The Illiquidity of Water Markets

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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, farmers who were part of the wealthy elite were not liquidity constrained. We estimate a structural dynamic demand model by taking advantage of the fact 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 show that the institutional change from an auction to a quota increased total efficiency for the farmers considered. Welfare increased by 23.4 real pesetas per farmer per tree, a 6 percent increase in total production relative to the market.

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

Keywords: Market Efficiency, Dynamic Demand, Auctions, Quotas, Vertical Integration, Financial Markets.

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 of frictions in 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. Furthermore, the relative efficiency is theoretically ambiguous. We develop a structural dynamic demand model, estimate it 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 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, when 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 a liquidity constrained farmer has higher valuation than farmers who are not liquidity constrained. In that case, a simple quota might allocate water more efficiently than a market.

We investigate the efficiency of a market relative to a non-market institution—the 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, during the summer, the price of water increased substantially in the market and some farmers did not have enough cash to pay for the water. Summer corresponds to Southeastern Spain's dry season, when the region's rapidly growing fruit trees require more water. These price and demand conditions made summer the critical or dry season.

In the leading article of the inaugural volume of the *American Economic Review,* Coman (1911) refers to the problem of liquidity constraints in water markets: "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 who grew the same crops 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.

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, an auction, to allocate river water for irrigation. 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 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.[1] 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 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. Under the quota 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. The natural question that arises is: 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

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

production before and after the institutional change. 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.[2]

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 free 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 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, crop, and number of trees the productivity of the farmers is assumed to be homogeneous up to the idiosyncratic shock. This specification allows to us 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 use data on only wealthy farmers who were not liquidity constrained, as described below.

We use the estimated dynamic demand system to compute welfare under markets and quotas. We show that a quota which allocates to each farmer a fixed amount of water every three weeks—similar to that implemented in Mula—increases welfare relative to the

[2] 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 the efficient allocation is more complex, as explain in Section 6.

market. 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 farmers are relatively homogeneous, liquidity constraints are present, and 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 quantify the efficiency impact 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. Welfare increased by 23.4 real pesetas per farmer per tree, a 6 percent increase in total production relative to the market.

Related Literature

Scholars have proposed 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 water is abundant. This hypothesis is supported by evidence from markets where water was extremely scarce (Musso y Fontes, 1847; Perez Picazo and Lemeunier, 1985). On the other hand, Garrido (2011) and González Castaño and Llamas Ruíz (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).

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 storability. There is a large empirical industrial organization literature on dynamic demand.[3] These articles do not examine how liquidity constraints affect demand. To the best of our knowledge, this paper is the first to propose and estimate a demand model with storability, seasonality, and liquidity constraints. Storability implies that disregarding past purchases would affect demand estimates as in Hendel and Nevo (2006). Past purchases affect current demand through storage, which is modeled as a state variable in the game and estimation. Timmins (2002) studies dynamic demand for water and is closest to our paper. 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 the 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 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.

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. 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. For example, on October 10, 1943, a total of 681 millimeters of rain fell in Mula, being the yearly average

[3] See, *e.g.*, Boizot *et al.* (2001), Hendel and Nevo (2006), and the references therein. See Aguirregabiria and Nevo (2013) for a survey and Donna (2021) for a recent article.

326 millimeters.

Figure 1.A maps Mula's location in 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 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 once per year. The weeks when farmers most need cash to purchase water for thirsty trees 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, as they need to pay for the water in cash.

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 might expect 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 Ruíz, 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.[4] 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 (Albuquerque and Hopenhayn, 2004). Hence, non-enforceable contracts would have prevented farmers from holding cash when they needed it most.

2.2 History and Institutions

History. The Kingdom of Murcia enjoyed stability under the reign of Ibn Hud, from 1228 until his murder in 1238. By 1242, Castile had conquered most of Murcia. Ibn Hud's son, Ahmed, traveled to Alcaraz (Toledo) to meet with prince Alfonso and begin peace talks. The Christian kingdom of Castile and the Muslim kingdom of Murcia signed the treaty of

[4]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.

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. The initial shock is similar to that in Chaney and Hornbeck (2016). 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.[5] During this transition period, the *Sindicato* paid a fixed price for each unit of river water and allocated it among farmers using quotas.

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.[6] Water was sold by the *cuarta* (quarter), a unit that denoted the right to use water flowing through the main channel for three hours. Property rights for 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, meaning each unit of water sold at auction (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 and four units for irrigation during the night on each weekday. Our sample consists of all water auctions in Mula from January 1955 until July 1966.

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

[6]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.

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. Crucially, farmers paid after the critical season; thus, they were not liquidity constrained. 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.

In the counterfactual analysis, we compare welfare under markets and the non-market institution of quotas.

2.3 Data

We built a unique panel data set using four main data sources.

Auction Data. The first source is the weekly auction data from Mula's municipal archive (Historical Archive in Mula, 1955-1966). 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 EstadÃstica*) from Uriel *et al.* (2000).

Rainfall Data. The second source is rainfall data. We obtained it from the Spanish National Meteorological Agency (AEMET) and linked it to the auction data. In regions with a Mediterranean climate, rainfall occurs mainly during spring and fall. Crops 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 of 1955. The third source is a cross-sectional agricultural census data from 1955. The data contain information on individual characteristics of the farmers' land: type of land and location, area, number of trees, production, and production sale price. We match the names of the farmers on each census card to the names of the auction winners.

Urban Real Estate Tax Data. The final source is urban real estate tax records from 1955. We use this information to identify wealthy farmers. This variable only measures urban wealth, not rural wealth nor farm value.

See Appendix A.1 for additional details and summary statistics.

2.4 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, orange growers 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* (*poor*) if the value of urban real estate of the farmer obtained from the urban real estate tax data is positive (zero). Because farmers grew their crops in rural areas, urban real estate constitutes non-agricultural wealth. We only use data from wealthy farmers for demand estimation. We make two observations. First, the value of farmers' urban real estate should not affect their production function (the farmer's willingness to pay for water), conditional on crop, size of plot, and number of trees; that is, after accounting for these covariates, 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 (apricot tree) production function. Second, we argue that wealthy Mula farmers were never liquidity constrained. Each of the wealthy farmers owned several urban properties. During the period under analysis, wealthy farmers' average annual urban real estate rental income was 5,702 pesetas, while their average annual irrigation water expenditure was only 500 pesetas. In 1963, the sample year when water expenditures were the highest, farmers' average annual water expenditure was 1,619 pesetas. No poor farmer owned any urban property, as defined above.

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).[7] 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.[8] Unconstrained farmers' demand for water is determined by their apricot trees' need for water. 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 have the same demand for water up to an idiosyncratic shock according to our model. For unconstrained farmers, there should be no relationship between water demand and monetary value of urban real estate. Figure 2 shows that this relationship

[7] 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.

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

only holds for wealthy farmers, 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 the critical season. 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. Wealthy farmers demand water as predicted by Table 1; they 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.[9]

In Table 2, we regress the number of units per tree purchased by farmer in a given week on several covariates; we use the number of units per tree to account for farmers' plot size. 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 the 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 grow the same, identical type of tree, the *búlida* apricot. The effect of liquidity constraints on water demand

[9]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.

is evident due to the large price increase during the critical season. For robustness, in columns 5 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. Appendix A.3 presents additional evidence.

3 Structural Dynamic Demand Model

We present the model used to compute efficiency.

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. In contrast to Donna and Espín-Sánchez (2018; henceforth, DE), we do not model the auction game and abstract from the within-week variation in prices, which is very low as shown by DE. 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. Second, we estimate the model using only 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 grew only 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; we interpret this feature as substantial competition and consider farmers to be price-takers in a given week conditional on covariates. 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. We believe that this assumption is sensible in our setting because it is unlikely that any individual farmer could affect the market price; see DE for details. We estimate a different price distribution for each week of the year that depends on rainfall during the previous week, as explained in Appendix B.

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 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 used in the production of the final good, apricot. Utility refers to farmers' profits and is measured in pesetas, not 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:

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

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, for instance, 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 (González Castaño and Llamas Ruíz 1991 and the references therein); that is, we require that $(\mu_{it} - p_t j_{it}) \geq 0$, $\forall j_{it} > 0$ (limited liability), where μ_{it} is the amount of money (wealth) of farmer i in period t. 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, might be binding for poor farmers. Poor farmers can 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 their evolution 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. The moisture level is obtained by applying the procedure from the agricultural engineering literature described in Appendix A.2. We construct an individual moisture level variable for each farmer. For the estimation, we treat moisture as an observable state variable similar to the inventory in Hendel and Nevo (2006). 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. Trees on a farmer's plot wither and die if soil moisture falls below the permanent wilting point, denoted by the scalar PW also 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.* (2006):[10]

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

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;[11] 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: $w_t = w_{t-1} + 1$

[10] 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.

[11] 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.

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, $h(j_{it}, M_{it}, w_t; \gamma)$. 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, 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 (see Appendix A.1). Third, there are weeks when no auction was run (no-supply weeks), as explained in Subsection 2.3. 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. (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.) 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 (see Appendix B for details).

Productivity Shock. The stochastic term for the productivity shocks, $\epsilon_{it} \equiv (\epsilon_{i0t}, ..., \epsilon_{iJt})$, are a choice-specific component of the utility function. Alternatively, one could refer to these shocks as a component of irrigation costs. The productivity shocks, ϵ_{it}, are drawn i.i.d. from a Gumbel distribution with CDF $F(\epsilon_{it}; \sigma_\epsilon) = e^{-e^{-\epsilon_{it}/\sigma_\epsilon}}$, where σ_ϵ is a parameter to be estimated. The variance of this distribution is given by ${\sigma_\epsilon^2 \pi^2}/{6}$. The higher the value of the parameter σ_ϵ, the more heterogeneous the distribution of productivity; see Section 4 for a discussion about identification and Section 6 for a discussion about its impact on welfare. We model farmers as having productivity shocks that are correlated across the decisions of buying and not-buying. We incorporate this feature by decomposing the stochastic term using the distributional assumptions of the nested logit, which we embed into the dynamic discrete-choice demand model.[12] As described above, the choice is not binary: $j_{it} \in \{0, 1, ..., J\}$. In Appendix B.4, we present closed-form expressions for the conditional choice probabilities (CCP) using this specification. In the CCP of equations B.6 and B.7 (Appendix B.4), the parameter λ is a nesting parameter such that $0 < \lambda \leq 1$. A larger value of λ corresponds to a greater correlation in the productivity shocks for the decision of buying water. A larger value of λ is, therefore, associated with less substitution between the decisions of buying, $j > 0$, and not buying, $j = 0$. When $\lambda = 1$, the model collapses to a standard dynamic discrete-choice model, where the productivity shocks, ϵ_{ijt}, are i.i.d. across *all* choices, $j_{it} \in \{0, 1, ..., J\}$.

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; 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.[13] 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:

$$Rev_{it} = \sum_{w_t=18}^{32} h\left(j_{it}, M_{it}, w_t; \gamma\right). \tag{5}$$

The production function measures production in pesetas. The actual price at which production is sold was determined in the international output market; it was the same for all farmers and it remained remarkably stable during our period of study.[14] 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.

[12] For some recent applications using the nested-logit structure in discrete-choice models see Grennan (2013), Ciliberto and Williams (2014), Donna *et. al.* (2022), and Donna *et. al.* (2023).

[13] As mentioned, we assume that wealthy farmers are never liquidity constrained. Equation 3 is not used in the demand estimation.

[14] See Appendix A.1.6 for details.

The value function is given by:

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

subject to the evolution of the state variables described above. The expectation is taken over r_t, p_t, ϵ_{it}, and ν_{it}. For wealthy farmers we assume that the constraint $j_{it}p_t \leq \mu_{it}$ is not binding. The constraint $M_{it} \geq PW$ is not an accounting constraint; it represents an absorbing state where the trees wither and the payoffs are zero afterwards.

The Apricot Production Function

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

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

where $h\left(j_{it},M_{it},w_t;\gamma\right)$ 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; $KS\left(M_{it}\right)$ 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 in Appendix A.2.[15] Substituting in the production function, the farmer's revenue in a given year is:

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

4 Identification and Estimation

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 (for discussions and robustness analyses see Section 2, and Appendices A.3 and C).

[15] The moisture variable, M_{it}, is a function of the amount of water purchased, j_{it}, as can be seen in the right-hand side of equation 2. Thus, the apricot production function in equation 7, $h(\cdot)$, is also a function of j_{it}. To keep the notation compact, we write M_{it} instead of $M_{it}\left(j_{it}\right)$.

We estimate the parameters that characterize demand, $\Theta \equiv (\gamma, \sigma_\varepsilon, \zeta, \lambda)$, using data from wealthy farmers. For the estimation we exclude data from poor farmers who may be liquidity constrained.

Dynamic Demand

Identification

The two main identifying assumptions are that that wealthy farmers are not liquidity constrained and that water demand for both the wealthy and poor farmers is determined by the technological constraint imposed by the apricot tree production function. Under these assumptions, the identification of Θ follows the standard arguments (*e.g.,* Rust, 1996; Magnac and Thesmar, 2002; and Aguirregabiria, 2005).

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 $\sigma_\epsilon = 1$ and estimate α with the utility function in utils. In such cases, α is not identified from $1/\sigma_\epsilon$. In our case the utility function is in pesetas, not utils, as explained above.

Finally, the nesting parameter, λ, is identified from variation in purchase and non-purchase instances conditional on the moisture and seasonality.

Estimation

To estimate the parameters that characterize demand, we construct a two-step conditional choice probability (CCP) estimator.

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 out analytically, as shown in the Appendix B. 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, 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. We estimate the CCP using a logistic distribution; that is, a multinomial logit regression (see Appendix B.1). We obtained similar results estimating the CCP non-parametrically using kernel methods to smooth both discrete and continuous variables (see Appendix B.3).

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. 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).

In Appendix B, we provide additional details regarding the estimation procedure, the properties of the estimator, the specification of the productivity shocks, and the specification used for the law of motion for prices and water.

5 Results

Table 3 displays the estimation results from the demand model in equation 6 using the estimation procedure described above. We present two sets of estimates. In columns 1 and 2, we perform the estimation with only one type of farmer who has the median number of trees in the sample. 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 $\hat{\gamma}_L = 0.12$. 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.[16] The estimated coefficient on the quadratic term of the transformation rate is small in magnitude, $\hat{\gamma}_Q = -1.02e-04$. 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. We report the mean $\hat{\Theta} \equiv \left(\hat{\gamma}, \hat{\sigma}_\epsilon, \hat{\zeta}, \hat{\lambda}\right)$ across types. The estimated scale parameter of the distribution of idiosyncratic productivity, $\hat{\sigma}_\epsilon$, is similar in magnitude across specifications. The higher the parameter σ_ϵ, the higher the variance of the distribution of idiosyncratic productivity. When $\sigma_\epsilon = 1$, the distribution of idiosyncratic productivity is a standard Gumbel. The estimated irrigation cost has the expected sign and a sensible magnitude.[17]

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

[17]We have also experimented using the following specifications of the model and obtained similar results: (i) a binary variable for the decision to buy water, (ii) a specification that allows for different transformation rates

For the welfare analysis, we use the estimates from specification 3, which is closest to the agricultural engineering specification, with estimated transformation rate $\hat{\gamma}_L = 0.05$. 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 29.09 pesetas per tree per week during the critical season which translates to 407.25 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 one uses the full sample of poor and wealthy farmers. 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.

6 Welfare Analysis

We use the estimated demand system to compare welfare under markets and quotas.

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 it *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 it *inefficiency due to decrasing marginal returns (DMR)*.

Quotas allocate water units uniformly. They always create inefficiency due to heterogeneity but never inefficiency due to DMR. 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

for pre-season ($18 \leq week \leq 23$) and in-season ($24 \leq week \leq 32$), and (iii) an autoregressive specification for the productivity error term.

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 heterogeneity in wealth creates liquidity constraints. Under the dynamics generated by the soil moisture, liquidity constraints create inefficiency due to DMR by allocating water to wealthy farmers with relatively high soil moisture levels. Heterogeneity in productivity is captured by the productivity shocks, ϵ_{ijt}. True, these shocks are drawn i.i.d. across individuals and over time, but the estimated value of σ_ϵ 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: $\mathbb{E}\left[\epsilon_{i1t} - \epsilon_{i0t} | j = 1\right] > \mathbb{E}\left[\epsilon_{i1t} - \epsilon_{i0t}\right] = 0 > \mathbb{E}\left[\epsilon_{i1t} - \epsilon_{i0t} | j = 0\right]$. 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 $\mathbb{E}\left[\epsilon_{i0t} - \epsilon_{i1t} | j = 0\right] > 0$; gains from trade are realized under the market. 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. 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, as discussed in the previous subsection.

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 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.[18]

The quota with random assignment 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. Beginning in 1966, Mula's quota allocated units in sequential rounds of three weeks (a *tanda*). The quota in Q-25% is closest to this system implemented in Mula. Next, we describe how we compute the welfare measures (see Appendix B.6 for details). 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.

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

[18]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.

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.

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 implemented in Mula, Q-25%, increased total efficiency relative to the market by 23.4 pesetas per farmer per tree, 6.3 percent ($^{394.13}/_{370.75} - 1$).

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. The *naive* quota, Q, which does not account for recent irrigation, decreases efficiency, as expected.

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 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.[19] 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. We analyzed the welfare implications of the institutional change from markets to quotas for farmers who grew apricots. These welfare results might not apply to farmers who grew other crops. For example, farmers who grew summer and winter crops (apricots and oranges) may smooth spending throughout the year. See Subsection 7.2 and Appendix D.2.

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

7 Discussion

7.1 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.

7.2 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.[20]

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 ruled 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 Ruíz, 1991). Farmers used manure and mules when farming the land (Lopez Fernandez and Gomez Espin, 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

[20] 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. 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.

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. 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 markets 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.

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 two times four kilometers. Weather and soil conditions are, thus, very similar. 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 5.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 crops (column 5; the table uses the data from the agricultural census of 1954, the only year when revenues are observed). Interviews with surviving farmers confirm this information. The differences between poor and wealthy farmers (columns 2, 3, and 4) are attributable to the larger plots owned by wealthy farmers.[21]

Table 5.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. For farmers who grew other crops in addition to apricots (*e.g.*, oranges), there are no substantial differences between wealthy and poor farmers. Revenue for oranges is not correlated with the

[21]The year responsible for the revenue reported in Table 5 was particularly dry. Water prices were substantially higher than other years in the sample. We would, therefore, expect particularly large differences in revenue per tree if differences in productivity were large.

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 crops 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 5.B confirm this 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; 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 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 diseconomies of scale discussed in Subsection 7.2.

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 actually negative, -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, $h\left(j_{it}, M_t, w_t; \gamma\right)$, 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 $\mathbb{V}(\vartheta_i) = 1$. 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.

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. (This procedure avoids having to arbitrarily choose the distribution of the white noise; results are almost identical using other distributions such as a standard normal.) 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, we first 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, $\rho_{w,p} = 0$, and the quotas Q-25% produce 6.3 percent more per farmer 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.[22] 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, $\rho_{w,p} = 0$.[23]

7.3 Frictions in the vertical market for water

Liquidity constraints can be viewed as a friction that makes the vertical market of water inefficient. 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 (crops) sold in the output market. Under quotas, farmers became owners of the water rights. Upstream and downstream players consolidated into a single entity; the cartel and the farmers vertically integrated. Under quotas, the farmers' association bought water property rights and dissolved the cartel. Since Coase (1937), economists have argued that vertical integration could be more efficient than a vertical market if frictions between upstream and downstream levels are present. Williamson (1975, 1985) and the literature that followed showed that vertical integration improves ef-

[22] 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 6.2. 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%.

[23] 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 assumption is inconsistent with the evidence presented in the empirical setting studied, as discussed above. If the production function is linear, and wealth and productivity are perfectly correlated, markets are always more efficient than any mechanism of quotas.

ficiency when uncertainty in the intermediate input market exists. A vertical merger may also involve additional effects. See Riordan and Salop (1995), Donna and Pereira (2023), Donna and Pereira (2024) for details. A system of quotas, interpreted as a vertical integration, ameliorates such frictions along the lines of Coase, Williamson, and the literature that followed, thus increasing efficiency.

7.4 Liquidity Constraints *v.* 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, 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. The same argument rules out the possibility that the results are driven by poor farmers being more impatient than wealthy farmers (lower discount factor).

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; (v) sharecropping; and (vii) attrition.

8 Concluding Remarks

Markets might not be efficient when liquidity constraints are present.

We quantified the efficiency of an auction relative to a quota in the presence of liquidity constraints, a specific type of market friction. In this case, the efficiency rank of a market relative to a quota is theoretically ambiguous. We used data from unregulated water markets in southeastern Spain and explored a specific change in the institutions to allocate water that switched from an auction to a quota. Frictions arose 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. Farmers who were part of the wealthy elite were not liquidity constrained.

We estimated a structural dynamic demand model 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 used the estimated model to compute efficiency, as a measure of welfare, under both institutions. We showed that the institutional change from markets to quotas increased production, as a measure of efficiency, for the farmers considered. This fundamental result shows the importance of choosing appropriate institutions to allocate goods in the presence of frictions.

The contributions of this paper are twofold. First, from a historical perspective, we quantify and provide empirical evidence of a source of inefficiency in water markets. Second, from an industrial organization perspective, we propose a structural 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. 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.

Problems associated with high market prices for water during the dry season are common in arid regions. For the 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).

The efficiency approach in this paper 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.

9 Data Availability Statement

The replication package underlying this research is available on Zenodo at `https://doi.org/10.5281/zenodo.17244564`.

References

[1] Aguirregabiria, V., 2005, "Nonparametric Identification of Behavioral Responses to Counterfactual Policy Interventions in Dynamic Discrete Decision Processes," *Economics Letters*, Vol. 87, 393–398.

[2] Aguirregabiria, V., and Mira, P., 2010, "Dynamic discrete choice structural models: A survey," *Journal of Econometrics*, Vol. 156, 38-67.

[3] Aguirregabiria, V., and Nevo, A., 2013, "Recent Developments in Empirical IO: Dynamic Demand and Dynamic Games," *Advances in Economics and Econometrics.*

[4] Aitchison, J., and Aitken, C. G. G., 1976, "Multivariate binary discrimination by the kernel method," *Biometrika*, Vol. 63, 413-420.

[5] Albuquerque, R., and Hopenhayn, H. A., 2004, "Optimal Lending Contracts and Firm Dynamics," *Review of Economic Studies*, Vol. 71, No. 2, 285-315.

[6] Allen, R. G., Pereira, L. S., Raes, D., and Smith, M., 2006, *Evapotranspiracion del cultivo.* Food and Agriculture Organization (FAO) 2006.

[7] Arcidiacono, P., and Ellickson, P. B., 2011, "Practical methods for estimation of dynamic discrete choice models," *Annual Review of Economics,* Vol. 3, No. 1, 363-394.

[8] Arcidiacono, P., and Miller, R. A., 2011, "Conditional choice probability estimation of dynamic discrete choice models with unobserved heterogeneity," *Econometrica*, Vol. 79, No. 6, 1823-1867.

[9] Boizot, C., Robin, J. M., and Visser, M., 2001, "The demand for food products: an analysis of interpurchase times and purchased quantities," *Economic Journal*, Vol. 111, No. 470, 391-419.

[10] Bubb, R., Kaur, S., and Mullainathan, S., 2018, "The Limits of Neighborly Exchange," WP.

[11] Chaney, E. and Hornbeck, R., 2016, "Economic Dynamics in the Malthusian Era: Evidence from the 1609 Spanish Expulsion of the Moriscos," *Economic Journal*, 126(594): 1404-1440.

[12] Che Y.-K., and Gale, I., 1998, "Standard Auctions with Financially-Constrained Buyers," *Review of Economic Studies*, Vol. 65, No. 1, 1-21.

[13] Che Y.-K., Gale, I., and Kim J., 2013, "Assigning Resources to Budget-Constrained Agents," *Review of Economic Studies*, Vol. 80, No. 1, 73-107.

[14] Ciliberto F, and Williams J.W., 2014, "Does multimarket contact facilitate tacit collusion? Inference on conduct parameters in the airline industry," *RAND Journal of Economics*, 45(4):764–791.

[15] CME, 2020, "CME Group to Launch First-Ever Water Futures Based on Nasdaq Veles California Water Index," News Release.

[16] Coase, R.H., 1937, "The Nature of the Firm," *Economica*, Vol. 4, No. 16, 386-405.

[17] Coman, K., 1911, "Some Unsettled Problems of Irrigation," *American Economic Review*, 1(1): 1-19.

[18] Connault, B., 2016, "Hidden rust models," Working Paper, University of Pennsylvania.

[19] Donna, J.D., 2021, "Measuring Long-Run Gasoline Price Elasticities in Urban Travel Demand," *RAND Journal of Economics*, Vol. 52, No. 4, 945-994.

[20] Donna, J.D., and Espín-Sánchez, J.A., 2018, "Complements and Substitutes in Sequential Auctions: The Case of Water Auctions," *RAND Journal of Economics,* Vol. 49, No. 1, 87–127.

[21] Donna, J.D., and Espín-Sánchez, J.A., 2021, "Water Theft as Social Insurance: Southeastern Spain, 1851-1948," *Economic History Review.*

[22] Donna, J.D., Pereira, P., Pires, T., and Trindade, A., 2022, "Measuring the Welfare of Intermediaries," *Management Science*, Vol. 68, 8083-8115.

[23] Donna, J.D. and Pereira, P., 2023, "Rivals' Exit and Vertical Merger Evaluation," Journal of Competition Law & Economics, 19(2), pp. 220-249, DOI: 10.1093/joclec/nhad002.

[24] Donna, J. D., and Pereira, P., 2024, "Structural Presumptions for Non-horizontal Mergers in the 2023 Merger Guidelines: A Primer and a Path Forward," Review of Industrial Organization, 65(1), 303-345.

[25] Donna, J.D., Pereira, P., Pu, Y., Trindade, A., and Yoshida, Y., 2023, "Direct Sales and Bargaining," RAND Journal of Economics, forthcoming, DOI: 10.2139/ssrn.3779962.

[26] Espín-Sánchez, J.-A., 2017, "Institutional Inertia: Persistent Inefficient Institutions in Spain," *Journal of Economic History*, Vol. 77, No. 3, 692-723.

[27] Franco, J. A., Abrisqueta, J. M., HernansÃ¡ez, A. and Moreno, F., 2000, "Water balance in a young almond orchard under drip irrigation with water of low quality," *Agricultural Water Management*, Vol. 42, 75-98.

[28] Garrido, S., 2011, "Governing scarcity. Water Markets, Equity and Efficiency in pre-1950s Eastern Spain," *International Journal of the Commons*, Vol. 5, No. 2., 513-534.

[29] Garrido, S., and Calatayud, S., 2011, "The price of improvements: agrarian contracts and agrarian development in nineteenth-century eastern Spain," *Economic History Review*, Vol. 64, No. 2, 598-620.

[30] González Castaño, J., and Llamas Ruíz, P., 1991, *El agua en la Ciudad de Mula, S. XVI-XX.,* Comunidad de Regantes Pantano de la Cierva*,* Mula.

[31] Grafton, R. Q., Libecap, G., McGlennon, S., Landry, C., and O'Brien, B., 2011, "An Integrated Assessment of Water Markets: A Cross-Country Comparison," *Review of Environmental Economics and Policy*, Vol. 5, No. 2, 219-239.

[32] Grennan M., 2013, "Price discrimination and bargaining: Empirical evidence from medical devices," *American Economic Review*, 103(1):145–177.

[33] Handel, B. R., and Kolstad, J. T., 2015, "Health Insurance for "Humans": Information Frictions, Plan Choice, and Consumer Welfare," *American Economic Review*, Vol. 105, No. 8, 2449-2500.

[34] Hendel, I., and Nevo, A., 2006, "Measuring the implications of sales and consumer inventory behavior," *Econometrica*, Vol. 74, No. 6, 1637-1673.

[35] Historical Archive in Mula. 1955-1966. *Water Auction Records, Agricultural Census, and Urban Real Estate Tax Records.* Historical Archive of Mula, Mula, Spain.

[36] Hoffman, P., 1996, *Growth in a Traditional Society: The French Countryside, 1450-1815*, Princeton University Press.

[37] Hotz, J., and Miller, R., 1993, "Conditional Choice Probabilities and the Estimation of Dynamic Models," *Review of Economic Studies*, Vol. 60, No. 3, 497-529.

[38] Hotz, J., Miller, R., Sanders, S., and Smith, J., 1994, "A Simulation Estimator for Dynamic Models of Discrete Choice," *Review of Economic Studies*, Vol. 61, No. 2., 265-289.

[39] Instituto Nacional de EstadÃstica (INE). 1948-1973. *Anuario Estadistico de Espana [Statistical Yearbook of Spain]*. Madrid, Spain: Instituto Nacional de Estadistica.

[40] Jayachandran, S., 2013, "Liquidity Constraints and Deforestation: The Limitations of Payments for Ecosystem Services," *American Economic Review Papers and Proceedings*, Vol. 103, No. 2, 309-313.

[41] Keane, M. P., and Wolpin, K. I., 1994, "The solution and estimation of discrete choice dynamic programming models by simulation and interpolation: Monte Carlo evidence," *Review of Economics and Statistics*, Vol. 76, No. 4, 648-672.

[42] Keane, M. P., and Wolpin, K. I., 1997, "The career decisions of young men," *Journal of Political Economy*, Vol. 105, No. 3, 473-522.

[43] Keane, M. P., and Wolpin, K. I., 2010, "The role of labor and marriage markets, preference heterogeneity, and the welfare system in the life cycle decisions of black, hispanic, and white women," *International Economic Review*, Vol. 51, No. 3, 851-892.

[44] Ketcham, J. D., Kuminoff, N. V., and Powers, C. A., 2016, "Estimating the heterogeneous welfare effects of choice architecture: An application to the medicare prescription drug insurance market," NBER working paper No. w22732.

[45] Libecap, G. D., 2011, "Institutional Path Dependence in Adaptation to Climate: Coman's "Some Unsettled Problems of Irrigation," *American Economic Review*, Vol. 101, No. 1, 64-80.

[46] Li, Q., and Racine, J., 2003, "Nonparametric estimation of distributions with categorical and continuous data," *Journal of Multivariate Analysis*, Vol. 86, 266-292.

[47] Li, Q., and Racine, J., 2007, *Nonparametric econometrics: theory and practice.* Princeton University Press, ISBN: 9780691121611.

[48] Lopez Fernandez, J. A., and Gomez Espin, J. M., 2008, "Abastecimientos Tradicionales de Agua a los Municipios de Mula, Pliego y Bullas. (Region de Murcia)," *Nimbus*, No. 21-22, 133-152.

[49] Luo, Z. Q., Pang, J. S., and Ralph, D., 1996, *Mathematical programs with equilibrium constraints*, Cambridge University Press.

[50] Maass, A., and Anderson, R. L., 1978, *... and the Desert Shall Rejoice: Conflict, Growth, and Justice in Arid Environments*, The MIT Press.

[51] Magnac, T., and Thesmar, D., 2002, "Identifying Dynamic Discrete Decision Processes," *Econometrica*, Vol. 70, No. 2, 801–816.

[52] Miller, R. A., 1984, "Job matching and occupational choice," *Journal of Political Economy*, Vol. 92, No. 6, 1086-1120.

[53] Musso y Fontes, J., 1847, *Historia de los riegos de Lorca*, Imprenta JosÃ© Carle-Palacios.

[54] Ohio Supercomputer Center. 1987, "Columbus OH: Ohio Supercomputer Center," http://osc.edu/ark:/19495/f5s1ph73.

[55] Pakes, A., 1986, "Patents as options: Some estimates of the value of holding European patent stocks," *Econometrica*, Vol. 54, No. 4, 755-784.

[56] Pérez-Pastor, A., Domingo, R., and Torrecillas, A., 2009, "Response of apricot trees to deficit irrigation strategies," *Irrigation Science*, Vol. 27, 231-242.

[57] Perez Picazo, Ma. T., and Lemeunier, G., 1985, "Agua y coyuntura economica. Las transformaciones de los regadios murcianos (1450-1926)," *Cuadernos de Geografia Humana.*

[58] Racine, Jeffrey S., 2008, "Nonparametric Econometrics: A Primer," *Foundations and Trends in Econometrics*, 3:1 1–88, 2008. DOI: 10.1561/0800000009.

[59] Rosenzweig, M. R., and Wolpin, K. I., 1993, "Constraints, Consumption Smoothing, and the Accumulation of Durable Production Assets in Low-Income Countries: Investments in Bullocks in India," *Journal of Political Economy*, Vol. 101, No. 2, 223-244.

[60] Rust, J., 1987, "Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher," *Econometrica*, Vol. 55, No. 5, 999-1033.

[61] Rust, J. 1994, "Structural estimation of Markov decision processes," *Handbook of Econometrics*, Vol. 4, 3081-3143.

[62] Rust, J., 1996, "Numerical Dynamic Programming in Economics," in *Handbook of Computational Economics*, Vol. 1, ed by. H. Amman, D. Kendrick, and J. Rust. Amsterdam: North-Holland, 619–729.

[63] Su, C. L., and Judd, K. L., 2012, "Constrained optimization approaches to estimation of structural models," *Econometrica*, Vol. 80, No. 5, 2213-2230.

[64] Timmins, C., 2002, "Measuring the Dynamic Efficiency Costs of Regulators' Preferences: Municipal Water Utilities in the Arid West," *Econometrica*, Vol. 70, No. 2, 603-629.

[65] Torrecillas, A., Domingo, R., Galego, R., and Ruíz-Sanchez, M. C., 2000, "Apricot tree response to withholding irrigation at different phenological periods," *Scientia Horticulturae*, Vol. 85, 201-205.

[66] Udry, C., 1994, "Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria," *Review of Economic Studies*, Vol. 61, No. 3, 495-526.

[67] Uriel, E., Molto, M. L. and Cucarella, V., 2000, "Contabilidad Nacional de Espana. Series enlazadas 1954-1997," CNEe-86, Fundacion BBV, Bilbao.

[68] Vörösmarty, C. J., McIntyre, P. B., Gessner, M. O., Dudgeon, D., Prusevich, A., Green, P., Glidden, S., Bunn, S. E., Sullivan, C. A., Reidy Liermann, C., and Davies, P. M., 2010, "Global threats to human water security and river biodiversity," *Nature*, Vol. 467, 555-561.

[69] Wang, M., and van Ryzin, J., 1981, "A Class of Smooth Estimators for Discrete Distributions," *Biometrika*, Vol. 68, 301-309.

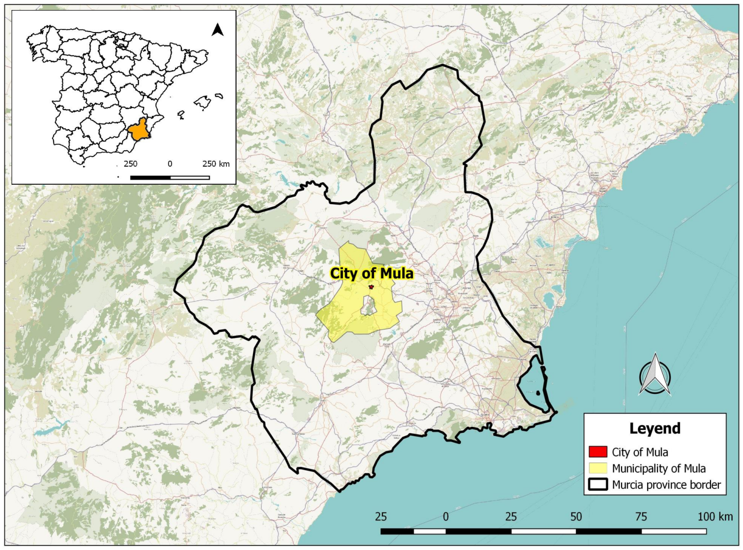
[70] Williamson, O.E., 1975, *Markets and Hierarchies: Analysis and Antitrust Implications*, Free Press.

[71] Williamson, O.E., 1985, *The Economic Institutions of Capitalism: Firms, Markets, Relational Contracting*, Free Press.

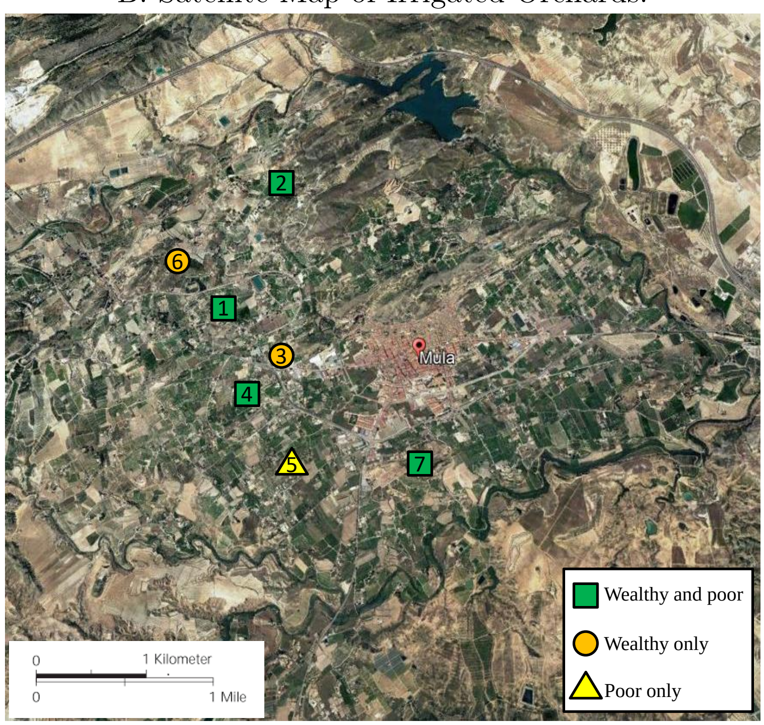
[72] Wolpin, K. I., 1984, "An estimable dynamic stochastic model of fertility and child mortality," *Journal of Political Economy*, Vol. 92, No. 5, 852-874.

Figure 1: Mula and the Irrigated Plots.

A. Map of Spain, Murcia and Mula.

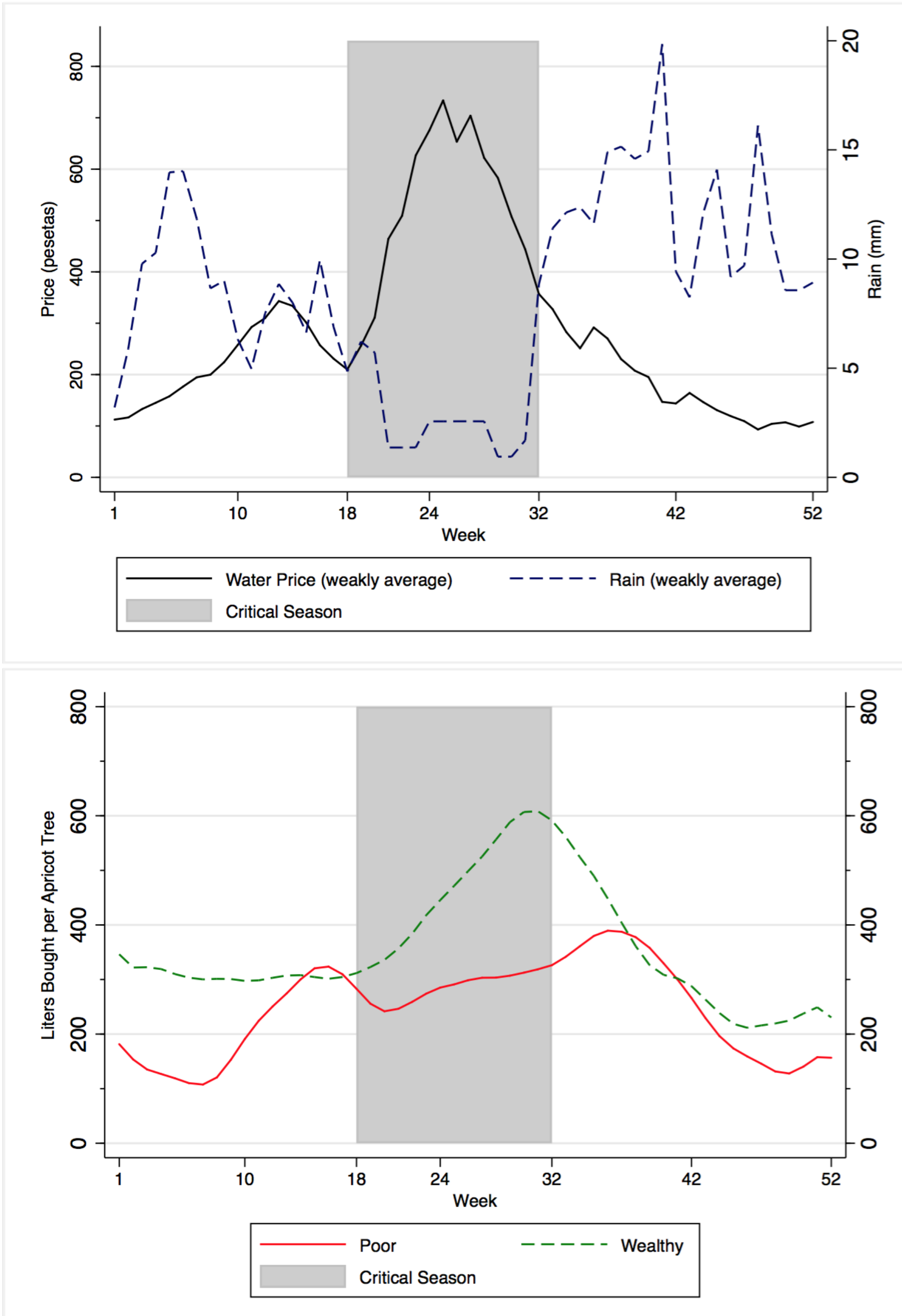


B. Satellite Map of Irrigated Orchards.



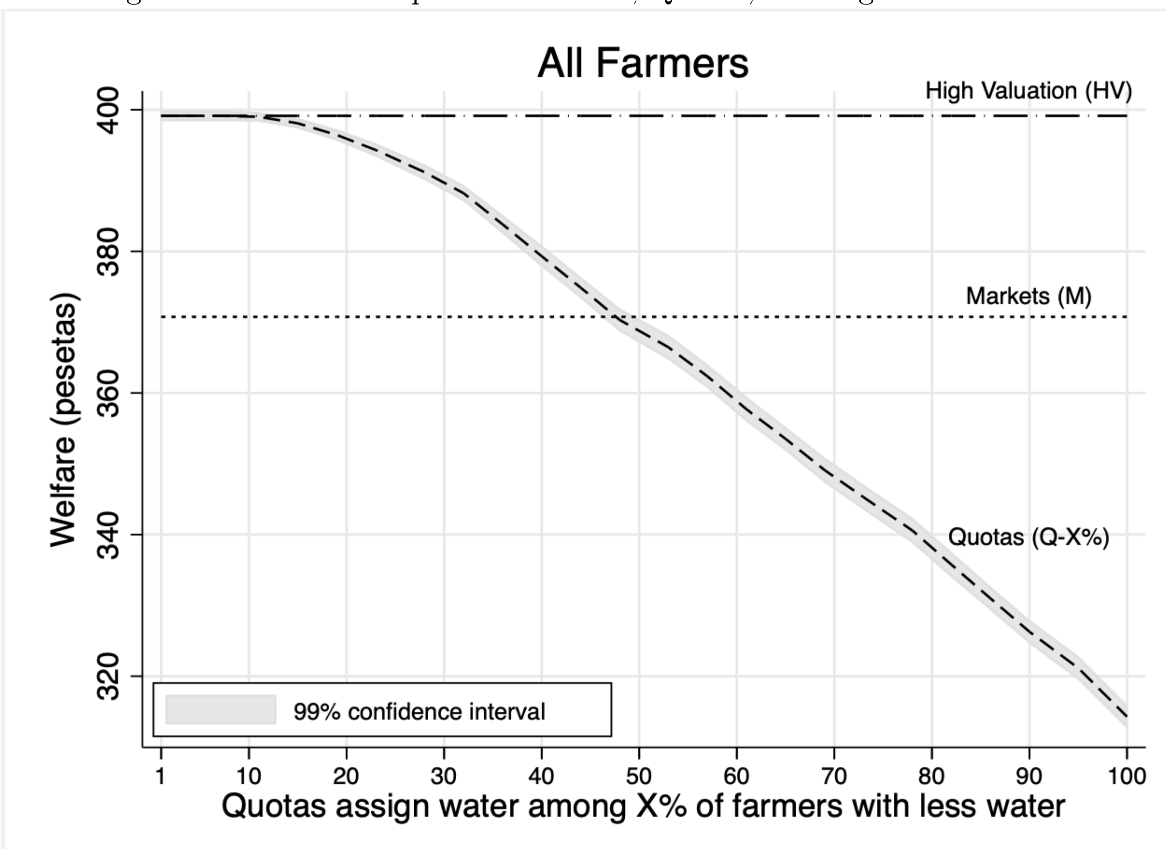
Notes: Panel A. Physical map of the region of Murcia. The Municipality of Mula is in yellow and the urban area in red. Panel B. Satellite map depicting the main subareas with more than one apricot farmer, 5km by 6km. Subareas ordered according to the number of plots, denoted by n: (1) *Trascastillo*, $n = 9$; (2) *Herrero*, $n = 9$; (3) *Penuelas*, $n = 4$; (4) *Palma*, $n = 3$; (5); *Carrasquilla*, $n = 3$; (6) *El Nino*, $n = 3$; (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.



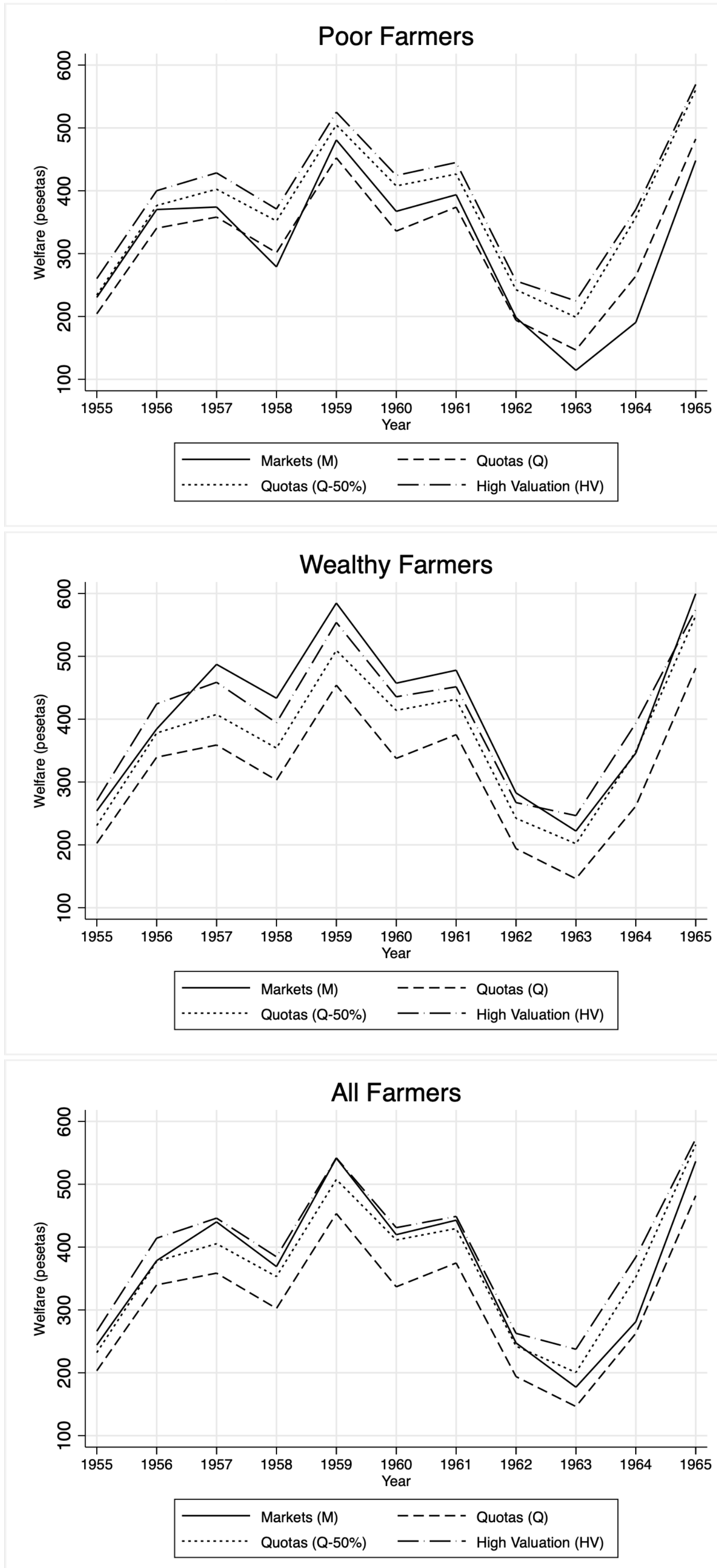
Notes: The top panel displays the average weekly prices of water paid in the market (left vertical axis) and the average weekly rain in Mula (right vertical axis) together with a shaded area for the critical season of apricots trees as defined in Table 1. The bottom panel displays the average liters bought per farmer and per tree disaggregated by wealthy and poor farmers using a least squares smoother 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.



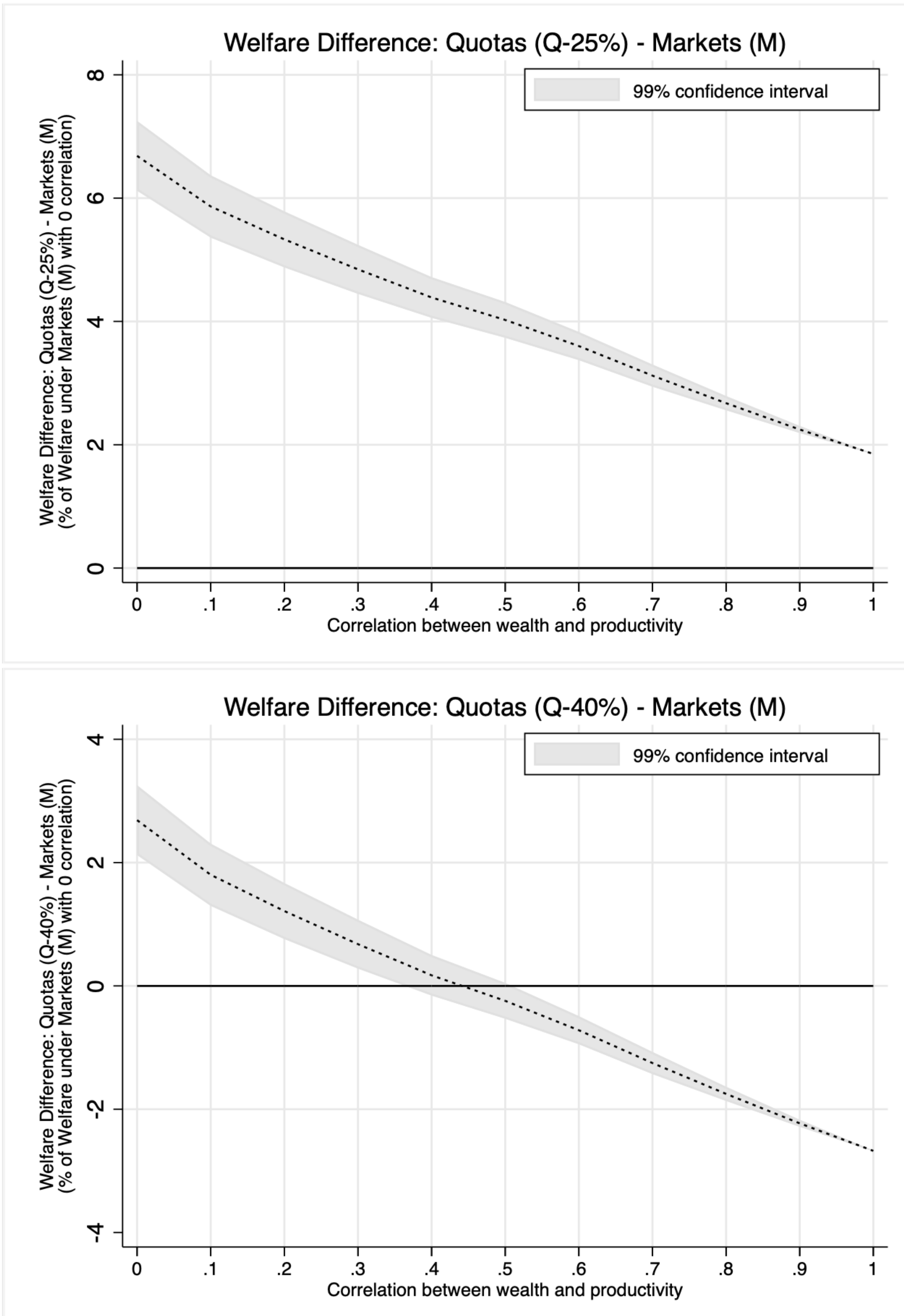
Notes: See Appendix B.6 for a discussion about the computation of the welfare measures. We obtained similar results to the ones in the figure using confidence intervals that account for uncertainty about the estimated parameters (by drawing from the asymptotic distribution) and across simulations.

Figure 4: Welfare by Year.



Notes: See Appendix B.6 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 B.6 for a discussion about the computation of the welfare measures in this figure. We obtained similar results to the ones in the figure using confidence intervals that 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></td><td></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: Source: 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: $\hat{\gamma}_L$	0.1176 (0.0021)	0.2445 (0.0457)	0.0511 (0.0010)	0.3153 (0.0270)
– Quadratic term: $\hat{\gamma}_Q$	–	-1.022e-04 (6.12e-05)	–	-2.73e-05 (3.63e-05)
Irrigating cost: $\hat{\zeta}$	90.3759 (2.4342)	94.4868 (11.6167)	2.5877 (1.1730)	72.3407 (5.6085)
Scale parameter of Gumbel distribution: $\hat{\beta}$	15.3119 (0.1111)	14.3565 (0.4234)	15.2736 (0.1612))	15.1290 (0.4634)
Nesting parameter: $\hat{\lambda}$	0.4992 (0.0073)	0.2646 (0.0682)	0.7919 (0.0069)	0.5171 (0.0587)
Marginal effect	0.1176	0.0660	0.0511	0.2681
Area heterogeneity	No	No	Yes	Yes

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. The number of observations used in all specifications is 8,008. See Section 4 for details.

Table 4: Welfare Results

	Auctions		Quotas				High Valuation
	A Revenue	A Welfare	Q	Q75%	Q50%	Q25%	HV
Welfare measures: (mean per farmer, per tree, per year)							
- All farmers pre-season	235.32	237.54	201.93	219.66	235.37	250.19	253.35
- All farmers on-season	131.03	133.21	112.07	124.57	135.08	143.95	145.68
- Poor farmers whole season	309.08	313.33	313.96	345.22	369.44	386.68	388.65
- Wealthy farmers whole season	407.25	411.76	314.02	343.52	371.16	399.46	406.44
- All farmers whole season	366.34	370.75	313.99	344.23	370.44	394.13	399.03
Amount of water allocated: (mean number of units per farmer)							
- Poor farmers whole season	19.60	19.60	27.08	27.41	27.19	26.54	26.53
- Wealthy farmers whole season	31.50	31.50	26.16	25.92	26.08	26.54	26.55
- Total units allocated whole season	637	637	637	637	637	637	637

Notes: See Appendix B.6 for a discussion about the computation of the welfare measures.

Table 5: Farmers characteristics and wealth.

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

	Area Total (Ha)	Area with trees (Ha)	Fraction with trees	Revenue (pesetas)	Revenue/ area (pesetas/m^2)
	(1)	(2)	(3)	(4)	(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	387	387	328	387	328

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 by crop.

		Apricot (only)	Orange (other)	Apricot (other)	Lemon (other)	Peach (other)	Lemon (only)	Peach (only)
		(1)	(2)	(3)	(4)	(5)	(6)	(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	256	215	58	41	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.