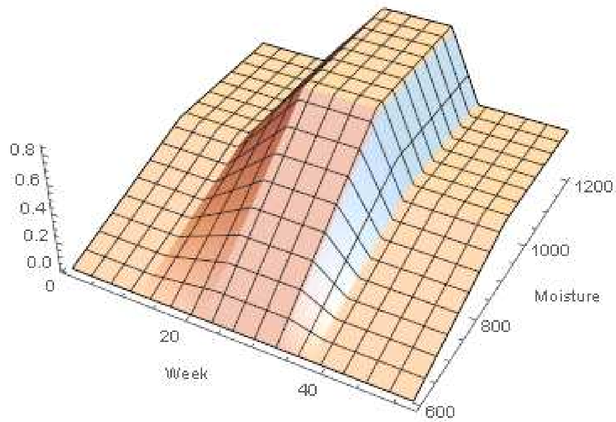
Figure A8 shows the combined effects of seasonality and HS on the ET coefficient, following equation A.2.

Finally, we have to take into account that, regardless of the amount of rain or irrigation, soil moistness can never go beyond the FC. The evolution of moisture M_t over time is:

$$M_t = min\{M_{t-1} + rain_{t-1} + irrigation_{t-1} - ET_{c,adj,t-1}(M_{t-1}), FC\}.$$

We obtain an average value for ET_c of 8.77, smaller than Franco *et al.* (2000) who find values of 23.1-30.8 millimeters per week (3.3-4.3 millimeters per day) for almond trees in the same region. Pérez-Pastor *et al.* (2009) report an ET of 1,476 millimeters per year (28.4 millimeters per week). This difference is because recent studies are performed using intensive dripping irrigation. Because the soil moisture level is greater, so is the ET.

Figure A8: Relation between the HS and seasonality, and the moisture level for apricots.



Notes: The figure represents the relation between the HS coefficient, KS, seasonality, and the level of moisture in the soil for apricot trees in southeastern Spain. The parameters are taken from Allen *et al.* (Figures 37 and 42, 2006).

A.2.2 Details about the Apricot Production Function

Following Torrecillas *et al.* (2000) we specify the weeks of the year in which irrigation is *critical* for apricot trees, as shown in Figure 2 in the paper. The critical weeks include the second rapid fruit growth period (Stage III) and two months after the critical, *i.e.*, Early Post-Harvest (EPH, henceforth). Both periods are located before and after the harvest season.

Stage III corresponds to the period of high growth before the critical season. This stage is critical because it is the stage at which trees transform water into fruit at the highest rate. The EPH period is also important because of trees' stress during the summer after the critical season. Before and during the critical season, trees use water at a rapid rate. Hence, the level of moisture in a tree is very low after the critical season. To survive the summer trees need to be irrigated properly, otherwise they will produce lower output during the next season (Pérez-Pastor *et al.,* 2009).

A.3 Additional Preliminary Analysis

Table A2 shows that the behavior of poor and wealthy farmers during the critical season is similar in regular years (*i.e.,* years without droughts). We expect poor farmers to be less likely to be liquidity constrained during regular years, when the price of water at auction does not increase substantially. Rainfall during the harvest year (*i.e.*, from week 25 in the previous calendar year until week 24 in the present calendar year) is an exogenous shock that shifts down both demand for water and water prices. Table A2 shows that purchase decisions of wealthy and poor farmers are different for dry and regular years. In Table 2 column 4 in the paper, the interaction between wealth and critical season is 0.0192. This is a weighted average between 0.0081 in regular years and 0.0393 in dry years. This interaction is smaller and insignificant in regular years. This result indicates that the different purchasing behavior during the critical season is attributable to dry years, when both demand for water and water prices during the critical season are high. In other words, purchasing behavior of poor and wealthy farmers is similar during regular years, when poor farmers are less likely to be liquidity constrained. This finding provides evidence about liquidity constraints among poor farmers.

Table A2: Demand for Water per tree and Urban Real Estate in dry and regular years.

	Regular Years		Dry Years	
# units bought per tree	(1)	(2)	(3)	(4)
Wealthy	0.0118**	0.0104**	0.0029	-0.0040
	(0.0046)	(0.0049)	(0.0081)	(0.0085)
Wealthy × Critical season		0.0081		0.0393**
		(0.0089)		(0.0155)
Covariates	Yes	Yes	Yes	Yes
Number of observations	9,456	9,456	4,992	4,992

Notes: All regressions are OLS specifications. The sample is restricted to farmers who only grow apricots. *Dry years* are defined to be the four driest harvest years in the sample, *i.e.*, lowest rain from week 25 in the previous calendar year to week 24 in the current calendar year. The dry years are 1960, 1962, 1964, and 1966. The remaining years are regular years. The dependent variable is the number of units purchased per tree by each individual farmer during a given week. *Wealthy* is a dummy variable that equals 1 if the farmer's value of urban real estate is positive and 0 otherwise. *Critical season* is a dummy variable that equals 1 if the observation belongs to a week during the critical season and 0 otherwise. *Covariates* are the farmer's purchase price at auction, the amount of rainfall during the week of irrigation, and the farmer's soil moisture level. Standard errors in parentheses. * p<0.10; ** p<0.05; *** p<0.01.

B Details about the Estimation and the Model

B.1 Estimation

We construct a two-step conditional choice probability (CCP) estimator following Hotz *et al.* (1994).

Step 1. In the first step we compute transition probability matrices for the following observable state variables: moisture, week, price, and rain. As described in the paper, the productivity shocks, ε_{ijt}, are assumed to be *i.i.d.* Gumbel. We integrate them analytically using the expressions in Subsection B.3. Moisture is a continuous variable and its evolution over time depends on the week of the year, and both farmers' decisions to buy water and rainfall. Therefore, certain values of moisture are never reached in the sample, even when their probability of occurrence is not zero. That is, certain combinations of the state-space variables are never reached in the sample, but their probability of occurrence is not necessary zero. To estimate demand, however, we need to integrate the value function over certain combinations of state-space variables not reached in the sample but simulated in step 2 (see footnote 6 for an example). Assuming that the CCP are zero for all values of the moisture not reached in the sample generates a downward bias on the estimated transformation rate: one would incorrectly assume that farmers buy less water than needed, thereby incorrectly estimating a lower transformation rate. For the estimation we proceed as follows. First, we estimate the CCP using the values of the state space reached in the sample. Then, we use the CCP estimator to predict the CCP on the values of the state space unreached in the sample. We call these the *smooth CCP* and describe their computation below.

We have estimated the CCP both parametrically (using the logistic distribution described in this section) and, for robustness, nonparametrically (using kernel methods to smooth both discrete and continuous variables described in Appendix C.1). There are four observable state variables in the structural model when the liquidity constraint is not binding (*i.e.,* for wealthy farmers): moisture, week of the year, water price, and rain. Moisture $M_{i,t}$ is a deterministic continuous variable that represents the amount of water accumulated in the farmers' plot; it goes from 300 to 1200. We discretize $M_{i,t}$ in $M = 80$ levels of moisture.[3] This is done by generating 80 linearly equally spaced points between $\underline{M}$ and $\overline{M}$, where $\underline{M}$ and $\overline{M}$ are the minimum and maximum levels of moisture in the grid, respectively. Week of the year w_t is a deterministic discrete variable; it goes from 1 to 52. Water price and rain are random variables. As explained in the paper, we assume that, holding fixed week of the year, farmers jointly draw

[3]For the main specification we obtained similar results using 200 discrete points. However, the computational burden increases substantially.

a price-rain pair, (p_t, r_t), among the 11 pairs (*i.e.,* the 11 years of the same week) available in the data with equal probability. Each week, prices may take three discrete values: low, high, or no-auction. Prices are week-specific; they thus vary from one week to the next. For each week, low price is the mean price below the median of the same week across years; high price is the mean price above the median of the same week across years. Each week rain may take two discrete values: no rain (*i.e.,* zero millimeter, which is the median of the rain distribution) or positive rain (in this case, we assign the median of the rain distribution conditional on rain being positive, 31 millimeter). Using this discretization for prices and rain we estimate the joint distribution of prices and rain non-parametrically using a frequency estimator.

For the results in Section 5 in the paper, we estimate the CCP parametrically using a logistic model (*i.e.,* multinomial logit). Let $S_{it} = (M_{it}, w_t, p_t, r_t) \epsilon \mathbb{R}^{\mathbf{4}}$ be the vector of state variables, where M_{it} is soil moisture level of farmer i in week t, w_t is week of year, p_t is water price at auction in week t, and r_t is rainfall in week t. Let $j_{ikt} = 1$ if farmer i bought k units in period t and 0 otherwise. We estimate the CCP by maximizing the following log-likelihood function $lnL = \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{k=0}^{J} j_{ikt} ln P_{ikt}$, where $P_{ikt} = \left(\frac{exp(\kappa' S_{it})}{\sum_j exp(\kappa' S_{it})} \right)$ and κ is the parameter vector. After the estimation, we generate a grid with the exhaustive enumeration of states; that is, every possible combination of the discretized values of the state variables (values of the discretized state variables both observed in the data and not observed in the data). Let us call this grid the *exhaustive grid*. Finally, we use the CCP estimator to predict the values on the CCP for each cell in the exhaustive grid. We call these the smooth CCP.

Step 2. We restrict the sample to the 14 farmers who are not liquidity constrained. We estimate the vector of structural parameters, $\Theta \equiv (\gamma, \sigma_\varepsilon, \zeta)$, using the conditional choice simulation estimator proposed by Hotz *et al.* (1994), which is based on the inversion theorem by Hotz and Miller (1993). We integrate the value function using the smoothed CCP as computed in the previous subsection. We set the discount factor β equal to 0.99. Prices and rain are simulated using the joint distribution of prices and rain estimated with the procedure described in step 1. The moisture's evolution is described by the equations in Subsection A.2 with the following values: $TAW = 1200$, $PW = 300$, $EAW = 0.5 \cdot TAW$, $E = 4$ (see Subsection A.2). As regards the moments, we match each farmer's decisions (that is, whether and how many units each farmer bought in each period). The number of discrete units that a farmer may buy varies between 0 to 4 units per week.

For the initial condition of the moisture we follow Hendel and Nevo (2006, p. 1,647) and use the estimated distribution of moisture to generate its initial distribution. We do this by starting at an arbitrary initial level of moisture of: $1/2 \times (\text{TAW} + \text{PW})$, where TAW and PW are described in Subsection A.2. In the empirical application studied, the initial moisture level has no impact on its evolution after a couple of weeks due to the ET rate and rainfall. We experimented with different initial conditions and obtained almost identical results as we show below.

We estimate the parameter vector Θ using a GMM estimator based on moment conditions proposed by Hotz *et al.* (1994). We use 200 simulations, each with 14 individuals, and $T = 572$ weeks per individual per simulation. That is, for each simulation and each individual, we use a total of $T = 11\, years \times 52\, weeks$ periods, which is the length of our panel, leaving a total of $8,008$ observations in each simulation. We perform the estimation using KNITRO, a solver for non-linear optimization, with tolerance level of 1.0e-12. With the estimated demand we recover annual revenue for all farmers, constrained and unconstrained.

B.2 Properties of the Demand Estimator

Following Aguirregabiria and Mira (2010), we now establish properties of the demand estimator. Time is discrete and indexed by t. Each period represents a week. We index farmers by i. Farmers have preferences defined over a sequence of states from period $t = 0$ until period $t = \infty$. The state at period t for wealthy farmer i has two components, a vector of state variables $s_{it} = (M_{it}, w_t, p_t, r_t, \varepsilon_{it})$ that is known at period t, and a decision vector j_{it} chosen at period t that belongs to the discrete set $j_{it} \in \{0, ..., J\}$. The vector of state variables, s_{it}, also includes the error vector $\varepsilon_{it} \equiv (\varepsilon_{i1t}, ..., \varepsilon_{iJt})$. The time index, t, can be a component of the state vector, s_{it}, which may also contain time-invariant individual characteristics. Farmer's preferences over possible sequences of states is represented by a utility function $\sum_{\tau=0}^{\infty} \beta^{\tau} U(j_{i,t+\tau}, s_{i,t+\tau})$, where $\beta \in (0, 1)$ is the discount factor and

$U(j_{it}, s_{it}) = h(j_{it}, M_{it}, w_t; \gamma) + \varepsilon_{ijt} - \zeta\,\mathbf{1}\{j_{it} > 0\} - j_{it}p_t$ is the current utility function. The decision at period t affects the evolution of future values of the state variables, and the farmer faces uncertainty about these future values. Liquidity constraints are never binding for wealthy farmers. The melting point constraint affects only the utility function as defined above, but not the choice set. The farmer's beliefs about future states can be represented by a Markov transition distribution function, $F(s_{i,t+1}|j_{it}, s_{it})$. These beliefs are rational in that they are the true transition probabilities of the state variables. Every period t the farmer observes the vector of state variables, s_{it}, and chooses an action $j_{it} \in J$ to maximize the expected utility:

$$\mathbb{E}\left(\sum_{\tau=0}^{\infty}\beta^{\tau}U(j_{i,t+\tau}, s_{i,t+\tau})\,|j_{it}, s_{i,t}\right).$$

This is the farmer's dynamic programming (DP) problem. Let $\alpha(s_{i,t})$ and $V(s_{i,t})$ be the optimal decision rule and the value function of the DP problem, respectively. By Bellman's principle of optimality the value function can be obtained using the recursive expression:

$$V(s_{it}) = \underset{j\in J}{max}\left\{h(j_{it}, M_{it}, w_t; \gamma) + \varepsilon_{jt} - \zeta\,\mathbf{1}\{j_{it} > 0\} - j_{it}p_t + \beta\int V(s_{i,t+1})\,dF(s_{i,t+1}|j, s_{it})\right\},$$

and the optimal decision rule is then $\alpha(s_{i,t}) = \underset{j\in J}{argmax}\{\bar{v}(j, s_{i,t})\}$ where, for every $j \in J$,

$$\bar{v}(j, s_{i,t}) \equiv h(j_{it}, M_{it}, w_t; \gamma) + \varepsilon_{jt} - \zeta\,\mathbf{1}\{j_{it} > 0\} - j_{it}p_t + \beta\int V(s_{i,t+1})\,dF(s_{i,t+1}|j, s_{it}).$$

We are interested in the estimation of the structural parameters in preferences and transition probabilities. Suppose that a researcher has a panel of N individuals who behave according to this decision model. For every observation (i, t) in this panel, the researcher observes the individual's action, j_{it}, and a subvector, (M_{it}, w_t, p_t, r_t), of the state vector, s_{it}. In summary, the researcher's data set is:

$$Data = \{j_{it}, M_{it}, w_t, p_t, r_t : i = 1, 2, ..., N; t = 1, 2, ..., \infty\}.$$

We now discuss the assumptions regarding the relationship between observable and unobservable variables following Aguirregabiria and Mira (2010).

Assumption AS (*Additive Separability*). The utility function is additively separable in the observable and unobservable components: $U(j_{it}, s_{it}) \equiv U(j_{it}, M_{it}, w_t, p_t, r_t, \varepsilon_{it}) = h(j_{it}, M_{it}, w_t; \gamma) + \varepsilon_{ijt} - \zeta\,\mathbf{1}\{j_{it} > 0\} - j_{it}p_t$, where ε_{ijt} is a real random variable with unbounded support.

Assumption IID (*i.i.d. Unobservables*). The unobserved state variables in ε_{it} are independently and identically distributed over agents and over time with cumulative density function $G_{\varepsilon}(\varepsilon_{it})$, which has finite first moments and is continuous and twice differentiable in ε_{it}.

Assumption CI-X (*Conditional Independence of Future*). Conditional on the current values of the decision and the observable state variables, the next period's observable state variables do not depend on current ε_{it}. This assumption holds trivially for w_t. It also holds for the other observable state variables. The covariates are constant for a given individual. Rain is exogenous conditional on the week of the year. This assumption also holds for prices as discussed in Section 3 in the paper. The law of motion of the moisture is independent of ε_{it}.

Assumption CLOGIT. The unobserved state variables ε_{ijt} are independent and follow a Gumbel distribution.

Assumption DIS (*Discrete Support*). The support of (M_{it}, w_t, p_t, r_t) is discrete and finite.

This model satisfies the assumptions in Hotz and Miller (1993) and Hotz *et al.* (1994), thus establishing the legitimacy of our simulation-based CCP estimator.

B.3 Specification of the Productivity Shock

We first introduce the notation for the case of *i.i.d.* shocks across choice alternatives, where the result below is well known in the industrial organization literature. In Subsection B.3.2 we extend these results to the case of shocks non *i.i.d.* across choice alternatives, the main specification used in the paper.

B.3.1 Specification with *i.i.d.* shocks across choice alternatives

Under this specification the productivity shocks, ε_{ijt}, are drawn *i.i.d.* across choice alternatives $j \in \{0, 1, \ldots, J\}$ (alternatives refer to different number of units), individuals, and over time. Let the value function be:

$$\begin{gathered} V\left(M_{it}, w_t, p_t, r_t, \mu_{it}, \varepsilon_{ijt}\right) \equiv \underset{j_{it}\in\{0,1,\ldots,J\}}{max} \left\{h\left(j_{it}, M_{it}, w_t; \gamma\right) + \varepsilon_{ijt} - \zeta\, \mathbf{1}\{j_{it} > 0\} - p_t j_{it} + \right. \\ \left. + \beta\mathbb{E}\left[V\left(M_{i,t+1}, w_{t+1}, p_{t+1}, r_{t+1}, \mu_{i,t+1}, \varepsilon_{i,j,t+1}\right) | M_{it}, w_t, p_t, r_t, \mu_{it}, j_{it}\right]\right\} \\ \text{s.t.: } M_{it} \geq PW \\ \text{s.t.: } j_{it} p_t \leq \mu_{it}, \forall j_{it} > 0 \end{gathered},$$

Rewrite it as (we omit the constraints in what follows):

$$V\left(X_{it}, \varepsilon_{ijt}\right) \equiv \underset{j_{it}\in\{0,1,\ldots,J\}}{max} \left\{H\left(\centerdot\right) + \varepsilon_{ijt} + \beta\mathbb{E}\left[V\left(X_{it+1}, \varepsilon_{ijt+1}\right) \,|X_{it}, j_{it}\right]\right\},$$

where $X_{it} \equiv (M_{it}, w_t, p_t, r_t)$, $H\left(\centerdot\right) \equiv h\left(j_{it}, M_{it}, w_t; \gamma\right) - p_t j_{it} - \zeta\, \mathbf{1}\{j_{it} > 0\}$.

Now rewrite the previous expression as:

$$V\left(X_{it}, \varepsilon_{ijt}\right) \equiv \underset{j_{it}\in\{0,1,\ldots,J\}}{max} \left\{v(j_{it}, X_{it}) + \varepsilon_{ijt}\right\},$$

where $v(j_{it}, X_{it})$ is the choice specific value function.

Then if the productivity shocks ε_{ijt} follow a Gumbel distribution with CDF $F_\varepsilon\left(\varepsilon_{ijt}; \sigma_\varepsilon\right) = e^{-e^{-\varepsilon_{ijt}/\sigma_\varepsilon}}$:

$$\mathbb{E}_\varepsilon V\left(X_{it}, \varepsilon_{ijt}\right) = \int_\varepsilon \underset{j_{it}\in\{0,1,\ldots,J\}}{max} \left\{v(j_{it}, X_{it}) + \varepsilon_{ijt}\right\} \mathrm{d}F_\varepsilon = \sigma_\varepsilon \ln\left(\sum_{j=0}^{J} \exp\left(\frac{v(j_{it}, X_{it})}{\sigma_\varepsilon}\right)\right) + \bar{\gamma}\sigma_\varepsilon, \tag{B.1}$$

where the last equality follows from the well-known properties of the Gumbel distribution and $\bar{\gamma} = 0.5772$ is the Euler's constant.

Then:

$$\mathbb{P}\left(j_{it} = d\right) = \mathbb{P}\left(\varepsilon_{idt} - \varepsilon_{ikt} > v(j_{it} = k, X_{it}) - v(j_{it} = d, X_{it}),\ \forall k \neq d\right).$$

Using the properties of the Gumbel distribution:

$$\mathbb{P}\left(j_{it} = d\right) = \frac{\exp\left(\frac{v^d}{\sigma_\varepsilon}\right)}{\sum\limits_{k=0}^{k=J} \exp\left(\frac{v^k}{\sigma_\varepsilon}\right)}, \tag{B.2}$$

where $v^r \equiv v(j_{it} = r, X_{it})$.

Replacing equation (B.2) into (B.1):

$$\mathbb{E}_\varepsilon V\left(X_{it}, \varepsilon_{ijt}\right) = v^d - \sigma_\varepsilon \ln\left(\mathbb{P}\left(j_{it} = d\right)\right) + \bar{\gamma}\sigma_\varepsilon. \tag{B.3}$$

B.3.2 Specification with shocks non *i.i.d.* across choice alternatives

We follow the same steps as in Subsection B.3.1. Now $\hat{j} \in \{0, 1\}$, where $\hat{j} = 0$ if $j = 0$ and $\hat{j} = 1$ if $j > 0$. Then the productivity shocks, $\varepsilon_{i\hat{j}t}$, are drawn *i.i.d.* across $\hat{j} \in \{0, 1\}$, so $\varepsilon_{i\hat{j}t} = \varepsilon_{i0t}$ for $j = 0$ and $\varepsilon_{i\hat{j}t} = \varepsilon_{i1t}$ for $j > 0$. Let the value function be:

$$V\left(X_{it},\varepsilon_{i\hat{j}t}\right)\equiv \underset{j_{it}\in\{0,1,\ldots,J\}}{max}\left\{h\left(j_{it},M_{it},w_t;\gamma\right)+\varepsilon_{i,\hat{j}=0,t}1\left\{j_{it}=0\right\}+\left(\varepsilon_{i,\hat{j}=1,t}-\zeta\right)1\left\{j_{it}>0\right\}-p_tj_{it}+\right.$$
$$\left.+\beta\mathbb{E}\left[V\left(X_{it+1},\varepsilon_{i,\hat{j},t+1}\right)|X_{it},j_{it}\right]\right\}.$$

Rewrite the previous expression as:[4]

$$V\left(X_{it},\varepsilon_{i\hat{j}t}\right)\equiv max\left\{v(j_{it}=0,X_{it})+\varepsilon_{i,\hat{j}=0,t},\underset{j^+_{it}\in\{1,\ldots,J\}}{max}\left\{v(j_{it}=j^+_{it},X_{it})+\varepsilon_{i,\hat{j}=1,t}\right\}\right\}.$$

Using the properties of the Gumbel distribution:

$$\mathbb{E}_\varepsilon V\left(X_{it},\varepsilon_{i\hat{j}t}\right)=\sigma_\varepsilon\ln\left(\exp\left(\frac{v^0}{\sigma_\varepsilon}\right)+\exp\left(\frac{v^{j^+}}{\sigma_\varepsilon}\right)\right)+\bar{\gamma}\sigma_\varepsilon, \tag{B.4}$$

and:

$$\mathbb{P}\left(j_{it}=0\right)=\mathbb{P}\left(\hat{j}_{it}=0\right)=\frac{\exp\left(\frac{v^0}{\sigma_\varepsilon}\right)}{\exp\left(\frac{v^0}{\sigma_\varepsilon}\right)+\exp\left(\frac{v^{j^+}}{\sigma_\varepsilon}\right)}, \tag{B.5}$$

$$\mathbb{P}\left(j_{it}=j^+_{it}\right)=\mathbb{P}\left(\hat{j}_{it}=1\right)=\frac{\exp\left(\frac{v^{j^+}}{\sigma_\varepsilon}\right)}{\exp\left(\frac{v^0}{\sigma_\varepsilon}\right)+\exp\left(\frac{v^{j^+}}{\sigma_\varepsilon}\right)}. \tag{B.6}$$

Replacing equations (B.5) and (B.6) into (B.4) and letting $v^1\equiv v^{j^+}$ we obtain:

$$\mathbb{E}_\varepsilon V\left(X_{it},\varepsilon_{i\hat{j}t}\right)=v^b-\sigma_\varepsilon\ln\left(\mathbb{P}\left(\hat{j}_{it}=b\right)\right)+\bar{\gamma}\sigma_\varepsilon.$$

B.4 Law of Motion for Prices and Water

We discuss the modeling assumptions for the evolution of the state variables for water price and rainfall, their fit to the data, and the role of serial correlation over time in rainfall and water prices.

Mula's climate is semi-arid. Farmers are under a long dry spell the vast majority of the time. As explained in Section A.2, ET is high. Rainfall is mostly evapotranspirated after a week. Rainfall therefore affects prices the week after it occurred but no later. The supply of river water comes from the mountains to the west of Mula. Snowmelt and rain in the mountains has little correlation with rain in Mula. Seasonal demand and water supply are the main determinants of water prices. We model the absence of an auction as an infinite price and compute the probabilities of its occurrence accordingly.

We model the evolution of prices and rainfall to capture two empirical regularities from our setting. First, the major determinant of water price is weather seasonality. Second, variation in prices and rainfall across years is low, conditional on the week of the year which captures seasonality. The data in this paper span 11 years. A period t denotes a week. We model the joint evolution of water price in period t and rainfall in period $t-1$ assuming that, holding fixed the week of the year, farmers jointly draw a price-rain pair, (p_t, r_{t-1}), *i.i.d.* among the 11 pairs (*i.e.,* the 11 years of the same week) available in the data with equal probability.

Serial correlation in water price arises because weather seasonality is its main determinant, and dry weather in a given week is usually followed by dry weather in a subsequent week. During summers, for example, prices are systematically higher for several weeks. We show below that water price displays serial correlation across weeks of

[4] The inner maximization process is deterministic. That is, conditional on buying, there is only one shock. Therefore, no integration is needed for the inner maximization process. This degeneracy is not problematic for the estimation in the empirical setting studied because very seldom the predicted behavior from the model conditional on buying is not able to rationalize the actual quantity purchased (for the estimated model Table A5 shows that conditional on buying this issue occurred less than 22 instances out of a total of 3,892 farmer-weeks instances when the farmers made water purchase decisions). Nevertheless, we performed a robustness analysis and reestimated the model using only two possible decision variables: buy *vs.* no-buy. The results are in Table A4. Similar results are obtained.

the year. Accounting for such serial correlation is important because it affects price dynamics and farmers' decisions, if such dynamics are taken into account when farmers bid in the auction.

Table A3 shows that our specification for the evolution of price and rainfall accounts for serial correlation in prices. The table compares the correlation patterns between water price, and lagged rainfall and water prices from both the data and the simulation (using the specification used in the structural model). The first column in panel A, labeled as "data," shows that there is a negative correlation between water price in week t and rainfall in previous week(s) as expected. The correlation tends to decrease with higher lags because the effect of rain on demand dissipates as time passes due to the ET of water. Again, this negative correlation is the main reason why water price displays serial correlation across weeks of the year. It is also the main reason why we use the conditional joint process described above to model water price and rainfall. The second column, labeled as "simulation," shows the same patterns from the simulated variables (water price and rainfall) used in the structural model. Panel B shows similar patterns using lagged prices. The correlation patterns from the simulated variables are similar to the ones from the data.

Table A3: Correlation between Price and Rain in the Data and Simulation.

Panel A

Data		Simulation	
	$Price_t$		$Price_t$
$Price_t$	1.000	$Price_t$	1.000
$Rain_t$	-0.154	$Rain_t$	-0.143
$Rain_{t-1}$	-0.102	$Rain_{t-1}$	-0.103
$Rain_{t-2}$	-0.073	$Rain_{t-2}$	-0.055
$Rain_{t-3}$	-0.112	$Rain_{t-3}$	-0.131
$Rain_{t-4}$	-0.094	$Rain_{t-4}$	-0.116
$Rain_{t-5}$	-0.062	$Rain_{t-5}$	-0.084
$Rain_{t-6}$	-0.071	$Rain_{t-6}$	-0.030

Panel B

Data		Simulation	
	$Price_t$		$Price_t$
$Price_t$	1.000	$Price_t$	1.000
$Price_{t-1}$	0.316	$Price_{t-1}$	0.365
$Price_{t-2}$	0.366	$Price_{t-2}$	0.460
$Price_{t-3}$	0.213	$Price_{t-3}$	0.341
$Price_{t-4}$	0.187	$Price_{t-4}$	0.193
$Price_{t-5}$	0.056	$Price_{t-5}$	0.063
$Price_{t-6}$	0.030	$Price_{t-6}$	0.025

Notes: Panel A displays the correlation between the price of water in week t, denoted by $Price_t$, and rain in period $\hat{t}$, denoted by $Rain_{\hat{t}}$, for $\hat{t} = t, t-1, \ldots, t-6$. Panel B displays the correlation between the price of water in week t, denoted by $Price_t$, and the price of water in period $\hat{t}$, denoted by $Price_{\hat{t}}$, for $\hat{t} = t, t-1, \ldots, t-6$. The columns labeled as "data" displays these correlations using the data (using the same sample as the one used in the structural model from Section 3 when the auction was run). The columns labeled as "simulation" displays these correlations using the simulated prices and rainfall used in the structural model as described in Section 3 in the paper.

C Robustness Analysis and Additional Results

C.1 Nonparametric CCP

We have also estimated the model using nonparametric CCP as described next and obtained similar results. Rather than using a traditional frequency-based approach in the presence of discrete variables, we smoothed both discrete and continuous variables to compute the CCP. There are two reasons for this. First, it allows us to extend the reach of the nonparametric methods to our empirical model. Nonparametric frequency methods are useful only when sample size is large and discrete variables take a limited number of values, meaning the number of discrete cells is less than the number in the sample.[5] Second, moisture is a continuous variable and its evolution over time depends on both farmers' decisions to buy water and the realizations of rain. Therefore, certain values of moisture are never reached in the sample even when their probability of occurrence is non-zero.[6] To estimate the demand, however, we need to integrate the value function over the relevant combination of state variables associated with nodes of some simulated future path of the farmer.[7] Thus, we estimate the CCP nonparametrically using kernel methods to smooth both discrete and continuous variables.

We now define the nonparametric CCP estimator. Following Li and Racine (2003) we use generalized product kernels for a mix of continuous and discrete variables. Let $S_{it} = \left(M_{it}, S_t^d\right) \epsilon\, \mathbb{R} \times \mathbb{R}^{\mathbf{3}}$ be the vector of state variables, where $M_{it} \epsilon\, \mathbb{R}$ is again moisture and $S_t^d = (w_t, p_t, r_t)\, \epsilon\, \mathbb{R}^{\mathbf{3}}$ is the vector of discrete state variables: week, price, and rain. Let s_k^d be the kth component of s^d and $S_t^d = (t = 1, \ldots, T)$. For $S_{tk}^d, s_k^d\, \epsilon\, \{0, 1 \ldots, c_k - 1\}$ (the support of each discrete variable) define the univariate kernel (Aitchison and Aitken, 1976):

$$l^u\left(S_{tk}^d, s_k^d, \lambda_k\right) = \begin{cases} 1 - \lambda_k & if \;\; S_{tk}^d = s_k^d \\ \frac{\lambda_k}{c_k - 1} & if \;\; S_{tk}^d \neq s_k^d \end{cases} .$$

We use the above kernel for prices and rain. For the ordered discrete variable week we use the kernel function from Wang and van Ryzin (1981): $l^o\left(w_t, v, \lambda_1\right) = \lambda_1^{|w-v|}$, where $\lambda_1 \epsilon\, [0, 1]$. Therefore, for the multivariate vector of discrete state variables we use the product kernel:

$$L\left(S_{it}^d, s^d, \lambda\right) = l^o\left(w_t, v, \lambda_1\right) \prod_{k=2}^{3} l^u\left(S_{tk}^d, s_k^d, \lambda_k\right) = \lambda_1^{|w-v|} \prod_{k=2}^{3} \left(\frac{\lambda_k}{c_k - 1}\right)^{N_{tk}(s)} \left(1 - \lambda_k\right)^{1 - N_{tk}(s)}, \tag{C.1}$$

where $\lambda = (\lambda_2, \lambda_3)$ and $N_{tk}(s) = \mathbf{1}\left(S_{tk}^d \neq s_k^d\right)$ is an indicator function that equals 1 if $S_{tk}^d \neq s_k^d$ and 0 otherwise. Let $f(s) = f\left(m, s^d\right)$ be the joint probability density function (PDF) of $S_{it} = \left(M_{it}, S_t^d\right)$. We use the following kernel estimator $\hat{f}(s) = \frac{1}{T} \sum_{t=1}^{T} L_{ts^d} W_{h,tM}$, where $W_{h,tM} = h^{-1} w\left(\frac{M_t - m}{h}\right)$, $w(\cdot)$ is a standard univariate second order Gaussian kernel, and $L_{ts^d} = L\left(S_t^d, s^d, \lambda\right)$ is given by equation C.1. We select bandwidth using likelihood cross-validation. To compute the smooth CCP we follow the same procedure described in Subsection B.1. First, we estimate $\hat{f}(s)$ using the observed values of the variables in the state space (in the sample). Then, we use the estimated density and evaluate it at the unobserved values of the state space needed to integrate the value function (out of the sample). The latter are the smooth CCP.

[5] The frequency approach is infeasible in our setting, even if we discretize the continuous variable moisture in a reasonable number of values. See Subsection C.4 for a thorough discussion.

[6] For example, for week 23 the joint probability of *no rain* and *low price* conditional on this week is 9.1 percent. This is because only 1 out of 11 years was registered *low rain* and *low price* in the week 23 (1/11 = .0909). The observed different values of inventories for the 14 unconstrained farmers are (at most) $14 \times 1 = 14$. In the simulation, however, a value of moisture different from, although close to, these 14 observed values may be reached. But the frequency estimator would not be defined for any value of moisture different from those 14 values.

[7] That is, we also need to integrate over values of moisture discussed in the previous footnote where the frequency estimator is not defined. These values of moisture are never reached in our sample.

C.2 Estimates of Additional Specifications of the Model

For robustness, we also present the demand estimates with a specification using a binary variable for the decision to buy water. Table A4 displays the demand estimates.

Table A4: Structural Estimates: Robustness Analysis

	(1)	(2)	(3)	(4)
Transformation rate ($18 \leq week \leq 32$):				
– Linear term: $\hat{\gamma}_L$	0.1194	0.0706	0.1288	0.1736
	(0.0106)	(0.0150)	(0.0114)	(0.0184)
– Quadratic term: $\hat{\gamma}_Q$	–	3.27e-05	–	5.95e-05
		(3.24e-06)		(3.37e-06)
Irrigating cost: $\hat{\zeta}$	38.9592	263.3704	34.1723	290.4195
	(1.8621)	(21.7248)	(1.0875)	(22.5458)
Scale parameter of Gumbel distribution: $\hat{\beta}$	8.2345	10.8419	7.5009	10.7549
	(0.6151)	(0.1745)	(0.5543)	(1.4861)
Marginal effect	0.1194	0.1280	0.1288	0.2780
Area heterogeneity	No	No	Yes	Yes
Number of Observations	8,008	8,008	8,008	8,008

Notes: Standard errors are computed using 200 bootstrap replications where we reestimate the demand transitions and conditional choice probabilities, and then minimize the GMM criterion function to find $\hat{\Theta}$. We bootstrap by individual farmer resampling an individual farmer's history for the whole period under analysis. The computed standard errors thus account for the history and serial correlation within farmers. Marginal effects reported at the mean moisture. See Section 4 in the paper for details.

C.3 Goodness of Fit

Table A5: Goodness of Fit

	Total units bought:		Number of farmer-weeks with farmers buying:									
			0 units		1 unit		2 units		3 units		4 units	
	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model	Data	Model
Outside critical season	257	323	2402	2386	60	55	15	21	5	6	38	52
Critical season	184	140	1294	1312	30	26	16	10	6	2	26	22
Total	441	463	3696	3698	90	81	31	31	11	8	64	74

Notes: The table displays the goodness-of-the-fit comparing the simulation of the estimated model and the observed decisions in the data. The estimated model was simulated 200 times using the realizations of prices and rainfal observed in the data. The reported numbers correspond to the mean rounded to the nearest integer. The total number of units from the data correspond to the total number of units purchased by the 14 wealthy farmers; that is, it corresponds to the decisions used in Table 3 (structural estimation). These farmers bought 441 units of water under the market system during the period under analysis. The total number of units in Table 4 (counterfactual) correspond to the total number of units purchased by all the 24 farmers, wealthy and poor. These farmers bought 637 units of water under the market system during the period under analysis.

C.4 Alternative Estimation Methods

We discuss two alternative approaches to estimate the model and their fit to the empirical setting studied. (a) The first alternative consists of estimating the probability of being liquidity constrained from Subsection C.5, using poor farmers' decisions outside the critical season, by replacing the smooth conditional choice probabilities with the choice probabilities from the structural model. (b) The second alternative consists of implementing simultaneously the demand estimation in Section 4 in the paper and the estimation of the probability of being liquidity constrained in Subsection C.5, using the decisions from all farmers, wealthy and poor, and estimating simultaneously both parameters that characterize demand and the probability of being liquidity constrained for all the farmers.

Both alternatives are considerably more complex than our approach because they would require including: (i) two additional state variables relative to the demand estimation as we implemented it in the paper, the cash holdings, μ_{it}, and the financial shock, ν_{it}; and (ii) an unobserved state variable, the cash holdings. The first point increases the dimension of the state space to five, plus the random shocks, ε_{it} and ν_{it}, thus increasing the computational complexity and, most importantly, the data requirements for identification and to obtain precise estimates, as discussed below. The second point precludes estimating the conditional choice probabilities as we did in the first step of the demand estimation in the paper, thus also precluding the "simple" application of the procedure from Hotz and Miller (1993) and Hotz *et al.* (1994).

In principle, one could implement the alternatives in the previous paragraphs using one of the following two approaches. First, a full-solution or nested-fixed-point procedure to solve the dynamic programming problem of the farmers.[8] In the case of alternative (a), one would solve the dynamic programming problem of poor farmers with two additional state variables relative to the demand estimation as implemented in the paper. In the case of alternative (b), one would solve the dynamic programming problem of all farmers. Second, an iterative procedure like, *e.g.*, Arcidiacono and Miller (2011) could be used to calculate the conditional choice probabilities with the unobserved state variable μ_{it}, using the expectation–maximization (EM) algorithm. The EM algorithm approach does not require solving farmers' dynamic programming problem, but it requires solving the maximization step multiple times, which can be computationally intensive if the unobserved state does not follow a Markov process, or if one needs to discretize a continuous state in small bins, as it is in our case for cash holdings, μ_{it}, as discussed next.[9]

The data requirements to obtain precise estimates when implementing the two approaches described in the first paragraph are substantially higher than in our approach. Alternatively, one would need to make additional assumptions that are difficult to justify in the empirical context of Mula, such as using larger discrete bins for the continuous state variable moisture or the unobserved state variable cash holdings, collapsing farmers' purchase decisions into a dummy variable for buying instead of modeling the decision of how many units to buy, assuming a Markov process for the unobserved state cash holdings or for the prices, *etc.* Consider, for example, the discretization of the state variables moisture and cash holdings. With five discrete variables, and assuming we discretize the continuous variable moisture into just 13 values, the cash holdings into just two values (*e.g.,* high and low cash), and the additional assumption that cash holdings follow a first order Markov process, the number of discrete cells that would arise is $13\times52\times3\times2\times2 = 8,112$. Thus, the average number of observations in each cell, the effective sample size for the conditional choice probabilities, would be $T/6,864 = 8,008/8,112 \approx 1$, where $T = 8,008$ is our sample size.[10] But discretizing moisture into 13 values and the cash holdings into two values would be too low because it will not capture the variability in the purchase decisions of the farmers. Importantly, the revenue of the farmers, η_{it}, that enters into the unobserved state cash holdings in equation C.2, depends on the seasonal effect,

[8] See, *e.g.*, Miller (1984), Pakes (1986), Rust (1987), and Wolpin (1984), and Keane and Wolpin (1994, 1997).

[9] A third approach would consist of using a mathematical program with equilibrium constraints, MPEC, (*e.g.,* Luo *et al.,* 1996; Su and Judd, 2012; Dubé *et al.,* 2012). The MPEC approach would only require solving for the equilibrium at the final estimate of the structural parameters, avoiding repeatedly solving for an equilibrium at each candidate of the parameter vector, thus reducing the computational burden (see, *e.g.*, Su and Judd, 2012, for an application of the MPEC approach to estimate the single agent dynamic discrete choice model by Rust, 1987). The main difficulty to apply the MPEC approach to our case is the presence of the latent states. We are not aware of any paper that uses an MPEC approach to estimate dynamic discrete choice models in the presence of latent states. See, *e.g.*, Connault (2016) for a discussion about dynamic discrete choice models with unobserved dynamics.

[10] $T = 8,008 = 14$ unconstrained farmers $\times$ 52 weeks per year $\times$ 11 years.

thus violating the simple Markov assumption. Although in principle one could discretize the continuous variable moisture in smaller bins, and keep track of cash holdings throughout the year, the computational and identification burden would increase as discussed below. Similarly, collapsing farmers' purchase decisions into a dummy variable for buying would eliminate, by construction, any variation in the number of units bought when farmers do buy. Such variation in the data is important because poor farmers are more likely than wealthy farmers to buy multiple units before the critical season to store such water as soil moisture in case they cannot buy water during the critical season due to liquidity constraints (*e.g.,* see Figure 2 in the paper). Not accounting for such variation would artificially generate lower revenue for poor farmers relative to wealthy farmers because poor farmers' soil moisture level would be artificially lower before the critical season.

There are also computational and identification limitations in implementing the alternative approaches presented above. The full-solution approach requires solving each farmer's dynamic programming problem at each candidate value of the parameter vector. The computational requirements of the full-solution approach increase substantially when there is an unobservable, time varying state variable like cash holdings in our setting. Keane and Wolpin (2010) is one of the few papers that we are aware of that performs a full-solution approach with unobservable, time-varying state variables. The EM algorithm approach requires repeating the maximization step multiple times. Integrating over the unobserved state complicates forming the likelihood of the data required to compute the conditional choice probabilities of being in particular values of the unobserved state. The computational requirements can be mitigated, to a certain extent, using some of the assumptions discussed in the previous paragraph. However, these assumptions are problematic in our case due to their fit to the empirical setting, as discussed above. Finally, identification of the unobserved state variables in both approaches is limited by the length of the panel and the variation in the observable state variables (see, *e.g.*, Arcidiacono and Miller 2011).[11]

The specificities of our setting allow us to separate the estimation into two parts, which in turn enables us to exploit variation in our data as described below. For the demand estimation, wealthy farmers are never liquidity constrained, as discussed in the paper. We do not use the model to estimate wealthy farmers' probability of being liquidity constrained. We determine their unconstrained status directly from the data by looking at the value of their urban real estate. Thus, we estimate the parameters that characterize demand without incorporating unobserved cash holdings. This simplifies the dimension of the state space to four observed state variables, plus the random shocks, ε_{it}, that we integrate analytically as described in Subsection B.3. This approach also allows us to use smaller (relative to the alternative approaches presented above) discrete bins for the continuous state variable moisture, and to use the variability in the moisture level resulting from the number of units purchased by farmers rather than a dummy variable for whether to buy. Because we do not have unobserved cash holdings as a state variable, we apply the procedure from Hotz and Miller (1993) and Hotz *et al.* (1994). In our case in particular, the forward-simulation procedure from Hotz *et al.* (1994) has two advantages. First, it allows us to incorporate the continuous variable moisture in a straightforward manner by using Monte Carlo simulations to approximate continuation values at states not observed in the data. Second, it requires only estimating future choice and transition probabilities associated with the nodes of some simulated future path of the farmer. Thus, by exploiting the representation by Hotz and Miller (1993), we avoid the full solution that would require solving each farmer's dynamic programming problem at each candidate value of the parameter vector. By using the forward-simulation procedure from Hotz *et al.* (1994), we avoid integrating value functions over all future paths. By determining the unconstrained status directly from the data, we avoid the EM algorithm that would require solving the maximization step multiple times. For the estimation of the probability of being liquidity constrained, we exploit the fact that in our setting purchase decisions during the critical season are determined by the apricot production function's technological constraint. Thus, we use the conditional choice probabilities of wealthy farmers during the critical season to obtain a lower bound on the probability that poor farmers are liquidity constrained. The lower-bound feature results from setting the unobserved consumption to zero in Subsection C.5.[12] The assumptions required to implement the estimation

[11] For further details about advances in the estimation of dynamic discrete choice models see Arcidiacono and Ellickson (2011).

[12] The estimation of the probability of being liquidity constrained in Subsection C.5 is not needed to perform the welfare analysis from Section 6 in the paper.

of the demand and the probability of being liquidity constrained are, respectively, that wealthy farmers are never liquidity constrained, and that poor and wealthy farmer have the same production function for apricots. We provide evidence to support these assumptions and discuss their validity in our empirical context in Section 7 in the paper and in Appendix E.

C.5 Lower Bound on the Probability of Being Liquidity Constrained

We discuss how to estimate a lower bound on poor farmers' probability of being liquidity constrained during the critical season (lower bound, henceforth). The demand estimates (Sections 4 and 5 in the paper) and welfare analysis (Section 6 in the paper) are unaffected by the estimates in this subsection. The estimates in this subsection provide additional evidence about the presence of the liquidity constraints and complement the evidence presented in the paper. In the data, we only observe whether a poor farmer buys water or not, in addition to the number of units they purchase. When a farmer does not purchase water, we do not know whether it is because the farmer does not demand water at that price and is not liquidity constrained, or whether the farmer is liquidity constrained.[13] By assumption, wealthy farmers are never liquidity constrained: the amount of cash they have does not play any role in their water purchasing decisions, *i.e.*, wealthy farmers' demand for water is determined by trees' water needs and is independent of cash holdings. We compute a lower bound on the probability that a poor farmer is liquidity constrained during the critical season using the demand estimates from Section 4, and assuming that the CCP of poor and wealthy farmers would coincide during the critical season if poor farmers were not liquidity constrained. In other words, to compute the lower bound, we further assume that poor farmers' purchasing behavior during the critical season is the same as the (CCP of) wealthy farmers, thus determined by trees' water needs and independent of cash holdings. Poor farmers who are unconstrained during a critical season may behave myopically and do not take into account that they may be unconstrained during, *e.g.*, the following critical season. This additional assumption used in this subsection is not needed either to perform the structural estimation nor the welfare analysis in the paper.

This assumption is reasonable in the context of Mula farmers for four reasons. First, farmers only derive utility from purchasing water once a year, after the harvest. Therefore, any resulting savings will take over a year to impact their utility. Second, there will be many opportunities to buy relatively cheap water between the current and the following summer (all weeks outside the critical season) in case the farmer needs to increase soil moisture. Third, there is a positive probability that medium or heavy rain occurs, therefore increasing the moisture level of the farmer's plot to the maximum. In that case, the purchase decision made during the current summer would be irrelevant for the moisture level of the following summer. Finally, as mentioned in the paper, poor farmers in Mula had only enough money for their basic necessities (González Castaño and Llamas Ruiz, 1991).

We provide evidence that the behavior of poor and wealthy farmers is similar during years that are not particularly dry in Table A2 in Subsection A.3.[14] The intuition is that farmers are heterogeneous in two dimensions, their productivity and their ability to pay for water or cash holdings. During the critical season purchase decisions are determined by the apricot production function. A potentially constrained farmer's purchasing behavior in the *unconstrained* state is the same as the purchasing behavior of a permanently unconstrained farmer. The identifying assumption for the analysis in this subsection is that poor and wealthy farmers have the same production function (*i.e.,* no persistent unobserved heterogeneity).[15]

[13] We restrict attention here to *tight* liquidity constraints, whereby if a farmer is liquidity constrained, the farmer cannot buy any water. We do not consider the case of *mild* liquidity constraints, whereby a farmer might be able to buy some water, but fewer units of water than would otherwise buy in the unconstrained state.

[14] Table A2 shows that, during regular years (*i.e.,* years without droughts), potentially constrained farmers who believe that they may be constrained during the critical season purchase more water than unconstrained farmers before the critical season (*i.e.,* before the uncertainty about rain is realized). However, their purchases are not statistically different from wealthy farmers' purchases during the critical season (*i.e.,* after uncertainty about rain is realized) in regular years (Table A2 column 2). In a dry year, however, when poor farmers are likely to be liquidity constrained, wealthy farmers do buy more water during the critical season (Table A2 column 4). We interpret this as evidence that, during the critical season and conditional on moisture, the CCPs of the wealthy (unconstrained) farmers can be used to infer the purchasing behavior of poor farmers (potentially constrained) in the counterfactual unobserved scenario that the latter were unconstrained.

[15] This subsection provides a simple procedure to obtain approximate estimates (*i.e.,* lower bounds) on poor farmers' probability of being liquidity constrained. In Subsection C.4 we discuss two alternatives to estimate the model and their fit to the data/setting

Farmer i's cash in period t, denoted by μ_{it}, evolves according to:

$$\mu_{it} = \mu_{i,t-1} - p_{t-1} j_{i,t-1} + \phi_{i0} + R_{it} + \nu_{it}, \tag{C.2}$$

$$i = 1, \ldots, I, \qquad t = 1, \ldots, T.$$

where ϕ_{i0} captures the weekly consumption of individual i that is constant over time; R_{it} is the farmer's revenue from selling their harvest that we define below; and ν_{it} is an idiosyncratic financial shock that we specify below. The farmer collects revenue after the harvest, in week 24. Thus, revenue, R_{it}, is

$$R_{it} = \begin{cases} 0 & \{t : w_t \neq 24\} \\ Rev_{it} & \{t : w_t = 24\} \end{cases}, \tag{C.3}$$

where $Rev_{it} = \sum_{w_t=1}^{52} h\left(j_{it}, M_{it}, w_t; \gamma\right) = \sum_{w_t=18}^{32} \gamma \cdot \left(M_t - PW\right) \cdot KS\left(M_t\right)$.

We assume $J = 1$ in this subsection and focus only on the decision of buying *vs.* not buying.[16] The probability that farmer i is liquidity constrained in period t, denoted by $\mathbb{P}\left(p_t j_{it} > \mu_{it}\right)$, is given by:

$$\begin{aligned} \mathbb{P}\left(p_t j_{it} > \mu_{it}\right) &= \mathbb{P}\left(p_t j_{it} > \mu_{i,t-1} - p_{t-1} j_{i,t-1} + \phi_{i0} + R_{it} + \nu_{it}\right), \\ &= \mathbb{P}\left(\nu_{it} < -C_{it}\right), \\ &= \mathbb{F}_\nu\left(-C_{it}\right), \end{aligned} \tag{C.4}$$

$$i = 1, \ldots, I, \qquad t = 1, \ldots, T,$$

where the first line follows from the equation in (C.2); $C_{it} \equiv \mu_{i,t-1} - p_{t-1} j_{i,t-1} + \phi_{i0} + R_{it} - p_t j_{i,t}$; and $\mathbb{F}_\nu(\cdot)$ denotes the cumulative distribution function of ν_{it}.

Similarly, the probability that farmer i is not liquidity constrained in period t, denoted by $\mathbb{P}\left(p_t j_{it} \leq \mu_{it}\right)$, is given by:

$$\begin{aligned} \mathbb{P}\left(p_t j_{it} \leq \mu_{it}\right) &= \mathbb{P}\left(\nu_{it} \geq -C_t\right), \\ &= 1 - \mathbb{F}_\nu\left(-C_t\right), \end{aligned} \tag{C.5}$$

$$i = 1, \ldots, I, \qquad t = 1, \ldots, T,$$

where the second line uses the symmetry of the distribution of ν_{it}.

We only observe whether a farmer buys water. When a farmer does not buy water, we do not know whether it is because (i) they do not need water and have a low valuation; or (ii) because they are liquidity constrained and have a high valuation. An additional complication is that, although we know that wealthy farmers are not liquidity constrained, we do not know which poor farmers are liquidity constrained.

There are three main difficulties in estimating the probabilities in equations (C.4) and (C.5) for poor farmers who are potentially liquidity constrained. First, the revenue, R_{it}, from the equation in (C.2) is unobserved in the data. Recovering revenue requires an estimate of the production function. We estimate such parameters in Section 4 in the paper.

Second, the conditional choice probabilities of the poor and the wealthy farmers may differ outside the critical

studied. The first alternative consists of implementing the analysis in this subsection using poor farmers' decisions outside the critical season. The second alternative consists of implementing simultaneously the demand estimation and the analysis in this subsection using all farmers' decisions. These alternatives are considerably more complex than our approach. In Subsection C.4 we discuss the complications and additional assumptions needed to implement them.

[16] See footnote 13.

season, but will coincide during the critical season if the poor farmers were not liquidity constrained under our assumption above. Outside the critical season, the purchase behavior of a potentially constrained poor farmer who is in the unconstrained state may differ from the behavior of a potentially constrained poor farmer who is in the constrained state. For example, a potentially constrained farmer may abstain from purchasing water outside of the critical season, even when feasible, to ensure not to be constrained during the critical season when the marginal return on water is higher. Similarly, a potentially constrained farmer who believes to be constrained during the critical season will purchase water before the critical season and store it by increasing the moisture. Part of the water will evaporate during the critical season, but this is the best the farmer can do being constrained during the critical season. The latter behavior can be seen in the paper in Figure 2 and Table 2. For these reasons, using the estimated CCP from the wealthy farmers would underestimate the probability of being liquidity constrained for a potentially constrained farmer who believes that may be constrained during the critical season. During the critical season, however, the purchase decision is determined by the tree's need for water (stages II, III, and the early post harvest as depicted in Table 1 in the paper) conditional on the soil's moisture. Thus, during the critical season the purchase behavior of a potentially constrained farmer who is in the unconstrained state is the same as the purchase behavior of a permanently unconstrained farmer. This is captured by their conditional choice probabilities as discussed below. In turn, these purchase behaviors are the same as the purchase behavior that would be observed for a potentially constrained farmer who is in the constrained state had the farmer not been constrained. In the procedure below we estimate the probability of being liquidity constrained for the poor farmers only during the critical season. Finally, weekly average consumption ϕ_{i0} is unobserved. In principle, the weekly consumption can be estimated using the procedure described below under the additional assumption that, during the critical season, the weekly consumption for a potentially constrained farmer who is in the unconstrained state is the same as the weekly consumption of a potentially constrained poor farmer who is in the constrained state. This assumption, however, may be violated if, for example, one of the poor farmers is permanently unconstrained. For this reason, rather than estimating the weekly consumption of the poor farmers, we set it equal to zero for all farmers and estimate a bound on the probability that the farmer is liquidity constrained. That is, with positive weekly consumption, the probability of being liquidity constrained will be higher than the one we estimate, but it will be contained within our bounds.

To summarize, we estimate the lower bound as follows. We generate the actual revenue of the farmer using the estimated demand system and the moisture level resulting from the actual purchase decision of the poor farmers. Then, we focus on the decisions under the critical season and exploit that, during the critical season, purchase decisions are determined by the production function of apricots if farmers are unconstrained. Finally, we set the consumption of the poor farmers equal to zero and obtain an upper bound on these probabilities. This procedure relies on three assumptions. First, the estimated annual revenue is the real revenue that the farmers obtain after the harvest. Second, poor farmers' purchasing behavior is identical as that of wealthy farmers during the critical season. Third, farmers' average weekly consumption is equal to zero. The last assumption is conservative, thus providing a lower bound on the probability that a farmer is liquidity constrained.

To simplify notation in what follows, we omit conditioning on state variables. Everything is, however, conditional on the state. Let the estimated CCP of not buying water, *i.e.*, $j_{it} = 0$, for a wealthy farmer be $\hat{\mathbb{P}}_{CCP}\left(j_{it} = 0\right)$. Similarly, let the estimated CCP of buying water, *i.e.*, $j_{it} = 1$, for a wealthy farmer be $\hat{\mathbb{P}}_{CCP}\left(j_{it} = 1\right)$. For potentially liquidity constrained farmers define the following variable:

$$\tilde{j}_{it} = \begin{cases} j_{it} & if \;\; p_t j_{it} < \mu_{it} \\ 0 & if \;\; p_t j_{it} \geq \mu_{it} \end{cases} .$$

During the critical season:

$$\mathbb{P}(\tilde{j}_{it_c}=0)=\mathbb{P}[(j_{it_c}=0\wedge p_{t_c}j_{it_c}<\mu_{it_c})\vee(p_{t_c}j_{it_c}\geq\mu_{it_c})],$$
$$=\mathbb{P}(j_{it_c}=0)\mathbb{P}(p_{t_c}j_{it_c}<\mu_{it_c})+\mathbb{P}(p_{t_c}j_{it_c}\geq\mu_{it_c}),$$

$$i=1,\ldots,I,\qquad t_c=\{t:18\leq w_t\leq 32\},$$

where the second equality follows because during the critical season purchase decisions are determined by the apricot production function.

Two points merit further discussion. First, the derivation above requires independence between j_{it} and μ_{it}, but it does not require independence between $\tilde{j}_{it}$ and μ_{it}. Trivially, for sufficiently low values of μ_{it}, $\tilde{j}_{it}=0$. Thus, $\tilde{j}_{it}$ and μ_{it} are not independent. Second, the independence between j_{it} and μ_{it} is a consequence of the additional assumption made in the first paragraph in this subsection. Such an assumption implies that the *ideal* purchase behavior during the critical season of a poor farmer depends only on the observable states and the *i.i.d.* productivity shocks.[17]

Then:

$$\hat{\mathbb{P}}\left(\tilde{j}_{it_c}=0;\chi\right)=\hat{\mathbb{P}}_{CCP}\left(j_{it_c}=0\right)\left[1-\mathbb{F}_\nu\left(-C_{t_c};\chi\right)\right]+\mathbb{F}_\nu\left(-C_{t_c};\chi\right),\tag{C.6}$$

$$i=1,\ldots,I,\qquad t_c=\{t:18\leq w_t\leq 32\},$$

where $\chi\equiv\left(\phi_{i0},\sigma_\nu^2\right)$ is a parameter vector.

Using the same argument:

$$\mathbb{P}(\tilde{j}_{it_c}=1)=\mathbb{P}[(j_{it_c}=1\wedge p_{t_c}j_{it_c}<\mu_{it_c})],$$
$$=\mathbb{P}(j_{it_c}=1)\mathbb{P}(p_tj_{it_c}<\mu_{it_c}),$$

$$i=1,\ldots,I,\qquad t_c=\{t:18\leq w_t\leq 32\}.$$

Thus:

$$\hat{\mathbb{P}}\left(\tilde{j}_{it_C}=1;\chi\right)=\hat{\mathbb{P}}_{CCP}\left(j_{it_C}=1\right)\left[1-\mathbb{F}_\nu\left(-C_{t_C};\chi\right)\right].\tag{C.7}$$

Note that $\mathbb{P}\left(\tilde{j}_{it_C}=0\right)+\mathbb{P}\left(\tilde{j}_{it_C}=1\right)=1$.

We estimate the parameter vector by maximizing the log-likelihood function:

$$\chi=\underset{\chi}{arg\,max}\sum\nolimits_{i=1}^{I}\sum\nolimits_{\tilde{t}_c}\mathbf{1}\left(\tilde{j}_{i\tilde{t}_c}=0\right)log\hat{\mathbb{P}}\left(\tilde{j}_{i\tilde{t}_c}=0;\chi\right)+\mathbf{1}\left(\tilde{j}_{i\tilde{t}_c}=1\right)log\hat{\mathbb{P}}\left(\tilde{j}_{i\tilde{t}_c}=1;\chi\right),$$

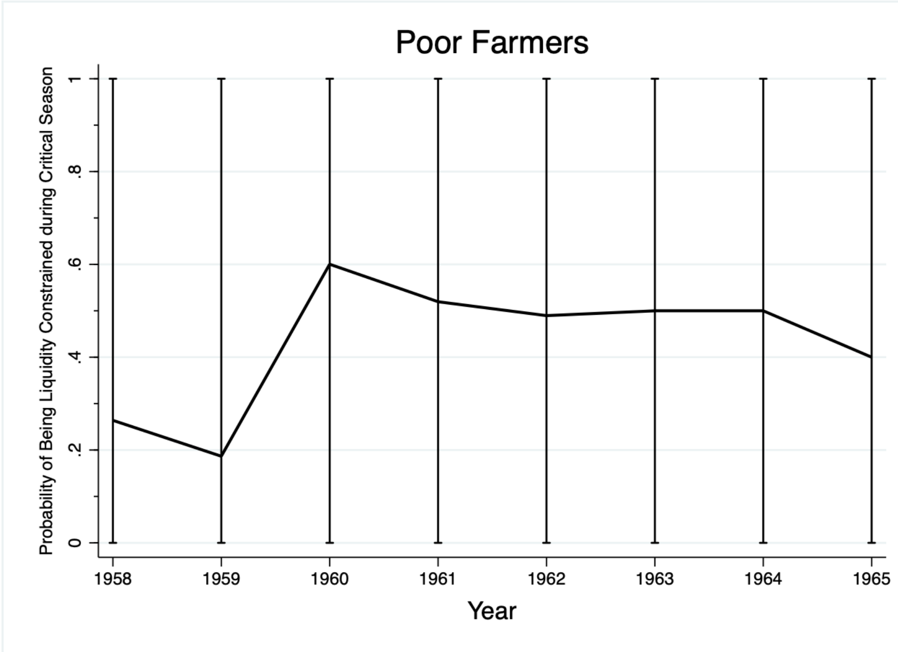
$$i=1,\ldots,12,\qquad \tilde{t}_c=\{t:18\leq w_t\leq 32\},$$

where $\hat{\mathbb{P}}\left(\tilde{j}_{it_C}=0;\chi\right)$ and $\hat{\mathbb{P}}\left(\tilde{j}_{it_C}=1;\chi\right)$ are given by the equations in (C.6) and (C.7), respectively; and i index poor farmers.

As discussed above, for the estimation we set $\phi_{i0}=0$. We let $\nu_{it}\sim\mathbf{N}\left(0,\sigma_\nu^2\right)$. Thus, $\chi=\sigma_\nu^2$. Finally, we use the estimated distribution of cash holdings to generate the initial distribution as follows: (i) start cash holdings at an arbitrary initial level of zero in 1955; (ii) use the first three years in the sample (years 1955, 1956, and 1957) to generate an initial distribution of cash determined by the model conditional on the parameter vector; and (iii)

[17] The independence result here is similar to local independence on latent variable models (Lazarsfeld and Henry, 1968). Here the latent variable is whether the farmer is liquidity constrained or not.

Figure A9: Lower Bound on the Probability of Being Liquidity Constrained.



Notes: The figure displays the estimated lower bounds of poor farmers' probability of being liquidity constrained (PLC) during the critical season using the procedure described in Subsection C.5. Each vertical line displays the distribution of the mean PLC across farmers, defined as the the mean across $\tilde{t}_c$ by farmer with $\tilde{t}_c = \{t : 18 \leq w_t \leq 32\}$. Each vertical line displays the maximum PLC (upper whisker), mean (solid line), and minimum PLC (lower whisker). For each year, the figure shows the distribution across poor farmers.

use the remaining years in the data (years 1958 to 1966) and the generated initial condition in (ii) to perform the estimation.[18]

Estimation Results

The estimated parameter for this subsection is $\hat{\sigma}_\nu^2 = 27.263$ with a standard error of 8.797. The standard error is computed by bootstrapping from the asymptotic distribution of the parameters in Section 4 in the paper.[19] The distribution of yearly estimated lower bounds of poor farmers' probability of being liquidity constrained during the critical season, defined as the mean across $\tilde{t}_c$ by farmer, where $\tilde{t}_c = \{t : 18 \leq w_t \leq 32\}$, are given in Figure A9. They correspond to $\hat{\mathbb{P}}\left(\tilde{j}_{it_C} = 0; \hat{\chi}\right)$ and $\hat{\mathbb{P}}\left(\tilde{j}_{it_C} = 1; \hat{\chi}\right)$, given by the equations in C.6 and C.7. In all years the estimated probabilities range from a minimum of zero to a maximum of one. The main message from Figure A9 is straightforward: Some poor farmers are liquidity constrained with probability one, while others are not liquidity constrained; that is, there are substantial heterogeneities in poor farmers' probabilities of being liquidity constrained during the critical season.[20] As expected, the mean probability increases in 1960, a particularly dry year.

[18]This is the standard approach in the industrial organization literature to deal with the unobserved initial condition of inventory (see *e.g.,* Hendel and Nevo, 2006, p. 1647, where our unobserved initial cash holding is analogous to Hendel and Nevo's unobserved initial inventory). We have also experimented using the following initial conditions: (i) zero cash holdings; (ii) cash holdings equal to the annual average revenue; and (iii) cash holdings equal to a random annual revenue obtained from a uniform distribution over the observed revenues. Results are presented in footnote 19.

[19]We obtain estimates (standard errors) of $\hat{\sigma}_\nu^2 = 27.283$ (8.803) and $\hat{\sigma}_\nu^2 = 27.277$ (8.911) if we use as initial conditions the cash holdings equal to the annual average revenue and cash holdings equal to a random annual revenue, respectively. The estimates not being sensitive to the choice of initial conditions is because we use the first three years of the data to generate an endogenous initial condition.

[20]The figure is informative about these heterogeneities because it displays the distribution of estimates *across* poor farmers.

D Welfare Measures

We describe next the welfare measures. Given rainfall and water allocation, the yearly average revenue per tree for farmer i net of the irrigation cost, denoted by NR_i, is:

$$NR_i = \frac{1}{\#\ trees_i}\frac{1}{Y}\left[\sum_{t=1}^{T} h\left(j_{it}, M_{it}, w_t; \gamma\right) - \zeta\,\mathbf{1}\{j_{it} > 0\}\right], \tag{D.1}$$

where the sum is over the total number of weeks, t, in the sample; and the denominator, Y, is the total number of years in the sample, used to compute the yearly average revenue.

We do not take into account water expenses because we are interested in welfare measures; that is, transfers are not taken into account. The welfare of farmer i, denoted by W_i, is:

$$W_i = \frac{1}{\#\ trees_i}\frac{1}{Y}\left[\sum_{t=1}^{T} h\left(j_{it}, M_{it}, w_t; \gamma\right) - \zeta\,\mathbf{1}\{j_{it} > 0\} + \varepsilon_{ijt}\right]. \tag{D.2}$$

Markets using Complete Units: M.

We compute both revenue and welfare.

- **Poor farmers.** We compute revenue using the estimated demand system, $\hat{\Theta} \equiv \left(\hat{\gamma}, \hat{\sigma}_\varepsilon, \hat{\zeta}\right)$, and actual purchases made by poor farmers. We use equations D.1 and D.2 for revenue and welfare, respectively, and the moisture level in farmers' plots; that is, the moisture resulting from their actual purchase decisions.

- **Wealthy farmers.** We compute revenue using the estimated demand system, $\hat{\Theta} \equiv \left(\hat{\gamma}, \hat{\sigma}_\varepsilon, \hat{\zeta}\right)$, and the actual purchases made by wealthy farmers. We use equations D.1 and D.2 for revenue and welfare, respectively, and the moisture level in farmers' plots; that is, the moisture resulting from their actual purchase decisions. Wealthy farmers' revenue can be greater than the HV average revenue. This feature is because poor farmers are sometimes liquidity constrained, so wealthy farmers buy more water than the amount required by the HV allocation.

Quotas: Q.

Revenue and welfare coincide under the quota system because farmers do not choose when to irrigate. We only report one measure that we call welfare. As explained in the paper, in this paper we focus on the 24 farmers who only grow apricot trees. These farmers bought 637 units of water under the market over the sample period. Under the quota system, we allocate the same 637 units of water during the same week when the units were purchased under market. We compute welfare under the following quota configurations, where we allocate units among the farmers as follows:

- **Quotas with random assignment of complete units,** Q**.** Every time we observe that a farmer purchased a unit of water during the market on a particular date, the complete unit of water is assigned uniformly at random, proportional to their amount of land, among all farmers.

- **Quotas with non-random assignment of complete units,** Q-X%**.** Every time we observe that a farmer purchased a unit of water during the auction on a particular date, the complete unit of water is assigned uniformly at random, proportional to their amount of land, among the X percent of farmers who had not received irrigation for the longest amount of time, on the same date. That is, we keep track of when the last time was that each farmer irrigated under the quota system. Then, to allocate a unit of water on week t, we only consider the subset of farmers whose last irrigation period was furthest away from t. This is the subset of farmers who value water most. Then we allocate the unit of water uniformly at random, proportional to farmers' amount of land, among this subset of farmers. The value of X defines how large this set is. For example, if X = 100%, then all farmers are included in the set and the unit of water is allocated uniformly at random, proportional to their amount of land, among *all* farmers. Formally, the subset is defined as follows. Let $t_i^{Last} < t$ be the last week farmer i was allocated a unit of water under the quota system. Let I be the total number of farmers and let $\mathcal{I}$ be the set of all farmers. Let us index the farmers according to the last time that each farmer irrigated, being farmer I the one who irrigated in the week closest to t and being farmer 1 the farmer who irrigated in the week farthest away from t. Then $t_1^{Last} \leq t_2^{Last} \leq t_3^{Last} \leq \cdots \leq t_I^{Last}$. (Such ranking can always be done and, typically, can be done using several strict inequalities, depending on how many units have been allocated in the past.) Let X $= {}^{x}/_{I} \times 100$ for $x \in 1, 2, \ldots, I$. So given X, we can compute $x = {}^{\text{X}}/_{100} \times I$. Then, under Q-X% we allocate the unit of water uniformly at random, proportional to farmers' amount of land, among the subset of farmers $\tilde{\mathcal{I}}_{X\%} \equiv \{i \in \mathcal{I} : i \leq x,\ with\ x = {}^{\text{X}}/_{100} \times I\}$. For example, if $I = 10$, $t_1^{Last} \leq t_2^{Last} \leq t_3^{Last} < t_4^{Last} \leq \cdots \leq t_{10}^{Last}$, and $X = 30\%$, then $x = {}^{30}/_{100} \times 10 = 3$ and $\tilde{\mathcal{I}}_{30\%} = \{1, 2, 3\}$. So, we allocate the unit of water uniformly at random, proportional to their amount of land, among farmers indexed as 1, 2, and 3. These are the three farmers whose last irrigation was farthest away from t. In case of ties, we include all tied farmers in the subset $\tilde{\mathcal{I}}$. In the previous example, if $t_1^{Last} \leq t_2^{Last} \leq t_3^{Last} = t_4^{Last} = t_5^{Last} < t_6^{Last} \leq \cdots \leq t_{10}^{Last}$, then $\tilde{\mathcal{I}}_{30\%} = \{1, 2, 3, 4, 5\}$. For example, in Q-50%, complete units of water are allocated among the 50 percent of farmers who did not receive irrigation the longest; in Q-25%, complete units of water are allocated among the 25 percent of farmers who did not receive irrigation the longest; and so on. As indicated before, under Q-X% we need to keep track of when the last time was that each farmer irrigated under the quota system. We do not have this information for the initial weeks in the sample. So, under Q-X%, we allocate units uniformly at random, proportional to farmers' amount of land, at the beginning of the sample as described in the procedure above. In Q and Q-X% units are allocated uniformly at random, proportional to their amount of land, among the corresponding set of farmers. We simulate the allocation $S = 1,000$ times under Q and Q-X%. In Table 4 in the paper we report the mean welfare measures across simulations.

In the empirical setting, the quota implemented was closest to Q-25%.

Highest Valuation using Complete Units: HV.

We compute the highest-valuation allocation using complete units, denoted by HV, as follows. Every time we observe that a farmer purchased a unit of water during the auction on a particular date, the complete unit of water is assigned to the farmer who values water the most on that date.

E Additional Discussion

E.1 Strategic Unit Size and Sunk Cost of Irrigation

The results obtained when comparing revenue from quotas and markets suggest that the choice of the unit size in the auction (*i.e.*, three hours of irrigation) was not innocuous. In particular, the fact that in some years poor farmers under the quota system produced higher revenue than wealthy farmers under the auction system suggests that the size of the units sold at the auction might be too large. The size of the units sold at auction had not changed since the middle ages. This feature could be due to institutional persistence or due to other reasons. For example, three-hour unit size might have maximized profits for the cartel. However, it did not maximized welfare.

As shown in Donna and Espín-Sánchez (2018), there is a sunk cost to the first unit of water allocated to a plot because the water was allocated using a dry channel dug into the ground that absorbed some water. Subsequent units associated with the same channel flow through a wet channel. Thus, the loss is negligible for subsequent units. In the auction system, subsequent units are allocated to different farmers depending on whom won each unit. The optimal unit size (*i.e.,* the unit size that maximizes welfare) would be determined by the trade-off between the sunk cost incurred every time that a farmer irrigates (due to the loss of water flowing through a dry channel) and the diminishing return of water. In the quota system, units are allocated to each farmer in geographical order (*i.e.,* every unit is allocated to a neighbor farmer down the channel with respect to the previous farmer). Therefore, the incurred sunk costs are minimized.

E.2 Optimal Crop Mix

Our analysis only considers the case of apricot farmers. Because different agricultural products have different irrigation needs in different seasons, the optimal crop mix involves diversifying among several agricultural products with different irrigation needs. For example, oranges are harvested in winter and their water need peaks in December. Apricots are harvested in summer and their water need peaks in May-June. Hence, a mix of crops with apricot and orange trees would outperform one with just apricot trees in terms of spending smoothing. We observe this optimal mix in the data. Many farmers have orange trees and either apricot, peach, or lemon trees, all three of which are harvested during summer. We focus on the set of farmers who only grow apricot trees because they have the same production function. This approach allows us to differentiate liquidity constraints from unobserved heterogeneity as discussed in the paper.

If farmers with a summer-winter crop mix can smooth spending and avoid liquidity constraints, then a natural questions is: why did all farmers not adopt such a crop mix? There are three main reasons to explain this behavior. First, the farmers in Mula inherited land from their parents who, in turn, inherited land from their parents... Therefore, from the point of view of the Mula farmers there was no initial choice of the crop type. Such choice was inherited. Second, if there are crop-specific fixed costs, some farmers may be better off growing a single crop. Finally, if some farmers lacked enough cash to buy water, they might also be unable to buy land to plant a second crop (*e.g.*, oranges).

E.3 Trees, Droughts, and Insurance

Quotas are desirable during a drought because they periodically allocate a certain amount of water to each farmer. Quotas also work as an insurance for farmers' trees. That is, quotas decrease farmer's uncertainty regarding making risky investments in trees. A tree takes several years to be fully productive, but it dies if it is not irrigated properly in any given year. Vegetables grow more quickly than trees and can be harvested within a year of planting. Hence, a farmer with a secure supply of water is more likely to plant trees and receive a higher expected profit from them.

E.4 Collusion

The presence of a centuries-stable market alongside repeated interaction among farmers raises a concern about bidding collusion in the auction. Historical sources (González Castaño and Llamas Ruiz, 1991) and personal interviews with surviving farmers point in the opposite direction.[21]

Rather than a system in which farmers colluded to pay a price lower than what would have prevailed without collusion, there seemed to be bitterness among farmers competing for water, and between farmers and employees of the cartel. Fights, loud arguments, and complaints were common. In many instances, police intervened during the auction to guarantee its normal development. See Donna and Espín-Sánchez (2018) for an investigation of bidding collusion in this setting.

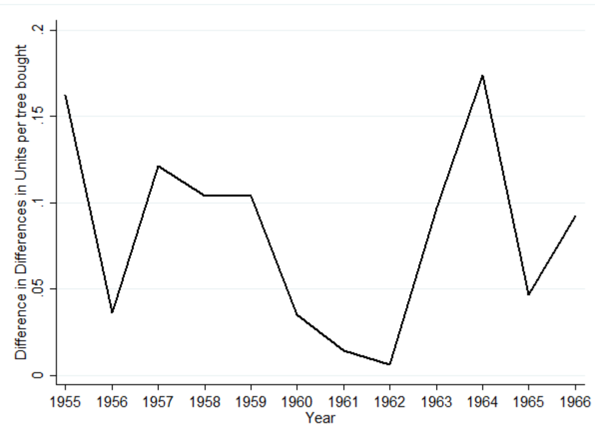
E.5 Attrition

While we have weekly panel data about water purchases, our data only contain one cross-sectional observation of farmers' characteristics. Farmers' cross-sectional characteristics were obtained from the agricultural census described in the paper. This agricultural census took place only once, in 1954/55, to estimate the national capacity to produce agricultural products. One concern about observing cross-sectional characteristics only once is potential *attrition*. For example, it could be that some farmers who only grew apricots in 1955 switched to growing apricots and oranges during the following decade. The incentives to plant other trees, in particular orange trees, would be greater for poor farmers facing liquidity constraints than for wealthy farmers for the reasons described in Subsection E.2. If poor farmers switched, then we should expect a change in poor *vs.* wealthy farmers' relative purchasing of water during the critical *vs.* non-critical season. This reasoning motivates the difference-in-differences analysis described next.

[21] A summary of the interviews is available here.

Figure A10 displays the difference in water bought (in *cuartas*, the unit sold at auction) per tree during the critical *vs.* non-critical season between wealthy and poor farmers over time. If poor farmers were switching, we would expect a downward trend in Figure A10. That is, over time, poor farmers growing only apricots will disappear. This is not what we observe. There are large differences between wealthy and poor farmers from year to year. During dry years (1955, 1957, and 1964) price differences in summer are large, so differences in water purchases are also large. During rainy years (1956, 1960, 1961, and 1962) price differences in summer are small, so differences in water purchases are small. There is no trend in the difference-in-differences data, suggesting that attrition is not a concern in the case of Mula. This evidence is consistent with the notion that switching costs are high, especially for poor farmers.

Figure A10: Difference in differences: Differences in liters of water bought per tree during the critical *vs.* non-critical season between wealthy and poor farmers.



Notes: For each year we compute the amount of water per tree bought: (i) during the critical season and outside the critical season, and (ii) by wealthy and poor farmers. The figure shows the evolution of the difference in differences for these groups: wealthy during the critical season, wealthy outside the critical season, poor during the critical season, and poor outside the critical season. The units of the vertical axis are *cuartas* (the unit sold at auction) per tree. One *cuarta* is approximately equal to 432,000 liters of water. See Section 2 in the paper.

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