Supply-Based Dynamic Ramsey Pricing
with Two Sectors: Avoiding Water Shortages

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Abstract

In many countries, current water-pricing policies are dictated by the sole objective of breaking-even in each period. This results in large withdrawals, which are not sustainable in the long-run, hence not optimal. In this paper, I derive the optimal dynamic water resource management policy of a benevolent government, which supplies water to households and agriculture. I compare the efficiency implications of the current and the optimal pricing policies using simulations. I endogenize crop-choice decisions and estimate the changes in the crop composition with the generalized method of moments. Using data from Turkey, I find that, under the policy of break-even prices, the average number of years before the government runs into the water shortage, when it cannot meet the sectoral demands, is eight years. In contrast, if the government were to choose water prices optimally, then water shortages would be practically nonexistent over the next century.

Keywords: Ramsey Pricing, Water Shortages, Stochastic Dynamic Programming, Irrigation

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1 Introduction

Two stylized facts characterize water markets: first, around ninety percent of all surface water reservoirs are managed by local or federal governments, so running a balanced budget has been a top priority. Water suppliers often set water prices to recover costs, which is known as the average-cost pricing (ACP) rule. The ACP rule does not reflect water scarcity, and it leads to large withdrawals, which are not sustainable in the long-run; see OECD [11]. Furthermore, inefficient pricing across sectors leads to inefficient distribution of water; see OECD [10]. Second, in many parts of the world (including sub-Saharan Africa, Middle East, and Southern Europe), countries suffer from water supply volatility accompanied by temporary but frequent water shortages; see Allan [1], Rossi and Somma [13], Shiklomanov [15], Thomsen [18]. Several OECD countries experience periodic water shortages, based on high levels of leakage in the water supply systems, or inefficient usage induced by inefficient pricing policies. Although low precipitation is often seen to be the biggest cause for these water shortages, inappropriate water-pricing systems, which cause excessive use of water, cannot be overlooked.

In this paper, I explain the extent to which an optimal pricing policy can help avoid these water shortages, by incorporating the multiple sectoral demands for water as well as revenue and dynamic resource constraints. To determine the effectiveness of water prices on water shortages, I set up a stochastic dynamic programming (SDP) model in which a benevolent government supplies water to households and agriculture. The policy function for the water prices will provide the "optimal" pricing rule, given the organizational restrictions, which I explain in the following sections. I take into account changes in crop composition in response to changes in water prices.

Regarding the literature on water shortages, Roibás et al. [12] and Woo [21] focused on interruption pricing in the residential water use. Both papers modeled that a consumer’s utility also depends on the length of service interruption. Roibás et al. considered the residential water demand to have two components: the first component is a standard Marshallian demand, while the second component reflects the effect of service interruption. While Woo computed the Hicksian compensating variation to calculate the welfare loss due to service interruption, Roibás et al. defined the social welfare function explicitly.

Elnaboulsi [4] analyzed the optimal capacity choice problem for a water utility which aims to maximize social welfare; i.e., the sum of consumer and producer surplus. Elnaboulsi assumed quasi-linear preferences for households and derived the demand for tap water and the optimal branch pipe size. In his model, the water utility uses an external water resource to supply the excess demand. He then derived the optimal price of tap water and branch
pipe.

Schuck and Green [14] analyzed the irrigation water pricing problem for a conjunctive water use system in a dynamic environment. They assumed that growers can irrigate their land through surface and underground water resources. They introduced a dynamic revenue constraint for the irrigation district, and analyzed the social planner’s finite-horizon dynamic Ramsey pricing problem. Using data from California, Schuck and Green provided policy suggestions on irrigation price, aquifer level, and energy use by growers.

I believe my work adds to the literature in several ways. First, I consider both revenue and resource constraints in the SDP problem. Therefore, the optimal prices reflect the effects of both the shadow price of water and the Ramsey pricing rule. Second, I consider multiple uses from the same reservoir. Since water quality often differs across different user groups, sectoral water prices can be quite different and the demand by these user groups cannot simply be aggregated. Third, I model that crop composition changes in response to water scarcity along with other factors. This is important for policy analysis because changes in the crop composition in response to water prices affect the aggregate demand for irrigation water. Therefore, the elasticity of irrigation water demand depends also on the crop composition. Finally, I allow the water supplier to charge higher water prices, if needed, to prevent a possible water shortage in the future. This action would lead to profits for the water supplier. Since water suppliers are not allowed to make profits, which is often enforced by law, I rebate all the profits back to the households as a lump-sum transfer. As a result, efficiency in water pricing can be achieved while still break-even.

Using the data from Turkey, I perform a structural estimation of the sectoral demands, and then examine several counterfactual experiments. My main finding is that, under the policy of break-even prices, the government delays a water shortage, when it cannot meet the sectoral demands, for an average of eight years. In contrast, if the government were to choose water prices optimally, then water shortages would be practically nonexistent over the next century. In fact, the government has to experience a series of significantly low inflows to the reservoir to be unable to meet the sectoral demands, but I compute the probability of such an event to be close to zero. Moreover, I find that, under the current policy pricing policy, a one-percent improvement in irrigation efficiency delays water shortages for about 12 years of no water shortage. Finally, an 11 percent increase in mean inflows reduces the probability of water shortages to almost zero under the ACP rule.

This paper proceeds as follows: in section 2 I introduce the model. In sections 3 and 4 I explain the data and perform the structural estimation of the parameters. In section 5 I discuss the simulation results. I conclude the paper in section 6.
2 Model

I assume that a (local) government supplies water for tap and irrigation uses. Households demand tap water monthly, whereas agriculture’s demand for irrigation water depends on the irrigation season. The timing of the problem is as follows: At the beginning of the year, the government predicts the sectoral demand for tap and irrigation water, and sets sectoral water prices yearly, depending on the available water stock. In each period (month), there is some amount of water in the reservoir saved from last period. During the period, stochastic inflows to the reservoir increase the water stock. The households and the agriculture observe the water prices, and withdraw water from the reservoir. The remaining water stock is saved for next period.

2.1 Households

In every period, households have a fixed income \( I \), which represents monthly labour income and other transfers. The households spend their entire income on two commodities—tap water \( w_1 \) and a composite good \( y \). The households maximize their per-period utility subject to the budget constraint:

\[
\max_{<w_1, y>} U(w_1, y) \quad \exists \quad p_1 w_1 + y = I
\]

where \( p_1 \) is the price of tap water. The price of the composite good is normalized to one, so all prices and income are in real values. The Marshallian demand for tap water \( W_1(p_1; I) \) can be found, accounting for the the number of households \( M \):

\[
W_1 = M w_1(p_1; I).
\]

Note that since the tap water demand is monthly, it may depend on the seasonal factors, such as precipitation and evaporation.

2.2 Agriculture

Changes in the irrigation price may have different effects on agricultural production. On the one hand, higher irrigation costs may force farmers to switch to better water-saving technologies; see de Fraiture and Perry \(^2\). On the other hand, an increase in the irrigation

\(^2\)I do not admit savings for households.
price may affect crop composition in the region via changes in land allocations; see Weinberg et al. [19]. Crop composition is crucial for policy analysis, because it affects the aggregate demand for irrigation water, so the revenue from supplying water. Thus, the government has to account for the changes in crop composition to predict the irrigation demand accurately.

I assume all farmers are identical, so I focus on a representative farmer’s profit maximization problem. Each farmer owns a unit of land, and he chooses how much land to allocate for different crops. Farmers can either allocate their land for crop production or leave some or all of it fallow. The crop production function has two inputs: land $\ell_c$ and water $w_{2,c}$:

$$F_c = F_c(\ell_c, w_{2,c}); \quad \forall \ c = 1, \ldots, N,$$

where $F_c$ denotes the output of crop $c$. The representative farmer solves a mixed-choice problem: with a unit of land, the farmer first chooses which crop to grow. Having chosen the crop, the farmer decides how much input to use and how much output to produce:

$$\Pi = \max (\Pi_1, \Pi_2, \ldots, \Pi_N, \Pi_{N+1})$$

$$\Pi_c = \max_{\langle \ell_c, w_{2,c} \rangle} p_F F_c(\ell_c, w_{2,c}) - p_2 w_{2,c} + \epsilon_c \ell_c; \quad \forall \ c = 1, \ldots, N,$$

$$\exists \ell_c \leq \bar{\ell} = 1,$$

$p_F$ denotes the final price of crop $c$, and $\Pi_c$ represents the profits from producing crop $c$. Outside option is denoted by $\Pi_{N+1}$, which is the value of leaving land fallow, and it is normalized to zero. Thus, all the profits generated by crop production are relative to the outside option. I assume a volumetric irrigation price, so $(p_2 w_{2,c})$ is the cost of irrigation for crop $c$.

I assume that farmers observe a series of private shocks, one for each crop. The need for these shocks is to prevent all farmers to allocate their land for the most profitable crop, which is not consistent with the data. Therefore, I assume that the vector of private shocks for each farmer are not observable to other farmers or to the econometrician, and the shock for crop $c$ is independently and identically distributed over time with mean $\mu_c$. To estimate

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2 There are many other inputs to food production, including capital, labor, and fertilizers. However, since the focus of the paper is on water allocation and prices, I assume that there is infinite supply of these inputs, and the farmers demand other inputs proportional to the land used for food production.

3 The water input $w_{2,c}$ may include all sources of water used in crop production, including irrigation water release, precipitation, and water release for flood control. However, there is no rainfall or other inflows during the months of irrigation in the data, so I consider only irrigation in this model.

4 The rationale for this demand shock is as follows: Since all farmers are identical, the deterministic profit function implies that all farmers choose to produce the crop with the highest profit at the equilibrium, which is not often consistent with the data since land is distributed across different crops. In a general equilibrium framework, aggregate demand and supply for crops would force the farmers to be indifferent between the
the land allocations, I further assume that these shocks are multiplied by the land allocated for crop $c$.

Let $a_c$ denote the decision made for crop $c$; i.e., $a_c$ equals one if crop $c$ is chosen, and zero otherwise. Given a distribution of the shocks, one can calculate the probability of choosing crop $c$, denoted by $\text{Pr}(a_c = 1 | p_2, p^F, \mu)$, which depends on the irrigation price, the vector of output prices, and the mean shock levels. Given the probability distribution over crops, farmers’ expected total profit, $E[\Pi(p_2)]$, and the expected aggregate demand for irrigation water, $E[W_2(p_2)]$, can be found accordingly.

### 2.3 Government

I assume that there is a single benevolent water supplier—the (local) government, which can also be seen as a water utility who can only break even. The government seeks to maximize the net social welfare of households and producers subject to several constraints. Because I admit nonzero profits in the agriculture, I assume that these agricultural profits (or losses) are given to the households, as part of the households’ income. Thus, the government’s objective function is the indirect utility function of the households, which includes th agricultural profits.

At the beginning of each year, farmers have to make their land allocation decisions and report to the government to signal their demand for irrigation water. Therefore, the government sets the water prices at the beginning of the year, without observing the stochastic shocks during the year. Consequently, the government faces the following problem in the first month ($m = 0$):

\[ V(w, p_{-1}; \theta, m = 0) = \max_{<w, p, \tau>} U(p, \tau; \theta, 0) + \beta E[V(w', p; \theta', 1)] \]  

\[ \exists S(w, \theta) - w' = E[W_1(p, \tau; \theta, m) + W_2(p, \tau; \theta)] \delta_m + W_3, \]  

\[ FC_1 + \tau_1/(1 - \lambda) = \sum_{m=0}^{11} (p_1 - VC_{1,m}) E[W_1(p, \tau; \theta, m)], \]  

\[ FC_2 + \tau_2/(1 - \lambda) = \sum_{m=0}^{11} (p_2 - VC_{2,m}) E[W_2(p, \tau; \theta)] \]

where the vector $\theta$ represents the vector of exogenous stochastic shocks (inflows, crop prices, crops, even though the farmers are all price-takers. Even though this model is only a partial equilibrium setup, one can generate the same crop distribution by introducing a private shock to the profit function. Such a shock causes heterogeneity in crop choices over farmers and time, and pins down the crop composition. Therefore, the profit function defined above is not the actual profit function, but it is the observed profit function by an econometrician.
etc.), and $\tau = (\tau_1, \tau_2)$ denote the amount of rebate the households receive from tap and irrigation water provision, respectively. The expectation operator $E(\cdot)$ is over this shock vector $\theta'$. Since the shocks are not observed when the prices are set, the solution gives us an ex-ante equilibrium.

In problem (2.1), the government has three constraints. First constraint is the dynamic resource constraint, given in equation (2.1b). The left-hand side (LHS) of equation (2.1b) is the water stock $S(w, \theta)$ minus the savings $w'$ for the next period, so it equals the supply of water available for current consumption. The right-hand side (RHS) is the sum of the expected demand by households $E[W_1(p, \tau; \theta, m)]$ and agriculture $E[W_2(p, \tau; \theta)]$, including water release for flood control $W_3$. Note that $\delta_m^\ast$ is an indicator function, which represents the seasonal irrigation water demand. It equals one in the months of irrigation, denoted by $m^\ast$, and zero otherwise.

The government has a revenue constraint for each sector, given in equations (2.1c) and (2.1d). The fixed cost for tap and irrigation water is denoted by $FC_1$ and $FC_2$, respectively. They may include both O&M costs and a fixed payment to the government to cover construction and maintenance costs of the dam. Meanwhile, let $VC_{1,m}$ and $VC_{2,m}$ represent the constant marginal cost of tap and irrigation water in month $m$, respectively. The marginal costs are mostly due to maintaining water quality; i.e., using chemicals and energy to sanitize water.

Note that the current policy of the government in many OECD countries is to have a balanced budget; i.e., expected revenue equals expected cost of water provision in each sector. I refer to the prices that balance the budget as the “break-even prices.” According to this policy, sectoral water prices are set equal to the average cost of producing water in each sector, so it is also known as the average-cost pricing (ACP) rule. The ACP rule does not take the water scarcity into account. In fact, low prices cause excess withdrawals due to inelastic demands, which may result in a water shortage. Then, the government faces the problem of not providing enough water to the sectors. To resolve this issue, I allow the government to charge higher prices depending on the water supply. Since this may lead to profits, I assume that some portion of the profits $(1 - \lambda)$ are rebated back to the households as a lump-sum transfer. In this way, the government still has a balanced budget, while it restores an efficient pricing rule across sectors.

Once the prices $p$ are set for the year, the government chooses how much water to save.
in the following months \((m = 1, \ldots, 11)\):

\[
V(w, p; \theta, m) = \max_{w'} U(p, \tau; \theta, m) + \beta \mathcal{E}[V(w', p; \theta', m + 1 \text{ mod } 12)]
\]

\[
\Rightarrow S(w, \theta) - w' = \mathcal{E}[W_1(p, \tau; \theta, m) + W_2(p, \tau; \theta)] - \delta^m_{m^*} + W_3.
\]

Let \(\eta\) and \(\zeta\) be the Lagrange multiplier on the tap- and irrigation-revenue constraints, respectively. Also, let \(\{\psi_m, \xi_m\}_{m=0}^{11}\) denote the Lagrange multipliers on the resource, and households budget constraints.\(^7\) Taking the first-order condition (FOC) with respect to \(p_2\) and rearranging terms gives us the optimal irrigation price:

\[
p_2 = \left\{ \frac{-\mathcal{E}[W_2]}{\partial \mathcal{E}[W_2]/\partial p_2} - \frac{\beta^m \partial \mathcal{E}[U_{m'}]/\partial p_2}{\zeta \partial \mathcal{E}[W_2]/\partial p_2} \right\} - \eta \zeta \sum_{m=0}^{11} \left( \frac{\partial W_{1m'}}{\partial p_2} - \beta^m \frac{\partial W_{1m'}}{\partial p_2} \right) + \beta^m \frac{\partial \mathcal{E}[\psi_{m'}]}{\partial \mathcal{E}[W_2]/\partial p_2} + \mathcal{E}(\psi_{m'}) \right\}. \tag{2.2}
\]

In equation (2.2), the first term on the RHS represents the effect of the irrigation-revenue constraint, which states that the less elastic the demand for irrigation water, the higher its price. This is also known as the inverse-elasticity rule. The second and third terms on the RHS result from the cross-price elasticity of tap water to irrigation price. Depending on the sign of this cross-price elasticity, a higher irrigation price may tighten or loosen the tap-revenue constraint. The last term on the RHS is due to water scarcity; i.e., the lower the water supply, the higher the shadow price of water \(\psi\), so the higher the irrigation price. However, it is discounted by \(\zeta\), which represents the tightness of the irrigation-revenue constraint.

Using the FOC with respect to \(p_1\), we can obtain a similar equation:

\[
- \sum_{m=0}^{11} \beta^m \mathcal{E}[\xi_{m'} W_{1m}] = \sum_{m=0}^{11} \beta^m \mathcal{E}\left[ \psi_m \frac{\partial W_{1m}}{\partial p_1} \right] - \eta \zeta \sum_{m=0}^{11} \left( (p_1 - VC_{1,m'}) \frac{\partial \mathcal{E}[W_{1m}]}{\partial p_1} + \mathcal{E}[W_{1m}] \right) \mathcal{E}(\psi_{m'}) \right\}. \tag{2.3}
\]

The LHS is the expected loss in utility in response to an increase in tap price. The first term on the RHS is the expected benefit in saving more water for the following periods, while the second term is the effect of a price increase on the tap-revenue constraint. To understand this equation better, suppose that the tap water price is set every month. Then, equation

\(^7\)For notational simplicity, I suppress the term \("(p, \tau; \theta, m)"\) in the derivations. Instead, I refer to \(W_1(p, \tau; \theta, m)\) and \(W_2(p; \theta)\) as \(W_{1m}\) and \(W_2\), respectively.
(2.3) simplifies to:

\[-\xi W_1 = \psi \left[ \frac{\partial W_1}{\partial p_1} \right] - \eta \left[ (p_1 - VC_1) \frac{\partial W_1}{\partial p_1} + W_1 \right] \]

\[ \Rightarrow p_1 = \left( \frac{\eta - \xi}{\eta} \right) \left[ \frac{-W_1}{\partial W_1/\partial p_1} \right] + \frac{\psi}{\eta} + \frac{VC_1}{\text{Marginal Cost}} \]

(2.4)

where the first term on the RHS is the effect of the tap-revenue constraint, which is also known as the inverse-elasticity rule. The less elastic the tap water demand, the higher tap price can be set. The second term reflects the degree of water scarcity, discounted by the inverse of the Lagrange multiplier on the tap-revenue constraint. Thus, the lower the water supply, the higher the shadow price of water, so the higher the tap water price. The last term on the RHS is the marginal cost of water, which equals the variable cost $VC_1$ in this model.

The crucial difference between the ACP rule and the dynamic Ramsey pricing (DRP) rule, described above, is that the ACP rule only accounts for the last term $VC_1$, given the constant marginal cost assumption. In contrast, the DRP rule reflects the effect of both revenue and resource constraints as well. Nonetheless, there is no analytical solution for the problem (2.1), so I will solve for the dynamic programming problem computationally using data from Turkey.

3 Data

The data provided by the State Water Works in Turkey (DSI, the Turkish abbreviation) concern two river basins in southern Turkey. This region is exceptionally important to Turkish agriculture because Cukurova, the largest alluvial plane in Turkey, is located here between the rivers Seyhan and Ceyhan, two of the biggest rivers in Turkey. The Kartalkaya Dam is located near the city Kahramanmaras. The dam belongs to Ceyhan basin, but has incoming flows from Aksu river, too. Construction was completed in 1972; since its completion, it has been serving water for irrigation and drinking purposes. Like most dams, this dam is also used for flood prevention in the area. The dam capacity is 173.173 hm$^3$ and the total irrigation area that it serves is 22,810 ha. The Kartalkaya Dam is one of the most important dams in the region, as it supplies water for agriculture to the parts of Cukurova plateau, and water to the city of Gaziantep. With a population of about 1.5 million in 2007, Gaziantep is the ninth largest city of Turkey and the largest city in Southeastern Anatolia Region.
### 3.1 Reservoir Flows

Data concerning the flows (in hm$^3$) into the Kartalkaya dam are available from January 1984 to August 2007 (with a total of 284 observations). I provide summary statistics for the flows data in table [1].

The need for a reservoir in this semi-arid region is obvious, as there is more rainfall during winter, but almost none during summer when irrigation is carried out. The volume of water in the dam averages around 92 hm$^3$, half of the reservoir capacity, but it is also quite volatile. The government releases water for three purposes: tap, irrigation, and flood control. Monthly tap water use varies between 5 and 10 hm$^3$ due to population growth, whereas irrigation water use is only positive during summer, when there is no precipitation. Due to households’ demand for water, tap water use is never less than 2.4 hm$^3$. Water release under flood control, which has a maximum of 298.5 hm$^3$, is to avoid overflows whenever available water supply is expected to exceed the reservoir capacity, particularly during winter. When released to avoid overflows, most of the water is directed to irrigation fields. However, it does not have any economic return. Inflows to the dam are important for water stock as they help the government determine the total stock of water at the reservoir. The inflows are much higher during winter and spring, while during the summer, the inflows drop to almost zero due to no rainfall; see figure [1].

### 3.2 Tap Water Use

The DSI supplies water for tap use to the city of Gaziantep, where the municipality is responsible for pricing tap water. The city has three water sources, but the Kartalkaya dam meets around eighty percent of the total demand. In the top graph in figure 2, I depict the relationship between the tap water use and the effective price, which equals the tap water price times the recovery rate. Although there seems to be an overall negative relationship between the quantity and the price, other factors may also be present, in particular in the last three years. The bottom graph in figure 2 shows the demand for tap water is inelastic with respect to its own price. This is consistent with the finding in the literature that the tap water demand is not very responsive to the tap water price.

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8The municipality has been unable to recover all the revenue from water sales. In fact, every year around 55–60 percent of the tap water supplied by the municipality has been “lost”: the revenues are uncollected. The recovery rate, which is the proportion of tap water that is actually paid for, was around twenty-five percent in 2003, but increased to almost forty-eight percent in 2007.
### 3.3 Irrigational Use

The water users associations (WUA) are responsible for managing irrigation water from the Kartalkaya Dam. Before 1994–5, the DSI set the irrigation prices. However, with the reforms in agriculture during mid-1990s, the DSI turned over the duty of price setting to the WUAs. The WUAs are non-profit organizations, so they still attempt to break-even. To achieve their goal, they began full-cost recovery, so this led to higher irrigation prices in real terms; see figure 3. In setting irrigation prices, the DSI and the WUAs adopted a per-area pricing scheme and determine the irrigation prices according to the crop water requirements—how much water per hectare a crop needs. This has two consequences: first, the irrigation prices (in real terms) for different crops have evolved almost the same way over time, and a constant proportion among prices is preserved throughout the time period. Second, the more water a crop requires during the growing period, the higher the irrigation price of the crop is, see figure 3. Consequently, the irrigation price of cotton and sugar beet is the highest, while wheat does not require much water during the growing period, so its irrigation price is the least. In fact, the irrigation price of cotton and sugar beet are the same throughout the period, perhaps due to the climatic and soil characteristics of the region, cotton and sugar beets require the same amount of water per area.

Even though I do not observe farmer-level data, the aggregate crop composition has changed considerably over the time period. The agriculture focused mostly on growing cotton in the mid-1980s, but after the DSI turned over the duty of setting water prices to the WUAs, the crop composition changed dramatically from the crops that require relatively more water (such as cotton and sugar beets) to those that require relatively less, such as wheat, see the top plot in figure 4. While this period coincides with the increase in maize productivity and the relative increase in the real price of maize to other crops, it is worth noting that the water shortages limited the actual area irrigated, especially between 1991 and 2003; see the bottom graph in figure 4. In fact, whenever a water shortage occurred, the government used consumption rationing and refused to provide irrigation to some portion of the land. As a result of these factors, the proportion of area allocated for cotton decreased from sixty–ninety percent range to almost fifteen–twenty percent. This decrease has been offset by allocating more area for crops such as maize and wheat. To distinguish the effects of these factors, I will describe the demand estimation procedure in the next section.
4 Estimation

Because the government adopted the ACP rule in the data, the sectoral water prices do not reflect water scarcity. Therefore, the sectoral water prices are set according to their respective cost structure. Thus, one can perform the estimation of the parameters in each sector in a static framework. First, I estimate the demand for tap and irrigation water separately. Once I obtain the parameter estimates, I solve the dynamic programming problem, and carry out counterfactual experiments for policy analysis.

4.1 Tap Water

Households' demand for tap water is mainly for two purposes: drinking and non-drinking. Assuming that tap water has no substitutes, drinking water may be considered as price-non-responsive component of the demand; see Gleick [6]. Meanwhile, households may adjust their demand for non-drinking use according to the price. This structure is used in estimating the demand for tap water in the literature; see Gaudin et al. [5]. The features of tap-water demand suggest that if one is to use a demand function for the estimations, it is important that the function delivers a non-constant inelastic demand. A potential candidate for such a function is the Stone–Geary utility function:

\[
U(w_1, y) = \pi_1 \log(w_1 - w_1) + (1 - \pi_1) \log(y)
\]

\[
w_1 = (1 - \pi_1)w_1 + \pi_1 \frac{I}{p_1}
\]

where \(w_1\) represents the Marshallian demand for tap water. The demand for water has two components: the subsistence level \(w_1\), and the price-responsive component, where \(\pi_1\) denotes the marginal budget share of tap water. The subsistence level for tap water can be thought as the demand for drinking water as well as the minimum amount of water to sustain the standards of living. The Stone-Geary preferences deliver inelastic water demand in its own price.

I use the data on tap water consumption and price from January, 2000 to December, 2008. All the prices and household income are relative to the 1994 prices. The municipality cannot recover all the revenue: some proportion of water supplied from the reservoir is unpaid for. To account for this, I use the volume of water actually billed and recovered as the response variable. I estimate the coefficients with the least-absolute-deviation (LAD) method, and compare the estimates with least squares (LS) method.

\[\text{The results are more robust to outliers in the LAD estimation than the LS method. Moreover, no specification is needed for the error term in LAD estimation.}\]
The coefficients and their standard errors (in parenthesis) are provided in table 4. In general, the LAD estimates tend to differ from the LS estimates. In fact, the constant term is not significant in the LS estimation. Moreover, I predict the subsistence level to be around 56.25 liters per capita per day. WHO [20] defines the subsistence level as 15–20 liters per capita per day. However, this result is likely due to low prices according to the ACP rule coupled with revenue recovery problems.

One disadvantage of the Stone-Geary functional form is welfare analysis. When a water shortage occurs, the households may end up getting less than subsistence level under the average-cost pricing rule due to consumption rationing. Thus, the utility function may diverge to \(-\infty\). To avoid this problem, I also try double-log demand function with or without partial adjustment; see Woo [21], Woo et al. [22]. Even though the correlation between logarithm of tap water and of tap price is negative in the data, the income predictor in the regression causes a positive coefficient for the tap price in these regressions, which is misleading for policy analysis. Consequently, I adopt the Stone-Geary preferences and use the parameter estimates to solve the dynamic programming problem.

4.2 Agriculture

Like the tap water demand, irrigation water demand is usually estimated to be inelastic; see de Fraiture and Perry [2]. To estimate the land allocations, Edwards et al. [3] uses nested constant elasticity of substitution, while normalized quadratic functional form are used in Moore et al. [8], Moore and Negri [9], Shumway [16]. Since I do not observe individual input demands in the data, I follow a different approach in my model.

Since the irrigation pricing is per-area based, and the ratio of the irrigation price for two equals the ratio of their water requirement, I assume the Leontief production function for crop \(c\) with inputs land \(\ell_c\) and water \(w_{2,c}\):

\[
F_c = \alpha_c \ell_c \min \left(1, \frac{w_{2,c}}{\gamma_c \ell_c}\right); \alpha_c, \gamma_c > 0; \forall \ c = 1, \ldots, N
\]

where \(\alpha_c\) is the crop land productivity, and \(\gamma_c\) is the per area crop water requirement. Since I assume that other inputs are used proportional to the land input, \(\alpha_c\) may change over time, because of changes in the productivities of the other inputs, such as improvement in the quality of seeds and the use of fertilizers. Given the Leontief production, the profit

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\[10\] The parameter \(\gamma_c\) denotes total amount of water needed for production of crop \(c\). Since I do not observe the irrigation practices in the data, this parameter also represents the effect of the irrigation technology; i.e., switching to a more efficient irrigation technology decreases \(\gamma_c\).
function for producing crop $c$ becomes:

$$
\Pi^o_c = \max_{<\ell_c>^c} \left( p^F_c \alpha_c - \gamma_c p_2 + \mu_c \right) \ell_c; \ \forall \ c = 1, \ldots, N
$$

$$
\exists \ \ell_c \leq \bar{\ell} = 1,
$$

where I assume that $w_{2,c}$ equals $\gamma_c \ell_c$, since any additional water does not change the agricultural output. I consider volumetric irrigation pricing to distinguish the effects of water scarcity and revenue constraint, so the cost of irrigation water equals $(p_2 \gamma_c \ell_c)$.

To be consistent with the literature on the multinomial logit models, I assume Type I Extreme Value distribution for the shocks. Given this distributional assumption, the probability of choosing a crop equals:

$$
\Pr(a_c = 1) = \frac{\exp(\Pi_c)}{1 + \sum_{c'=1}^N \exp(\Pi_{c'})}, \ \forall \ c = 1, \ldots, N.
$$

The agricultural model has three sets of parameters: land productivity $\alpha$, water requirement $\gamma$, and the mean of the demand shocks $\mu$. Even though these parameters can be separately identified, the estimates were not significant because of little variation in the data of crop prices and the irrigation prices. Hence, I divide the estimation procedure into two steps:

1. I calibrate the technological parameters $\alpha$ and $\gamma$.

2. I estimate the mean shock levels across crops.

Although the productivity of cotton, wheat, and sugar beet have not changed significantly over time, the productivity of maize has increased about seven times over the last two decades. In the SDP problem, I assume the most recent year–2007 values for these land productivities. In the first step, I calibrate the water requirements $\gamma$ from the data on irrigation prices.

In the second step, I collect the yearly data on land allocations from 1984 to 2007, and I consider four crops (cotton, maize, wheat, and sugar beet), as the land allocated for these crops amount to about ninety percent of the total irrigated area. I use the generalized method-of-moments (GMM), and provide the estimation results for the mean shock levels $\mu$ in table 2. Since this is a two-step estimation procedure, one would need error correction

---

12 The maximum-likelihood method is often used for this type of models. However, I do not observe the number of farmers; the data on land allocations and irrigation water use are aggregated to the region. Since all the farmers are ex-ante symmetric, the probability definitions in the maximum-likelihood estimation would be misleading.
for the parameters estimated in the second step. To overcome this issue, I use the actual non-volumetric data on irrigation prices and the yearly data on land productivities $\alpha$ in the second step.

The mean shock levels are significantly different from zero. In particular, sugar beet has the lowest mean shock level. This low value can be attributed to the high cost of labor in sugar beet production. As I have discussed in section 3, recent developments in maize productivity and the increases in maize prices have led to more land allocated for maize. Meanwhile, some land has been allocated away from cotton and to wheat. This is likely due to the decrease in irrigation water release, which farmers react by switching to crops that require less water.

One advantage of the structural model is to account for the change in the crop composition and calculate the elasticity of the irrigation demand with respect to the irrigation price. I find that the demand for irrigation water is inelastic. Furthermore, the own-price elasticity increases with the irrigation price from 0.05 to 0.8, which can be attributed to the changes in crop composition in response to increasing irrigation price.

5 Results

To solve the SDP problem, I assume that the exogenous stochastic shocks in this economy stem from two components: inflows and crop prices. Inflows to the reservoir vary considerably over the months. Among the crop prices, only the crop price of cotton has changed significantly over the last two decades, while the crop prices of wheat, maize, and sugar beet have stayed almost constant during the time period. To incorporate these stochastic shocks, I use the empirical distribution of the inflows with four grid points, which depend on the month. I assume log-normal distribution for the crop price of cotton, estimate the autoregressive process of length one, and derive the transition matrix using Tauchen’s algorithm; see Tauchen [17]. I assume the year–2006 values for the other crops, and the year–2007 values for the land productivities. I also discretize the water savings $w'$, the tap water price $p_1$, and the irrigation price $p_2$ using 60, 25, and 25 grid points, respectively. In total, each monthly value function is solved for 450,000 different combinations of the state variables, including three and four grid points the cotton price and inflows, respectively.

I will first analyze how well the model predicts the water shortages in the data, and I compare the policy implications of the optimal prices with the current pricing policy; i.e., the break-even prices.

13I tried both linearly- and nonlinearly-spaced grid points (finer at lower ends) for these variables, but displayed the results for the linearly-spaced grid points.
5.1 Model Fit

Even though both households and agriculture are affected adversely from a water shortage, the implications on the irrigation water use are more emphasized in the data. This is often due to large seasonal demand by agriculture and the priority rule in favor of household water use. For this reason, I focus on the yearly decreases in irrigation water use. I first calculate the annual irrigation water use, then compute their deviation of from the sample mean during the data period (1984–2006). Since it has no formal definition, I define a water shortage when the irrigation water use is less than 0.65 times its standard deviation below the sample mean.\(^4\) I display the irrigation water use and the annual inflows in figure 5.

In table 3, I illustrate that water shortages occurred eight times in the data. Under the ACP rule, my model and parameter estimates replicate almost all of these water shortages, with the only exception in 2005. Although inflows seem to be the main factor to cause water shortages, it is important to investigate the need of a pricing policy that accounts for water supply volatility. Therefore, I carry out Monte-Carlo simulations and discuss the results in the next section.

5.2 Monte Carlo Simulations

To compare the implications of the ACP and DRP rules on the frequency of water shortages, I run Monte Carlo simulations. I generate pseudo-random values for the inflows and the crop price of cotton. I start the water supply as the median water level for December in the data, which equals 35.55 hm\(^3\). I simulate the economy 5,000 times for a century under both pricing rules. Whenever the supply cannot meet the demand in a given month, I treat it as a water shortage, and I record the years of water shortage along with the water stock, water savings, and sectoral water use. Then, I compute their mean and standard deviation, and display the results in table 5.

I describe the ACP rule as the benchmark model in table 5. Using the ACP rule, the government delays water shortages for eight years, on average. More importantly, the standard deviation of the delay is also about eight years, so the current water management policy is quite vulnerable to water shortages due to high volatility in inflows. Furthermore, the average number of water shortages equals 10, which implies that the probability of facing a water shortage in a given year is 10 percent. The average monthly water stock is 137 hm\(^3\), which is about 80 percent of the capacity. Since the water prices are low under the ACP rule, the consumption is quite high for both sectors, another factor affecting the frequency.

\(^4\) Although changes in crop choices by the farmers will affect the irrigation water demand, I assume that farmers cannot adjust their crop-choices once they face a water shortage during the irrigation season.
In case of a water shortage, the government pro-rates agriculture by an average of 7 percent, which equals $1 - \rho$ given in the table. Note that before- and after-rebate water prices are equal because the government does not generate any profits.

In the next two scenarios, I consider how demand- and supply-side improvements can help avoiding water shortages under the ACP rule. First, I focus on different levels of reduction in irrigation water use as a demand-side improvement. Suppose that crops are produced in a more water-efficient way, perhaps through adopting more efficient irrigation technologies. An example is to switch from a surface to a sprinkler or to a drip irrigation technique. Hence, less irrigation water is needed for agricultural production, even though a crop’s need for water is the same. I report the simulation results for various percent improvements in irrigation water use in table 5. If all crop water requirements reduce uniformly by one percent, then the government may delay water shortages for about 12 years. Therefore, the probability of facing a water shortage decreases from 10 percent to 7.5 percent. If the improvement in irrigation increases to five percent, then water shortages can be avoided as long as 69 years, on average, which decreases the chance of a water shortage below 1 percent. For every additional percent reduction in irrigation water use, the average water stock increases by 0.5 hm$^3$, while the irrigation water use decreases more than one hm$^3$. In case of a water shortage, the rate of rationing seems to be slightly affected with this demand-side improvement.

A supply-side improvement may be due to preventing leakages. While being channeled to the reservoir, some portion of inflows is often lost due to leakages. With a more efficient technology, the government can store more inflows. In this scenario, I increase the mean inflows during the year by an additional hm$^3$ and report the results in table 5. A unit increase in mean inflows corresponds to a 2.3455 percent proportional increase, which delays the water shortages for 17 years, on average. Meanwhile, the probability of a water shortage goes down to 5 percent compared to 10 percent in the benchmark case. An increase in inflows further leads to a higher water stock and savings. The rate of rationing during water shortages goes down to 5 percent when the mean inflows increase by 5 hm$^3$. In this last case, the water shortages are almost non-existent. In fact, the delay in the water shortages is close to a century.

Finally, I consider the implications of the DRP rule, which is the solution to the SDP problem. Since the DRP rule is to ensure there are no shortages, the water prices are set higher to control the sectoral water demands when needed. Consequently, the probability of water shortage is empirically zero. Note that the government rebates all the profits back to the consumers and producers under the optimal pricing rule. Therefore, it is possible to calculate the after-rebate water prices, especially for agriculture.

In the last two scenarios given in table 5, I compute the after-rebate irrigation price
along with the other variables. In the fourth scenario, I assume the reservoir capacity in the data. According to the simulation results, the average after-rebate irrigation price is about 1.6 times the break-even price under the ACP rule. In other words, to ensure the efficient distribution of water and to avoid water shortages, the government may need to increase the irrigation price about 60 percent. Even though this is a big increase, the ratio of the irrigation to tap water price is still very low. Nonetheless, the change in the irrigation water use is even more drastic compared to the increase in the irrigation price. The government on average supplies only 90 hm$^3$ of water to agriculture, which will further change the crop composition in favor of the crops with lower crop-water requirements, such as wheat. To further investigate the effect the reservoir capacity on the water prices, I increase the reservoir capacity to 400 hm$^3$. I display the results at the end of table 5. As the reservoir capacity increases, the government can store more water. Therefore, it is possible to charge lower water prices when water supply is higher. In fact, the average after-rebate irrigation price is very close to the break-even price under the ACP rule. Moreover, the average water supply increases substantially to 354 hm$^3$. This implies that even when the government stores water at the maximum reservoir capacity 173 hm$^3$ in the benchmark case, there is still a significant chance of facing water shortages under the ACP rule. As a result, water shortages are also affected by the reservoir capacity along with inefficient pricing policies and high volatility in inflows.

6 Conclusion

It is argued that the average-cost pricing policy is more convenient for equity and accessibility reasons, because charging prices only to recover costs leaves water users more income to spend on other commodities. However, in water provision, low water prices result in large withdrawals, which makes water management vulnerable to water shortages. During a water shortage, when the government cannot supply the sectoral demands, the government may refuse to provide water to agriculture as well as households, which may be quite costly to the economy. Although the purpose of the ACP rule is to break even, alternative pricing policies can ensure a balanced budget as well as optimal intertemporal allocation and efficient distribution of water. To incorporate the effect of water scarcity on water prices, I set up a dynamic model where the government aims to maximize households’ utility while facing sectoral revenue and dynamic resource constraints, and rebates all profits from water provision back to the agents.

I analyze the effects of the current and optimal water pricing policies on the water resource management. I find out that the average number of years to experience a water shortage is
around eight years under the average-cost pricing rule. In contrast, using the optimal water prices, the government does not run into water shortages for a century. Aside from adopting the optimal water prices, the government may have other alternatives including reducing water requirements or enhancing supply-side technologies to prevent leakages.

References


A  Derivation of the Optimal Rules

• Optimal water savings: First-order and transversality conditions with respect to \( w' \) are as follows:

\[
\begin{align*}
\text{FOC: } & \quad \beta \frac{\partial \mathcal{E}[V(p, w', \theta', m + 1 \mod 12)]}{\partial w'} = \psi_m; \, \forall \, m = 0, 1, \ldots, 11 \\
\text{TC: } & \quad \frac{\partial \mathcal{E}[V(p, w, \theta, m)]}{\partial w} = \psi_m \frac{\partial S(w)}{\partial w}; \, \forall \, m = 0, 1, \ldots, 11.
\end{align*}
\]

Iterating the TC for \( w' \) gives equation (A.1):

\[
\psi_m = \beta \mathcal{E}\left[\psi_{m+1} \frac{\partial S(w', \theta)}{\partial w'}\right]; \, \forall \, m = 0, 1, \ldots, 11. \tag{A.1}
\]

• Optimal irrigation price: To find the optimal pricing rule for the irrigation water, it is noteworthy that aggregate agricultural profits and profits made from supplying irrigation water are both rebated to households in month \( m' \), when irrigation is carried out. Thus, a representative household’s utility maximization problem is:

\[
\max_{<W_1, y>} U(W_1, y : m) \geq p_1 W_1 + y = I + \frac{\tau_1}{M} + \delta_m' \frac{\tau_2 + \mathcal{E}[\Pi(p_2; \theta)]}{M}
\]

where \( M \) denotes the number of households, \( \tau_1 \) and \( \tau_2 \) are aggregate profits made from supplying tap and irrigation water, and \( \mathcal{E}[\Pi(p_2; \theta)] \) is the expected aggregate agricultural profits. Agricultural sector affects households’ income only when the irrigation is carried out, which is denoted by the indicator function \( \delta_m' \). Thus,

\[
\frac{\partial U(p, \tau; \theta, m)}{\partial p_2} = \delta_m' \xi_m \frac{\partial \mathcal{E}[\Pi(p_2; \theta)]}{\partial p_2}; \, \forall \, m = 0, 1, \ldots, 11 \tag{A.2}
\]

where \( \xi_m \) denotes the Lagrange multiplier on the household’s budget constraint.

Meanwhile, the FOC of the value function with respect to \( p_2 \) is:

\[
0 = \beta \frac{\partial \mathcal{E}[V(p, w', \theta', 0)]}{\partial p_2} + \zeta \left\{ p_2 \frac{\partial \mathcal{E}[W_2(p, \theta)]}{\partial p_2} + \mathcal{E}[W_2(p, \theta)] \right\} + \\
\eta (p_1 - VC_{1,m'}) \frac{\partial \mathcal{E}[W_1(p, \tau, \theta, m')]}{\partial p_2} \quad (A.3)
\]

where the first term is the discounted expected cost of an increase in \( p_2 \), while the last
two terms represent the expected benefit today. The TC is also given below:

$$\text{TC: } \frac{\partial E[V(p, w, \theta, m)]}{\partial p_2} = \frac{\partial U(p, \tau; \theta, m')}{\partial p_2} - \psi m' \frac{\partial W_1(p, \tau, \theta, m')}{\partial p_2} + \partial W_2(p, \tau).$$  (A.5)

After iterating the TC, and combining terms in equations A.2, A.3, A.5, one derives equation 2.2.

- **Optimal tap price:** Noting that the irrigation water depends only on the irrigation price, one can write down FOC and TC for $p_1$ in the following way:

$$\frac{\partial E[V(p, w, \theta, m)]}{\partial p_1} = (1 - \delta_m^0) \left\{ \frac{\partial U(p, \tau; \theta, m)}{\partial p_1} - \psi_m' \frac{\partial W_1(p, \tau, \theta, m)}{\partial p_1} + \beta \frac{\partial E[V(p, w', \theta', m + 1 \mod 12)]}{\partial p_1} \right\}; \forall m = 0, 1, \ldots, 11$$

where the indicator function $\delta_m^0$ is one if the month equals zero, and zero for all other months. Using these two equations and Roy’s Identity, one can derive equation 2.3.
B Tables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>StDev</th>
<th>Minimum</th>
<th>Median</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Volume</td>
<td>92.06</td>
<td>55.92</td>
<td>5.65</td>
<td>94.02</td>
<td>173.17</td>
</tr>
<tr>
<td>Tap Water</td>
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<td>1.94</td>
<td>2.40</td>
<td>4.50</td>
<td>10.71</td>
</tr>
<tr>
<td>Irrigation Water</td>
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<td>0.00</td>
<td>61.40</td>
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<tr>
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<td>33.73</td>
<td>0.00</td>
<td>0.00</td>
<td>298.50</td>
</tr>
<tr>
<td>Inflows</td>
<td>32.47</td>
<td>37.79</td>
<td>0.20</td>
<td>17.95</td>
<td>307.30</td>
</tr>
</tbody>
</table>

Table 1: Summary Statistics for Reservoir Flows

<table>
<thead>
<tr>
<th>Cotton</th>
<th>Maize</th>
<th>Wheat</th>
<th>Sugar beets</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficient</td>
<td>1.4963</td>
<td>-2.7698</td>
<td>0.7233</td>
</tr>
<tr>
<td>Standard Error</td>
<td>0.1761</td>
<td>0.4333</td>
<td>0.1818</td>
</tr>
<tr>
<td>Gradient ($\times 10^{-4}$)</td>
<td>0.0001</td>
<td>0.4333</td>
<td>0.1818</td>
</tr>
<tr>
<td>Objective ($\times 10^{-6}$)</td>
<td>0</td>
<td>0</td>
<td>-0.0001</td>
</tr>
<tr>
<td>Number of Observations</td>
<td>24</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Estimation of Land Allocations

<table>
<thead>
<tr>
<th>Source</th>
<th>Pricing Rule</th>
<th>Years of Water Shortage</th>
</tr>
</thead>
</table>

Table 3: Water Shortages in the Turkish Data
Table 4: Estimation of Tap Water Demand

<table>
<thead>
<tr>
<th>Variable</th>
<th>Stone-Geary</th>
<th>Double Log</th>
<th>Double Log PA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LS LAD</td>
<td>LS LAD</td>
<td>LS LAD</td>
</tr>
<tr>
<td>Constant</td>
<td>1.6969</td>
<td>1.8418</td>
<td>-0.1750</td>
</tr>
<tr>
<td></td>
<td>(0.1160)</td>
<td>(0.1223)</td>
<td>(0.0708)</td>
</tr>
<tr>
<td>$I/p_1$</td>
<td>0.0005</td>
<td>0.0005</td>
<td>-0.1750</td>
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<tr>
<td></td>
<td>(0.0002)</td>
<td>(0.0002)</td>
<td>(0.0006)</td>
</tr>
<tr>
<td>$\log p_1$</td>
<td>-</td>
<td>-</td>
<td>0.2517</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.1022)</td>
</tr>
<tr>
<td>$\log I$</td>
<td>-</td>
<td>-</td>
<td>0.7941</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.1853)</td>
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<tr>
<td>$\theta_1$</td>
<td>-0.0019</td>
<td>-0.0019</td>
<td>-0.0009</td>
</tr>
<tr>
<td></td>
<td>(0.0005)</td>
<td>(0.0005)</td>
<td>(0.0006)</td>
</tr>
<tr>
<td>$\log Lw_1$</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.0002)</td>
</tr>
<tr>
<td>$N_{Obs}$</td>
<td>108</td>
<td>97</td>
<td>108</td>
</tr>
</tbody>
</table>

Note: I use the least-squares method (LS) and the least-absolute deviation (LAD) methods to estimate all three functional forms. Standard errors for the LAD regressions are computed using the quantile regression sandwich formula and the Hall-Sheather bandwidth rule. The notation in this table is as follows:

$I/p_1$: ratio of income to tap water price, $\log p_1$: natural logarithm of prices, $\log I$: natural logarithm of income, $\theta_1$: precipitation rate, $\log Lw_1$: natural logarithm of lagged tap water consumption, $N_{Obs}$: number of observations.
### Dynamic Ramsey Pricing

#### Benchmark

| $Y_{WS}$ | $N_{WS}$ | $S$ | $w'$ | $w_1$ | $w_2$ | $\rho | WS$ | $p_1$ | $p_2$ | $\tilde{p}_2$ |
|----------|----------|-----|------|-------|-------|----------|-------|-------|------------|
| 8.23     | 10.68    | 137.01 | 117.85 | 7.49 | 146.58 | 0.93 | 0.02 | 1.7e-4 | 1.7e-4 |
| (8.12)   | (2.97)   | (0.53) | (0.53) | (0)  | (0.33) | (0.01) | (0)  | (0)  | (0)        |

#### Average-Cost Pricing Rule with Decrease in Irrigation Use

| Change | $Y_{WS}$ | $N_{WS}$ | $S$ | $w'$ | $w_1$ | $w_2$ | $\rho | WS$ | $p_1$ | $p_2$ | $\tilde{p}_2$ |
|--------|----------|----------|-----|------|-------|-------|----------|-------|-------|------------|
| 1 %    | 12.10    | 7.45     | 138.07 | 118.42 | 7.49 | 145.42 | 0.93 | 0.02 | 1.7e-4 | 1.7e-4 |
| (12.48) | (2.97)   | (0.53) | (0.53) | (0)  | (0.33) | (0.01) | (0)  | (0)  | (0)        |
| 2 %    | 22.53    | 4.23     | 138.54 | 119.01 | 7.49 | 144.24 | 0.93 | 0.02 | 1.7e-4 | 1.7e-4 |
| (22.10) | (1.95)   | (0.52) | (0.53) | (0)  | (0.32) | (0.01) | (0)  | (0)  | (0)        |
| 3 %    | 41.71    | 2.09     | 139.02 | 119.61 | 7.49 | 142.95 | 0.93 | 0.02 | 1.7e-4 | 1.7e-4 |
| (32.81) | (1.39)   | (0.52) | (0.52) | (0)  | (0.31) | (0.01) | (0)  | (0)  | (0)        |
| 4 %    | 59.37    | 0.81     | 140.00 | 120.83 | 7.49 | 140.09 | 0.93 | 0.02 | 1.7e-4 | 1.7e-4 |
| (36.20) | (0.89)   | (0.51) | (0.52) | (0)  | (0.30) | (0.01) | (0)  | (0)  | (0)        |

#### Average-Cost Pricing Rule with Increase in Annual Inflows

| Change | $Y_{WS}$ | $N_{WS}$ | $S$ | $w'$ | $w_1$ | $w_2$ | $\rho | WS$ | $p_1$ | $p_2$ | $\tilde{p}_2$ |
|--------|----------|----------|-----|------|-------|-------|----------|-------|-------|------------|
| 1 hm$^3$ | 17.36    | 5.25     | 139.45 | 119.66 | 7.49 | 147.09 | 0.93 | 0.02 | 1.7e-4 | 1.7e-4 |
| (17.73) | (2.11)   | (0.50) | (0.50) | (0)  | (0.31) | (0.01) | (0)  | (0)  | (0)        |
| 2 hm$^3$ | 58.45    | 1.19     | 141.04 | 121.25 | 7.49 | 147.43 | 0.93 | 0.02 | 1.7e-4 | 1.7e-4 |
| (36.02) | (1.07)   | (0.51) | (0.52) | (0)  | (0.31) | (0.01) | (0)  | (0)  | (0)        |
| 3 hm$^3$ | 78.13    | 0.52     | 142.28 | 122.49 | 7.49 | 147.49 | 0.94 | 0.02 | 1.7e-4 | 1.7e-4 |
| (32.30) | (0.71)   | (0.45) | (0.45) | (0)  | (0.32) | (0.00) | (0)  | (0)  | (0)        |
| 4 hm$^3$ | 96.58    | 0.06     | 143.40 | 123.60 | 7.49 | 147.51 | 0.94 | 0.02 | 1.7e-4 | 1.7e-4 |
| (14.88) | (0.36)   | (0.42) | (0.43) | (0)  | (0.32) | (0.00) | (0)  | (0)  | (0)        |
| 5 hm$^3$ | 99.81    | 0.00     | 144.24 | 124.45 | 7.49 | 147.52 | 0.94 | 0.02 | 1.7e-4 | 1.7e-4 |
| (3.81)  | (0.05)   | (0.41) | (0.42) | (0)  | (0.32) | (0.00) | (0)  | (0)  | (0)        |

#### Dynamic Ramsey Pricing Rule with Increase in Reservoir Capacity

| Capacity | $Y_{WS}$ | $N_{WS}$ | $S$ | $w'$ | $w_1$ | $w_2$ | $\rho | WS$ | $p_1$ | $p_2$ | $\tilde{p}_2$ |
|----------|----------|----------|-----|------|-------|-------|----------|-------|-------|------------|
| 173 hm$^3$ | 100      | 0        | 153.60 | 137.73 | 6.58 | 90.95 | -       | 0.17  | 2.7e-3 | 2.7e-4     |
| (0)      | (0)      | (0.37)   | (0.37) | (0.01) | (0.21) | -      | 1e-3   | 1e-6  | 1e-6       |

| Capacity | $Y_{WS}$ | $N_{WS}$ | $S$ | $w'$ | $w_1$ | $w_2$ | $\rho | WS$ | $p_1$ | $p_2$ | $\tilde{p}_2$ |
|----------|----------|----------|-----|------|-------|-------|----------|-------|-------|------------|
| 400 hm$^3$ | 100      | 0        | 354.83 | 331.17 | 7.48 | 145.67 | -       | 0.02  | 2.6e-4 | 1.7e-4     |
| (0)      | (0)      | (0.71)   | (0.70) | (1e-3) | (0.46) | -      | 1e-3   | 1e-5  | 1e-6       |

**Table 5: Simulation Results**

**Note:** The values provided in this table are the mean and the standard deviation (in parentheses) of the variables of interest in 5,000 century-long simulations. I use the following notation in this table: $Y_{WS}$: number of years before the first water shortage, $N_{WS}$: number of water shortages in a century, $S$: water stock, $w'$: water savings for the next period, $w_1$: tap water use, $w_2$: irrigation water use, $\rho | WS$: rate of rationing during a water shortage, $p_1$: gross tap water price (before rebate), $p_2$: gross irrigation water price (before rebate), $\tilde{p}_2$: net irrigation water price (after rebate).
C Figures

Figure 1: Reservoir Flows (January–December)

Figure 2: Tap Water Use and Price
Figure 3: Irrigation Water Prices

Figure 4: Crop Composition
Figure 5: Water Shortages in the Turkish Data