Do changing weather patterns warrant more flexibility in quota policy for irrigation water conservation? A case study in Mexico

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1. Introduction

In many regions of the world, irrigation is the backbone of agricultural production. But water supply is not unlimited, and it can even become severely scarce relative to its demand. Consequently, it is critical that water resources are managed in a sustainable way. In most unregulated situations this is not a forgone conclusion as irrigators (farmers) do not internalize the externalities associated with their own water use (Fishman, 2018). Agricultural water management policies aim to induce farmers to internalize those externalities and reduce consumption. Perhaps three of the most prominent policies include a cap or quota on water use, tier pricing (so that prices approximately reflect raising marginal cost), and a flexible cap that is adjusted as new weather information arrives during the growing season. In this paper, we compare these instruments based on their relative efficiency. We do so by deriving formal expressions for the expected deadweight loss associated with each instrument and quantifying those expressions based on data from irrigation districts in Mexico.

The first instrument we consider is a cap or quota (hereafter fixed quota). Under a fixed quota policy, the government assigns or sells a fixed amount of permits (the "quota") to irrigators. A fixed quota policy ensures water conservation by limiting total water use, which is the sum of permits allocated to individuals.[1] A key challenge of fixed quota policies is to first identify the correct (efficient) level of total water use. The efficient cap is where the marginal social benefit (MSB) of water equals the marginal social cost (MSC). But MSB and MSC are inherently stochastic, so when their random realizations do not coincide with their predicted levels (based on which the fixed quota is set), then ex-post deadweight losses arise.

[1] CAP policies are not exclusive to water, of course. They have been implemented to curb air pollution as well (e.g. the EU Emissions Trading Scheme (EU-ETS) and the US Regional Greenhouse Gas Initiative (RGGI)) (https://ec.europa.eu/clima/policies/ets/reform_en, https://www.rggi.org/program-overview-and-design/elements)

Two prominent mechanisms have been proposed that add flexibility to a fixed quota policy and lower average deadweight losses. First, a *hybrid* mechanism, whereby agents can use an amount of water higher (lower) than the cap paying a fee (receiving a subsidy) that is higher than market price. This mechanism is called hybrid because it combines elements of quantity- and price-based policies. A hybrid policy is equivalent to tier-pricing (where the price is the opportunity cost) of water. Second, an *index quantity* mechanism, whereby the government changes the cap as new information regarding MSB and MSC arrives. While MSB and MSC are themselves unobservable, this mechanism relies on observable measures that are correlated with MSB and MSC, called an index (e.g. an observable measure of weather).

Previous studies demonstrated that the ability of flexible mechanisms to mitigate deadweight losses associated with a fixed quota depends crucially on i) the relative slopes of MSB and MSC (Weitzman, 1974), ii) the degree of uncertainty in MSB (Jacoby and Ellerman 2004; Jotzo and Pezzey 2007) and MSC (Leard, 2013; Pizer, 2002; Quirion, 2005), and iii) the strength of the correlation between the chosen index and MSB and MSC (Newell and Pizer, 2008; Webster et al., 2010). This underscores the fact that efficiency gains from flexible mechanisms are, ultimately, an empirical question. In this study we empirically examine the extent to which flexible mechanisms would mitigate deadweight losses in heavily irrigated agricultural districts in Mexico.

The strategy is as follows. We first estimate a structural model of water demand, where the marginal value of water is a function of weather.[2] Second, we combine this with computed probability distributions of weather variables to estimate the probability distribution of the

[2] While uncertainty in both MSB (Jacoby and Ellerman 2004; Jotzo and Pezzey 2007) and MSC (Leard, 2013; Pizer, 2002; Quirion, 2005) matters for policy performance, we focus on the former. This is because uncertainty related to MSB is particularly relevant in the context of water conservations as demand is highly sensitive to realized weather conditions (Haqiqi, 2019). As a result, in this study we are primarily concerned with uncertainty on MSB.

marginal value of water (MSB). Third, we use this probability distribution to formally characterize the optimal design of each policy instrument: the optimal level of the fixed quota, the optimal subsidy/cap/tax combination of the hybrid policy, and the ex-post adjustment of the indexed quantity. Fourth, and conditional on these designs, we derive formal expressions for deadweight loss for each policy instrument. Finally, we compute probability distributions of deadweight losses for a range of slopes of MSC. This is motivated by the fact that the slope of MSC is unobservable to us, so our objective is then to welfare-rank policies for a range of slopes of the MSC curve.

We find that the use of a hybrid policy can increase efficiency substantially. This is true relative to both a fixed cap and an indexed quantity. The flexibility provided by a hybrid policy not only raises efficiency on average but also reduces downside risk, i.e., it shrinks the lower tail of the efficiency distribution. Therefore, the hybrid policy dominates the other two alternatives based on a second order stochastic criterion. Our analysis allows for a systematic comparison of instruments when reliable estimates of the slope of MSC are not available.

The performance of competing policy instruments crucially depends upon the probability distribution of MSB, which in turn is shaped by weather patterns characterized by the probability distribution of temperature and precipitation. A key issue in the context of water conservation policies is how changes in weather patterns due to climate change will affect the relative performance of competing policy instruments. Perhaps more fundamentally, the question we raise is whether climate change is likely to enhance or lessen the value of adding flexibility to water conservation policies. We examine this issue by conducting counterfactual experiments in which we compare policies under future, projected weather patterns.

To compute our counterfactual scenarios, we first estimate probability distributions of current and projected weather patterns (i.e., we estimate the data generating process underlying random weather occurrences). We combine these with the structurally estimated water demand and generate probability distributions of the MSB curve. We subsequently obtain random draws of MSB from those distributions and compute deadweight losses for each policy instrument. We iterate this procedure to obtain a probability distribution of deadweight losses for each policy and each scenario of projected weather patterns. Finally, we use these probability distributions to compare policies.

We find that projected changes in weather patterns will increase the value of flexibility and, especially, of the type of flexibility provided by a hybrid policy. But the efficiency gains (or prevented losses) from flexible water conservation policies are very sensitivity to the slope of MSC relative to MSB. It is important to note that, over time, MSC curves may become steeper as water sources are increasingly exhausted. This development would favor a fixed quota policy, undermining the benefits of flexibility under a changing climate.

Our paper is related to studies on quota or cap policies addressing air pollution. But it is closest to other studies examining water conservation policies. Yet many of those studies consider policies that are more typical of a developed country context, in which creation and enforcement of property rights are robust. For example, previous studies have considered water rights or well retirement programs through payments (Tsvetanov and Earnhart, 2020), zoning (Drysdale and Hendricks, 2018), and trading restrictions (Bigelow et al 2019). However, little is known about the empirical performance of policies that are more commonly implemented in developing countries such as quotas (flexible or not) and energy tier-pricing to reflect the marginal cost of extraction. Our paper contributes to fill this gap in the literature.

2. Conceptual framework

2.1. Policy Mechanisms

We start by considering a conventional fixed quota policy where we characterize an expected demand for water; i.e. which is the estimated demand for water evaluated at average prices and weather conditions. Consider, as plotted in the left panel of Figure 1, a situation where the cap Q^{FQ} is set where expected demand ($E[MB]$ in Figure 1, panel A) intersects MC. However, realized demand may be above or below expected demand. Random realizations of demand take place according to a probability distribution. If realized demand is higher (MB_H) than expected demand and MC is not vertical, then the socially optimal amount of irrigation (Q_H^{SO}) is higher than the quota level (Q^{FQ}). If no flexibility is introduced to the cap, then the conventional quota policy results in a substantial deadweight loss, indicated by area in gray shadow. The opposite case is also true where the realized demand is lower than the expected demand (MB_L) which generates inefficiently too small cap level at Q_L^{SO}. Providing additional flexibility to the cap can reduce those deadweight losses. We examine two mechanisms to provide flexibility to the cap: a *hybrid* cap policy, and *index quantity* cap policy.

In the hybrid cap policy, irrigators can use an amount of water that exceeds the cap, as long as they pay a pre-defined price for additional water, denoted by $p^{ceiling}$ and p^{floor} in panel B. This system provides a cost containment as well as price containment mechanism in situations where the marginal value product of water is very large (or small), raising (or reducing) the socially optimal amount of water at Q_H^{so} (or Q_L^{SO}). Then, depending on the realized demand $(MB_H \text{ or } MB_L)$, the price mechanism becomes relevant and total irrigation water is allocated at Q_H^{HB} (or Q_L^{HB}) which deviates from Q^{FQ}. Thus, this adjustment still results in a deadweight loss denoted by gray area in panel B, which is smaller than the shaded area in panel A, the deadweight loss without flexibility. Under the hybrid cap policy, the pre-defined price at which irrigators can procure additional water rights is set to minimize deadweight loss, conditional on the probability distribution of water demand. We will formally characterize the derivation of $p^{ceiling}$ and p^{floor} in the model section.

In contrast to the hybrid policy which determines a flexibility mechanism ex-ante (previous to the realization of water demand and MSC), the index quantity policy changes the cap ex-post to adjust the policy to realized (as opposed to expected) demand. Since demand is not directly observable, the cap is adjusted based on a certain observable measure that is correlated with demand. This observable measure is called an index.

If, for instance, rainfall is scarce and temperatures are high during the growing season, both factors that are associated with higher water demand, then the cap can be increased. Panel C in Figure 1 portrays a situation where an index X associated with realized demand is observed, and then the cap is raised to Q_H^{IQ} or decrease to Q_L^{IQ} resulting from adjustment of fixed quota at point a. Since the index X is not perfectly correlated with demand, the adjusted cap will not precisely correspond to the socially optimal level (Q_H^{SO} or Q_L^{SO}) and some degree of deadweight loss will take place. The stronger the correlation between the chosen index and realized demand, the smaller deadweight loss. In panel C, we plot a situation in which the correlation is strong enough (the estimated demand is sufficiently close to realized demand) so that the deadweight loss under the index quantity cap (gray area) is smaller than the gray area in panel A, the deadweight loss under status quo, a fixed quota policy.

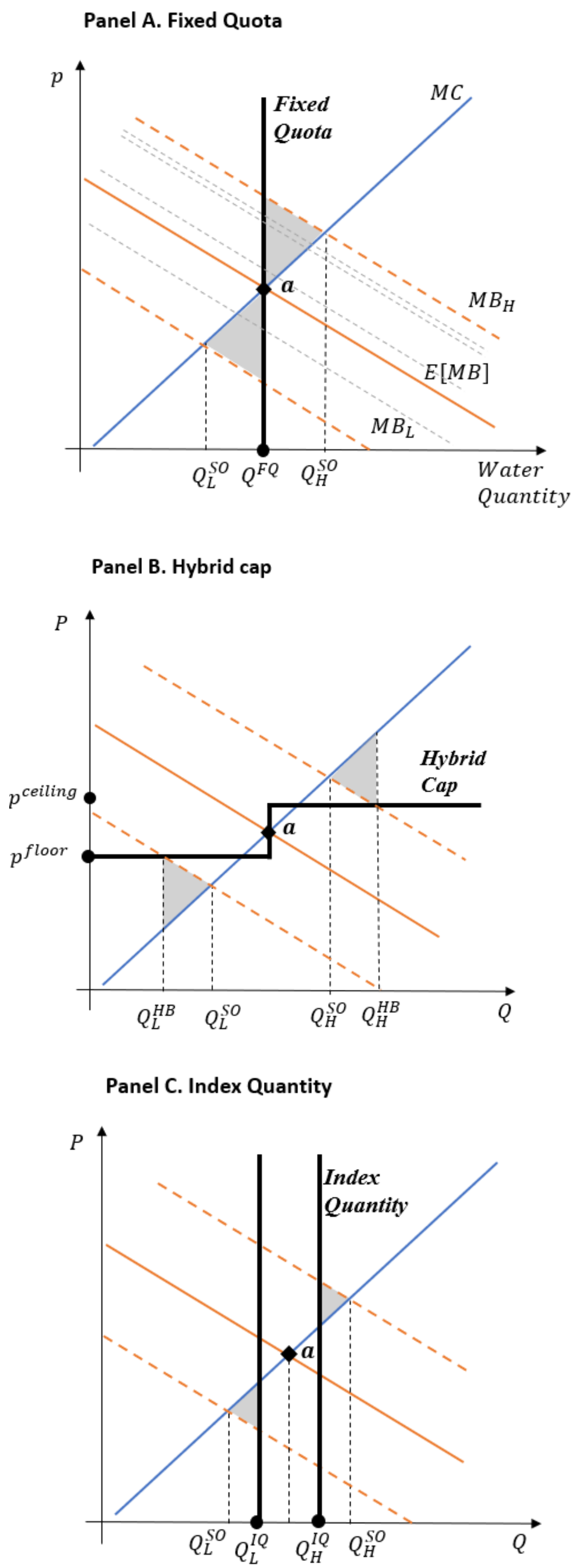


Figure 1 The cap allocating mechanisms and their expected deadweights loss

3. Analysis

The objective of this study is to empirically develop a policy rule; i.e. identify the optimal policy mechanism under different conditions regarding the slope of MSC. The optimal policy in each circumstance is the one maximizing total surplus (i.e., minimizing deadweight loss). To compute deadweight losses (DWL), it would be ideal to estimate the marginal social cost of irrigation water. Unfortunately, the data necessary to do so is simply not available, which is a prevalent problem in environmental economics (Auffhammer 2018).[3] Therefore, instead of pursuing the futile task of estimating MSC, we conversely back out the slope of MSC around the current prevailing caps in Mexican municipalities that would make a government indifferent between pairs of policy mechanisms. Specifically, the following steps describe analysis strategy.

1. Estimate water demand at the municipality level (point a in Figure 1).
2. Find the amount of water at the average cap and compute the height of demand at that cap; that is the height of MSC (point a in Figure 1).
3. Introduce modifications to the cap according to policy alternatives (panel A, B, and C).
4. Simulate realizations of demand and, conditional on MSC slope, compute DWL for each policy and each realization (gray area in panel A, B, and C).
5. Repeat 100 times and take the average across the realized gray area (panel A, B, and C)
6. Compare the values of DWL.
7. Repeat 1-6 for different MSC slopes.
8. Find the threshold slopes of flexible CAP policies at which the size of ABC is equal to the size of gray area in panels A, B, and C.

[3] Some that quantify costs of irrigation water utilize hedonic model wherein damage due to water depletion is the lost value of land value (Perez-quesada et al., 2020; Sampson et al., 2019). However, such costs do not fully capture the variation of social costs due to the weather shock.

Completing these iterative procedures will allow me to plot the relationship between the changes of DWL in relative slopes under each institution. One of the meaningful results of this study is to find the threshold level of slope, if there exists, at which any two cap allocating mechanisms can be compared so ranking is determined. Since we compare three cap mechanisms, there will be three sections created by the two threshold slopes. Based on these results, our goal is to identify an optimal policy that produces the least DWL within the specified ranges of slopes. Fully identifying policy schedules based on the welfare ranking as a function of the relative slope of MSC and MSB is the main contribution of this study.

4. Model

In this section, we develop two models in preparation for comparative welfare analysis as described. Our first model is to estimate the water demand function with which we can quantify welfare under different cap policy simulations. In that welfare quantification process, we use the welfare formula derived from our second model where we explicitly derive the analytical expression to calculate deadweight loss under each cap policy. The first and second models are followed in the following sections.

4.1. Water demand estimation model

Many studies estimating water demand use direct observations on water use in combination with exogenous variation in water prices to identify demand parameters (Bruno and Jessoe, 2019; Schoengold et al., 2006). However, farmers do not pay a price for irrigation water in Mexico. Alternatively, without price information, some studies use pumping costs (energy cost) as a proxy for water prices (Hendricks and Peterson, 2012; Pfeiffer and Lin, 2014). However, pumping costs are not a relevant proxy to identify water demand in Mexico because they are heavily subsidized and little exogenous variation is observed over time. In fact, Mexican irrigators operate under binding volumetric concessions (quota). At the level of the concession the marginal benefit of water use is considerably higher than the marginal cost. Therefore, we estimate the shadow price of water by exploiting exogenous variation in the level of the binding cap at which farmers operate.

In our data set, we have information on farm revenue, crop production, water cap, weather (rainfall and temperature), crop prices, and land allocation to farming. The strategy for estimation of water demand is a direct corollary of available data. we use a revenue function (where revenue is a function of crop prices, water, weather, and land) and apply Hotelling's lemma to derive the supply for each crop. we use data to estimate the revenue function and derived supplies simultaneously (to increase estimation efficiency). We then derive a water demand function by taking a partial derivative of revenue with respect to the binding water cap. We use estimated parameters and available data to compute the shadow price of water for agents in the sample; the shadow price as a function of prices, weather, and land constitutes a formal characterization of water demand.

As a functional form, we use a normalized generalized quadratic revenue function. We consider producer behaviors by aggregating crop outputs into four groups such as grain irrigated, non-grain irrigated, non-grain not irrigated, and grain not irrigated using the price aggregation method introduced by Jorgenson, Gollop, and Fraumeni (1987) where output prices are weighted by own revenue share. We also separate inputs like water and others because the main interest is the quantity of water consumption. The revenue function is specified as

$$\begin{aligned} R_{it}\{\boldsymbol{W}, p_j, \boldsymbol{z}\} = {} & \alpha_0 + \alpha_1 p_{j_{\text{it}}} + \alpha_2 p_{j_{\text{it}}}^2 + \alpha_3 p_{j_{it}} p_{-j_{\text{it}}} + \alpha_4 q_{\text{it}} + \alpha_5 l_{it} \\ & + \alpha_6 q_{\text{it}}^2 + \alpha_7 l_{\text{it}}^2 + \alpha_8 q_{it} l_{it} + \alpha_9 p_{j_{it}} q_{\text{it}} + \alpha_{10} q_{it} \boldsymbol{W}_{\text{it}} \\ & + \alpha_{11} p_{j_{it}} l_{it} + \alpha_{12} \boldsymbol{W}_{it} + \alpha_{13} p_{j_{it}} \boldsymbol{W}_{it} + \varepsilon_{it} \end{aligned} \tag{1}$$

where *i* and *t* are indexes to represent municipality *i* and year *t*. *j* is the index of the normalized crop types and *p* is output price such that $p_j \in \{p_g/p_{g,d}, p_{ng}/p_{g,d}, p_{ng,d}/p_{g,d}\}$ is a vector of output crop prices which consist of grain irrigated (p_g), non-grain irrigated (p_{ng}), and non-grain not irrigated ($p_{ng,d}$) normalized by the price of non-grain irrigated ($p_{g,d}$). $\boldsymbol{z} \in \{q, l\}$ is an input vector of irrigation water (z_w) and other inputs used in which land sizes planted are a proxy (l). $\boldsymbol{W} \in \{Temp, Preci\}$ is a vector of weather variables for temperature and precipitation.

Crop supplies can be readily derived from the revenue function through the application of Hotelling's lemma, by taking partial derivatives of these revenue functions with respect to the corresponding crop prices. Under a binding volumetric concession, the crop-specific supply functions are:

$$\frac{\partial R_{it}}{\partial p_j} = y_{j_{it}} = \alpha_1 + 2\alpha_2 p_{j_{it}} + \alpha_3 p_{-j_{\mathrm{it}}} + \alpha_9 q_{\mathrm{it}} + \alpha_{11} l_{it} + \alpha_{13} \boldsymbol{W}_{it} + \varepsilon_{it} \tag{2}$$

where $y_j \in \{y_g, y_{ng}, y_{ng,d}\}$. y_g and y_{ng} depict supply of irrigated grain and non-grain crops respectively, and $y_{ng,d}$ depicts supply of rainfed non-grain. These supplies depend on prices but also on effective water which is both a function of the volumetric concession q. Note that our panel data provides enough data in equilibrium that our estimated revenue coefficient is likely to be efficient. Since these coefficients estimated at the municipality level will be used in constructing marginal benefit function, efficient estimation due to panel data are important in our specification.

Finally, we derive the value of marginal productivity of water by taking the partial derivative of estimated revenue function *w*ith respect to water consumption (equal to the marginal value product of water), which allows me to find water demand function in municipality level *i* by aggregating data over time as well as recovering the normalizing factor ($p_{g,d}$).

(3) $$MB_i = f_i(\widehat{b_1}_{i,t}|\boldsymbol{W}_{it}) + E_t[\widehat{b_2}_{it}]q_i$$

where $\widehat{b_1}_{it} = p_{g,d}{}_{it}\{\hat{\alpha}_4 + \hat{\alpha}_8 l_{it} + \hat{\alpha}_9 p_{j}{}_{it} + \hat{\alpha}_{10}\boldsymbol{W}_{it}\}$, $\widehat{b_2}_{it} = p_{g,d}{}_{it}\{2\hat{\alpha}_6\, q_{it}\}$.

Thus, water demand functions are fully recovered (intercept and slope). Since weather variables affect demand only through the intercept of the demand function, any weather variations will shift the demand curve in a parallel manner without distorting the slope.

To simplify our policy analysis, we use the one representative marginal benefit curve for Mexico's water uses by aggregating MB_i, originally constructed at the municipality level, to state levels. This state level cross-sectional data gives variance in intercept of the representative marginal benefit function and its mean serves as the slope. This as the realized marginal benefit curve estimated at the state level.

(4) $$MB(\theta) = f_s(\widehat{b_{1,s}}) + \widehat{b_2}q$$

We parameterize the variance from the variation in the intercept of equation (4) and denote it as σ^2. Therefore, the y-intercept of the state representative realized water demand function is bounded by lower and upper bound of the uniform distribution, $f_s(\widehat{b_1}) \sim U(E[\widehat{b_1}], \sigma^2)$. In our notation, we denote the uncertainty θ as the deviation from the mean $E[\widehat{b_{1,s}}]$, hence θ is distributed with zero mean and standard deviation σ. For computational simplicity, we use uniform distribution of $\theta \sim U(-\sigma, \sigma)$ where σ is estimated from our data.

4.2. Alternative cap allocation policy

In this section, we consider two flexible cap policies: (i) hybrid and (ii) indexed quantity in to compare with the status quo, a fixed quota policy. Here, we use expected net benefits to measure the compare each policy instead of deadweight loss discussed in the previous chapter because either measure will generate the same comparison results based on the relationship, $DWL^k = NB^C - NB^k$ where NB^C is welfare at competitive equilibrium.

4.2.1. Fixed quota policy (status quo)

Following Weitzman (1974), the cost and benefits function of water consumption (q) is expanded around the optimal fixed quota quantity Q^{FQ}.

(5) $$C(Q) = c_0 + c_1(Q - Q^{FQ}) + \frac{c_2}{2}(Q - Q^{FQ})^2$$

(6) $$B(Q) = b_0 + (b_1 + \theta)(Q - Q^{FQ}) - \frac{b_2}{2}(Q - Q^{FQ})^2$$

where Q denotes water consumption, $c_0, c_1, c_2, b_0, b_1, b_2$ are parameters to be estimated. θ represents stochastic uncertainty.

Then, by taking derivative we obtain our basic demand and supply function of water as follows.

(7) $$MC(Q) = c_1 + c_2(Q - Q^{FQ})$$

(8) $$MB(Q) = (b_1 + \theta) - b_2(Q - Q^{FQ})$$

As noted in (6) water demand curve shifts vertically only overtimes. Under the fixed quota policy, the optimal policy decision is to set the level of quota that minimizes the expected deadweight loss with uncertainty, which can be expressed as

(9) $$\underset{Q}{\text{Min}}\ E_\theta(DWL^{FQ}; \theta)$$

In solving this optimization problem, regulators equalize the expected marginal benefits and marginal costs $E_\theta[MB] = MC$. Assuming that distribution of uncertainty θ as symmetry, the optimal quantity is same as the quantity under fixed quota, $Q^* = Q^{FQ}$.

(10) $$Q^* = Q^{FQ}$$

We quantify deadweight loss under fixed quota policy when the realized marginal benefits deviate from the expected marginal benefit curve. A bootstrap approach is appropriate to perform this work where a random draw is generated from the known uniform distribution 100 times. Recall that the distribution is known because we estimate the variance of water demand. Since each draw (θ_i) forms a realized water demand curves that deviate from the fixed quota, deadweight loss arises for any positive deviation ($\theta_i > 0$). We quantify this inefficiency of each draw by the following equation. Notice that the second bracket term has no uncertainty associated with it because the quota is fixed regardless of the realized water demand, which is $DWL_i^{FQ} = \{B(Q_i^{SO};\theta_i) - C(Q_i^{SO};\theta_i)\} - \{B(Q_i^{FQ}) - C(Q_i^{FQ})\}$. The representative deadweight loss of the hybrid policy is then determined by taking an average of over 100 times of repetition. Simplifying this equation, we get the analytical expression.

(11) $$DWL^{FQ} = E_i\left(\theta_i^2(Q^{SO} - Q^{FQ}) - \frac{1}{2}(b_2 + c_2)(Q^{SO} - Q^{FQ})^2\right)$$

This is our benchmark of fixed quota policy with no flexibility. Next, we consider a hybrid policy where, by design, some flexibility in allocating cap is added.

4.2.2. Hybrid policy

As noted in Figure 1, the hybrid policy uses the combined price mechanisms using $p^{ceiling}$ and p^{floor} at which farmers can purchase extra water permits or subsidize for selling water quantities. Designing a hybrid policy requires to set a price ceiling (or price floor) at which more (or less) water quantity can be adjusted. This is equal to say that hybrid policy is not different from the fixed quota policy unless the price ceiling or floor become activated. Thus, setting the optimal level of price ceiling and price floor is the key decision for hybrid policy. Regulators can do so by minimizing deadweight loss of the expected payoffs including the case where either price ceiling or price floor bind and where they do not. The binding price condition can be expressed as the deviation is high enough to be beyond some threshold level of uncertainty $\tilde{\theta}$ (i.e., $\theta \geq \tilde{\theta}$ or $\theta \leq -\tilde{\theta}$). The probability of binding price mechanism is, therefore,

$Prob(\theta \geq |\tilde{\theta}|)$ and the probability of non-binding price mechanism is $Prob(\theta \leq |\tilde{\theta}|)$. The optimization problem is set by

$$\text{(12)} \qquad \underset{\tilde{\theta}}{\text{Min}} \left\{ \underbrace{Prob(\theta \geq |\tilde{\theta}|)E_{\theta}(DWL^{HB}|\theta \geq |\tilde{\theta}|)}_{Price\ control} + \underbrace{Prob(\theta \leq |\tilde{\theta}|)E_{\theta}(DWL^{HB}|\theta \leq |\tilde{\theta}|)}_{Quantity\ control} \right\}$$

This optimization problem provides the optimal level of price ceiling and price floor using the solution of $\tilde{\theta}^* = \underset{\tilde{\theta}}{\text{argmin}}\ E(DWL^{HB})$ such as $p^{ceiling} = b_1 + \tilde{\theta}^*$ and $p^{floor} = b_1 - \tilde{\theta}^*$. The solution is therefore dependent upon the distribution of water demand shock θ which follows some distribution f.

$$\text{(13)} \qquad \theta \sim f(m(\theta), \sigma(\theta))$$

In this study, we use uniformly distributed uncertainty with zero mean to derive an analytical solution. Hence, $m(\theta) = 0$ and $\theta \sim U(-\sigma, \sigma)$. Under the uniform distribution assumption, we further expand the equation (13) as follows. $Prob(\theta \geq |\tilde{\theta}|) = \int_{\tilde{\theta}}^{\sigma} \frac{1}{2\sigma} d\theta = \int_{-\sigma}^{-\tilde{\theta}} \frac{1}{2\sigma} d\theta = \frac{1}{2} - \frac{\tilde{\theta}}{2\sigma}$ and $Prob(\theta \leq |\tilde{\theta}|) = \int_{-\tilde{\theta}}^{\tilde{\theta}} \frac{1}{2\sigma} d\theta = \frac{\tilde{\theta}}{\sigma}$. The conditional expected value of DWL under hybrid under the price mechanism (i.e., when price ceiling or floor is binding) is $E_{\theta}(DWL^{HB}|\theta \geq |\tilde{\theta}|) = 2\int_{\tilde{\theta}}^{\sigma} \frac{E(B(Q^{SO};\theta) - C(Q^{SO})) - E(B(Q^{HB};\theta) - C(Q^{HB}))}{(\sigma - \tilde{\theta})} d\theta$. The conditional expected value of DWL under the quantity mechanism (i.e., when price ceiling or floor is not binding) is $E_{\theta}(DWL^{HB}|\theta \leq |\tilde{\theta}|) = \int_{-\tilde{\theta}}^{\tilde{\theta}} \frac{E(B(Q^{SO};\theta) - C(Q^{SO})) - E(B(\bar{Q};\theta) - C(\bar{Q}))}{(2\tilde{\theta})} d\theta$. Solving the first-order condition finds the optimal threshold level of uncertainty, $\tilde{\theta}^* = \frac{c_2\sigma}{2b_2 + c_2}$. This determines price ceiling and price floor such as $p^{ceiling} = b_1 + \tilde{\theta}^*$ and $p^{floor} = b_1 - \tilde{\theta}^*$. Thus,

(14) $$p^{ceiling} = b_1 + \frac{c_2\sigma}{b_2(2 + (c_2/b_2))}$$

$$p^{floor} = b_1 - \frac{c_2\sigma}{b_2(2 + (c_2/b_2))}$$

Note that these prices are determined endogenously based on the relative slope of MSB and MSC functions. For example, the hybrid policy will place higher weights on price mechanism as the slope of MSC (c_2) gets flatter by narrowing the gap between $p^{ceiling}$ and p^{floor}. However, more weights will be given to quantity mechanism with a steep slope of MSC (c_2) by increasing the difference between p^c and p^f. In that sense, the relative slopes (c_2/b_2) can be fully endogenized in the quantity under hybrid policy.

(15) $$Q^{HB} = Q^{FQ} \pm \left(\theta - \frac{(c_2/b_2)\sigma}{2 + (c_2/b_2)}\right)\frac{1}{b_2}$$

where it notes that quantity will be adjusted increasing when price ceiling binds ($e.g., +$ sign) but the quantity will be lowered when price floor binds ($e.g., -$ sign). Of course, if either price ceiling or price floor does not bind (i.e., the demand deviation (θ) is small), then the quantity under the hybrid policy is the same as fixed quota ($i.e., Q^{HB} = Q^{FQ}$).

Also, we note that hybrid quantity may be larger or smaller than the socially optimal cap quantity denoted by $Q^{SO} = Q^{FQ} + \frac{\theta}{b_2(1+(c_2/b_2))}$ depending on two factors: the relative sizes of parameters $\left(\frac{c_2}{b_2}\right)$ and the distributional information σ. In expectation, however, hybrid cap policy produces quantity identical to the fixed quota policy under the assumption of mean zero shock.

(16) $$E[Q^{HB}] = E[Q^{SO}] = Q^{FQ}$$

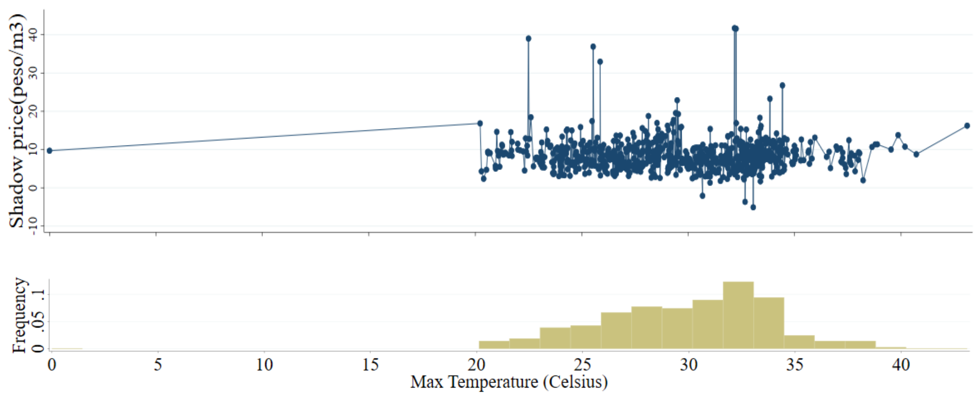
We compute DWL using a bootstrap approach where a random draw is generated from the known uniform distribution 100 times. Since each draw(θ) forms a realized water demand curve, deadweight loss is likely to occur by the difference between the drawn water demand and the targeted water demand given the hybrid policy. The deadweight loss is calculated by the following formula for each random draw $i = [1,100]$ which is $DWL_i^{HB} = \{B(Q_i^{SO};\theta_i) - C(Q_i^{SO};\theta_i)\} - \{B(Q_i^{HB};\theta_i,\sigma) - C(Q_i^{HB}:\theta_i,\sigma)\}$. The deadweight loss of the hybrid policy is then determined by taking the average over the 100 times of repetition.

$$DWL^{HB} = \begin{cases} E_i\left[\theta_i(Q^{SO} - Q^{FQ}) - \frac{1}{2}(b_2 + c_2)(Q^{SO} - Q^{FQ})^2\right] & if\ Not\ binding \\ E_i\left[\theta_i(Q^{SO} - Q^{HB}) - \frac{1}{2}(b_2 + c_2)((Q^{SO} - Q^{FQ})^2 - (Q^{HB} - Q^{FQ})^2)\right] & if\ Binding \end{cases} \quad (17)$$

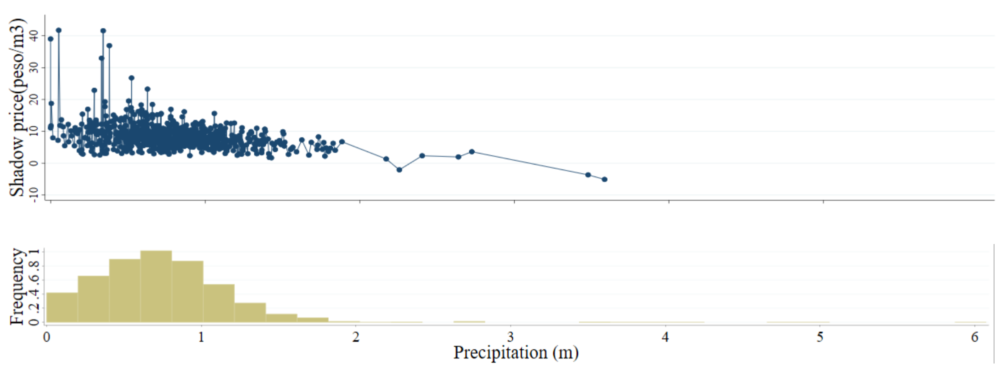
4.2.3. Indexed quantity (IQ)

The use of available information to determine cap quantity is known as index quantity policy (Newell and Pizer 2008). In our study, index quantity policy uses weather information to add some flexibility to the fixed quota policy. To practitioner, the main advantage of IQ policy is the simplicity because they can just use observable information instead of estimating water demand in every season which requires various other information as well such as production input and output. Hence, even though IQ policy does not rely on a perfect estimation of water demand, it uses a proxy of the realized water demand using weather information as an index.

Of water demand relevant weather information (max temperature and precipitation), we focus on rainfall information to adjust water cap level compared to fixed quota. Indeed, we also considered temperature information as the candidate of index information because it is known that high temperature is also related to high water demand. In our data, however, we observe that the degree of uncertainty of water shadow price is more sensitive to rainfall fluctuation (i.e., below-average precipitation) than temperature variation (i.e., above-average maximum temperature). This is illustrated in Figure 2 in which panel B shows strong relationship between greater variation in water demand and lower precipitation. On the other hand, panel A shows relatively weak relationship between water demand variation and maximum temperature. Specifically, we denote the coefficient of the relationship between water demand and rainfall by η. We calibrate η from the rainfall variable in RHS of Equation (3) where $MB = \eta \times Preci \text{ and } \eta = E\left[p_{g,d}\right] \times \hat{\alpha}_{10}$. The calibrated η has mean and standard deviation, -0.0034 and 0.002 respectively, showing a clear negative relationship between rainfall and water demand shock.



Panel A. Variation of Maximum Temperature and Water Shadow Price



Panel B. Variation of Precipitation and Water Shadow Price

Figure 2 The relationship of water demand uncertainty with respect to weather information (Panel A is for maximum temperature and Panel B is for precipitation)

In this study, the extra cap is allocated than a fixed quota if rainfall is short compared to the average rainfall level, but less cap is allocated if the observed rainfall information is greater than the average level of rainfall in each state. In this setup, the only policy parameter under IQ is the degree of flexibility by which the existing fixed quota level is increased or decreased. We employ symmetric allocation rule to simplify the analysis using the parameter ρ where $\rho \in [0,1]$. As a base level, we use $\rho = 0.2$, but we also consider the varying level of ρ in chapter 6.2.1.

(18)
$$Q^{IQ} = \begin{cases} (1+\rho)Q^{FQ} & if\ Preci_t < E[Preci] \\ (1-\rho)Q^{FQ} & if\ \ Preci_t > E[Preci] \end{cases}$$

where $Preci_t$ is related to the random realization of water demand shock (θ) defined in Equation (*13*). Since the calibrated relationship between rainfall and water demand is η_i, each simulation produces precipitation from $Preci_t = \eta \times \theta$.

The expected cap allocated under IQ policy can be expressed as a function of variable precipitation, $Preci$, which is $E(Q^{IQ}) = \int_{Preci}\{(1+\rho)Q^{FQ}\ f(Preci)\}\ d(Preci) + \int_{Preci}\{(1-\rho)Q^{FQ}\ f(Preci)\}\ d(Preci)$. Similar to hybrid policy, under the symmetric assumption of rainfall distribution with zero mean of uncertainty, the expected quantity under IQ policy is equal to the fixed quota. Therefore, in expectation, all three policies (index quantity, hybrid, and fixed quota) have the same cap quantity as the socially optimum level.

(19)
$$E[Q^{HB}] = E[Q^{IQ}] = Q^{FQ} = E[Q^{SO}]$$

The deadweight loss under IQ policy is computed by taking differences of welfare between social optimal quantity and the IQ cap quantity, expressed as $DWL_i^{IQ} = \{B(Q_i^{SO};\theta_i) - C(Q_i^{SO};\theta_i)\} - \{B(Q_i^{IQ};R_i) - C(Q_i^{IQ};R_i)\}$. We simulate 100 times of water demand shock (θ_i) to generate the representative DWL^{IQ}.

(20)
$$DWL^{IQ} = E_i\left[\theta_i(Q^{SO} - Q^{IQ}) - \frac{1}{2}(b_2 + c_2)((Q^{SO} - Q^{FQ})^2 - (Q^{IQ} - Q^{FQ}\ )^2)\right]$$

5. Data and Identification

We use nationwide Mexican irrigation and agricultural production panel data spanning over 8 years from 2007 to 2015 except for 2010 provided by Sesmero and Schoengold (2020). It covers

30 states, 248 municipalities, and 86 irrigation districts with a total of 1,713 observations at the municipality level. Under this dataset, we have access to crop production, prices, water volumetric concessions, and agricultural land acreage data. All of the data is aggregated at the municipality level given that each dataset is collected at a different level. The following sections describe each type of data more in detail.

The crop-level production data is available at the municipality level, which is initially collected from the Estadística de Producción Agrícola report. The collected production data includes crop-level information on the area, crop price, and thus value (revenue) of production for each municipality. Values are recorded separately for irrigated and rainfed production. In terms of crop-types, since there are ranges of crop types counted in municipalities of the whole country, potential issues (e.g. model tractability and censored problems) might arise noted by Sesmero and Schoengold (2020). Thus, crop types are aggregated into four types (grains/ irrigated, grains/non irrigated, non-grains/irrigated, and non-grains/non-irrigated). To generate the aggregate price, Jorgenson's exact aggregation method is used where the aggregate price is calculated using each crop's price and share of total revenue. Thus, the final production dataset includes output (tons), revenue (millions of pesos), hectares planted (ha), hectares harvested (ha), and price (pesos) for every four categories.

The water consumption data is collected at the irrigation district. The data is collected from the annual reports of Estadísticas Agrícolas de Los Distritos de Riego, published by the Comisión Nacional Del Agua (CONAGUA). In each irrigation district, total water allocation is summed by surface water and groundwater allocation (m^3). To compute data on the crop mix by irrigation source and total area irrigated, water data is combined with the production data. To do so, water data is processed to only include agricultural-related water use, which means that municipalities with only rainfed production are not included due to irrelevancy. Another data processing issue is that since the geographical jurisdiction of irrigation districts do not always match with the ones of municipalities, merging the irrigation district data and municipality data takes the extra steps. The key difficulty is that there is no information on the water use within irrigation districts. Therefore, the irrigated area and water use of an irrigation district are simply equally divided between municipalities where that irrigation district is located. For example, if one irrigation district is in three municipalities, 1/3 proportions of the associated water use and irrigated area are allocated to each municipality. Then, water use and irrigated area in each municipality are generated by summation.

The weather data is collected at the weather station level from Servicio Meteorológico Nacional. The data includes daily information on total precipitation (mm) and maximum/minimum temperature (℃). The daily data for each station is aggregated to calculate annual precipitation and the average maximum and minimum daily temperature. To be consistent with other data, weather data is also aggregated at municipality level based on average of the weather observations for weather stations located in the municipality. If there is no weather station in the municipality, the average of all stations in the state is used.

We estimate the system (1) and (2) jointly by linear seemingly unrelated regression with fixed effects. We have a total of 24 cross-equation restrictions. Since we estimate the model by fixed effects, which means we do not estimate intercepts, we only have 21. We estimate our model at the municipality level. We estimated our model using 173 municipalities for a period of 8 years (2007 to 2015 with 2010 missing). Therefore, we have a total of 1,389 observations.

Endogeneity of the water variable in estimation is not a source of great concern because volumetric concessions are binding, as confirmed by the fact that the estimated shadow price of water is substantially higher than the computed extraction cost. To minimize the risk of omitted variable bias, we include both municipality-level fixed effects and time fixed-effects. The former control for unobservables at the municipality level that may be correlated both with water and revenue or outputs. The latter controls for macro shocks that greatly affect revenue, productivity, and crop mix in a given year, but do so uniformly across municipalities (e.g. currency depreciation). We cluster errors at the municipality level which means we allow for correlation of errors within the municipality, but not across municipalities, or overtime. Table 1 shows the descriptive statistics of our data.

Table 1 Descriptive statistics of data

	Mean	Std.dev.	Median
Planting			
Non-grain irrigated Planted Area(ha)	2,816.6	(6,562.2)	650.0
Grain Irrigated Planted Area (ha)	2,201.8	(7,291.1)	479.0
Non-grain Non-irrigated Planted Area(ha)	8,819.5	(20,366.7)	2,745.5
Grain Non-irrigated Planted Area (ha)	8,112.7	(11,861.8)	3,817.0
Harvesting			
Non-grain irrigated Harvested Area(ha)	2,594.1	(6,076.7)	601.4
Grain Irrigated Harvested Area (ha)	8,332.0	(18,360.2)	2,639.0
Non-grain Non-irrigated Harvested Area(ha)	1,875.3	(6,699.4)	286.6
Grain Non-irrigated Harvested Area (ha)	7,044.1	(10,409.8)	3,310.5
Price			
Non-grain Irrigated Price (Peso)	5,452.8	(6,105.3)	4,152.2
Grain Irrigated Price (Peso)	1,743.1	(1,340.7)	1,503.2
Non-grain Non-irrigated Price (Peso)	5,570.1	(4,627.0)	4,595.7
Grain Non-irrigated Price (Peso)	2,383.1	(1400.3)	2,462.9
Weather			
Municipality Max Temperature (ºC)	29.7	(3.7)	30.0
Municipality Min Temperature (ºC)	13.6	(5.0)	12.9
Municipality Precipitation (mm)	737.0	(470.7)	703.9
Water			
Water Cap Allocated ($10^6 m^3$)	152.7	(303.2)	55.0

6. Results

6.1. Water demand estimation

We first report the water demand estimation result in Table 2 where we note two features about Mexican irrigation water demand. Firstly, our estimation result shows that the water demand presents highly flat slopes which leads to welfare implications and thus, impacts on policy ranking analysis in section 6.3. For example, the flat slope of the water demand is likely to make high relative slopes between supply and demand, which consequently disfavors flexible cap policies over the quota policy. Secondly, we observe that Mexican irrigators experience large uncertainty in water demand as shown by the estimated intercept variation. Such large degree of demand shocks and its resulting inefficiency are discussed in the following section.

Table 2 Water demand information

	Unit	Mean	sd	Median
Estimated parameters				
Slope(b_2)	$\$/10^6(m^3 \cdot m^3)$	0.32	0.17	0.32
Intercept(b_1)	$\$/m^3$	0.45	0.21	0.44

Note: (i) The slope and intercept correspond to specifications in Equation (*4*). (ii) We convert currency from Mexican pesos to USD using the exchange rate of 0.05.

6.2. Flexible cap policy mechanism

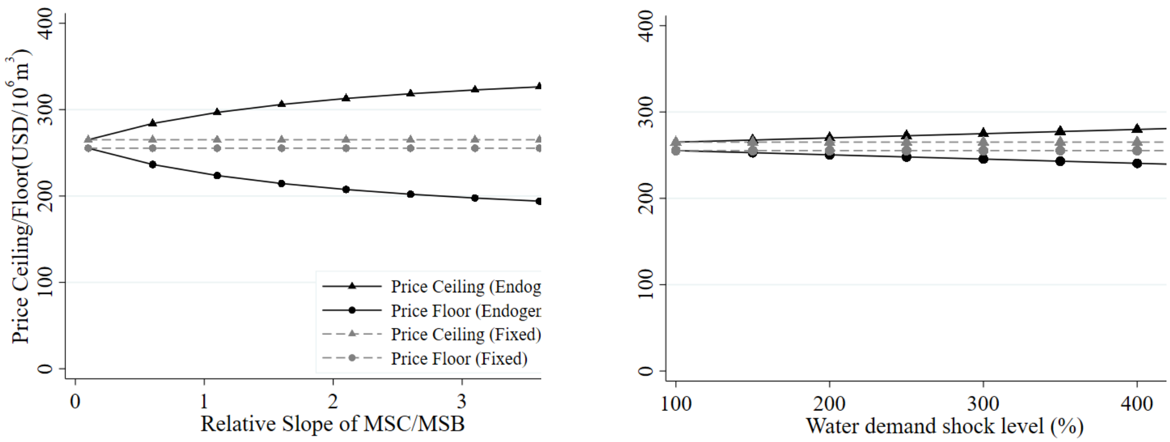
This section presents how the two factors (relative slopes and size of uncertainty) affect the mechanism of each flexible cap policy. We begin with the hybrid cap policy analysis followed by the IQ policy mechanism.

6.2.1. Hybrid cap policy

In the hybrid policy, price ceiling and price floor are the mechanisms to allocate cap flexibly (i.e., adjusting fixed quota policy). When the positive water demand shock is greater than the price ceiling, the additional cap is allocated according to this price ceiling. Similarly, given the sufficiently large size of a negative shock, the price floor will determine how much cap to be decreased. Thus, price ceiling and floor play are of our focus in this section.

To enrich our understanding about hybrid policy mechanisms, this section introduces two types of hybrid policies. The first hybrid policy is when the hybrid policy is fully optimized but the second hybrid policy is when it is not fully optimized. Our mathematical illustration in section 4.2.2 represents the first policy. More specifically, the fully optimized hybrid policy means that price ceiling and floor are fully endogenized to the varying factors such as the level of the relative slope of MSC/MSB (i.e., b_2/c_2) and the level of water demand shock (i.e., σ). Thus, we call endogenous hybrid policy and denote by $HB-E$. In contrast, the second hybrid policy for which the price ceiling and floor are not fully endogenous, instead, they are fixed at the initial level of b_2/c_2 and the fixed level of water demand shock (σ). Hence, the second hybrid policy is called hybrid policy with fixed price ceiling and floor and is denoted by $HB-F$.

Figure 3 illustrates the difference between the endogenous hybrid policy versus fixed hybrid policy. Under $HB-E$ policy, price ceiling and floor deviate farther away as the relative slope increases. However, in $HB-F$, price ceiling and floor do not respond to any changes in the relative slopes or the level of a demand shock. Note that increasing gap between price ceiling and floor means that flexible cap allocation is less likely because it imitates more quantity mechanism like a fixed quota. In other words, increasing price gaps under $HB-E$ policy indicate that it updates price ceiling and floor such that it relies less on price mechanism but relies more on quantity mechanism because that is the efficient policy behaviors. However, absent such policy updating process, $HB-F$ does not change the level of price ceiling or floor from the initial level. The welfare effects of this difference in responsiveness between these two mechanisms are carefully discussed in section 6.2.2.



Panel A. Panel B.

Figure 3 The effect of relative slope of MSC/MSB (panel A) and water demand shock (panel B) on price ceiling and price floor

Note: Panel A is based on the 100% of water demand shock and Panel B is based on $\frac{c_2}{b_2} = 0.1$.

6.2.2. IQ policy

Having a simple rule of cap allocation shown in Equation (*18*), IQ policy has only one policy parameter (ρ). By varying the level of ρ parameter, we determine the degree of flexibility under IQ policy. For example, $\rho = 0.2$ means that 20% of additional cap are allocated in addition to the quota level originally allocated under fixed quota policy if the rainfall is realized below the average rainfall level. On the contrary, cap quantity is reduced by 20% compared to the fixed quota level if more rainfall than the average rainfall is observed in that region. It is worth noting that rainfall is just a part of information of water demand shock; thus, IQ cap allocation is unlikely to provide efficient cap flexibility to the changing water demand. However, this simple rule adds a partial degree of flexibility, and our empirical results show that this can effectively improve welfare efficiency compared to the status quo (fixed quota) policy.

Figure 4 shows that IQ policy produces smaller DWL in almost all levels of ρ and of relative slope. Also notice that this degree of welfare enhancement, represented by the gap size between red and black lines, increases as more flexibility is allowed in IQ policy (i.e. higher ρ). However, too much flexibility (e.g., $\rho = 0.4$) can increase DWL as the relative slopes get steeper as is shown in panel D of Figure 4. This result provides similar sentiments to the analysis of prices versus quantity mechanisms in that welfare efficiency is sensitive to the interaction between the degree of flexibility of cap institutions (i.e., the choice of ρ in our context) and the underlying contextual factors such as the slopes between demand and supply.

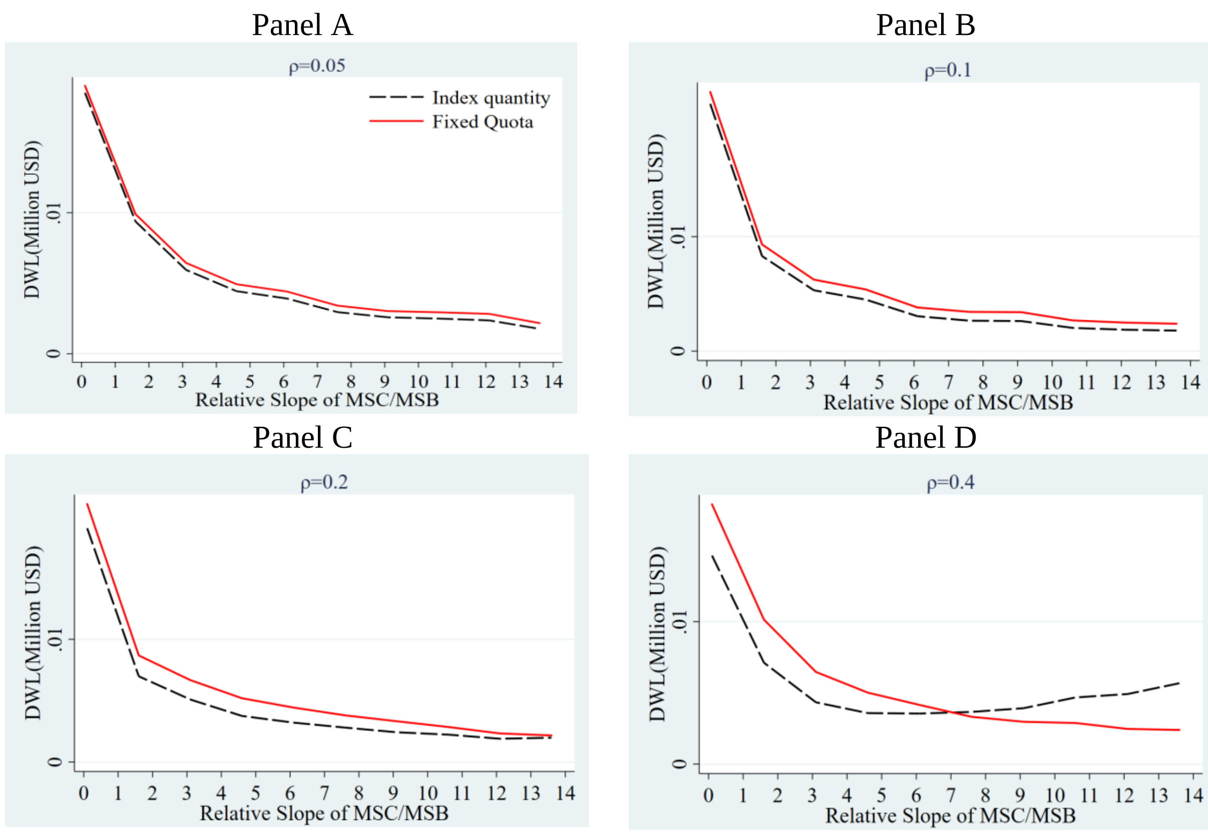


Figure 4 The effect of welfare under index quantity policy compared to fixed quota policy in relative slopes of MSC/MSB.

6.3. Cap policy ranking analysis

Based on the understanding of the mechanism, in this section, this section reports the main finding of this paper. The relative policy ranking is presented by comparing deadweight loss under each cap policy. We examine this comparison especially focusing on how ranking changes in two ways: i) the relative slopes of MSC/MSB, and ii) the degree of a water demand shock. We begin with the first aspect.

6.3.1. The welfare effects of relative slopes

Figure 5 shows deadweight loss under four cap policies relative to efficient cap policy (i.e., zero DWL). The red line represents the status quo, fixed quota policy, in which deadweight loss decreases as the relative slope of MSC/MSB increases. The coarse dashed line is the index quantity policy which closely follows the pattern of fixed quota because index quantity directly adjusts the level of cap allocation of fixed quota policy. Given the chosen level of index parameter $(\rho = 0.2)$, IQ policy produces less deadweight loss compared to the fixed quota policy regardless of the level of relative slopes. Thus, IQ policy holds its welfare improving property in a robust manner with respect to the relative slopes changes.

On the contrary, all hybrid policy does not necessarily improve welfare inefficiency of fixed quota policy. In fact, one might think that hybrid policy is maybe always worse than fixed quota policy when relative slopes get steeper because the hybrid policy has more flexibility in allocating caps than the fixed quota policy. Our result suggests that this argument is true only in the fixed hybrid policy but not in the endogenous hybrid policy. In Figure 5, the dotted and solid black line represent fixed hybrid policy $(HB - F)$ and endogenous hybrid policy $(HB - E)$, respectively. The fixed hybrid policy produces increasing deadweight loss as the slope of MSC/MSB gets steeper. This is due to the fixed price ceiling and floor where the same level of cap flexibility remains regardless of the slope changes. In consequence of this rigidity in quantity, $HB - F$ results in substantial deadweight loss when the slopes are very steep. However, this problem does not exist under $HB - E$ policy because it allows price ceiling and floor to endogenously change correspondingly to the changing relative slopes. As a result, the endogenous hybrid policy always produces smaller deadweight loss than the fixed quota policy because it optimizes price ceiling and floor for each level of relative slope.

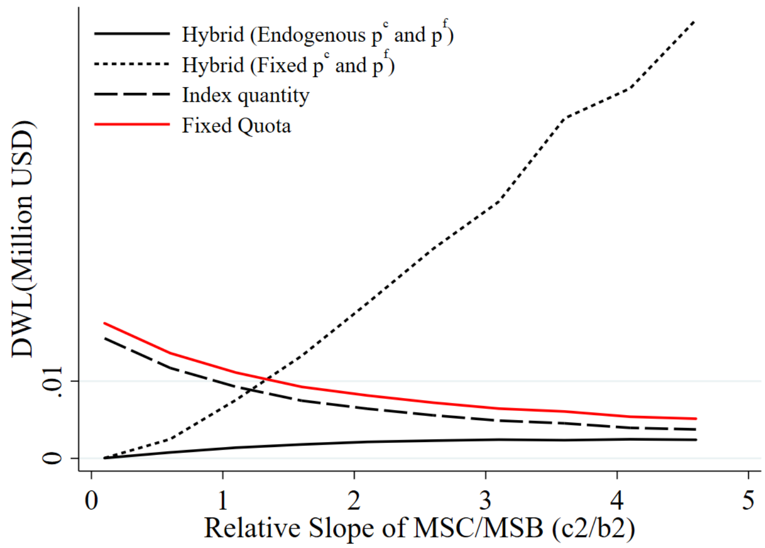


Figure 5 The changes in DWL by the relative slopes of MSC and MSB.

Note: Here IQ policy parameter is assumed at $\rho = 0.2$.

Table 3 reports simulation results in detail where we consider two levels of relative slopes; (i) when relative slopes of MC/MB is small as 0.6 (i.e., flat MC) and (ii) when it is large as 5 (i.e., steep MC). As are highlighted in gray colors, the worst policies differ between these two levels of relative slopes. First, the fixed quota policy produces the largest DWL in a small level of relative slopes. However, with the large relative slopes context, the fixed hybrid policy brings the largest DWL because too much flexibility in policy can lead to substantial deviation from the socially optimum level of cap. Perhaps more importantly, we note that the size of DWL in the latter case is much larger than the former case, which suggests that implementing an inaccurately designed hybrid policy may hamper the welfare much larger than remaining under the fixed quota policy.

Table 3 A policy comparison by simulation results: Quantity allocated and DWL.

	Unit*	Mean	sd	Median
(i) MSC/MSB=0.6				
Allocated Cap Quantity Deviated from Social Optimum Level $(\Delta Q = Q^{policy} - Q^{SO})$				
Fixed quota ($\lvert\Delta Q^{FQ}\rvert$)	$10^6 m^3$	147.5	6.1	144.3
Index quantity ($\lvert\Delta Q^{IQ}\rvert$)	$10^6 m^3$	127.8	6.2	124.7
Hybrid: Endogenous price ceiling/floor ($\lvert\Delta Q^{HB-E}\rvert$)	$10^6 m^3$	33.5	1.3	33.8
Hybrid: Fixed hybrid ($\lvert\Delta Q^{HB-F}\rvert$)	$10^6 m^3$	54.8	3.3	54.1
Deadweight Loss				
Fixed quota (DWL^{FQ})	M \$	0.014	0.0012	0.013
Index quantity (DWL^{IQ})	M \$	0.012	0.0011	0.012
Hybrid: Endogenous price ceiling/floor (DWL^{HB-E})	M \$	0.001	0.0001	0.001
Hybrid: Fixed hybrid (DWL^{HB-F})	M \$	0.003	0.0003	0.002
(ii) MSC/MSB=5				
Allocated Cap Quantity (ΔQ)				
Fixed quota ($\lvert\Delta Q^{FQ}\rvert$)	$10^6 m^3$	51.1	0.7	51.5
Index quantity ($\lvert\Delta Q^{IQ}\rvert$)	$10^6 m^3$	38.1	0.8	38.1
Hybrid: Endogenous price ceiling/floor ($\lvert\Delta Q^{HB-E}\rvert$)	$10^6 m^3$	35.3	0.4	35.1
Hybrid: Fixed hybrid ($\lvert\Delta Q^{HB-F}\rvert$)	$10^6 m^3$	145.7	2.6	146.0
Deadweight Loss				
Fixed quota (DWL^{FQ})	M \$	0.005	0.0003	0.005
Index quantity (DWL^{IQ})	M \$	0.004	0.0002	0.004
Hybrid: Endogenous price ceiling/floor (DWL^{HB-E})	M \$	0.002	0.0001	0.002
Hybrid: Fixed hybrid (DWL^{HB-F})	M \$	0.053	0.0025	0.053

*Note: All unit is per year per state.

6.3.2. The welfare effects of the water demand shock

This section studies the welfare effects of varying levels of water demand shocks. Figure 6 illustrates the welfare effects in varying levels of water demand uncertainty. Albeit different extents of DWL under fixed quota policy depending on the relative slopes, the absence of flexibility in fixed quota policy is heavily affected by increasing the levels of demand uncertainty. It is noticeable that inefficiency under fixed quota policy in red lines increase more than any other policies in all panel of Figure 6, which positively supports the idea of adding flexibility to improve welfare efficiency especially when water demand experiences a high level of uncertainty. In contrast, all four flexible cap policies show they effectively reduce DWL in fixed quota policy. Moreover, the degree of welfare improvement increases with a higher degree of demand uncertainty. For example, in panel B, the welfare improvement increases by 80% from a smaller shock (Δ1) to a bigger shock (Δ2).

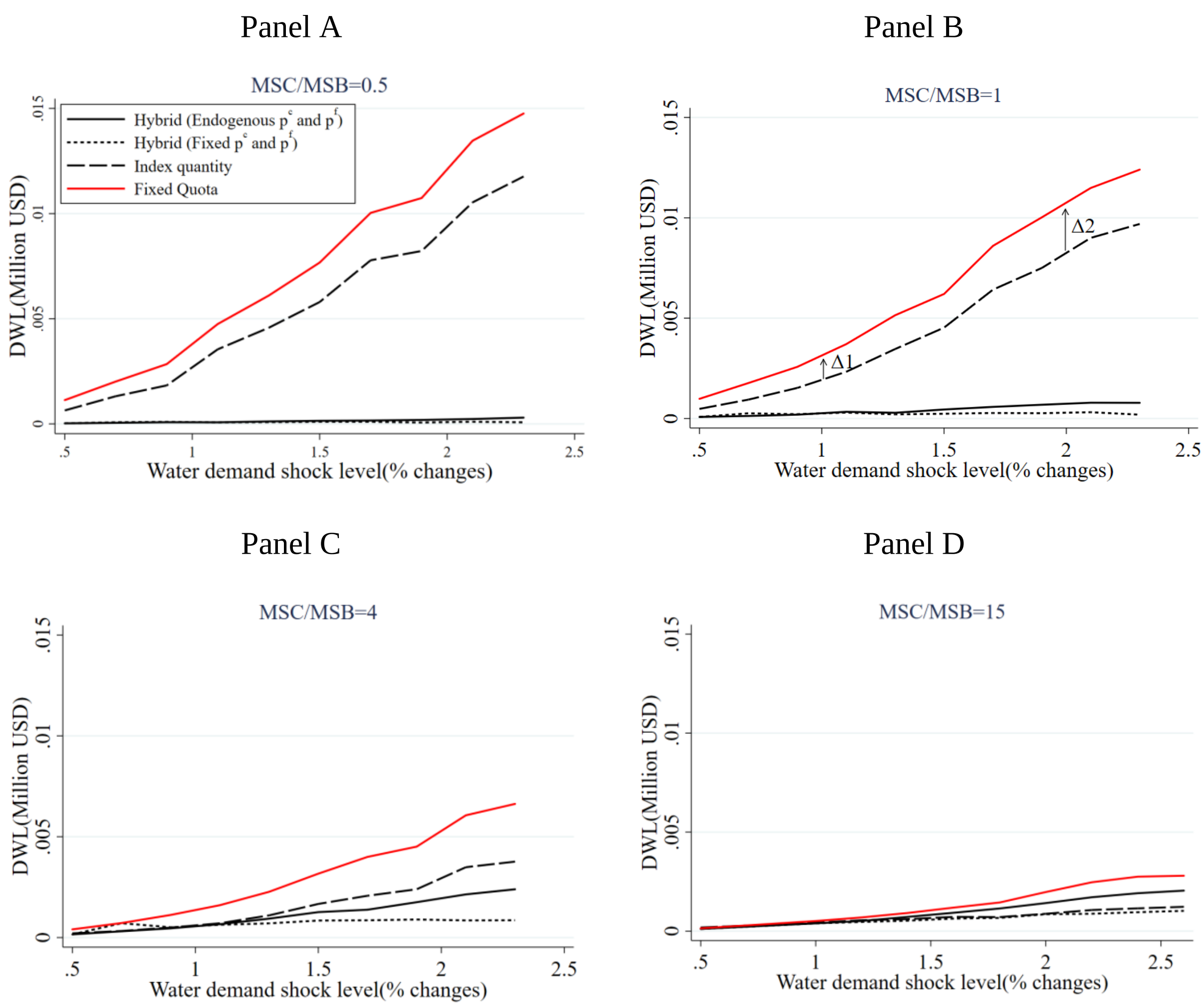


Figure 6 The effects of a water demand shock on a policy comparison.

Note: Here IQ policy parameter is assumed at $\rho = 0.2$. Hybrid cap policy (both HB-E and HB-F) is based on the fixed relative slopes specified in each panel. The price ceiling and floor for HB-F policy use a fixed level of demand shock at 100% whereas HB-E policy accounts for a varying level of a demand shock.

7. Policy Performance under Projected Weather Patterns

TO BE COMPLETED

8. Discussion and Conclusions

Implementing efficient institutions for water management is critical because of increasing water constraints in Mexican agriculture. Under the current institution (fixed quota policy), however, efficiency loss is unavoidable because the fixed quota has no mechanism to flexibly deal with stochastic water demand which inherently occurs due to the *ex post* realized weather (temperature or precipitation). Reforming to a flexible cap policy might help reduce efficiency loss; however, doing so does not always warrant welfare improvements because even larger inefficiency under flexible cap policies is possible depending on the relative slope between MSB and MSC (Weitzman 1974). Moreover, the degree of water demand uncertainty affects the degree of inefficiency as well. Failing to account for these contextual factors would hinder designing an efficient water policy. This study considers three flexible cap policies (i.e., index quantity, endogenous hybrid policy, and fixed hybrid policy) and empirically ranks the efficiency of competing cap mechanisms by comparing welfare improvement compared to the status quo, fixed quota policy.

Our results first show that there exists a large degree of uncertainty in irrigation water demands due to the weather variations in Mexico. Our empirical results reveal that Mexican irrigators bear substantial economic losses due to the inefficient cap allocation under the status quo. Introducing a flexible cap system can effectively mitigate the inefficiency, consistent with theoretical predictions. Specifically, our results suggest that the index cap policy performs generally well in the sense that welfare improvement from using an index cap policy is robust to the slope of MSC over reasonable ranges. On the other hand, the hybrid policy can be significantly worse than the status quo as the slope of MSC gets steeper than MSB, if it is not carefully designed. Only when the hybrid policy perfectly endogenizes the varying environments in relative slopes and size of uncertainty (i.e., frequently updating price ceiling and floor), hybrid policy is welfare robustly enhancing of status quo. However, realistically speaking, it might be difficult to update policy rules; hence our analysis favors the use of index quantity policy. Moreover, we observe that greater uncertainty leads to greater efficiency loss under the fixed quota policy, making index quantity policy more attractive in the face of climate uncertainty.

However, the relative cap policy ranking is ultimately sensitive to how specific parameter choices of each institution interact with ranges of contextual factors. Therefore, proper caution is still needed before adopting the index quantity mechanism for irrigation water management. To sum up, while no *one* policy dominates others globally (for the whole domain of relative slopes of MSB and MSC), an index quantity seems to be quite robust; outperforms other policies for a rather large range of relative slopes of MSB and MSC.

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