Micro-Climate Engineering for Climate Change Adaptation in Agriculture

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Abstract

Can farmers adapt to climate change by altering weather conditions on their fields? We define the concept of "Micro-Climate Engineering" (MCE), where farmers change the effective temperatures on their crops by means of shading or heating, and document such implementation by California pistachio growers. With rising winter temperatures and declining winter chill portions, pistachio growers in California could face adverse climatic conditions within 20 years. Treating dormant trees with a chemical mix, acting as a shading technology, has shown to increase winter chill count to acceptable levels. Modeling a market with heterogeneous sub-climates, we run simulations to estimate potential gains from MCE in the year 2030 for California pistachio. Our results show an expected yearly welfare gain ranging between $1-4 billion. While positive in total, profits gains are highly heterogeneous given the differences in baseline climates. Market power drives gains up, pointing to a less explored intersection of IO, agriculture, and climate change.

1 Introduction

Climate change poses a great challenge for agriculture, as predicted shifts in temperature and precipitation patterns may harm existing crops (Zilberman et al., 2004). Economic studies on climate change first focused on the impacts of changing mean temperatures, and more recent literature emphasizes the importance of temperature variance and extreme heat thresholds, especially during the warm growing season (Auffhammer and Schlenker, 2014). Adding plant biology to the equation, threshold of more sophisticated climate metrics exist for certain crops, and could have a great effect during the cold seasons as well. This

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paper sets to assess the potential effects of climate change on California pistachio production through such a metric, and the potential gains from a novel adaptation technique that lowers the effective orchard temperature in the winter days. This solution concept, which we term "Micro-Climate Engineering" (MCE hereinafter) could play a significant role in climate change adaptation. Unlike the geo-engineering, which proposes interventions that would change global temperature distributions (Keith, 2001), the concept of MCE involves the adjustment of temperatures in very specific place and time.

MCE as an adaptation technique stems from the nature of the challenge posed on crops by climate change. Economic research has shown that this challenge is often temporary, perhaps lasting only a few days, and that relatively small changes in temperatures can have significant effects. **?**auffhammer2014empirical) and Carleton and Hsiang (2016) survey a body of research which found non-linear negative yield responses to temperature extremes in staple crops. For example, Schlenker and Roberts (2009) show sharp drops in the yields of corn, soybean, and cotton, when exposed to degree days above $28-30^0C$. When, notwithstanding favorable climate, such short term events cause major damages to crops, we refer to them as "climate bottlenecks". With leading climate change scientists concluding that "It is very likely that heat waves will occur with a higher frequency and duration" as the global mean temperatures increases (IPCC, 2013), it seems likely that tightening bottlenecks, rather than changes in mean temperatures, will be responsible for temperature related damages in agriculture for the next few decades. We note that few adaptation techniques seem to address them directly.

In this paper, we assess the potential benefits of a novel adaptation technique, targeted at a rapidly developing climate bottleneck for California pistachio. Warming winter days, with temperatures far below the yearly maximum but high enough to disrupt the normal tree metabolism, could harm output to a great extent. This bottleneck stands out in the existing literature in two ways: first, while much of the climate change in agriculture literature focuses on annual crops, pistachio trees are perennial. Moreover, the bottleneck occurs not in the "growing season", but on the winter months when trees are dormant. Second, while many researched bottlenecks are temperature distribution right side tail effects (for example, Schlenker and Roberts 2009) our bottleneck is not at the extreme yearly temperatures. Rather, higher winter day time temperatures cause a decline in a special temperature metric known as chill portions. Weakly correlated with the mean yearly temperature, this change is easy to be missed by researchers focusing on traditional climate metrics. As we will see, this non-intuitive change in climate, at a non-intuitive season to explore, could have effects in the billions of dollars for pistachio.

Scientists at the University of California Cooperative Extension have been experimenting with a new technique for dealing with the risk of insufficient winter chill, caused by raised winter daytime temperatures. The treatment consists of covering the dormant pistachio trees with a non-toxic chemical mix, which blocks the sunlight and prevents overheating of tree buds. This acts as a *de-facto* shading device, lowering daytime temperatures from December to February. Similar solutions, such as installing nets for partial shading in orchards, are being explored in other fruit crops.

The literature on adaptation considers many options, including adoption of existing technologies and innovations. Among the innovations, the emphasis has been on irrigation technologies, diversification in varieties, and weather information (Zilberman, Zhao, and Heiman, 2012; Leslie Lipper et al., 2018). The concept of MCE has not been explored, even though the technologies used for this purpose need not be completely new to farmers. Unrelated to climate change, existing MCE solutions for frost can be witnessed in Northern California's vineyards. Frosts are bottlenecks: they last a few hours and create great damages to crops. Many growers are equipped with wind machines and propane gas heaters, preventing frost damage by circulating warm air around the vines on frost nights. A similar MCE solution for frost is implemented by some almond growers in California, who reportedly hire helicopters to fly over their orchards (Langer, 2016). Almonds and wine being the first and fourth top agricultural exports of California (CDFA, 2016), the benefits of MCE in these crops are probably very high.

I love the following paragraph, but perhaps it's a distraction Archaeologists have identified implementation of MCE by the Tiwanako civilization in the 7-12 centuries. On the shores of lake Titikaka, a cold and arid area, frosts are common. To deal with this (and other challenges), the Tiwanako raised their fields artificially with sediment. The fields were irrigated by canals carrying water diverted from nearby springs, and the moist soil served as a heat storage unit that protected crops during frosts (Kolata and Ortloff, 1989). At the height of the Tiwanako civilazation, this practice supported a population estimated 10 times larger than the area's population in the 1990's (Binford et al., 1997). **end distraction**

We offer the first (to our knowledge) documentation of a MCE implementation for climate change adaptation, and believe this concept could be substantial in its economic analysis. In some cases, techniques for dealing with new or enhanced climate bottlenecks, targeting them on the field level, could delay the eventual crop transition for decades. Our case study shows substantial benefits from MCE for one crop in California, yet similar style solutions might be developed and used for other crops in other parts of the world.

The remaining of this paper is organized as following: Section 2 borrows from the pest control literature to create a micro-economic model for MCE application. In section 3, we adapt this model to California pistachio, and present the functional forms and parameters used for simulations. Section 4 presents the simulation results, and section 5 concludes.

2 A Model for Micro-Climate Engineering

2.1 Individual Grower

The model draws from the pest control literature (see for example Lichtenberg and Zilberman 1986; Chambers and Lichtenberg 1994; Sexton et al. 2007; Waterfield and Zilberman 2012). Consider a grower with a production function $H(z)$; and facing a damage function $L(x) \in [0,1]$, which is decreasing with an abatement input x (pesticide, MCE input). $H(z)$ is sometimes referred to as the *potential output*, where z is an input vector unrelated to the damage function. The damage function can take some baseline level of "natural" input (pest density, weather), which can vary in time and space. The grower's problem is:

$$\max_{(x\,,\,z)} \ \pi = p \cdot [1 - L(x)] \cdot H(z) - p_z^T \cdot z - p_x \cdot x \tag{1}$$

This model allows the grower to respond to changes in prices (and the natural amenity) both by input z and abatement x. In many cases, including ours, the abatement technology requires that we set a condition that $x > 0$. That is, there is no negative abatement. We abstract from this constraint for the time being, and return to it later. Assuming the usual regularity conditions, we are guaranteed a unique solution to this maximization. A solution would have to fulfill the first order conditions:

$$\frac{\partial \pi}{\partial z} = p \cdot [1 - L(x)] \cdot H_z(z) = p_z \tag{2}$$

$$\frac{\partial \pi}{\partial x} = p \cdot [L_x(x)] \cdot H(z) = p_x \tag{3}$$

Combining these we get an equation for the optimal x and z:

$$\frac{p_z}{p_x} = \frac{1 - L(x^*)}{L_x(x^*)} \cdot \frac{H_z(z^*)}{H(z^*)} \tag{4}$$

$$= \frac{1 - L(x^*)}{L_x(x^*)} \cdot \frac{\eta_z(z^*)}{z^*} \tag{5}$$

$$\implies z^* = \frac{1 - L(x^*)}{L_x(x^*)} \cdot \eta_z(z^*) \cdot \frac{p_x}{p_z} \tag{6}$$

where η_z is the output elasticity in z. For the purpose of simulations, we choose a convenient Cobb-Douglas production function, $H(z) = \alpha \cdot (z)^\beta$, i.e. $\eta_z = \beta$. Plugging the expression for z^* at the first order condition in equation (3), and using the specified Cobb-Douglas function H, we get an implicit function in one parameter, whose solution is the optimal choice for abatement level x:

$$p \cdot (L_x(x^*)) \cdot \alpha \cdot \left(\beta \cdot \frac{p_x}{p_z} \cdot \frac{1 - L(x^*)}{L_x(x^*)}\right)^{\beta} = p_x \tag{7}$$

With the optimal x^* from equation (7), supply can be be written explicitly. Here, we return to the constraint of $x^* > 0$. When this requirement is met, the value of x^* can be plugged in equation (6), to get an expression for z^*, and then in the production function. However, when the FOC results in $x < 0$, we treat the case as if the grower effectively faces the constraint that $x = 0$. Therefore, the "normal" Cobb-Douglas form with the naturally occurring loss $L(0)$ is used.

$$q^* = \begin{cases} [1 - L(x^*)] \cdot \alpha \cdot \left[\beta \cdot \frac{p_x}{p_z} \cdot \frac{1-L(x^*)}{L_x(x^*)}\right]^{\beta} & \text{if } x^* \geq 0 \\ [1 - L(0)] \cdot \alpha \cdot \left[\frac{p_z}{[1-L(0)]\cdot\alpha\cdot\beta}\right]^{\frac{\beta}{\beta-1}} & \text{if } x^* < 0 \end{cases} \tag{8}$$

2.2 Market Supply

All growers in our model are assumed to have the same production technology and face the same prices for inputs and output. However, they are heterogeneous in climate conditions: some face warmer climate than others. Our production data is aggregated on the county level, with about 96% of California pistachio grown in five counties. Therefore, we model supply as the sum of 5 independent counties, each with a different baseline climate and number of growers (recall that the Cobb-Douglas form is aggregable). We therefore have five equations for optimal x_i (one for each county), and five county supply functions that are added together for market supply.

We now turn to calibrate these supply functions, so they reflect some realistic values. To do so, note that without the option for MCE, i.e. when the loss share cannot be changed by the grower, this becomes a textbook Cobb-Douglas production technology. When x is forced to zero, the grower problem translates to a supply function of the form:

$$q(p, p_x, p_z) = [1 - L(0)] \cdot (\alpha)^{\frac{1}{1-\beta}} \cdot (\beta)^{\frac{\beta}{1-\beta}} \cdot (p_z)^{\frac{-\beta}{1-\beta}} \cdot (p)^{\frac{\beta}{1-\beta}}$$

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Indeed, in the year 2014, there was no MCE available for pistachio, yet there was sufficient chill in all our counties to have virtually zero climate related loss, i.e. $L(0) \approx 0$. We know the market price and county harvests (in tons) for this year. Therefore, following our functional form assumption, for county i:

$$q_{i,2014} = (\alpha_i)^{\frac{1}{1-\beta}} \cdot (\beta)^{\frac{\beta}{1-\beta}} \cdot (p_z)^{\frac{-\beta}{1-\beta}} \cdot (p_{2014})^{\frac{\beta}{1-\beta}} \tag{9}$$

This is an iso-elastic supply function, for which we know the price and quantity values in 2014. Note that parameters α_i, β, and p_z are constant, and do not change with the output price p. Of course, with one equation we cannot solve for all these parameters. Nor can we use price-quantity data from multiple years to try and estimate these parameters empirically, as more factors come to play (endogeneity with demand, growth trends, and other unobserved confounding factors). However, if we assume the elasticity of supply ε_S, we can solve this supply function in the following way:

$$\beta \equiv \frac{\varepsilon_S}{1+\varepsilon_S} \tag{10}$$

$$\left[\alpha \cdot \left(\frac{\beta}{p_z}\right)^{\beta}\right]^{\frac{1}{1-\beta}} \equiv \frac{q_{i,2014}}{(p_{2014})^{\frac{\beta}{1-\beta}}} \tag{11}$$

Plugging the results from equations (10)-(11) in equation (7), and with some simplifying algebra (see Appendix A.1), we get the following expression for each county i:

$$(p)^{1+\varepsilon_S} \cdot [L_x(x_i^*)] \cdot [1 - L(x_i^*)]^{\varepsilon_S} \cdot \left[\frac{q_{i,2014}}{(p_{2014})^{\varepsilon_S}}\right] = p_x \tag{12}$$

Equation (12) must hold for for each county in an internal solution. There are as many equations as counties, since the baseline damage rate can be different: the chill deficit is not the same in different geographic areas, and so the optimal abatement could be different.

Once x_i^* are obtained, each county's supply can be calculated. Similar to equation (8), cases where $x_i^* < 0$ are treated as the regular Cobb-Douglas supply with no abatement (we further explore the algebra in Appendix A.2). Supply for each county is defined in the following way:

$$q_i = \begin{cases} [1 - L(x_i^*)]^{\frac{1+2\cdot\varepsilon_S}{1+\varepsilon_S}} \cdot \left[\frac{q_{i,2014}}{(p_{2014})^{\varepsilon_S}}\right]^{\frac{1}{1+\varepsilon_S}} \cdot \left[\frac{p_x}{L_x(x_i^*)}\right]^{\frac{\varepsilon_S}{1+\varepsilon_S}} & \text{if } x_i^* \geq 0 \\ [1 - L(0)] \cdot \left[\frac{q_{i,2014}}{(p_{2014})^{\varepsilon_S}}\right] \cdot (p^*)^{\varepsilon_S} & \text{if } x_i^* < 0 \end{cases} \tag{13}$$

2.3 Market Demand

We model demand as iso-elastic, with elastic demand. While some estimates for demand elasticity for pistachio can be found in the literature (Gray et al., 2005; Zheng, Saghaian, and Reed, 2012), we found no investigation into the demand shape itself. In empirical demand estimations, we usually find either linear or iso-elastic functions. We find the linear form less suitable for our purposes, as with a low enough price demand becomes inelastic, a situation we find unlikely. We use the iso-elastic form, and pay the price of assuming out a choke price. This has some consequences in scenarios where supply is greatly diminished, but this relatively fatter tail of the distribution of simulated welfare outcomes does not change the mean results in a very significant way. To be sure, we later report both mean and median welfare results of our simulations. To calibrate our demand, assuming the elasticity ε_D, we use the 2014 data, in a similar way we did for supply, resulting in a demand function of the form:

$$D(p) = \left[\frac{q_{2014}}{(p_{2014})^{\varepsilon_D}}\right] \cdot (p)^{\varepsilon_D} \tag{14}$$

For each simulation, the drawn elasticity gives us the demanded quantity at the equilibrium price.

2.4 Market Power, Market Clearing, and Solution

We now move to integrate supply and demand, to form an equation system determining simulated price and quantity. At this point, we add some complexity to our model by incorporating market power measures. To do so, we adapt an approach from Sexton and Zhang (2001). The micro-foundation of this model uses a representative intermediary, which buys from growers and sells to consumers with zero transaction cost. This intermediary can have market power downstream and/or upstream, and optimizes the total processed quantity such that the price for growers (p^S) and price for consumers (p^D) are related by the following equation:

$$p^D \cdot \left(1 + \frac{\psi_D}{\varepsilon_D}\right) = p^S \cdot \left(1 + \frac{\psi_S}{\varepsilon_D}\right)$$

where $\psi_D \in [0, 1]$ is a market power measure w.r.t. the consumer sector (monopolistic market power), where zero is no market power and 1 is monopoly. Likewise, $\psi_S \in [0, 1]$ is a market power measure w.r.t. the growers (monopsonistic power), where 0 is no market power and 1 is a monopsony. The elasticity terms are the same we used so far. This equality results in a power coefficient that can be used in the demand equation to express consumer price.

$$PC \equiv \frac{p_D}{p_S} = \frac{1 + \psi_S/\varepsilon_S}{1 + \psi_D/\varepsilon_D} \tag{15}$$

Note that, since the elasticity of demand ε_D is always negative, the range of PC is bounded below: $PC \in [1, \infty)$. As expected ,the price for consumers will be higher than the price for growers. Moreover, PC increases with market power (on any side), and decreases when supply or demand are more elastic.

In fact, our PC coefficient is an approximation of the real one, as we only use the no MCE elasticity of supply. The real supply elasticity should include a term that expresses the increased supply through the MCE process as well. However, since we do not have a closed form solution for x^*, we use this approximation, and note that this (weakly) downward bias in supply elasticity lowers the power coefficient. As we see later, that seems to attenuates the estimates for MCE gains, making the simulation results more conservative.

One last parameter we include in the model is a growth coefficient. As we model the market in 2030, county supplies and total demand need to change from their current state. We use γ_i as the supply growth rate for each county. The growth in demand by 2030 is modeled equal the average county growth, weighted by current share in supply. The full equation system for our model is:

$$(p)^{1+\varepsilon_S} \cdot [L_x(c_i + x_i)] \cdot [1 - L(c_i + x_i)]^{\varepsilon_S} \cdot \left[\gamma_i \cdot \frac{q_{i,2014}}{(p_{2014})^{\varepsilon_S}}\right] = p_x \tag{16a}$$

$$q_i = \begin{cases} [1 - L(x_i^*)]^{\frac{1+2\cdot\varepsilon_S}{1+\varepsilon_S}} \cdot \left[\frac{q_{i,2014}}{(p_{2014})^{\varepsilon_S}}\right]^{\frac{1}{1+\varepsilon_S}} \cdot \left[\frac{p_x}{L_x(x_i^*)}\right]^{\frac{\varepsilon_S}{1+\varepsilon_S}} & \text{if } x_i^* \geq 0 \\ [1 - L(0)] \cdot \left[\frac{q_{i,2014}}{(p_{2014})^{\varepsilon_S}}\right] \cdot (p^*)^{\varepsilon_S} & \text{if } x_i^* < 0 \end{cases} \tag{16b}$$

$$\sum_i q_i = \frac{q_{i,2014}}{(p_{2014})^{\varepsilon_D}} \cdot (PC \cdot p)^{\varepsilon_D} \cdot \sum_i \left(\frac{\gamma_i \cdot \frac{q_{i,2014}}{(p_{2014})^{\varepsilon_S}}}{\sum_i \frac{q_{i,2014}}{(p_{2014})^{\varepsilon_S}}} \right) \tag{16c}$$

where c_i is each county's natural chill (baseline environmental endowment), to which our input x_i is added. In out case, we assume the input has a linear effect on chill portions, and we add the artificial chill directly. Part (a) is the FOC, similar to equation (12). In equilibrium, x_i^* must equate both sides. Part (b) is the supply function, as in equation (13): with the abatement choices x_i^*, county supplies are calculated. Part (c) is the market clearing equation, using the sum of county supplies and the demand function from equation (14).

Equation system (16) is the mathematical expression of our model. It has six endogenous parameters: five county abatement decisions x_i and the grower market price p. We use this model to run numerical simulations, which will give us distributions for outcome prices, quantities, and subsequent welfare outcomes. To do so, we need to specify the exogenous parameters: elasticities (ε), power coefficient (PC), growth rates (γ), and climate realizations (c_i) are drawn by randomly from pre-specified ranges detailed below. While we cannot find closed form solutions for our endogenous parameters, we solve this system numerically using the "rootSolve" package for *R* (Soetaert and Herman, 2008).

Once we numerically solve for p^* and x_i^*, we can calculate welfare measures. Consumer surplus is the area between the inverse demand function and the equilibrium consumer price, from $Q = 0$ to the market equilibrium quantity. Producer profits are calculated by county. When the county's x_i^* is negative, the county profit is the area between the market price and the county's inverse Cobb-Douglas supply function (where $L(0)$ is used for damage). When the county's x_i results in a positive number, we do not have the functional form of supply: the optimal x_i changes with the price. Therefore, we approximate the profits by using the area between the market price and the inverted Cobb-Douglas supply function (where $L(x_i^*)$ is used for damage) minus the total cost of MCE for the county.[1] Adding county profits

[1] We find that using this form results in market price based quantities very close to the actual simulation

and consumer surplus results in total welfare. One last issue to consider are the profits of the virtual intermediary, embedded in our model to include market power. These rent are distributed between growers and consumers, according to each side's share in the total market power measure.

3 Simulations for MCE in California Pistachio

Introduced to California more than 80 years ago, and grown commercially since the mid 1970's, pistachio (*Pistachia Vera*) was the state's 9th leading agricultural product in gross value in 2014, generating a total revenue of $1.65 Billion. California produces virtually all the pistachio crop in the US, and competes internationally with Iran and Turkey (2/3 of revenues are from export). In 2014, five California counties were responsible for a 96.2% of the state's pistachio crop: Kern (24.3%), Fresno (23.3%), Tulare (22.7%), Madera (17.7%) and Kings (8.2%) (CDFA, 2016). Since the year 2000, total harvested acres in these counties have been increasing by roughly 10% yearly. Each increase represent a 6 - 7 year old investment decision, as trees need to mature before commercial harvest (CPRB, 2009).

Like many other fruit and nut trees, pistachio requires a minimal input of winter chill, a temperature metric measured in portions. This brief explanation of chill is based on Erez (2000). Many fruit and nut trees have a dormancy phase during winter. This phase is an evolutionary adaptation, allowing the tree to "hibernate" and protect sensitive organs while harsh weather conditions take place. Trees prepare for dormancy by storing energy reserves, shedding leaves, and developing organs to protect the meristems. Once a tree went into dormancy, it needs to calculate when to optimally "wake up". Blooming too early might expose the foliage to frost. Blooming too late means not taking advantage of available resources (sunlight), and eventually being out-competed.

Temperatures and day lengths affect both entry and exit from dormancy. Agronomists stipulate that, once dormant, tree buds "count" chill portions and measure day lengths, until threshold levels of both are reached. Only then will the buds break and the tree will start blooming. Failure to attain a threshold chill count, varying between crops and cultivars, leads to low and non-uniform bud breaking, which is linked to low yields at harvest. Thus chill accumulation is critical for growers, especially in warmer areas where the chill constraint might be binding.

To accumulate a chill portion, temperatures need to remain below certain levels for a few days. Roughly speaking, when temperatures go above 6^oC, accumulation slows down. When temperatures exceed 15^oC, the count reverses, quickly rounding down to the last integer portion that has been "banked". Thus, rising winter daytime temperatures can have

results.

a detrimental effect on chill count, even if the temperatures themselves are not extreme on the yearly distribution.

Agronomists estimate the minimum requirement for the common pistachio cultivars in California at 54 - 58 portions. Compared to other popular fruit and nut crops in the state, this is a high threshold (Pope, 2015), putting pistachio on the verge of not attaining its chill requirements in some California counties. In fact, there is evidence of low chill already hurting yields (Pope et al., 2015; Doll, 2015).

Chill in most of California is predicted to decline in the next decades. Luedeling, Zhang, and Girvetz (2009) estimate the potential chill drop for the southern part of San Joaquin valley, where over 96% of California pistachio is currently grown. For the measure of first decile, i.e. the amount of portions fulfilled in 90% of years, they predict a drop from an estimate of 64.3 ($\pm$2.9) chill portions in the year 2000 to estimates ranging between 50.6 ($\pm$3.8) and 54.5 ($\pm$3.6) (climate change scenario depending) in the years 2045-2060.

Scientists at the University of California Cooperative Extension have been experimenting with potential solutions for the threat of low chill. One solution, tested successfully on a small scale experiments, involves spraying a non-toxic chemical mix, based on kaolin clay, on the dormant pistachio trees. Acting as a *de-facto* shading device, this creates a special micro-climate for the chill counting tree buds. Shaded from winter sunlight, they now experience lower effective daytime temperatures, which raises their count of chill portions. In experiments, the chill portion count on treated trees was higher than on untreated trees; and the treated trees produced more pistachio clusters (Doll, 2015). Kaolin itself is already used by growers for other purposes, and research continues on the potential of other commonly used reflecting substances for this task (Beede and Doll, 2016). With relatively cheap application costs, this technique can help raise the chill counts in orchards, and at times save harvests.

To assess the potential gains from this new technology, we follow Zilberman et al. (1991) and Hueth, Cohen, and Zilberman (1998) to create simulation outcome distributions by randomly drawing parameter values from pre-determined ranges and solving the model in equation (16). Parameters includes the climate prediction distribution, elasticities of supply and demand, and a range of MCE prices. The parameter ranges and distributions are specified in subsections below. To calculate the gains from MCE in our simulations, outcomes need to be compared to a benchmark or counter-factual, a world where MCE does not exist. To do this, we run the simulations again, but restricting $x_i = 0$ for all counties. This results in the no MCE market outcomes, where the weather bottleneck damages are not abated. Comparing simulations with and without MCE, yet identical in all other parameters, we can calculate the profit gains (total and by county), consumer surplus gains, and total welfare gains from MCE in our model.

We abstract away from a benchmark with increased storage, which could alleviate interyear fluctuations, for two main reasons. First, pistachio is usually stored for up to one year (Thompson and Adel A, 2016). Second, the alternate bearing nature of pistachio means a great amount of storage is already in place. In 2005, the stock to output ratio in California pistachio was 0.37 (Gray et al., 2005). Given the limited storage time and already existing supply smoothening storage operations, it seems unlikely that extra storage would serve as a meaningful solution to the new threat of insufficient chill.

3.1 Loss Function

The agronomic literature suggests a minimum threshold of chill portions for a successful spring bloom and eventual harvest. The lower bound of the estimates, for California's most common variety, are 54 chill portions (Pope, 2015). Rather than a discontinuous "switch" like function, we chose to model loss with a continuous, sigmoid function. This reflects the uncertainty of the threshold estimates, and the fact that weather varies within each county. Therefore, we can look at the loss function as the expected loss under the representative county weather in a given year. Moreover, while grower risk aversion is left for future research, continuous loss allows for a more nuanced abatement response. Our (net of) loss function is based on hyperbolic tangent, a sigmoid, continuous function with smooth derivatives. We cap the maximum yield loss at a 90%. Where c is the naturally occurring chill, and x are the chill portions added by MCE, the net-of-loss function and derivatives are:

$$1 - L(c,x) = 1 - 0.9 \cdot (0.5 \cdot tanh(53 - c - x) + 0.5) \in [0.1, 1] \forall (c,x) \tag{17}$$

$$\frac{d(1 - L(c,x))}{dx} = -L_x(c,x) \cdot (-1) = 0.45 \cdot sech^2(53 - c - x) \tag{18}$$

$$\frac{d(1 - L(c,x))}{d^2x} = -L_{xx}(c,x) = 0.9 \cdot sech^2(53 - c - x) \cdot tanh(53 - c - x) \tag{19}$$

Figure 1 shows the values of the net-of-loss function and its derivatives. We chose the critical value at 53, rather than 54, as a conservative measure. At 53 portions the loss rate is 55%, and at the threshold of 54 chill portions, the net of loss rate is 89%.

The loss function is not concave, and therefore a solution for the FOC in equation (12) needs not necessarily be the one maximizing profit. However, equation (12) has up to 2 roots, and we show in Appendix A.3 that a root satisfying $x_i + c_i > 53 + \delta(\varepsilon_S)$ is a local maximum, and a root satisfying $x_i < 53$ is in an area convex in x and therefore cannot be profit maximizing. Thus the global maximum profit is attained at a root that satisfies $x_i + c_i > 53 + \delta(\varepsilon_S)$. In the simulations, we choose the highest root of equation (12) and make sure that it is the point of maximum profit.

3.2 Climate Data and Simulated Parameters

We cannot use the above-mention chill predictions by Luedeling, Zhang, and Girvetz (2009), as they uniformly cover all of our counties and use a first decile statistic which we find less useful. We therefore present our county specific calculations for current and future predicted chill at each county.

A winter's chill portion count is calculated from a vector of hourly temperatures. Observed temperatures for 2007-2016 come from the California Irrigation Management Information System (CIMIS, 2016), a network of weather stations located in many counties in California, operated by the California Department of Water Resources. Given that goal of CIMIS is to provide decision making data for farmers, stations are located in rural areas. We use the location of stations to set the reference point at each of the five counties: the representative point at each county is the centroid of active (as to February, 2017) CIMIS stations at that county. This seems better than using the counties' geographic centroid, as many of them extend east of the San Joaquin Valley into the less cultivated Sierra.

To estimate future chill, we use temperature predictions of a CCSM4 model from CEDA (2016). These predictions use an RCP8.5 scenario. This scenario assumes a global mean surface temperature increase of $2^o C$ between 2046-2065 (from a baseline of 1986–2005) (IPCC, 2013). The predicted temperatures for the years 2025-2040 are produced for each county. Following Leard and Roth (2016), we perform quantile calibration on the 2007-2016 past predictions, which can be compared with the actual observed temperatures[2]. Figure 2 shows a map of the counties, reference points, CIMIS stations, and interpolation points.

Once we have the observed temperatures from CIMIS and the predicted future temperatures, we calculate the past and predicted chill count for each winter at each county, as specified in Erez and Fishman (1997). Figure 3 compares the distributions of observed chill (winters of 2007-2016) and predicted chill (2025-2050). In three out of the five pistachio producing counties, the chill distribution is predicted to lower in such manner, that low chill years (below 54 portions) would be quite common. Madera and Tulare seem not to suffer an adverse change in chill counts. More details on the climate data processing are found in Appendix B.

We test this 5-county chill prediction matrix in 2025 - 2050 for a the null hypothesis of multivariate-normally distributed chill predictions, and fail to reject it.[3]. Therefore, by specifying the means and covariance matrix of predicted chill in our five counties for 2025-2050, we simulate the natural chill realization from a 5D multivariate normal distribution.

[2]In our case, calibration attenuates the predicted change.

[3]This was done with the "MVN" package for R (Korkmaz, Goksuluk, and Zararsiz, 2016)

3.3 Growth Scenarios and Acreage Shares

To determine the potential growth in pistachio output by the year 2030, we consider bearing acreage growth in the past. Since the year 2000, harvested acreage grew by an average 10% yearly. Since 2010, the average rate was 13.5% (CDFA, 2016). To assess the gains from MCE in the year 2030, we need to stipulate the total acreage at that year, and its distribution among our counties. We create acreage growth scenarios to get the edges of a potential acreage range in 2030. Two factors influence scenarios: growth rate and geographic distribution.

For a high growth rate scenario, we let the total acreage grow by 13.5% yearly for six years (assuming this growth rate is already happening in pre-harvested orchards), and then by then 10% yearly until 2030 (total growth by factor of 5.11). For a low growth scenario, we let acreage grow by 10% yearly for six years, then by 5% yearly until 2030 (total growth by factor of 2.74).

Some counties are more prone to low chill years than others, and future growth in acreage might take this into account. If the counties' acreage shares stay the same, i.e. all grow at the same rate, each county's acreage in 2015 is thus multiplied by the growth factor to calculate county acreages in 2030. This represents a world where growers might not be aware of the perils of climate change, or trust MCE in solving future problems even in the risky counties. However, growers could also divert growth to the less affected counties, Madera and Tulare. To model this, we increase each county's 2015 acreage by the appropriate growth factor for the first 6 years (10% or 13.5%), to account for acres already planted. The difference between the sum of predicted acreage in 2021 and the total predicted acreage in 2030 (scenario pending) is then allocated evenly between Tulare and Madera.

Combining the above, we get four scenarios: **High-North**: high growth rate, new growth in Tulare and Madera[4]; **Low-North**: lower growth rate, new growth in Tulare and Madera; **High-Same**: High growth rate, even in all counties; **Low-Same**: Low growth rate, even in all counties. Table 1 summarizes the scenarios, and presents the mean potential loss rate in each of them in the year 2030.

These scenarios should capture what we would consider the extremes of behavior on the supply side. Of course, combinations of them are possible. These scenarios assume that existing orchards are not uprooted, even in the risk prone counties. On the other hand, they set an upper bound on the total acreage growth in the more risk prone counties, such as Kern county. We conservatively assume out a scenario where, once MCE exists and the climate change challenge is solved, the riskier counties (Kern, Kings) accelerate acreage growth at the expense of the cooler counties.

[4] Tulare county is not really to the north, but we find this terminology convenient as we are discussing climate change in the northern hemisphere.

3.4 Other Parameters

- Elasticity of demand: $\varepsilon_D \sim U[-2, -1.05]$ (Gray et al., 2005; Zheng, Saghaian, and Reed, 2012; Dhaliwal, 1972 as summarized by Nuckton, 1978). Demand for pistachio is considered elastic, as much of it is exported and it is not a staple food. The elasticity is capped, reflecting low substitutibility because of pistachio's unique flavor.

- Elasticity of supply: $\varepsilon_S \sim U[0.1, 0.3]$, reflecting the usual assumption that short term elasticity in agricultural goods is low.

- Monopolistic power measure: In 2016, 55% of California pistachio output was grown by one producer (Blank, 2016), and a marketing order for pistachio is in place. We find it likely that some degree of market power is being exercised, and set the distribution as $\psi_D \sim T[0.25, 0.75]$, where $T[\cdot]$ is an isosceles triangle probability distribution with the above mentioned range serving as base edge. Of course, it is assumed that these conditions apply in 2030 as well.

- Monopsonistic power measure: $\psi_S \sim T[0, 0.5]$, where $T[\cdot]$ is an isosceles triangle probability distribution. This reflects the potential of large packaging and processing plants to drive down prices paid to growers.

- Price of chill portion per acre: Assuming one application of kaolin lasts about a week, and yields one additional chill portion, the cost is estimated around \$55 per acre[5]. We let the price go up to 4 times higher, so $P_x \sim U[55, 220]$. Note that, in each simulation, the cost per acre is is multiplied by the acreage of the county. This means each county sees a different p_x, that is the cost of increasing chill count by one portion over all of its pistachio acreage.

Parameters are drawn independently, so their correlations are virtually zero. However, we trim our simulated parameter matrix for combinations that generate a power coefficient of 6 or above. That is done to keep the ratio of consumer price to grower price reasonable, reducing the size of our simulation matrix to 942 observations. Another result of the cap on PC is the creation of minor correlations between the elasticities of supply and demand, and the monopolistic and monopsonistic power variables (their absolute value of their correlation coefficients are all below 0.1).

[5]We thank Donald Stewart from UCANR's Agricultural Issues Center for data on material and deployment costs. We used pounds per acre ratios from (Doll, 2015) to calculate total cost per acre. We conservatively assume that one application increases chill count by one portion.

4 Results

First, we want to get a sense of the magnitude of loss, brought by insufficient chill *without* MCE. Figure 4 shows the empirical cumulative distribution of total potential loss rate by scenario. For each simulation, the chill realization is used to construct a vector of county specific loss rate. This is multiplied by the share of that county in total acreage in 2030, which varies by scenario. Summing these, we get the weighted average loss rate for all our counties. The figure shows, as expected, that scenarios in which acreage growth is shifted north have lower probabilities of large loss events. About 30% of chill portion vector draws result in virtually no loss. The CDFs seem step-like, indicating the sharp decline in yield at the chill threshold for each affected county. The average expected loss by scenario is specified in Table 1.

In our simulations, MCE seems to revert the market outcomes of insufficient chill almost completely. When simulated without MCE, the outcome market price ranges between $5,625 / ton (baseline 2014 price) and $36,019. However, simulation with MCE result in a price range between $5,625 and $5,704 - a minimal increase. This is probably the result of a relatively low price of MCE, compared to the output price. To get a better sense of the effect, Figure 5 shows the distributions of MCE effects in percent change for price and quantity. That is, the percent increase in quantity and decrease in price when using MCE, compared with the non MCE simulation. The mean price decrease is 13-31%, and the mean quantity increase is 32-88% (both scenario depending). These averages include years, where the climate damages are nearly zero for all counties, about a third of simulations. Thus, the actual effects in insufficient chill years are actually higher.

We now turn to look at the gains from MCE on aggregate profits, consumer surplus, and total welfare. Figure 6 presents the distribution of these gains, and they are almost exclusively positive. That is not very surprising for consumer surplus, as MCE lowers the price on a good with modeled elastic demand. Average consumer surplus gains from MCE range between $0.68 - 2.60 billion ($0.40-1.67 billion medians), scenario depending.

Grower profits gains are almost always positive as well, with an average ranging between $0.49 - 1.22 billion ($0.32-1.06 billion medians). This result was less obvious *a priori*, as there is some measure of oligopolistic power in each simulation. These gains in grower profits are not distributed evenly between counties. As the baseline climate is not homogeneous among counties, and climate change might be different as well, not all counties would be affected the same. Sharing the market with Kern and Kings counties, which are more susceptible to insufficient chill, the cooler counties of Madera and Tulare are predicted to be less affected by climate change. Yet, MCE lowers the price and their share of the market on years with insufficient chill, compared to the non-MCE baseline. That is, while the industry gains in total are positive, these counties' profits are mostly negative. Figure 7 shows the profit gains distribution by county. Kern and Kings counties have mostly positive profit gains. Madera and Tulare counties have mostly negative gains, and positive ones only in the worst chill years, when they lack chill portions as well. Fresno county is somewhere in the middle. This result reflects a broader aspect of climate change and adaptation. Areas who are affected very little by climate change can still feel its effects. As there are winners and losers from climate change, there will be winners and losers from MCE.

A main contributor of heterogeneity in gains future geographic distribution of acreage growth. Note how the gain distributions vary between scenarios. The two "Same" scenarios, keeping the distribution of future acreage the same as 2014's, but varying in total acreage by roughly a twofold, generate gain distributions that are closer to each other than to the "North" scenarios with respective growth rates.

To see the effect of other parameters on welfare outcomes, we plot them separately. In Figure 8, the gains are plotted against each parameter, using the "High Same" acreage growth scenario. Recall that, since we did not include parameter realizations resulting in $PC > 6$, there are slight correlation between the parameters. This is therefore an approximation of an "all else equal" plot, which we still consider useful to see the effects of each parameter on gains. To start, we note that the gains from MCE increase with the potential loss rate, as expected. The profit gains seem to increase linearly with the potential loss rate, but consumer surplus seems to grow exponentially. This is probably due to the choice of our demand function: with elastic demand, the inverse demand function is an exponential function with negative exponent that is greater than (-1). Therefore, the integral below the inverse demand function, from zero to any quantity, is infinite. As the potential loss rate increases, this integral should grow in a non-linear fashion.

When demand is more elastic, gains from MCE increase for growers and decrease for consumers, as expected. When supply is more elastic, gains from MCE decrease for everyone, as expected. Looking at the effects of market power, we notice that monopolistic power seems rather uncorrelated with consumer surplus. This is somewhat surprising, as we expected monopolistic power to decrease consumer's benefits from MCE. However, note that we assumed monopolistic power does not change with loss rate. Had we modeled them with a correlation, the trend line would probably slope up. Monopsony power increases consumer surplus, probably through the monopsony rents: as demand is elastic, restricting quantities lowers surplus. An increase must be the result of the rents. In a more realistic situation, where these rents are not necessarily included in consumer's surplus, the result might be different. However, this does not change the total welfare outcomes. With respect to the entire market power measure, PC, it seems to increase both consumer surplus and profits from MCE. This also means that the potential losses from insufficient chill increase with market power, a point worthy of consideration in other settings as well.

5 Conclusions

Extreme events and other "weather bottlenecks" could be a major source of loss from climate change in agriculture, at least for the next few decades. When feasible, Micro-Climate Engineering could benefit growers and consumers by tackling short lived adverse weather events. Growers have already been using MCE strategies to deal with challenging climates, and we believe that the benefits of MCE for climate change adaptation might be quite significant. As a case study, we model the pistachio sector in California and assess the expected yearly welfare gain from MCE in 2030 at the low billions.

We expect to find more examples of MCE for dealing with climate change in agriculture. However, the research and implementation of these techniques depends on economic and institutional circumstances, which vary around the world. MCE could increase the global disparities in climate change loss incidence, especially if it is mainly used in the more affluent parts of the world. Not all countries have public research institutions to develop MCE methods such as the kaolin technique, or have the access to the application rigs used to treat the dormant trees. At the same time, MCE could also accelerate the transition of agricultural practices closer to the poles, sometimes referred to as the "fertilization effect" (Zilberman et al., 2004). As climatic conditions in these areas change, the main obstacles for some crops at some point could be weather bottlenecks, such as frosts. For example, as winter temperatures get milder on average, grapes could be grown in areas too cold for them at present, with the help of the same MCE frost solution already used in warmer climates today.

Our results show increased gains from MCE with higher degrees of market power. This points in two directions or future research. First, that the adverse effects of climate change could be exacerbated by market power. This often overlooked intersection of industrial organization and climate change economics has, at least in our model, a large role in welfare outcomes. The second point is that, if gains from MCE increase total welfare, and grow with market power, then public investment in R&D for MCE could be economically justifiable even in the presence of some market failures.

This simulation based valuation methodology has its caveats. Modeling supply and demand as constant elasticity functions is obviously a simplification. Our assumptions on growth and distribution of acreage are based on past growth patterns, and might not reflect unexpected future changes in market conditions. Our future chill predictions are in line with other predictions by climatologists, yet might fail to materialize. Nevertheless, by choosing various scenarios, basing our parameter ranges in the literature, and choosing conservatively when possible, we believe to have gotten a reasonable range for the potential gains from MCE in California pistachio. The values calculated here should approximate the actual ones, at least in the order of magnitude. Averaging simulation results from the entire predicted climate distribution, even in years when chill is sufficient, the expected gains could be thought of as the value of the option to use MCE when necessary. They are in the low billions for a crop of secondary importance to California agriculture. We believe this shows the potential importance of MCE for climate change adaptation in general.

6 Figures and Tables

	High Growth: 13.5% yearly in the first 6 years, then 10% yearly until 2030	**Low Growth:** 10% yearly in the first 6 years, then 5% yearly until 2030
Same: Same acreage growth rate for all counties	**High-Same** $E[Loss] = 0.31,\ Sd[Loss] = 0.25$	**Low-Same** $E[\alpha]0.31,\ Sd[Loss] = 0.25$
North: As of 2021, all acreage growth in Tulare and Madera	**High-North** $E[Loss]0.14,\ Sd[Loss] = 0.14$	**Low-North** $E[Loss]0.20,\ Sd[Loss] = 0.18$

Table 1: Growth scenarios and total loss rates means

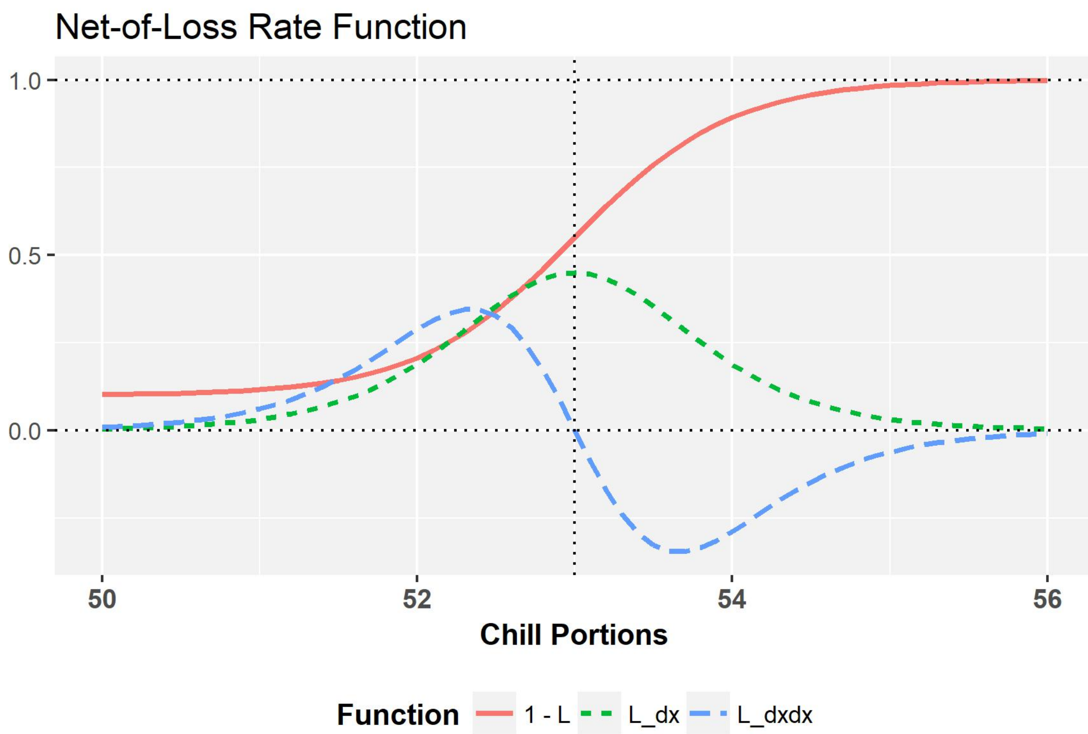

Figure 1: Net of loss function and its derivatives.

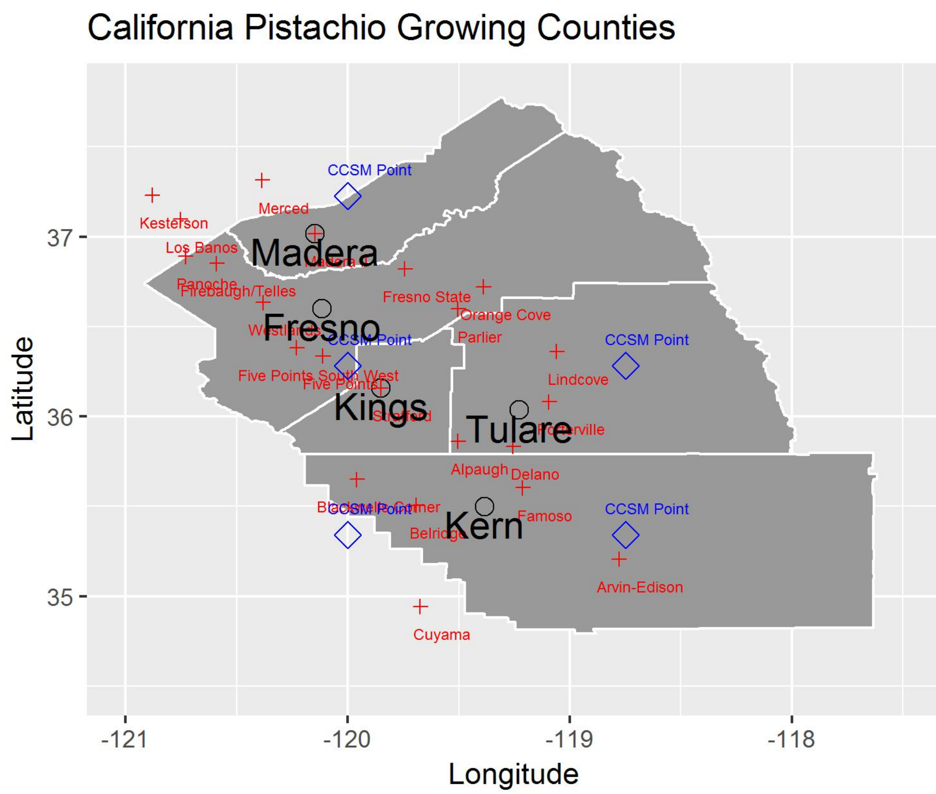

Figure 2: California main pistachio growing counties, CIMIS weather stations used (red), and CCSM4 interpolation points used. The black circles are the counties' centroid of CIMIS stations.

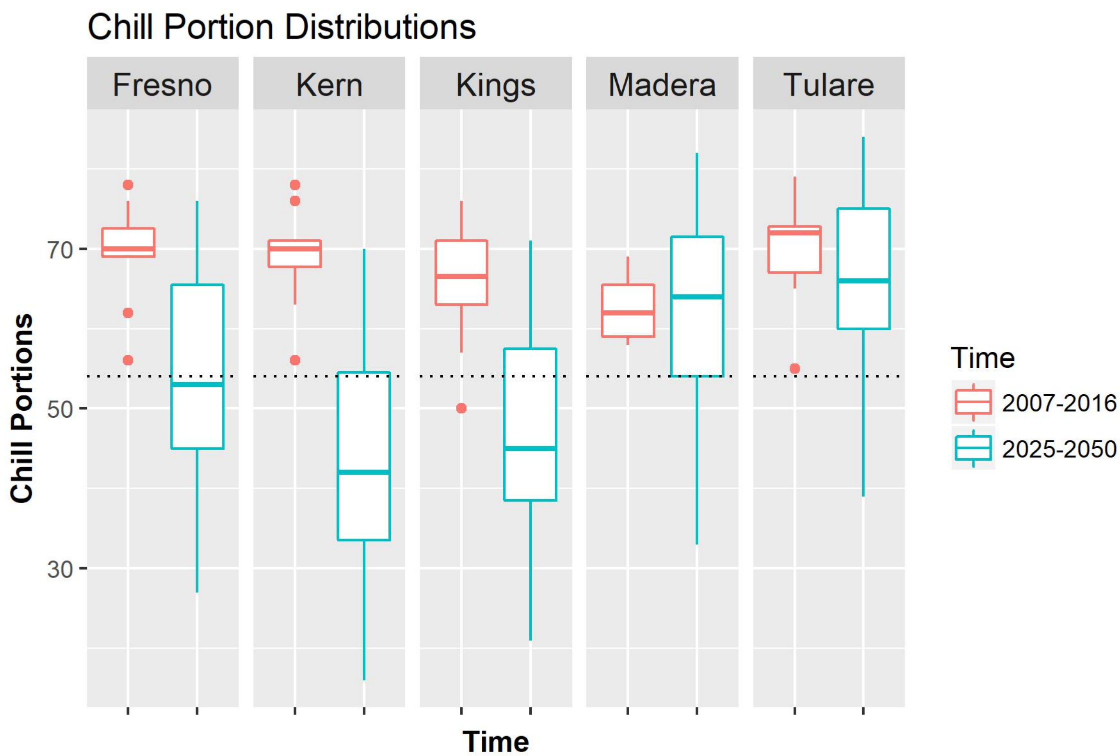

Figure 3: Winter chill portion distributions for our counties. The 2006-2017 distributions are processed from CIMIS data. The 2025-2050 distributions are processed from our calibrated climate model.

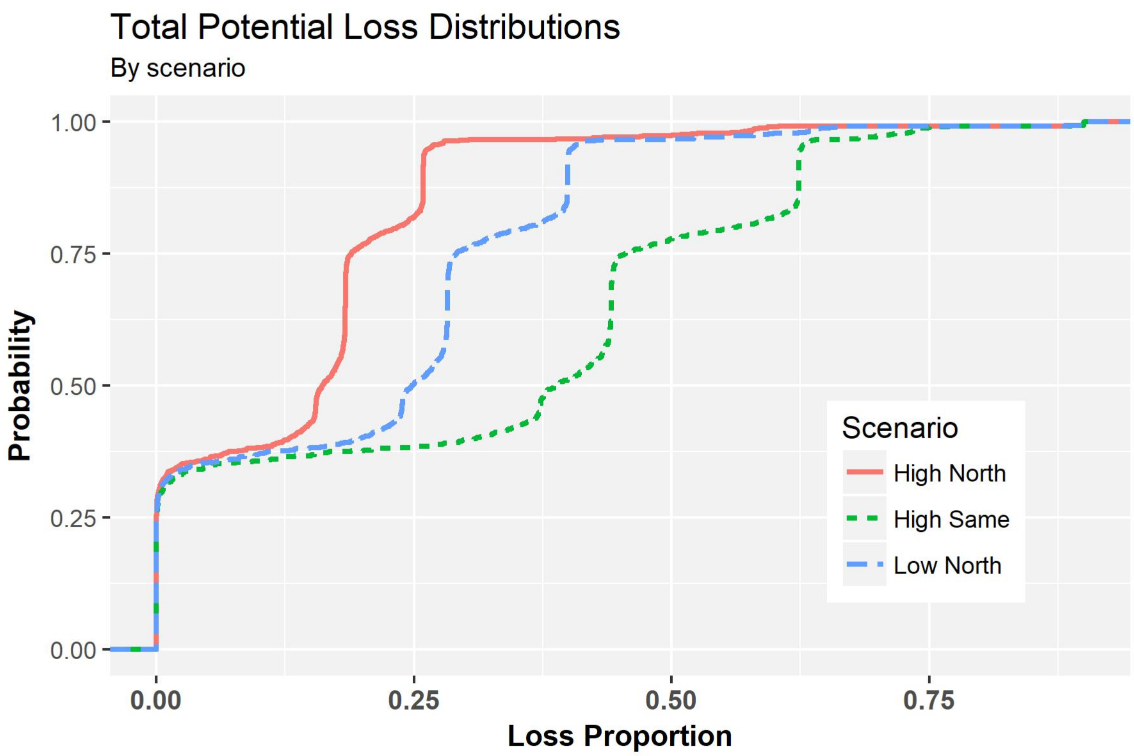

Figure 4: Distributions of potential loss rate from insufficient chill, by scenario.

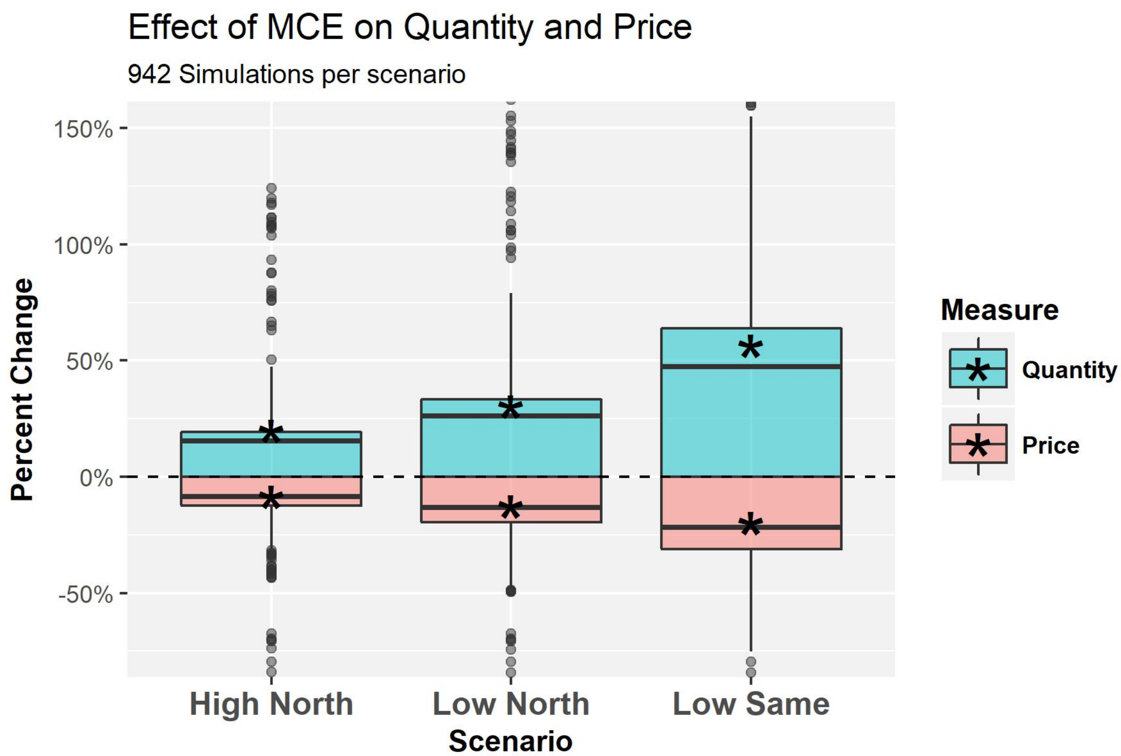

Figure 5: Boxplots of MCE effect in percent changes on quantity (positive)and price (negative) for each scenario. Asterisks indicate the mean effect.Some positive outliers are left out for clarity of figure. Note that, since these are relative changes, the outcome distribution for the two "same" acreage growth scenarios are identical, and only one is presented.

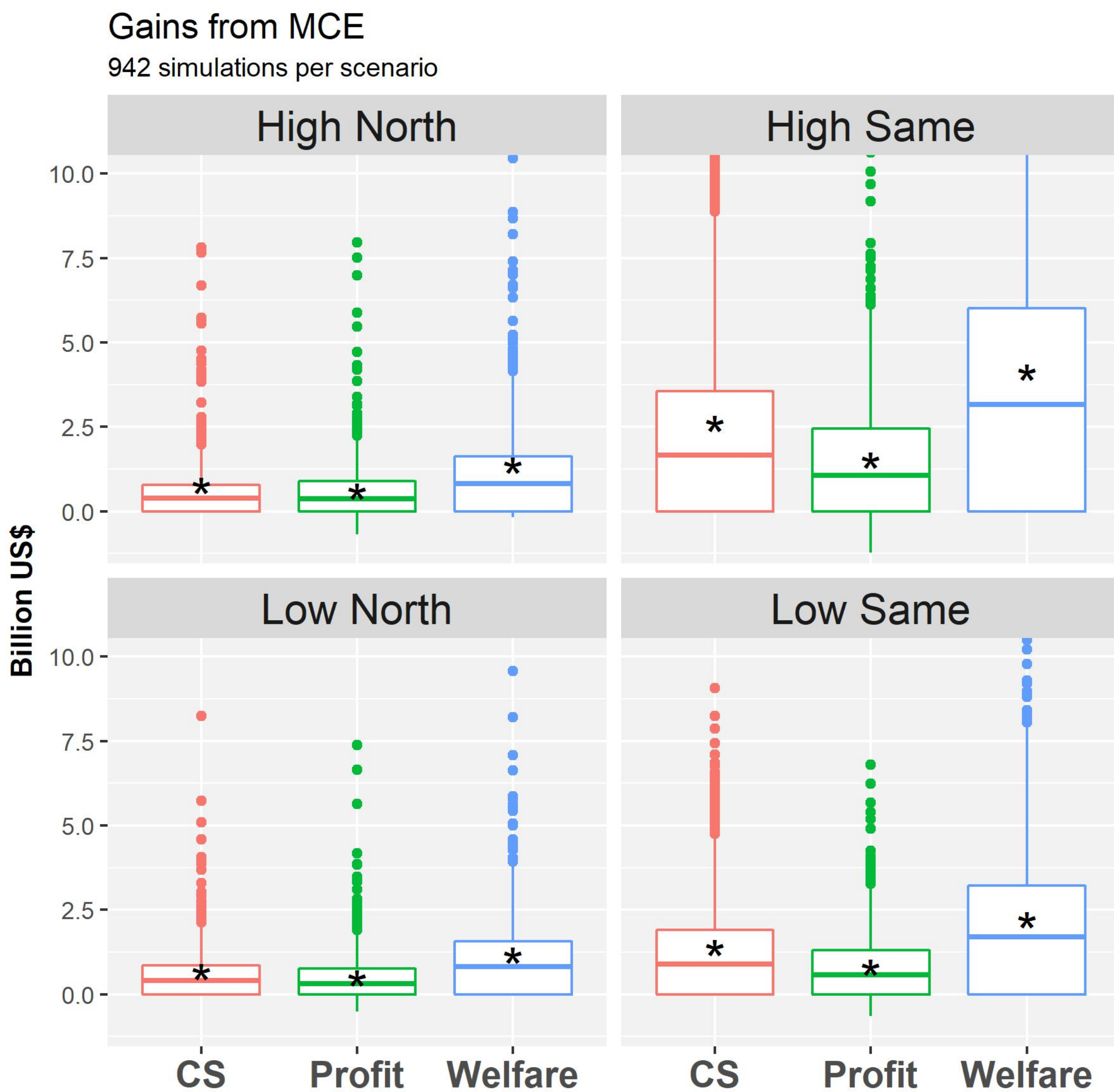

Figure 6: Total gains distribution by scenario. Middle line in box plot indicates median, the asterisk is the average. Some positive outliers are left out for clarity of figure.

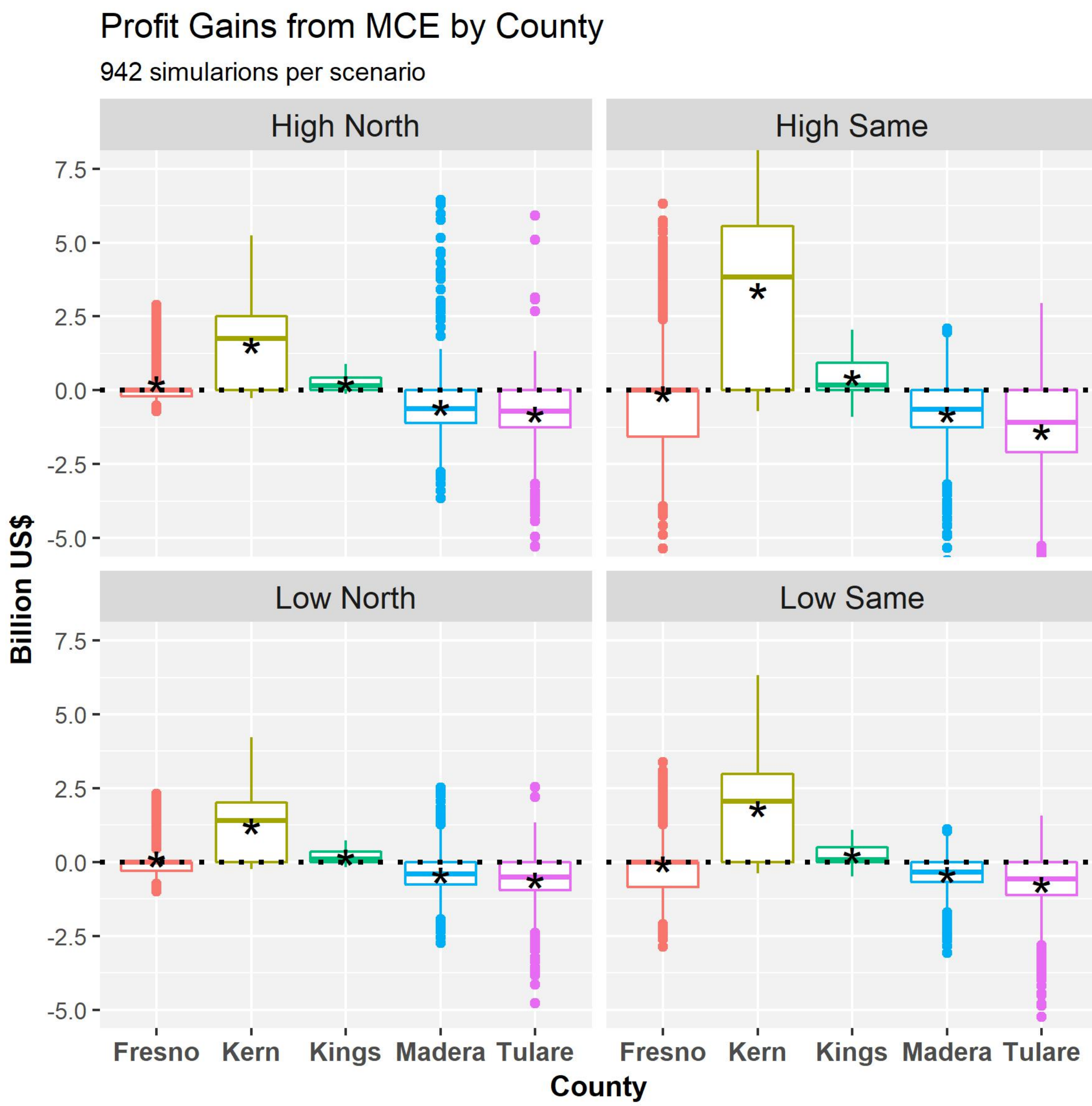

Figure 7: Distributions of profit gains by county in simulations. Asterisks represent means. Some positive outliers are left out for clarity of figure.

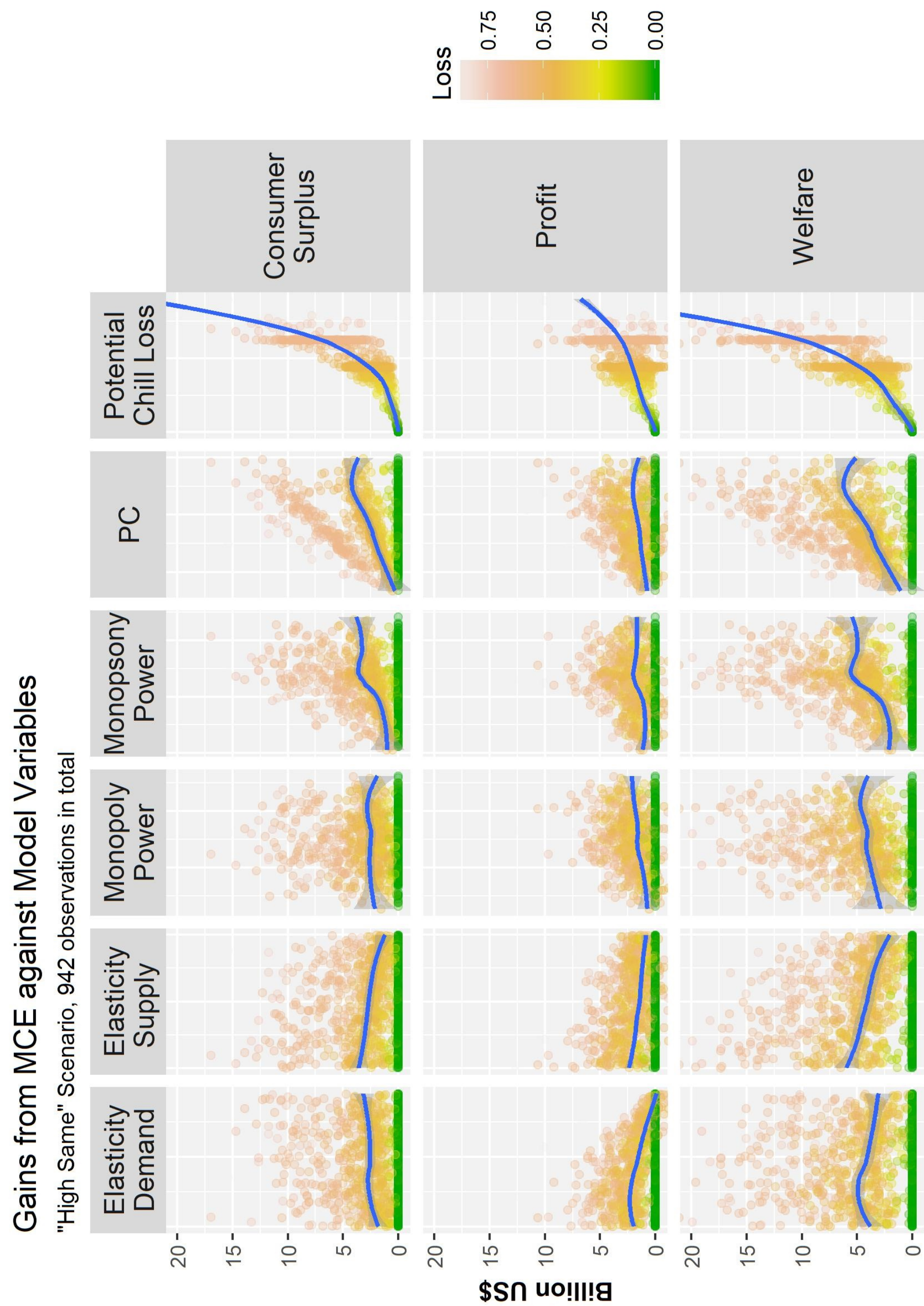

Figure 8: Gains from MCE plotted against different model parameters. To clearly see the correlations, this point in these plots are for simulations where the potential loss ratio, given the simulated chill realization, was greater than 0.1: when there is no loss, the gains are about 0 regardless of the parameters. The blue line is the result of a local 2nd degree polynomial regression. Note that the horizontal axis is different for each variable. Some outliers are excluded for clarity of figure.

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A Model Details

A.1 Getting to equation (12)

Starting with equation (7):

$$p \cdot (L_x(x^*)) \cdot \alpha \cdot \left(\beta \cdot \frac{p_x}{p_z} \cdot \frac{1 - L(x^*)}{L_x(x^*)}\right)^\beta = p_x$$

$$p \cdot (L_x(x^*))^{1-\beta} \cdot \left[\alpha \cdot \left(\frac{\beta}{p_z}\right)^\beta\right] \cdot [1 - L(x^*)]^\beta \ \cdot (p_x)^\beta = p_x$$

$$p \cdot (L_x(x^*))^{1-\beta} \cdot \left[\frac{q_{i,2014}}{(p_{2014})^{\frac{\beta}{1-\beta}}}\right]^{1-\beta} \cdot [1 - L(x^*)]^\beta = (p_x)^{1-\beta}$$

$$p \cdot (L_x(x^*))^{\frac{1}{1+\varepsilon_S}} \cdot \left[\frac{q_{i,2014}}{(p_{2014})^{\varepsilon_S}}\right]^{\frac{1}{1+\varepsilon_S}} \cdot [1 - L(x^*)]^{\frac{\varepsilon_S}{1+\varepsilon_S}} = (p_x)^{\frac{1}{1+\varepsilon_S}}$$

$$(p)^{1+\varepsilon_S} \cdot L_x(x^*) \cdot [1 - L(x^*)]^{\varepsilon_S} \cdot \left[\frac{q_{i,2014}}{(p_{2014})^{\varepsilon_S}}\right] = p_x$$

which is equation (12).

A.2 Getting to a Supply Function equation (13)

Once we have x^*, we can calculate our supply:

$$\begin{aligned}
q_i &= [1 - L(x^*)] \cdot \alpha \cdot (z^*)^\beta \\
&= [1 - L(x^*)] \cdot \alpha \cdot \left(\frac{1 - L(x^*)}{L_x(x^*)} \cdot \beta \cdot \frac{p_x}{p_z}\right)^\beta \\
&= [1 - L(x^*)] \cdot \left[\alpha \cdot \left(\frac{\beta}{p_z}\right)^\beta\right] \cdot \left[\frac{1 - L(x^*)}{L_x(x^*)} \cdot p_x\right]^\beta \\
&= [1 - L(x^*)] \cdot \left[\frac{(q_{i,2014})^{1-\beta}}{(p_{2014})^\beta}\right] \cdot \left[\frac{1 - L(x^*)}{L_x(x^*)} \cdot p_x\right]^\beta \\
&= [1 - L(x^*)] \cdot \left[\frac{(q_{i,2014})^{\frac{1}{1+\varepsilon_S}}}{(p_{2014})^{\frac{\varepsilon_S}{1+\varepsilon_S}}}\right] \cdot \left[\frac{1 - L(x^*)}{L_x(x^*)} \cdot p_x\right]^{\frac{\varepsilon_S}{1+\varepsilon_S}} \\
q_i &= [1 - L(x^*)]^{\frac{1+2\cdot\varepsilon_S}{1+\varepsilon_S}} \cdot \left[\frac{q_{i,2014}}{(p_{2014})^{\varepsilon_S}}\right]^{\frac{1}{1+\varepsilon_S}} \cdot \left[\frac{p_x}{L_x(x^*)}\right]^{\frac{\varepsilon_S}{1+\varepsilon_S}}
\end{aligned}$$

This is assuming that there are no constraints on x^*, i.e. it could be negative. For that to happen, the natural chill portions have to be high, and the price rate p_x/p needs to be high enough for the growers to want, theoretically, to sell chill portions. In that case, we apply the simple Cobb-Douglas (as the grower can't manipulate the chill portions down, nor would he buy any). Thus, for a given MCE price p_x, the inverse supply curve has two parts: one, where the resulting x^* is positive, is the first case of (12). The second, where x^* is negative, is the more inelastic Cobb-Douglas supply. Equating both parts of equation (13) gives us the price, given the natural chill C and p_x, where the two parts of the supply curve meet. That's the minimal price of pistachio required to promote buying chill portions.

$$p = (p_x)^{\frac{1}{1+\varepsilon_S}} \cdot \frac{1 - L(0 \mid C)}{L_x(0 \mid C)} \cdot \left[\frac{(q_{i,2014})}{(p_{2014})^{\varepsilon_S}} \right]^{\frac{-1}{1+\varepsilon_S}}$$

As this expression shows, the higher the price of MCE, p_x, the higher this transition price is. Also, this transition price increases when the loss rate is either very low or very high. When this transition price is is either very low or very high, we will see one supply curve *de facto*: either the Cobb-Douglas or the one we derived above.

A.3 Profit Maximizing Solution

Our production function is:

$$G(x,z) = [0.55 - 0.45 \cdot tanh(53 - x)] \cdot \alpha \cdot (z)^{\beta} \tag{1}$$

The partial derivatives are:

$$\begin{aligned} G_x &= -0.45 \cdot sech^2(53 - x) \cdot (-1) \cdot \alpha \cdot (z)^{\beta} > 0 \\ G_z &= [0.55 - 0.45 \cdot tanh(53 - x)] \cdot \alpha \cdot \beta \cdot (z)^{\beta - 1} > 0 \end{aligned}$$

And the Hessian is:

$$\begin{pmatrix} G_{xx} & G_{xz} \\ G_{zx} & G_{zz} \end{pmatrix} = \begin{pmatrix} 0.9 \cdot sech^2(53 - x) \cdot tanh(53 - x) \cdot \alpha \cdot (z)^{\beta} & 0.45 \cdot sech^2(53 - x) \cdot \alpha \cdot \beta \cdot (z)^{\beta - 1} \\ 0.45 \cdot sech^2(53 - x) \cdot \alpha \cdot \beta \cdot (z)^{\beta - 1} & [0.55 - 0.45 \cdot tanh(53 - x)] \cdot \alpha \cdot \beta \cdot (\beta - 1) \cdot (z)^{\beta - 2} \end{pmatrix}$$

Since $tanh(53 - x) < 0$ *i.f.f* $x > 53$, and $0 < \beta < 1$, note that $G_{zz} < 0$ and $G_{xx} < 0$ when $x > 53$. As for the sign of the determinant:

$$\begin{aligned} det(H) = \; & \left[0.9 \cdot sech^2(53 - x) \cdot tanh(53 - x) \cdot \alpha \cdot (z)^{\beta}\right] \cdot \\ & \left[(0.55 - 0.45 \cdot tanh(53 - x)) \cdot \alpha \cdot \beta \cdot (\beta - 1) \cdot (z)^{\beta - 2}\right] - \\ & \left[0.45 \cdot sech^2(53 - x) \cdot \alpha \cdot \beta \cdot (z)^{\beta - 1}\right]^2 \\ = \; & \alpha^2 \cdot \beta \cdot (z)^{2\beta - 2} \cdot sech^2(53 - x) \cdot \\ & \left[0.9 \cdot tanh(53 - x) \cdot (0.55 - 0.45 \cdot tanh(53 - x) \cdot (\beta - 1) - \left(0.2025 \cdot sech^2(53 - x)\right) \cdot \beta\right] \end{aligned}$$

Note that α, β, z, and $sech^2$ are always positive, so the sign of the term in brackets will determine the sign of the whole determinant. When chill is in deficit, i.e. $x < 53$, the first term in the big brackets is negative and the second is positive, so the whole determinant is negative. However, when chill is in surplus, i.e. $x > 53$, the both terms are positive, and the sign is ambiguous without further exploration. Plotting the term in bracket for our range of β, it turns out that sign of the determinant is positive when $x > 53 + \delta(\beta)$, the threshold depending on β with very small differences for our range of β. In all of our simulations, the total chill $x_i + c_i > 54.92$.

The FOC in equation (13) is solved by up to two x values, as its shape is unimodal. For our range of parameters, the function plots show that that lower valued root will be to the left of 53, indicating that the simulation solutions are the only possible ones that are a local maximum.

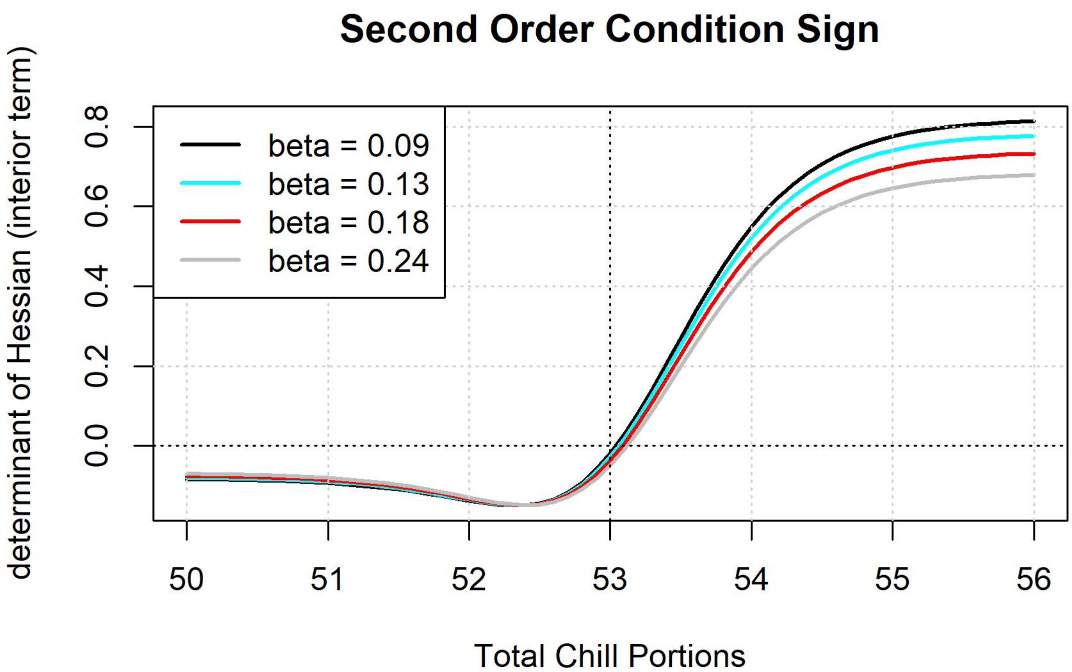

Figure 9: Concavity area of production function. The range of beta corresponds to our range of supply elasticities, $[0.1 - 0.3]$, by equation (10).

B Climate Data

A winter's chill portion count is calculated from a vector of hourly temperatures. Observed temperatures for 2006-2015 come from the California Irrigation Management Information System (CIMIS, 2016), a network of weather stations located in many counties in California, operated by the California Department of Water Resources. Each county's reference point is at the centroid of CIMIS stations in that county.

After setting the reference point, the representative temperature was calculated as the (inverse) distance weighted temperature of all stations within 100Km from the reference point [6]. Dropping stations with 5% or higher missing observation rate for winter months (November-February), we are left with 22 stations in total. Remaining missing values were calculated using the nearest available station, predicting those missing values using the following estimated model:

[6] For Kings and Madera counties, both with a single CIMIS station, that station's readings were taken as representative temperatures

$$T_t^A = T_t^B + (T_t^B)^2 + \gamma_M + \phi_H + \varepsilon_t$$

Where T_t^A is the temperature vector in the station with missing observations, T_t^B is the nearest station, γ_M and ϕ_H are month and hour fixed effects. When the nearest neighbor had a missing value at the same time as well, we turned to the next nearest neighbor, and so on.

To estimate future chill, we use temperature predictions of a CCSM4 model from CEDA (2016). These predictions use an RCP8.5 scenario. This scenario assumes a global mean surface temperature increase of $2^o\,C$ between 2046-2065 (from a baseline of 1986-2005) (IPCC, 2013). The data are available with predictions starting 2006, and include daily maximum and minimums on a 0.94 degree latitude by 1.25 degree longitude grid. To interpolate hourly temperatures from the predicted daily extremes, we use a procedure involving the latitude and date (coded in R by Luedeling, 2017). Having obtained the predicted hourly temperature vectors at the grid points, we generate the county representative temperature vectors by (inverse) distance weighted averaging of the predicted temperature vectors on the CEDA grid within 100Km from our reference points. This gives us a predicted temperature vector for the years 2006-2100 for the five counties. Following Leard and Roth (2016), we perform quantile calibration on the 2006-2016 past predictions, which can be compared with the actual observed temperatures.

Once we have the observed temperatures from CIMIS and the predicted future temperatures, we can calculate the past and predicted chill portion count for each winter at each county. Erez and Fishman (1997) produced an Excel spreadsheet for chill calculations, which we obtain from the University of California division of Agriculture and Natural Resources, together with instructions for growers (Glozer, 2016). We converted it to R code for computational convenience.