Micro-Climate Engineering for Climate Change Adaptation in Agriculture: The Case of California Pistachios

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Abstract

Can farmers adapt to climate change by altering effective weather conditions on their fields? Technologies for small scale temperature adjustment are used by farmers, yet receive little attention in the economic literature. These technologies allow farmers to cool down plants by a few degrees on hot days, reducing the damage from excess heat. With non-linear effects of high temperature on yields, slight cooling can bring significant gains in many crops. I call this approach "Micro-Climate Engineering" (MCE), and note that it could be useful as a climate change adaptation concept. Climate change is predicted to harm crops mainly by change of the temperature distribution tails, rather than by change of the averages. I develop a model to analyze grower choice and market outcomes with MCE under adverse climate, and apply it to assess the potential gains from an existing MCE technology in California pistachios, which are threatened by warming winters. The expected yearly gains from MCE technologies by the year 2030 are assessed at 153 - 540 million US dollars under several scenarios. Simulation results show a total negative gain from MCE for the pistachio growing sector, but the positive gains for consumers surpass them. Adding market power in the growing sector increases consumer gains from MCE, but grower incentives to apply MCE technologies (and invest in new ones) become sensitive to market conditions.

1 Introduction

Climate change poses a major challenge for agriculture, as predicted shifts in temperature and precipitation patterns around the world affect agricultural productivity (Zilberman et al., 2004; Carleton and Hsiang, 2016). Early studies on climate change in agriculture 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 growing season (Auffhammer and Schlenker, 2014). For example, Schlenker and Roberts (2009) show sharp drops in the yields of corn, soybean, and cotton, when exposed to degree days above $28-30^0C$. Thus, even when the climate is generally favorable to a crop, short term weather events can cause major damages. Leading climate change scientists affirm that “it is very likely that heat waves will occur with a higher frequency and duration” as the global mean temperatures increases (IPCC, 2013). A major challenge posed climate change is therefore not necessarily the rise in average temperatures, but rather the increased probability of high temperature days, i.e. the growing temperature distribution tails.

Could there be a way for farmers to target these tails directly? If so, such technologies could have potential uses for climate change adaptation. It so happens that farmers already deal with temperature extremes, and are capable of tweaking the tails of temperature distributions to avoid losses. A common practice deals with a left side temperature tail - spring frost. Farmers have been using “air disturbance technology” in the US since the 1950’s (Hu et al., 2018). The principle of these technologies is straight forward: on frost nights, cold air sinks to the ground level, causing plants to freeze. Using large wind generators (fans), or in some cases helicopters, the cold air is mixed with the warmer air laying on top of it. This raises the temperatures around plants by a few degrees, and helps prevent the frost damages. This technology is used for wine grapes, fruits, and even tea. In some cases, a similar effect can be achieved with sprinklers (Olen, Wu, and Langpap, 2015; Lu et al., 2018).

Solutions for right side temperature tails exist as well. Of course, shading plants using nets or fabric is an existing practice, but involves substantial costs and implies a less flexible intervention in the temperature distribution, as setting and adjusting these technologies is labor intensive and time consuming. However, there are products that reflect sunlight and lower plant exposure to excess heat in more flexible ways. Perhaps the most common ones are based on a fine kaolin clay powder, which is mixed with water and sprayed directly on plants to form a reflective coating, sometimes referred to as a “particle film”. These products have been commercially available since 1999, and are shown to effectively lower high temperature damages by literally keeping plants cooler (Sharma, Reddy, and Datta, 2015). Some manufacturers report a canopy temperature reduction of up to 6^oC when using their products. We think of this technology as cheap, disposable shading.

The technologies mentioned above are examples of an approach we call “Micro-Climate Engineering” (MCE). These are relatively small interventions in temperature distributions, limited in space and time, which aim to avoid the nonlinear effects of the extremes. Farmers know the available technologies for MCE and use them regularly, but the economic literature has paid little, if any, attention to this phenomenon[1]. Moreover, the tweaking the temperature distribution tails with MCE technologies has not been examined as a concept. I think MCE could be very important for climate change adaptation in agriculture, especially when considering the role of extreme temperatures on predicted future losses. Using MCE solutions, where feasible and profitable, could assist in preserving current crop yields and delaying more costly adaptation strategies.

This paper sets to assess the potential gains of MCE for California pistachios. Specifically, pistachios are threatened by warming winter days, which could threaten existing acreage even in the medium run (the years 2020-2040). This challenge stands out in the existing literature in three ways: first, while much of the climate change literature focuses on annual crops, pistachios are perennial. This means that the opportunity costs of variety switching are higher. Second, the challenge does not occur in the "growing season", but on the winter months when trees are dormant and seemingly inactive. This emphasizes the importance of climate change effects year round, rather than just in the spring and summer. Moreover, while many papers deal with end-of-century climate predictions, the threat for pistachios is imminent. Third, the challenge stems from a biological mechanism that is not heat stress. Heat stress is perhaps the most obvious process by which rising temperatures can have adverse effects on yields, and by far the most studied one in the economic literature on climate change. Incorporating agronomic knowledge, this paper broadens the perspective on the effects of climate change on agriculture.

Scientists at the University of California Cooperative Extension have been experimenting with kaolin clay applications on pistachios, and the results seem promising (Doll, 2015; Beede and Doll, 2016). This could mean a great deal to growers and consumers. In the following sections, we try to asses the potential gains from this technology by the year 2030. The remaining of this paper is organized as following: Section 2 present the case of California pistachios, their climatic requirements, and the threat of climate change on their yields. In section 3 I model the pistachio market and set the functional forms and parameters used to simulate the gains from MCE. Section 4 shows the results of our simulations under varying market conditions. Section 5 concludes.

2 California Pistachios And Climate Change

Introduced to California more than 80 years ago, and grown commercially since the mid 1970's, pistachio (*Pistachia Vera*) was the state's 8th leading agricultural product in gross

[1]Searching EconLit for "frost" in article titles returns only four results involving actual frost in agriculture, none dealing with temperature altering. A search in the abstracts of papers published by the American Journal of Agricultural Economics results in two papers, neither mentioning air disturbance technologies. Searches for "kaolin" and "particle film" returned no results.

value in 2016, generating a total revenue of \$1.82 billion dollars. According to the California Department of Food and Agriculture (2017), California produces virtually all pistachio in the US, and competes internationally with Iran and Turkey (2/3 of revenues are from export). In 2016, five California counties were responsible for a 97% of the state's pistachio crop: Kern (35%), Fresno (28%), Tulare (15%), , Madera (11%) and Kings (8%). 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).

The challenge for California pistachios has to do with their winter dormancy and the temperature signals required for spring bloom. The following brief explanation of dormancy is based on Erez (2000). Many fruit and nut trees, including pistachios, have a dormancy phase during winter. This phase is an evolutionary adaptation, allowing trees 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 goes 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. Trees use environmental signals to trigger bud breaking and bloom. These signals include day length and temperatures. Failure to attain a threshold signal level, varying between crops and varieties, leads to late, low, and non-uniform bud breaking, which is linked to low yields at harvest. This threshold mechanism means that small changes in the temperature distribution can have large effects on yields, especially in the warmer areas where the chances of not reaching the temperature threshold signal are higher.

There are several agronomic models for the temperature signal. Some, such as the Utah Model, use a degree day type approach, counting hours at various temperature ranges and developing an index using the sums. A different approach is set by the Dynamic Model, which seems to be more precise in predicting bloom in many temperate areas such as California (Luedeling, 2012). The Dynamic Model uses a metric of chill portions, which are calculated with a vector of hourly temperatures. The formula is sequential, mimicking chemical dynamics which depend on the concentrations of substrate and product. Chill portion build up depends on these concentrations and on the ambient temperature staying within some thresholds. 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 a detrimental effect on chill count, even if the temperatures themselves are not extreme on the yearly distribution, because they interfere with the build-up of chill portions. In fact, for the areas covered in this study, chill portions are strongly (and negatively) correlated with the 90^{th} temperature percentile (Q90) between November and February, the dormancy season for pistachios. The correlation is very strong, with a goodness of fit rating of about 0.91. In essence, insufficient chill is a right side temperature tail effect, comparable with similar such effects in the climate change literature.

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). Declining chill is therefore considered a threat to California pistachios.

2.1 Climate and Damage Predictions

Chill in most of California has been declining in the past decades, and is predicted to decline further in the future. Luedeling, Zhang, and Girvetz (2009) estimate the potential chill drop for the southern part of San Joaquin valley, where virtually all 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. Agronomists and stakeholders in California pistachios recognize this as a threat to this valuable crop (Doll, 2017; Jarvis-Shean, 2017). Together with increasing air temperatures, a drastic drop in winter fog occurrence in the Central Valley has also been observed. This increases tree bud exposure to direct solar radiation, raising their temperature even further (Baldocchi and Waller, 2014).

The estimates cited above virtually cover the entire pistachio growing region, and the first decile metric is less useful for a thorough analysis of pistachios. I create down-scaled temperature maps, interpolated on a 1km grid in pistachio growing areas, where the growing areas are identified by satellite (Boryan, Yang, and Willis, 2014). Two sources for temperature data are used. Observed temperatures for 2000-2018 come from the California Irrigation Management Information System (CIMIS, 2018), a network of weather stations operated by the California Department of Water Resources and located in various counties in California. Stations are usually located near agricultural areas, making them especially adequate for this purpose. Data from a total of 27 stations is used. Future temperature predictions come from a CCSM4 model by CEDA (2016). These predictions use an RCP8.5 scenario, assuming a global mean surface temperature increase of $2^o C$ between 2046-2065, from a baseline temperature average in 1986–2005 (IPCC, 2013).

For each of the 2,165 interpolation points, I create a yearly vector of past and future temperatures by inverse distance weighted average from the relevant data points (CIMIS stations or CEDA interpolation points). Following Leard and Roth (2016), I perform quantile calibration using the 2007-2016 past castings of the model, which can be compared with the actual observed temperatures. The past observed temperatures and future calibrated predictions are then used to construct chill portions for each point-year, as specified in Erez and Fishman (1997). Figure 1 shows the geographic distribution of chill in the 1/4 warmest years of observed climate (winters of 2000-2018) and predicted climate (2020-2040). More details on the climate data processing are found in Appendix A.

To assess the potential damage to pistachios from climate change, a yield-chill response function is required. I mention earlier a rough estimate of 54-58 portion threshold. However, the literature does not offer a precise estimate for it, nor for the shape of the response function around it. In Appendix B I estimate a threshold response function using a panel of California county yields from 1984 to 2016, and the heterogeneity in chill portions within counties. Using a logistic loss function, the estimation results are the two functional parameters: location (mean) of 46.63 chill portions and scale (proportional to variance) of 7.18. This estimate is aligned with the agronomic view of a threshold around 54-58 portions. In the bottom panel of Figure 1, I use this damage function to shows the calculated loss rates from the observed and predicted 1/4 warmest years in the data. While not very substantial in the past, these losses are predicted to reach up to 50% in some regions in the future.

3 Modeling Micro-Climate Engineering in Pistachios

This section develops a model to assess the gains from MCE in pistachios. The basic model has growers and consumers. This is a single year, short run market model, solving for price and quantity under different winter chill realizations[2]. Equilibrium price and quantity are used to calculate welfare outcomes such as grower profits, consumer surplus, and the total welfare. For each realization, the model is solved twice: once with an option to use MCE, and one without it. The differences in welfare outcomes with and without MCE under the same conditions are the welfare gains from MCE. Note that in both cases, agents will act optimally. MCE gains are therefore to be interpreted as the difference in welfare measures between a world with MCE and a world without it.

[2]I abstract from a benchmark with increased storage, which could theoretically alleviate inter-year fluctuations. Pistachios are usually stored for up to one year (Thompson and Adel A, 2016). The potential loss rates in a bad weather year are significant. Coping by storage in a meaningful way would require multi-year, double digit storage rate, which seems technically unfeasible.

3.1 Growers

The individual grower 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). Growers are considered to be small, facing the same prices for inputs and outputs, risk neutral, and fully informed about the prices and climatic conditions on all California plots. Consider a grower with a production function $H(z)$, increasing with input z. The function $H(z)$ is sometimes referred to as the *potential output* function, where z is an input vector unrelated to the potential weather damage.

The grower also faces a damage or loss function $L(c) \in [0, 1]$. This loss depends on the chill realization this grower sees. The grower knows c before making input decisions z. This is especially realistic in our case, considering that most inputs (water, fertilizer, pest management, labor) are applied in the spring and summer, after the trees exit dormancy. The grower maximizes profits, manipulating the input level z.

3.1.1 Supply without MCE

A grower without MCE takes the weather related climate loss as exogenous, and maximizes profits by choosing an optimal level of input z:

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

Without loss of generality, I treat $\mathbf{z}$ as a single, aggregate input. Note that the weather related loss is exogenous and constant. The grower's problem is solved by equating the value of marginal productivity of z to its price:

$$p \cdot [1 - L(c)] \cdot H_z(z) = p_z \tag{2}$$

The first order condition is solved for an optimal z^*, and the grower supplied quantity can then be calculated. The potential output function is specified as: $H(z) = \alpha + \beta \cdot \sqrt{z}$, which results in linear supply for the grower:

$$q(p,\, c) = [1 - L(c)] \cdot \left(\alpha + [1 - L(c)] \cdot \frac{\beta^2}{2p_z} \cdot p \right) \tag{3}$$

As expected, with higher price and/or higher net-of-loss rates, supply increases. To get some realistic values, calibration of this function is required. Mainly, the coefficients of the potential output function need to be established. Note that the linear form implies aggregability of growers of same size and weather realizations. We have 2,165 weather interpolation points of the same pixel size (1 Km^2), which we treat as individual growers. Ideally, each one would have the its own coefficients α and $\beta^2/2p_z$. While this could work for the no-MCE case, as the supply functions are explicit, the inclusion of MCE will require a numeric solution for the growers. Solving for 2,165 growers would make this solution computationally unfeasible. For this reason, and since the available yield reporting is at the county level, we aggregate for county chill-deciles, assuming that the non-weather conditions within each county are the same for all growers. For each county-year, the 10% of interpolation points with the lowers chill are the the first decile; the next 10% chill points are the second, and so on. Note that for each county, the number of growers in each decile is different, reflecting different acreage and capacity of each county. Altogether, the sum of county-chill decile supplies should approximate the total supply.

To calibrate coefficients for county deciles, I use market outcomes from 2016: the grower price and county quantities are taken from the California Department of Food and Agriculture annual crop report. To pinpoint a linear supply function, I also need a slope for supply, and use a short run supply elasticity parameter to calculate it. Short run elasticity in agricultural goods is usually considered very low (Alston, Norton, and Pardey, 1995, p. 321), and the 6-7 year setup requirement for pistachios should place its elasticity on the lower end even within this category. Others have modeled pistachio supply as completely inelastic (e.g. Gray et al., 2005), yet I think it is more realistic to take a positive parameter, as inputs such as harvesting effort can surely change supply. Estimates for supply elasticity are hard to come by in the literature. For an approximation, Russo, Green, and Howitt (2008) estimate the elasticity of almond supply w.r.t. one year lagged own price to be 0.19[3]. I take this as a starting point for the pistachio own price short run supply elasticity and use it in the main specifications.Later, I present results with other elasticities as well.

With county quantities, market price, county-decile losses in 2016 (very low in all cases), and an elasticity, I can back out county coefficients for the supply function[4]. The county-decile coefficients are one tenth of the county coefficients, e.g. $\alpha_{c,d} = 0.1\alpha_c$. The total supply without MCE is the total sum of these county supplies:

$$Q(p) = \sum q_{c,d}(p) = \sum [1 - L(t_{c,d})] \cdot \left[\alpha_{c,d} + \frac{\beta_{c,d}^2}{2 \cdot p_z} \cdot (1 - L(t_{c,d})) \cdot p\right] \tag{4}$$

[3]This estimate is not statistically significant (p-value = 0.2)

[4]The equations is:

$$\frac{\beta_c^2}{2 \cdot p_z} = \frac{\varepsilon_s}{\sum 1 - L(t_{c,d}^{2016})} \cdot \frac{q_{c,2016}}{p_{2016}} \implies \alpha_c = q_{c,2016} - \frac{\beta_c^2}{2 \cdot p_z} \cdot p \cdot \sum \left(1 - L(t_{c,d}^{2016})\right)$$

3.1.2 Supply with MCE

When MCE is available, the grower can also adjust the loss incurred due to weather. The profit maximizing problem is now:

$$\max_{x,z}\ \pi = p \cdot [1 - L(x,\, c)] \cdot H(z) - p_z \cdot z - p_x \cdot x \tag{5}$$

where x is the MCE input. Note that the natural chill itself, c, is still exogenous. This formulation assumes separability in output between x and z, i.e. that input x only affects yields through the chill mechanism. Although some MCE products also have some other useful properties (e.g. some pest control capabilities and lowering water requirements), these properties are not very useful at time of tree dormancy. Hence, this assumption seems reasonable in this case.

An internal solution for the grower problem is found with the two first order conditions, equating the value of marginal productivity of each input to its price:

$$p \cdot [1 - L(x)] \cdot H_z(z) = p_z \tag{6}$$

$$p \cdot [L_x(x)] \cdot H(z) = p_x \tag{7}$$

Combining these, we get an expression of optimal z^* as a function of optimal x^*:

$$\frac{p_z}{p_x} = \frac{1 - L(x^*)}{L_x(x^*)} \cdot \frac{H_z(z^*)}{H(z^*)} \tag{8}$$

$$= \frac{x^*}{\delta(x^*)} \cdot \frac{\eta(z^*)}{z^*} \tag{9}$$

$$\implies z^* = x^* \cdot \frac{\eta(z^*)}{\delta(x^*)} \cdot \frac{p_x}{p_z} \tag{10}$$

where η is the elasticity of potential output in z, and δ is the elasticity of (net-of) loss ratio in x[5]. This can be plugged in a FOC to get a necessary conditions for profit maximization:

$$p \cdot L_x(x^*) \cdot H\left(z^*(x^*)\right) = p_x \tag{11}$$

Solving for this equation will be part of the simulation. To better understand the concept of MCE as a solution for climate challenges, let us differentiate the FOC w.r.t. the output price p and the optimal MCE input x^*. We get (after some simplification):

$$\frac{\Delta x^*}{\Delta p} = \frac{L_x(x^*) \cdot H\left(z^*(x^*)\right)}{-L_{xx}(x^*) \cdot H\left(z^*(x^*)\right) + L_x(x^*) \cdot H_z(z^*(x^*)) \cdot z^*_x(x^*)} \tag{12}$$

[5]Note that $L(x)$ is decreasing in x, hence the derivative of the net-of loss function w.r.t. x is positive.

Where regularity conditions ensure us this ratio is positive (the loss function should be concave in the solution area). Naturally, an increase in output price is related to an increase in the optimal MCE input. Note that a significant increase requires a large marginal MCE effect, i.e. $L_x(x^*) \gg 0$ in the numerator. Where this does not happen, i.e. $L_x(x^*) \to 0$, increase in price will result in very little increase in x^*. Rather, the grower response would be through changes in z^*.

To specify a loss function with MCE, I assume that each application of kaolin increases the chill count by one portion. Therefore, "artificial" chill is simply added to the natural chill realization. Note that the cost of increasing the chill count by one portion depends on the total acreage. The cost of one additional portion per acre is estimated at \$55[6]. In the real world, there is a limit to the potential cooling effects of kaolin clay. Applying more reflective mix on trees already coated with a hefty layer would not be useful. However, as the layers are prone to washing off with winter rain, I take these costs and effects as linear for the model. The total required "extra" chill portions, usually about 15 on a warm year, seems feasible with weekly applications starting early in the winter.

With an identical potential outcome function as the no-MCE case, an explicit solution for z^* can be found (see Appendix C.1 for the algebra). The supply of a grower with MCE is

$$q_{c,d} = \left(\alpha_{c,d} + \beta_{c,d} \cdot \frac{-\alpha_{c,d} + \sqrt{\alpha_{c,d}^2 + 2 \cdot \frac{\beta_{c,d}^2}{p_z} \cdot \frac{1-L(x)}{L_x(x)} \cdot p_x \cdot Acres_{c,d}}}{2 \cdot \beta_{c,d}} \right) \tag{13}$$

Note that the $\beta_{c,d}$ terms cancel out, and we are left with an expression which we can calculate with the coefficients we calibrated before. This is the supplied quantity at a some price p, where equation (11) solves for the MCE level x^*.

3.2 Market Demand

Demand is modeled as linear in price and elastic. Estimates of elasticity of demand for pistachios can be found since the 1970's, yet I could find no investigation into the demand shape itself. In empirical demand estimations, we usually find either linear or iso-elastic functions. Linear demand allows for a choke price (i.e. price where zero units are wanted) and demand elasticity that varies with the price. I therefore use the demand function

$$D(p) = a - b \cdot p \tag{14}$$

Again, to pin-point a demand function, I need to calibrate these parameters with a point and a slope. For a point, I use the 2016 price and quantity again. Most estimates for

[6] I thank Donald Stewart from UCANR's Agricultural Issues Center for data on material and deployment costs of kaolin clay. Pounds per acre ratios and the expected weekly effect are from (Doll, 2015). I assume a weekly rain event during winter washes off the treatment, which needs to be applied again

demand elasticity for pistachios are between -1 and -2. Demand for pistachio is considered elastic, as much of it is exported and it is not a staple food. The elasticity is capped, reflecting relatively low substitutibility because of pistachio's unique flavor. The earliest demand elasticity estimate I found is from the 1970's: Dhaliwal (1972), in Nuckton (1978), estimated it at -1.5. Awondo and Fonsah (2014) try to calculate demand elasticity by using total production and averaging consumption among the US population, using an AIDS based model. They estimate a price elasticity of $-0.96(0.04)$. Gray et al. (2005) cite a report by Lewis, estimating ranges of elasticity: $(-1.66, -1.44)$ for domestic demand, and $(-2.31, -1.59)$ for export demand. Cheng et al. (2017) estimate local demand elasticity using micro-data (the Nielsen barcode data) and get an (uncompensated) price elasticity of $-1.25(0.11)$. Zheng, Saghaian, and Reed (2012) estimate an export demand elasticity of $-1.79(0.34)$, which produces a range quite similar to the 1999 study by Lewis. I chose to combine the latter (more recent) two estimates, given that 2/3 of pistachios are exported. The combined elasticity distribution is $\varepsilon^D \sim N(-1.61, 0.23^2)$. I assume an elasticity of $\varepsilon_D = -1.61$ and later show results with other elasticities as well.

3.3 Market Clearing and Numerical Solution

Figure 2 sketches the short run market moodel. The linear supply curves take weather as given. On a year with warm winter, the supply curve is multiplied by a coefficient smaller than one, i.e. shifts left and rotates. With MCE, a modified supply curve "bends" to the right. This guarantees positive gains from MCE in terms of total welfare and consumer surplus: the price is lower and quantity is higher than without MCE available. As for the growing sector gains, their sign will depend on the various parameters and functional form.

I solve the model, for a yearly chill realization, in the following way. First, I solve the model without MCE. This is done simply by calculating the sum of county-deciles supplies (equation 3) and a clearing the market with demand (equation 14). The results is a single price price, which is then used to calculate quantities. Welfare measures are calculated as the respective triangle or trapezoid areas under the curves.

Following the non-MCE solution, I solve the model with MCE. This is a bit more complicated. I have 60 equations such as equation (11) to determine the equilibrium quantity of MCE input x^*_{cd} for each county-decile. These values are then used to calculate the county-decile supplied quantities, such as in equation (13). The sum of this quantity is equated with demand to clear for a price. This system of 61 equations is numerically solved for one price and 60 levels of x^*_{cd} for county-deciles. The optimal price and MCE levels are then transformed to supplied quantities. The consumer surplus is calculated, as before, using the area under the linear supply curve. For grower profits, I need the area under a supply curve for which I have no explicit form. I therefore solve for county-decile supplied quantities under a range of 20 equally distanced prices from zero to the equilibrium price, and use these to approximate for the grower profits by summing the rectangle areas.

With a production function that is not concave over its entire domain, and an input that adds to an existing natural weather "endowment", a few technical problems might arise with the FOC (equation 11) based solution when the functional forms do not meet the usual regularity conditions. Appendix C.2 explains how I deal with these difficulties and make sure my numerical solution represents the growers' optimal choices.

3.4 Acreage In The Year 2030

Before I present these gains, there is one more piece in the puzzle. The calibrated model is set with 2016 acres. Pistachio acreage by 2030 is likely to be different, and most likely higher than that. However, the model does not include endogenous growth of planted and harvested pistachio acres. To give some bounds on the expected gains, I run the simulations with four different acreage growth scenarios, each specifying a different pistachio acreage in 2030. For each acreage scenario, the model is run with the 2020-2040 climate predictions.

The first scenario is "No Growth", meaning that 2020-2040 climate predictions are cast over the current acreage. The second scenario is "Low Growth", allowing existing planted but not yet harvested acres to develop, but sets a satiation level right after that. The yearly growth of harvested acres until the year 2022 is set at 9.6%, the average rate since 2000, and the growth rate between 2023 to 2040 is set to zero (total acreage growth of 75%). The third scenario is "High Same". This sets the growth rate until 2022 at 14.6%, the average rate since 2010, and then lets pistachio acreage follow the path of almonds in California (total acreage growth of 260%). That is, the growth rate of almonds when they had the corresponding pistachio acreage. One potential concern with acreage growth is that growers might switch new acreage to unaffected counties, or plant more heat tolerant varieties. For this, the "High North" scenario takes the high growth rate, but all new acreage harvested from 2023 is located in an imaginary "North" county, where chill damages are virtually zero. Note that planting in the unaffected north has the same effect on supply than planting a more heat tolerant variety near the existing locations (assuming that the potential output, both in the north and of the new variety, are identical to the current one). A summary of the growth rates is depicted in Figure 3. In all scenarios, demand grows by the total rate of supply growth.

4 Simulations Results

The model is run on the climate predictions for 2020-2040. As I mention above, each scenario-year simulation is run twice: once with the options for applying MCE, and one without it. The gains from MCE are the difference in welfare outcomes. The yearly temperature predictions are not supposed to pinpoint the forecast for a specific year, but rather to present the climate trend and variation around it. For a given set of parameters and acreage scenario, I interpret the average gains from the 2020-2040 simulation runs as the expected gains in 2030. I think of these expected gains as the economic value of having the MCE technology available in 2030, before knowing this year's actual weather realization. Table 1 presents the average welfare outcome gains in each scenario[7]. As economic principles would suggest, the total welfare gains from MCE technologies are positive, for the market as a whole and for consumers specifically. Total welfare gains are between \$153 million in the "No Growth" scenario to \$540 million in the "High Same" scenario. Consumer surplus gains range from \$221 million to \$758 million for the same scenarios. The reader might guess by now that the profit gains for growers are negative. Indeed, they range from -68 million dollars in the "No Growth" scenario to -218 million in the "High Same" scenario. This is true not only on average, but also in almost every predicted year and scenario.

The average loss for growers is not the result of a distortion. Growers in the model make optimal decisions given the market conditions. MCE expands supply and lowers prices, increasing the total grower revenue[8] but hurting the total profits. As the year gets warmer, the grower gains get more negative. The bottom panel of Table 1 shows the results for warm years, those with loss rate of 25% or higher in the main growing counties (about one out of four years). The total loss for growers, overall gains for consumers, and total welfare gains are higher than the average. However, the increase in grower losses is more moderate than the increase in total consumer and welfare gains. Growers losses from MCE in hot years are 12-75% higher than average, while consumer surplus gains are 150% higher.

The main specification takes certain values of elasticities for supply and demand, as well as a price for unit of MCE per acres. What would be the gains from MCE if we changed in these parameters? We run the simulations with different values to find out. For the main specification MCE price (\$55 per acre per chill portion) I use the values $\varepsilon_S = 0.1, 0.19, 0.3$ and $\varepsilon_D = -0.5, -1.1, -0.61, -2$. Table 2 Shows the results for the "High North" scenario in a convenient format. As expected, the less elastic the supply, and the more elastic the demand, consumer gains (and total welfare gains) decrease and grower profits increase. While the

[7]Standard errors are presented as well. To calculate them, future chill predictions are first regressed on a third degree polynomial of years, plus dummy variables for counties. The residuals from this regression should be free of the climate trend, and are plausibly *i.i.d.* 300 bootstraps of these residuals are added to the predicted values from the regression. Thus, for each scenario, 300 "independent draws" of a 2020-2040 prediction are created. For each one, the simulation is run and the average gains are calculated. The standard error of these 300 average gains is the reported standard error

[8]We have a linear demand system where the "perfect weather" equilibrium has elastic demand. On a warm year, the quantity drops to a point with even more elastic demand. The quantity increasing effect of MCE must therefore increase consumer expenditures.

profits and surplus vary a lot between the different elasticity pairs, the movement is opposite in such way that the total expected welfare gains are relatively stable: the lowest total welfare gain in the table is only 34% lower than the highest. Gains move in expected directions with p_x as well: the higher the price of MCE, the lower its usage and therefore the total change in gains for growers and consumers. The bottom panel in Table 2 shows how doubling the price of MCE roughly lowers the effects for growers and consumers by about a half.

4.1 Introducing Market Power

So far, the assumption has been that consumers buy directly from growers, and the market is competitive. In fact, pistachios are processed and marketed by intermediaries, and Blank (2016) reports that about half of output is marketed by one firm. Combined with high entry costs (no income for at least 6 years as young trees grow), it would seem plausible that some market power is being exercised. Therefore, it is interesting to see the gains from MCE under some degree of market power in the supply chain. The purpose of this exercise is not to try and evaluate the existing market power in pistachios, or to assess the potential welfare effects of market power relative to a competitive market. Rather, the question is: what would be the gains from MCE if market power exists?

To include market power in the model, I use a flexible market power with a intermediary or middleman which can have market power on consumers (see Sexton and Zhang, 2001; Just, Hueth, and Schmitz, 2005, p. 386-388)[9]. This intermediary manipulates the price for growers and consumers to maximize its profit. Maximum profit is attained when the intermediary equates the marginal revenue from sales to consumers with marginal outlay paid to growers plus extra costs in the supply chain. The result is a fixed ratio between the price for consumers and the marginal cost of the intermediary, which is the grower price plus the processing and handling costs[10]:

$$p^{CONSUMER} \cdot \left(1 + \frac{\psi}{\varepsilon^D}\right) = p^{GROWER} + \delta \tag{15}$$

where $\psi \in [0,1]$ is a market power measure w.r.t. the consumer sector (oligopolistic market power), where zero is no market power and 1 is monopoly.

The actual measure of market power ψ is unknown. Since the supplied quantity and

[9]In fact, the model can also accommodate market power on the growers (monopsonistic power, e.g. from large retail chains). For simplicity, and since determining a range for the real degree of monopsonistic market power is complicated, I only use the monopolistic market power part.

[10]This is, of course, an extension of the celebrated work by Lerner (1934), who realized that the price-cost margin is evidence of monopoly strength, and that this margin should - in theory - be equal to the inverse of demand elasticity. The explicit derivation, relating the marginal revenue to price and elasticity, is a well known textbook result (e.g. Carlton and Perloff, 2005, p. 92)

prices are endogenous for a firm exercising market power, a modern econometric framework requires a source of exogenous variation in demand or supply of pistachios, which would allow for a causal interpretation of an estimated market power measure (Perloff, Karp, and Golan, 2007). This type of study is beyond the scope of the paper. However, it is useful to think of a reasonable upper bound for the market power parameter, to get a reasonable bound for gains under market power.

To get a sense of the potential bounds for the market power parameter, I try to back out a current distribution for ψ, given the known distributions of grower prices, consumer prices, the costs of processing, and the simple theoretic framework above (see Appendix D for details). The mean of this distribution is 0.45. I therefore run the simulations with $\psi = 0.5$ as upper bound, and $\psi = 0.2$ for a middle point between the upper bound and the competitive market simulations reported above.

Applying market power means limiting the supplied quantities. This might increase or decrease the "raw" grower profits, while creating positive profits for the intermediary. To get a sense of the total oligopsonist gains, I add both the grower and intermediary gains together, resulting in "Agribusiness" gains. Table 3 Shows the results from these simulations, ordered by the gains for agribusiness sector. It turns out that only under the rather extreme parametric assumptions of our model, including market power measure, does the agribusiness sector see positive gains from MCE. Generally speaking, market power increases the absolute value of the gains. For example, our preferred specification with no market power (highlighted in the figure) becomes worse for agribusiness when adding market power, and better for consumers. The total welfare gains are always higher when market power exists.

The model is set in such way that the derivative of gains w.r.t. the parameters are not immediately clear from the equations. To show how these parameter values affect the gains from MCE, Figure 4 shows the "ceteris paribus" picture for gains under the "High Same" scenario. This plot shows the outcomes from running the model on 3,000 variable parameter combinations, including the year, drawn independently. The solid line in each panel is the prediction from a local polynomial regression, a sort of empirical derivative. Grower and Agribusiness profit gains decrease when demand is more elastic and supply is less elastic, as expected. Consumer surplus gains behave in the opposite way. The total welfare gains from MCE decrease with demand elasticity. The changes w.r.t. supply elasticity are not very clear, perhaps bacause the range of reasonable elasticities is very small. The price of MCE, p_x, ranges from 10 to 300 in the plot. As it increases, consumer and total welfare gains from MCE decrease, as less MCE input is used by growers, as expected. The profit and agribusiness gains first become more negative, and then start moving towards zero. This change in trend unexpected, but has a simple explanation. The trendline is the combination of two types of years: cool years, when MCE is not really required, and hot years, when it might be. On cool years, growers might try to "squeeze" a little higher yield using MCE, if the input price p_x is low enough. This is an optimal strategy for an individual grower, that nevertheless reduces total industry profit by a very small amount (as the output effects are very small). However, this strategy stops being profitable quickly as p_x increases, and the profit gains (and losses) go to zero at the slope sign change point. The trendline for gains on warm years starts very negative and attenuates as p_x increases. The combination of these two patterns creates the trendline with changing directions. The effects of market power ψ are positive for consumers and total welfare (again, this does not mean they are better off under market power, only that the gains from MCE are higher). Profit gains (net of market power rents) decrease with as ψ increases, and so do Agribusiness gains. Note, however, that there are many points where Agribusiness gains are actually positive and high. The trendline only shows the effect of the gain average under all elasticity values, but some values do create positive gains for the growing sector.

5 Discussion and Conclusion

MCE could help overcome a climate challenge for California pistachios. I assess the potential welfare gains from using reflective coating technologies at the hundreds of millions of dollars by 2030. These gains mostly stem from consumer surplus gains, as the total gains for growers in the main specifications are negative. While less tangible (and taxable) than actual registered profits, consumer surplus gains are real economic benefits enjoyed by the public. This point holds even when discussing a narrower welfare framework for California alone. Part of the modeled gains in consumer surplus are enjoyed elsewhere, as the majority of pistachio output is currently exported. However, export demand is usually considered more elastic than domestic demand, making the share of local consumer surplus gains disproportionate to the share of local consumption. At a share of 1/3 of total consumption, the California net economic gains could still be positive and high, especially on the warmer years.

The scope of consumer surplus gains brings us to the potential gains from public investment in research in R&D for MCE solutions. With social returns from investments largely exceeding private ones, this type of research is a good candidate for prioritizing in public research fund allocation (Alston, Norton, and Pardey, 1995, p. 491). The case for public research is made stronger by the low incentive to invest in MCE in our case. We see MCE technologies mostly as an adaptation of existing techniques to solve a climate problem. Therefore, innovations in the field would be hard to make proprietary of the innovator. Moreover, innovators are likely to be from the industry: a large growing firm would have the resources and access to enough pistachio acreage to run experiments and develop new MCE solutions. But if this firm sees that a world with MCE (adopted by everyone) is worse, why invest in innovation? Adding market power to the equation makes an even stronger potential case for public R&D: the total welfare gains are higher, and the incentives for innovation could be even lower.

What might be the implications of MCE technologies in a broader sense? One could imagine, with further agronomic research, other MCE technologies applied to other fruit and nut crops, and even for annuals such as corn or soybeans. Of course, these are less profitable than pistachios, but they face similar challenges, and MCE solutions are not necessarily very expensive. Other implications could be in the distribution of climate change damage incidence. Technologies might only be available (and affordable) to growers in countries better off financially, further exacerbating international income disparities as climate change advances. An interesting potential for MCE technologies could be in accelerating the transition of agricultural practices closer to the poles, sometimes referred to as the "crop migration" (Zilberman et al., 2004). For example, MCE solutions for frost could accelerate the expansion of viticulture to higher latitudes. Thus, MCE might be a key adaptation concept on both geographic frontiers of climate change.

The simulation based valuation methodology in this paper has its caveats. Modeling supply and demand as linear is obviously a simplification. The assumptions on growth and distribution of acreage are based on past growth patterns, and might not reflect unexpected future changes in market conditions. The future chill predictions are in line with other predictions by climatologists, yet might fail to materialize. Nevertheless, by choosing various scenarios, basing the parameter ranges in the literature, and choosing conservatively when possible, I believe to have gotten a reasonable range for the potential gains from MCE in California pistachios. They are in the hundreds of millions of dollars for a crop of secondary importance to California agriculture. The potential of MCE as a climate change adaptation strategy seem to be untapped at present.

Tables

Scenario	Profits	Consumer	Welfare
No Growth	-68 (3)	221 (11)	153 (10)
Low Growth	-113 (6)	376 (18)	263 (17)
High North	-180 (8)	501 (25)	321 (19)
High Same	-218 (11)	758 (37)	540 (34)

Scenario	Profits	Consumer	Welfare
No Growth	-78 (6)	539 (25)	462 (28)
Low Growth	-129 (11)	924 (43)	796 (48)
High North	-316 (11)	1,259 (60)	939 (55)
High Same	-244 (22)	1,886 (89)	1,642 (100)

Table 1: Average gains (million $US) from MCE in all years (top panel) and warm years (bottom panel) within 2020-2040. Standard errors in parentheses.

Grower ; Consumer Welfare	$\varepsilon_D = -2.0$	$\varepsilon_D = -1.61$	$\varepsilon_D = -1.1$	$\varepsilon_D = -0.5$
$\varepsilon_S = 0.10$	-64 ; 347 283	-137 ; 425 288	-301 ; 602 301	-839 ; 1,183 345
$\varepsilon_S = 0.19$	-99 ; 415 316	**-180 ; 501** **321**	-356 ; 688 333	-867 ; 1,236 369
$\varepsilon_S = 0.30$	-194 ; 585 392	-294 ; 689 395	-500 ; 902 402	-1,019 ; 1,446 427

Grower ; Consumer Welfare	$\varepsilon_D = -2.0$	$\varepsilon_D = -1.61$	$\varepsilon_D = -1.1$	$\varepsilon_D = -0.5$
$\varepsilon_S = 0.10$	-68 ; 199 131	-110 ; 247 136	-208 ; 357 149	-555 ; 747 192
$\varepsilon_S = 0.19$	-83 ; 234 150	-130 ; 286 156	-234 ; 403 169	-568 ; 775 207
$\varepsilon_S = 0.30$	-136 ; 327 192	-195 ; 392 197	-321 ; 531 210	-666 ; 909 243

Table 2: Average gains (million $US) from MCE under varying elasticities in the "High North" scenario. The top panel gains are calculated with MCE price of $p_x = \$55$. The lower panel doubles that price to $110. In each cell, the top left is grower gains, top right is consumer gains, bottom is total welfare gains. The emphasized cell correspond to the main specification.

ε_D	ε_S	ψ	Agribusiness	Consumer	Welfare
-2.00	0.10	0.5	163	545	709
-2.00	0.19	0.5	43	809	852
-1.61	0.10	0.5	22	823	845
-2.00	0.10	0.2	-5	412	406
-2.00	0.19	0.2	-61	528	466
-2.00	0.10	0.0	-64	347	283
-2.00	0.19	0.0	-99	415	315
-1.61	0.10	0.2	-100	540	440
-1.61	0.10	0.0	-137	425	288
-1.61	**0.19**	**0.0**	**-180**	**501**	**321**
-1.61	0.19	0.2	-189	691	502
-2.00	0.30	0.0	-194	585	392
-2.00	0.30	0.2	-204	803	599
-2.00	0.30	0.5	-233	1,372	1,139
-1.61	0.19	0.5	-244	1,242	998
-1.61	0.30	0.0	-294	689	395
-1.10	0.10	0.0	-301	602	301
-1.10	0.19	0.0	-356	688	333
-1.10	0.10	0.2	-388	897	509
-1.61	0.30	0.2	-388	1,024	636
-1.10	0.30	0.0	-500	902	402
-1.10	0.19	0.2	-559	1,125	566
-1.61	0.30	0.5	-780	2,057	1,276
-1.10	0.30	0.2	-916	1,600	685
-1.10	0.10	0.5	-942	2,050	1,108
-1.10	0.19	0.5	-1,984	3,100	1,116
-1.10	0.30	0.5	-3,500	4,636	1,136

Table 3: Average gains (million $US) from MCE under varying elasticities and market power in the "High North" scenario. Agribusiness gains are grower plus intermediary gains. The emphasized numbers correspond to the main specification.

Figures

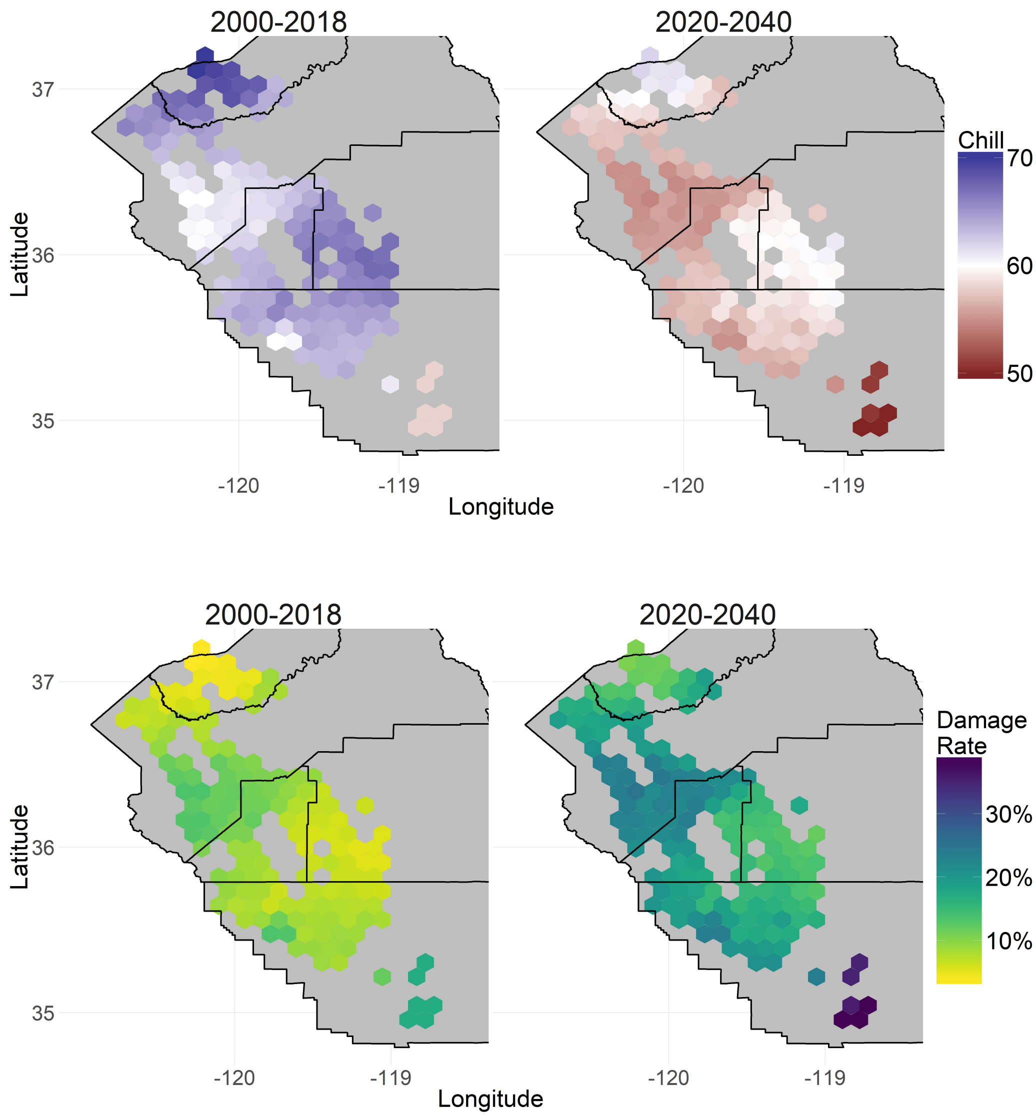

Figure 1: Chill portions and damage rate in the 1/4 warmest years in pistachio growing counties. 2000-2018 observed chill, 2020-2040 calibrated chill predictions. Damage is calculated with the damage function.

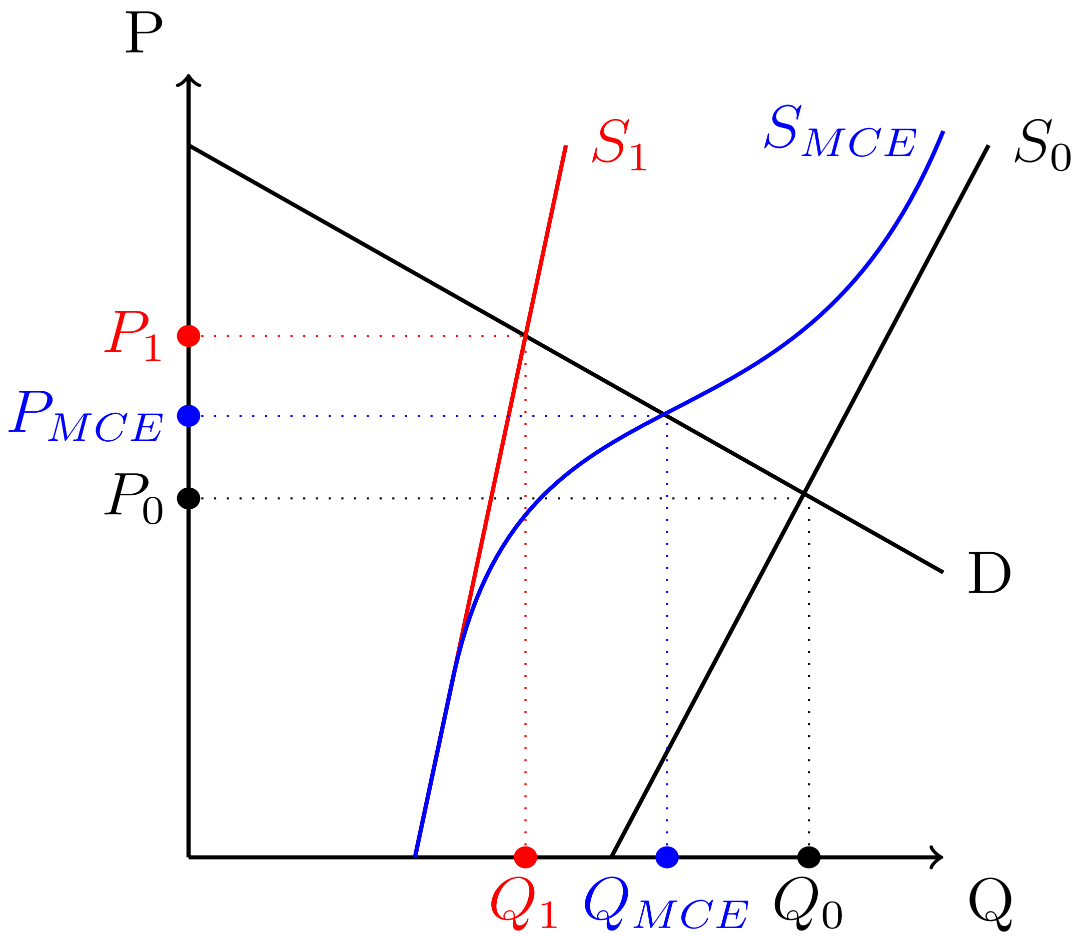

Figure 2: Sketch of market model for pistachios with micro-climate Engineering. S_0 is the supply curve under perfect weather. S_1 is the supply curve in a warm year, where yields are lower. S_{MCE} is the supply with micro-climate engineering. Note that, when the market price for pistachios is low (and the relative price of the MCE input is high), this curve coincides with S_1. As the price increases, S_{MCE} is asymptotically parallel to S_0, with a vertical distance equal to the fixed (by satiation) cost of tweaking the temperatures to optimum using MCE.

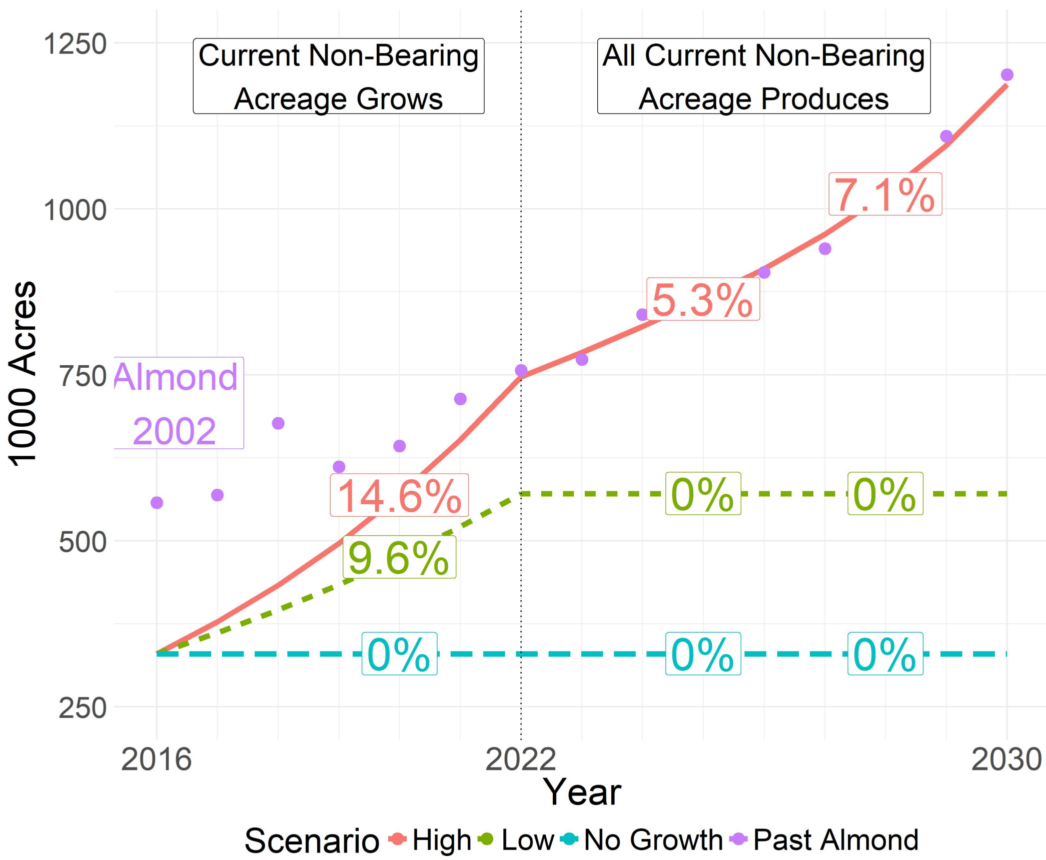

Figure 3: Growth rate development for different scenarios

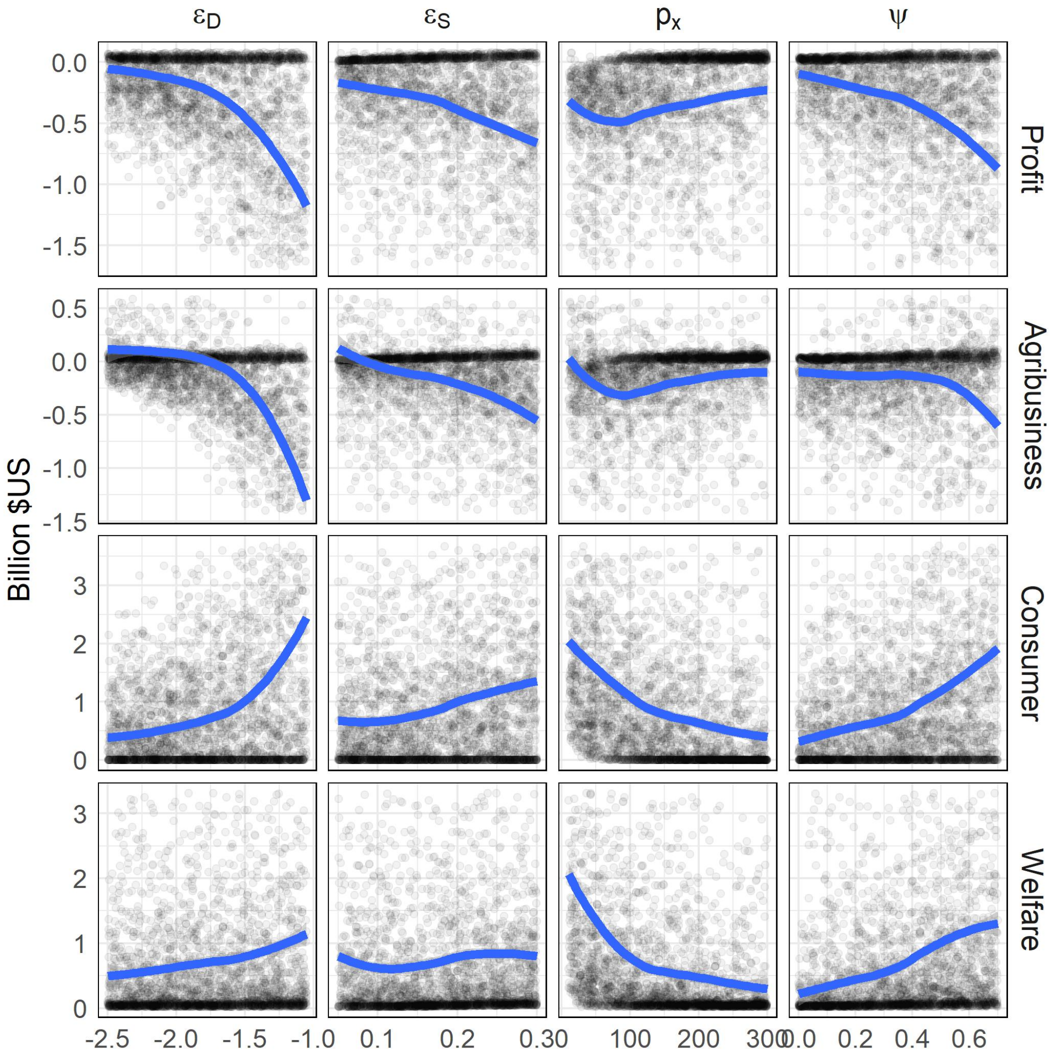

Figure 4: Effect of model variables on MCE gains

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A Climate Data

Pistachio growing areas are taken from USDA satellite data (Boryan, Yang, and Willis, 2014) with pixel size of roughly 30 meters. About 30% of pixels identified as pistachios are singular. As pistachios don't grow in the wild in California, these are probably miss-identified pixels. Aggregating to 1km pixels, we keep those pixels with at least 20 acres of pistachios in them. There is some variability between years as well. From 2008-2017, I keep those 1km pixels with at least 6 pistachio identifications. These 2,165 pixels are the grid on which we do temperature interpolations and calculations.

A winter's chill portion count in a pistachio growing point is calculated from a vector of hourly temperatures. Observed temperatures for 2000-2018 come from the California Irrigation Management Information System (CIMIS, 2018), a network of weather stations located in many counties in California, operated by the California Department of Water Resources. A total of 27 stations are withing 50km of my pistachio pixels. Missing values at these stations are interpolated within (i.e., using the average temperature difference at that week-hour from the nearest station).

For future chill, I 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, I use a procedure involving the latitude and date (coded in R by Luedeling, 2017).

Future predicted temperatures are calibrated using quantile calibration (Leard and Roth, 2016), with a week-hour window. Having past and future calibrated temperatures for each interpolation point, I move to calculate winter chill portions for each each point season. Erez and Fishman (1997) produced an Excel spreadsheet for chill calculations, which I obtain from the University of California division of Agriculture and Natural Resources, together with instructions for growers (Glozer, 2016). For speed and ease of calculations, I translated the spreadsheet to an R function (available at https://github.com/trilnick/miniChill).

B Estimating The Damage Function

B.1 General Estimation Challenge

Agronomists agree that too few chill portions result in late an uneven bloom for pistachios. The chill thresholds can be experimented with in controlled experiments, but for various reasons the relationship between chill and yield does not necessarily reflect the same relationship (Pope et al., 2015). Various studies try to link chill portions and yields, which turns out to be a non-trivial task. Given the natural variability of yields and the fact that pistachios are usually planted in areas suitable for them, few low chill events are available for statistical inference. An ideal experiment would involve a randomized chill treatment over entire orchards, but that is not feasible. Researchers resort to yield panels, which usually are small in size (i.e. small number of yield reporting units), short (in years), or both.

Zhang and Taylor (2011) Investigate the effect of chill portions on bloom and yields in two pistachio growing areas in Australia, growing the "Sirora" variety. Using data from "selected orchards" over five years, they note that on two years, where chill was below 59 portions in one of the locations, bloom was uneven. Yields were observed, and while no statistical inference was made on them, the authors noted that "factors other than biennial bearing influence yield". Elloumi et al. (2013) Investigate responses to chill in Tunisia, where the "Mateur" variety is grown. They find highly non-linear effects of chill on yields, but this seems to stem from one observation with a very low chill count. Standard errors are not provided, and the threshold and behavior around it are not really identified. Benmoussa et al. (2017) use data collected at an experimental orchard in Tunisia with several varieties. They reach an estimate for the critical chill for bloom purposes. Chill is positively correlated with tree yields, but it was not clear what the relationship was for chill portions which were not very far from the threshold. Pope et al. (2015) use Bayesian methodologies to try and compare bud breaking (bloom) requirements and chill requirements in California pistachios (mostly "Kerman" variety). Using a panel of California county yields, they reach the conclusion that "Without more data points at the low amounts of chill, it is difficult to estimate the minimum-chill accumulation necessary for average yield".

B.2 Data and First Look At Chill Yield Effects

Ideally, with enough orchard observations and sufficient variation across a range of winter chill counts, I could estimate the yield-response function with a polynomial fit or non-parametrically. Unfortunately, this data does not exist, and producing it is prohibitively costly. My data includes a county-year yield panel, and the data on chill in 2,165 pistachio growing areas, interpolated from weather stations. As I show in the main paper, intra-county chill varies, even within the same year. The observation unit in my panel is county-year

(1984-2016 for Kern, Kings, Fresno, Madera, and Tulare counties). The dependent variable is county-year yield. The independent variables are the shares of acres exposed to chill portions between 38 (the lowest) and 86 (the highest). This measure of share acres exposed to each level of chill is calculated as the share of interpolated points with that chill at each county and year.

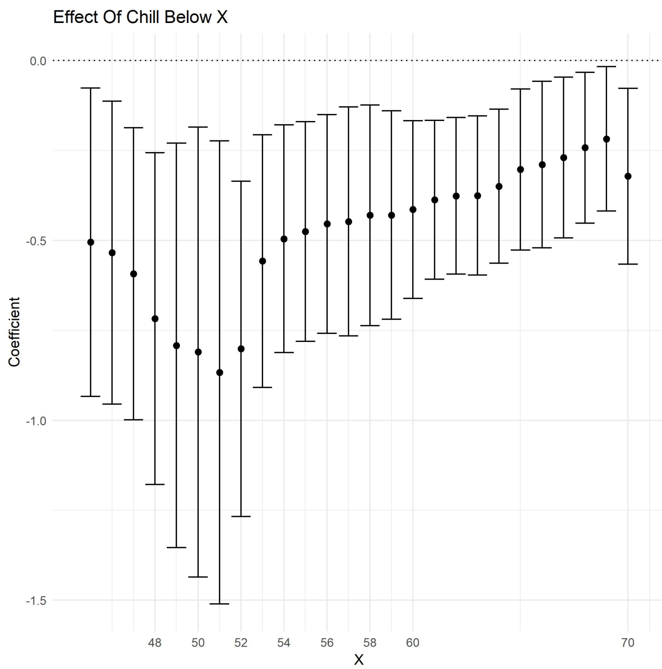
The first instinct for an empirical researcher is probably to try and estimate a flexible model on the panel, regressing yields on county shares of each chill portion count, in the following way:

$$Yield_{c,t} = \sum_{X} \beta_X \cdot Share(chill_{c,t} = X) + \varepsilon_{c,t}$$

where $Share(chill_{c,t} = X)$ is the share of county c at year t that had X chill portions. However, including more than one share control generates an interpretation puzzle. The coefficients are interpreted as the effect of increasing the share of the county under X chill portions by 1, that is, in most cases, having an area larger than the actual county. Even if we are willing to accept this linearized effect assumption, what is the interpretation of estimating the effect of more than one chill level share at the same time? The county cannot have, at the same time, two different levels of X covering 100% or more of its area. Therefore, the effect would need to be estimated for each X separately. These estimates would be biased: if some share of the county has a measure of chill X, it is likely that other shares of the county have similar measures, and they would have an effect on the county yield as well. However, looking at the results from this exercise might be informative. I present the result of cumulative chill effects, taking into account the threshold like effect of chill on yields. The plot below shows us the coefficients and standard errors from regressing, for each chill portion X separately, the following equation:

$$Yield_{c,t} = \beta_X \cdot Share(chill \leq X) + Yield_{c,t-1} + Yield_{c,t-2} + FE_{c,\,decade} + \varepsilon_{c,t} \tag{1}$$

where $Share(Chill_{c,t} < X)$ is the share of acreage in county c and year t, where the measured chill is equal or less than X. This formulation takes into account a cumulative effect of chill. All estimates are negative, as one would expect (high share below 70 indicates potentially a high share below 50). The negative effect seems to increase gradually, and hit a big shock at 54 or 53 portions. The estimates at the very low X increase, probably because of an attenuation effect: the counter factual of having all of the county under 48 chill portions still had some probability mass in slightly higher chill portions which already cause much damage. Altogether, these estimates seem to indicate some sort of threshold around 54 portions, as expected by Pope (2015). However, they are biased, and the response shape is not very clear.



B.3 Main Model and Estimation

I model the yield as a function of the potential yield, times a function that takes chill as input, and some disturbance term. This draw from the pest control literature (e.g. Zilberman et al., 1991). For an orchard:

$$Yield_{i,t} = f(Chill_{i,t} \mid \delta) \times PY_{i,t} \times e^{\varepsilon_{i,t}} \tag{2}$$

Where yield is measured at the orchard-year level (i,t). The function $f()$ takes both chill and a parameter vector δ as arguments, s.t. $f() \in [0,1]$. The expression $PY_{i,t}$ stands for potential yield, the yield that could be attained under optimal chill conditions. This could change by year, or be held fixed, depending on other agronomic data and assumptions. If chill is not optimal, the yield decreases below the potential yield. There is also a disturbance term, which adds randomness to the model and allows the measured yield to vary for factors other than chill. $\varepsilon_{i,t}$ are assumed to be spherical and centered around zero for each level of chill. Eventually, we are interested in understanding the shape of $f()$, and the effects of chill and δ on its value. To easily estimate the model, I can take logs and get:

$$log(Yield_{i,t}) = log\left(f(Chill_{i,t} \mid \delta)\right) + log\left(PY_{i,t}\right) + log\left(\varepsilon_{i,t}\right) \tag{3}$$

The county yield should be the weighted average of the county's orchards yields. Assume all of them have the same potential output (i.e. conditions other than chill realization), and the equation becomes:

$$log(Yield_{c,t}) = log\left[\sum_X Share(Chill_{c,t} = X) \cdot f(Chill_{i,t} \mid \delta)\right] + log(PY_{c,t}) + \epsilon_{c,t} \tag{4}$$

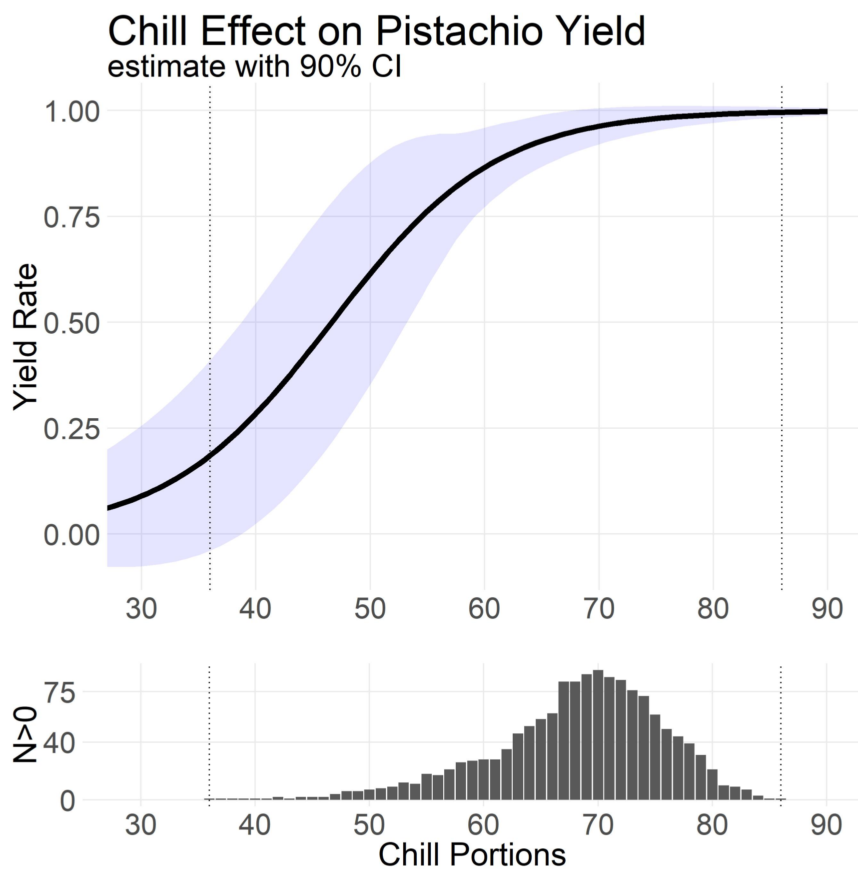
Assuming a functional form for $f(Chill_{i,t} \mid \delta)$, I can estimate the parameter vector δ with nonlinear least squares. I'll assume this to have a shape derived from a logistic function. This function is bounded between zero and one, and has a threshold behavior which is expected by agronomists. δ would have two parameters: location (which is also the mean and median of the distribution) and scale (a second moment parameter, in fact a multiple of the distribution variance).

What is the Potential Yield? In theory, the potential yield is the counter-factual yield, that would have been attained, *ceteris paribus*, at optimal chill conditions at that year. In fact, yields are determined by a variety of factors: chill, but also alternate bearing, other climatic conditions, irrigation, harvesting intensity, etc. I take the counter-factual to be the county average yield, partitioned by decade: 1980's, 1990's, 2000's, and 2010's. The partition can control for county-decade unobserved traits, such as growing practices, droughts, etc. The assumption is that these decade long traits are independent from insufficient chill events, which seems plausible.

The parameters are found numerically by solving:

$$\min_{l,s} \sum \left[log(Yield_{c,t}) - log(PY_{c,t}) - log\left(\sum_X Share(Chill_{c,t} = X) \cdot \frac{1}{1 + exp(\frac{l - Chill}{s})}\right)\right]^2 \tag{5}$$

The resulting output is below. The first estimate is for the location parameter, and the second is for the scale. I can look at the distribution of $f()$ below. A noticeable decline (25% loss or more) starts at about 54.5 portions. For standard errors, I sample location-scale pairs from a 2D normal distribution with the estimated means and covariance matrix, as the coefficients are asymptotically joint normal. After trimming a few draws resulting in negative scale, I build the curves for each pair, and calculate the standard deviation of the curves value for each chill portion. The 90% confidence interval is drawn below. The histogram underneath shows the number of panel observations, where the share of a county experiencing some chill portion value is greater than zero. The dotted lines show the edge of the support.




```
Parameters:
     Estimate Std. Error t value Pr(>|t|)
[1,]   46.628      4.654   10.02   <2e-16 ***
[2,]    7.180      2.761    2.60   0.0102 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.4067 on 166 degrees of freedom
Number of iterations to termination: 16
Reason for termination: Relative error in the sum of squares is at most ‘ftol’.
```

C Model Details

C.1 Getting an expression for z^*

The representative county grower maximizes profit. γ_i represent acreage growth for the grower by 2030, and needs to pre-multiply p_x and the production coefficients.

$$\max_{(x\,,\,z)} \pi = \gamma_i \cdot p \cdot [1 - L(x_i)] \cdot (\alpha + \beta \cdot \sqrt{z_i}) - p_z^T \cdot z_i - \gamma_i \cdot p_x \cdot x$$

Taking first order conditions:

$$\begin{aligned}
\gamma_i \cdot \ p \cdot L_x(x) \cdot (\alpha + \beta \cdot \sqrt{z_i}) &= \gamma_i \cdot p_x \\
\gamma_i \cdot \ p \cdot (1 - L(x)) \cdot \frac{\beta}{2 \cdot \sqrt{z_i}} &= p_z
\end{aligned}$$

Combining them:

$$\begin{aligned}
\frac{p_z}{\gamma_i \cdot p_x} &= \frac{\gamma_i \cdot \ (1 - L(x))}{\gamma_i \cdot \ L_x(x)} \cdot \frac{\frac{\beta}{2 \cdot \sqrt{z_i}}}{\alpha + \beta \cdot \sqrt{z_i}} \\
\implies \alpha + \beta \cdot \sqrt{z_i} &= \frac{p_x}{p_z} \cdot \frac{(1 - L(x))}{L_x(x)} \cdot \frac{\beta}{2 \cdot \sqrt{z_i}} \cdot \gamma_i \\
\alpha \cdot \sqrt{z_i} + \beta \cdot z_i &= \frac{p_x}{p_z} \cdot \frac{(1 - L(x))}{L_x(x)} \cdot \frac{\beta}{2} \cdot \gamma_i
\end{aligned}$$

$$\beta \cdot z_i + \alpha \cdot \sqrt{z_i} - \frac{p_x}{p_z} \cdot \frac{(1 - L(x))}{L_x(x)} \cdot \frac{\beta \cdot \gamma_i}{2} = 0$$

$$\sqrt{z_i^*} = \frac{-\alpha \pm \sqrt{\alpha^2 + 2 \cdot \frac{\beta^2}{p_z} \cdot \frac{1 - L(x)}{L_x(x)} \cdot p_x \cdot \gamma_i}}{2 \cdot \beta}$$

Note that, later one, the β in the denominator cancels out in the production function. Thus we are not required to calculate it directly. Since $\alpha > 0$, and z_i has to be a real number, I only consider the positive solution.

C.2 One Optimal Solution For Grower With MCE

A few challenges arise with our problem specification. First, since we are adding "artificial" chill portions (x) to a natural chill realization, the optimal level of MCE could turn out negative. In this case, the grower is set to supply the quantity with zero MCE (the no-MCE case) as chill portions can be "bought" but not sold. A second challenge is that, given that the production function is not quasi-concave over its support, there might not be an internal solution at all. In this case, I show below that this must be due to the price of input p_x

being too high to justify any level of x, and therefore the grower is again set to supply the no-MCE quantity. In Figure 2, this is the area where the supply with MCE coincides with the no-MCE supply. A third challenge is that, for the same non-regularity, there might be more than one solution for x^* which solves the grower FOC. Visually, this is evident in Figure 3 where the MCE supply curve slopes at different prices are not necessarily unique. In this case, I prove below that there are up to two solutions for the FOC, and the highest one is a local maximum and profit maximizing one. In the numerical solution, I make sure to choose the higher one when there are two.

Proposition 1. *There is a unique choice of MCE level for a glower which maximizes his profits.*

Lemma 1. *The value of marginal productivity of the MCE input x is positive and has a maximum.*

Proof. The VMPx is: $p \cdot L_x(x^*) \cdot H\left(z^*(x^*)\right)$ All the components are positive and continuous, therefore VMPx is positive and continuous. Note that $\lim_{x\to\infty} VMPx = 0$ and $\lim_{x\to-\infty} VMPx = 0$. Therefore, there exists some closed interval of x for which at least some values of VMPx are weakly greater than any value outside that interval. On that closed interval, the continuous VMPx attains a maximum value by the extreme value theorem. Since there are values inside the interval that are weakly greater than any values outside of it, that maximum value is the maximum of VMPx for any x. □

As a corollary from this lemma, we can also say that no solution for the equation $p \cdot L_x(x^*) \cdot H\left(z^*(x^*)\right) = p_x$ means that the price p_x (which is positive) is just too high for any choice of x: $VMPx < p_x \; \forall x$. In this case, the profit maximizing solution would be to use zero x.

Lemma 2. *VMPx is unimodal, i.e. has one local maximum.*

Proof. From the previous lemma, we know VMPx attains a maximum and has at least one critical point. To find how many critical points there could be, derive the VMPx and equate to zero, setting $t = exp(m + nx)$:

$$\frac{n^2 \cdot t}{(1+t)^4} \cdot (1-t) \cdot \left[\alpha + \sqrt{\alpha^2 + 2 \cdot \frac{\beta^2}{p_z} \cdot \frac{1+t}{n} \cdot p_x \cdot \gamma_i}\right] + \frac{n \cdot t}{(1+t)^2} \cdot \frac{2 \cdot \frac{\beta^2}{p_z} \cdot \frac{n}{n} \cdot p_x \cdot t}{2\sqrt{\alpha^2 + 2 \cdot \frac{\beta^2}{p_z} \cdot \frac{1+t}{n} \cdot p_x}} = 0$$

$$\frac{n}{(1+t)^2} \cdot (1-t) \cdot \left[\alpha + \sqrt{\alpha^2 + 2 \cdot \frac{\beta^2}{p_z} \cdot \frac{1+t}{n} \cdot p_x \cdot \gamma_i}\right] + \frac{\frac{\beta^2}{p_z} \cdot p_x \cdot t}{\sqrt{\alpha^2 + 2 \cdot \frac{\beta^2}{p_z} \cdot \frac{1+t}{n} \cdot p_x}} = 0$$

Note that the right side is always positive, and the left side is also positive with the exception of $1-t$. Morover, $1-t$ is monotonically decreasing in x. Therefore, there will be only one point where this derivative is zero. Hence VMP_x has only one critical point, which must be a maximum according to the previous lemma. Note that this maximum is attained when $t>1$, i.e. at an x value which is higher than the location parameter of the logistic distribution which is taken as the damage function. This is the range where the logistic distribution is in fact concave. □

Lemma 3. *The grower FOC has up to two solutions.*

Proof. Since VMPx is unimodal, the FOC: $p \cdot L_x(x^*) \cdot H\left(z^*(x^*)\right) = p_x$ only has up to two solutions. □

Lemma 4. *If there are two internal solutions, the one with higher x is more profitable for the grower.*

Proof. Two internal solutions means that p_x intersects the unimodal $VMPx$ at two points. These intersections create an interval between the intersection points, where $VMPx > p_x$ for any x in the interval. Moving from the lower to the higher, the grower earns the difference between value of marginal productivity of x and it's price. Hence the intersection with higher x has higher profits. □

In the code, I make sure to verify that the higher solution for the FOC of each county-decile is chosen if more than one exists. The numerical solution of the entire equation system, which includes a market clearing equation, seems to always reach the higher root anyway. This might be because the lower solution is likely to be in an area where the damage function is actually convex in x, and the numerical solver looks for a steady state.

Proof of proposition 1. If there is no internal solution for the FOC, or if the solution is negative (not feasible), there is one optimal solution: $x^*=0$. If there is a positive internal solution for the FOC, lemmas 1 - 4 assure us that there is only one level of x^* where the grower maximizes profits. □

D Monopolistic Power Distribution

With about half of California pistachios marketed by one firm, it reasonable to believe that market power is being exercised in pistachios. This appendix sets to find a reasonable upper bound for the monopolistic power parameter in the main paper. This is not an estimation with causal interpretation, but rather an imputation exercise, taking grower and consumer price distributions and other parameters, subject to a simple model. I assume growers and retailers are competitive, and market power is exercised in the supply chain between them. I can impute a distribution for the market power parameter, ψ, using the following identity:

$$p^{RETAIL} \cdot \left(1 + \frac{\psi}{\varepsilon^D}\right) = p^{GROWER} \cdot (1 + \phi) \tag{6}$$

$$\implies \psi = \left[\frac{1 + \phi}{\frac{p^{RETAIL}}{p^{GROWER}}} - 1\right] \cdot \varepsilon^D \tag{7}$$

The left side in equation (7) is the marginal revenue from sales in the pistachio sector, and the right side is the marginal cost. This cost is expressed as the price for growers times a growth rate in actual cost (as opposed to market power mark up) in the supply chain from the farm gate to the consumer. ϕ is a percent increase in these costs, imputed using a procedure detailed below. It will serve us for two purposes: first, in the direct simulation of ψ, as in equation (5); and second, to set a lower bound for the covariance between grower and retailer prices. I start with this price ratio.

Isolating ψ from equation (7), I encounter the price ratio p^{RETAIL}/p^{GROWER}. Cheng et al. (2017) report the average and standard deviation of retail prices in 2004-2014: 0.33 (dollars per ounce) and 0.1. This paper does not mention adjusting prices for inflation, yet inflation in these years was very low in general. I have the grower prices from California's crop reports in the same years: 2.2 dollars per pound, or 0.138 dollars per ounce on average, with a standard deviation of 0.044. I assume both prices are distributed log-normally, with the adjusted parameters according to the observed means and standard deviations. Just for a verification, the range of observed (581 weekly averaged) prices in Cheng et al. is $[0.19, 0.55]$, corresponding to the 4^{th} and 97^{th} percentiles of such log-normal distribution; the range of observed (11 annually averaged) prices in the crop reports is $[0.084, 0.223]$, corresponding to the 7^{th} and 96^{th} percentiles of the log-normal distribution.

Now, for the imputing of ϕ. Suppose $(1 + \phi) = (1 + \phi_1) \times (1 + \phi_2)$, where ϕ_1 be the extra cost ratio between the farm gate and retailer, and ϕ_2 the cost ratio of the retailer. For ϕ_1, I use a study by Sumner et al. (2016), where the authors use industry data to calculate the impact of almonds of California's GDP, computing these with IMPLAN software. While almonds are a different nut, this should give us a reasonable approximation for pistachios as well. The authors do not disclose actual costs, but do report "direct effect" on the value added to GDP in different stages of the supply chain: grower, huller-sheller, handler, and manufacturer. I interpret these as the real extra costs of production down the supply chain. Summing the direct-effect value-added terms for all segments but the growers, and dividing by the direct effect for "value of grower output" (total grower revenue), I get about 10% added costs past the farm gate for both 2012 and 2013. Therefore, a post-grower pre-retail added cost rate of $\phi_1 = 0.1$ seems reasonable.

Let ϕ_2 be the extra cost added in retail. Retail itself is assumed to be competitive, and the markup in this sector is assumed to include "real" costs only. Specific retail markups are usually hard to estimate, as retailers keep their buying costs confidential. However, financial reports in the filings of publicly traded retailers can give us a crude accounting estimate for food retail markups in general. This approach is used as benchmark by Nevo (2001, Table III), where the retail price in ready-to-eat cereals is 25% higher than the manufacturer price. To get a more recent estimate, I look at the SEC filing of retail chains.

Walmart, Inc (2017, p. 33), the largest retailer in the US (and probably the world), reports a gross profit margin of 24.6% on average in 2015 - 2017. This excludes "Operating, selling, general and administrative expenses". The share of costs out of net sales is 0.754, and the inverse of this is 1.326. Assuming that the gross profit margin is mostly the outcome of sales minus purchasing costs, this arguably translates to an average price growth rate in Walmart retail: $\phi_2 = 0.326$.

Costco Wholesale Corporation (2017, p. 18) is probably the second largest retailer, with net sales of about a quarter of Walmart's. Costco reported a gross profit margin of 11.26%, translating to $\phi_2 = 0.127$. It is widely accepted that Costco's profits mainly attribute to their membership fees, and their profits net of those fees are zero or slightly negative. Thus this measure of price growth might reflect more accurately a neutral pass-through retail pricing.

Both Walmart and Costco sell a variety of products besides food items. For example, only 55% of Costco's net sales in 2017 were from "foods", "sundries", and "fresh foods" categories (pistachio sales probably fall under the first two, either as ingredients in other food items or snacks). Unfortunately, margins are not reported for product segments for neither of the two chains. The profits margins of Walmart and Costco might therefore not reflect a food centered operation. Albertsons Companies, Inc (2017) is another retail company, with net sales of about one tenth of those by Walmart. It is mostly focused on food and pharmacy, and reports operating "2,318 stores across 35 states and the District of Columbia under 20 well-known banners". The largest brand, in terms of number of stores, is Safeway. Albertsons costs of sales, as percent of net sales and other revenues, was 72.5% on between 2015-2017. According to the filings, these costs of sales mostly include the costs of purchasing and handling of products. Albertsons' filings show a slightly higher price growth than Walmart's: $\phi_2 = 0.379$. The difference might be attributed to different pricing strategies, different mix of products with varying profit margins , or other reasons.

I believe Albertsons' figures to be more representative for food retail. Choosing the highest ϕ_2 term makes the lowest, arguably more conservative estimate of market power in pistachios. Altogether, the total increase in cost, from the farm gate to the consumer, is $(1+\phi) = (1+\phi_1) \times (1+\phi_2) = 1.517$. This ratio is assumed to hold for consumers of exported pistachios as well.

Assuming log-normality for both prices, their ratio is also distributed log normal, and its mean is the difference of their means. The variance of this ratio will depend on the covariance of the two prices, which I do not observe. To maximize the confidence interval of this ratio, I would like to set this covariance as low as possible. However, I want to avoid ratio draws that results in the retailer selling at a loss price. That is, the covariance should be such that the ratio almost always exceeds $(1 + \phi)$. Moreover, this covariance should be such that the eventual random variable of interest, ψ, is almost always bound within $[0, 1]$.

To comply with these to requirements, I use an optimization procedure to find the minimal correlation coefficients that would satisfy each, and use the maximum of these two. Of course, since the support of all log-normal distributions is $(0, \infty)$, there is always a theoretical chance of a non-compliant draw. Therefore, I find a correlation coefficient that sets the probability of the price ratio being in $(0, 1 + \phi)$ at 0.1% (correlation coefficient of 0.881); and the correlation coefficient that sets the probability of ψ being greater than 1 or smaller than 0 at 0.1% (correlation coefficient of 0.880). I take the maximum value of $\rho = 0.881$ and set the covariance accordingly. The resulting retail/grower price ratio is log-normally distributed, with mean of 2.43 and standard deviation of 0.36.

The resulting distribution of ψ is simulated, with a mean of 0.45 and standard deviation of 0.13. The differences from Costco based values are not very large: simulating market power using Costco's figures increases the mean market power only by 0.06 units, from 0.45 to 0.51. Below is its density plot, using the Safeway and Costco figures.