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? Empirical literature has demonstrated the non-linear effects of extreme weather events on yields. Climate change is thus predicted to harm crops mainly by change of the temperature distribution tails, rather than by the change in the mean temperatures. Targeting these few high temperature days, by altering effective temperatures locally in time and space, could serve as an adaptation concept. I call this "Micro-Climate Engineering" (MCE), and note that techniques for lowering temperatures locally are already used by growers. Existing MCE techniques could therefore be used to address climate change in some cases. 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 MCE in California pistachios. Warming winters are predicted to hurt pistachios within the next two decades. Treating trees with a reflective, non-toxic mix, has been shown to lower effective tree temperatures. The model is applied to simulate the pistachio market in 2030 under various acreage growth scenarios, and gains from MCE are calculated for growers and consumers. Results show a total negative gain from MCE for growers, but the positive gains from consumers surpass them. The total, yearly expected welfare gains from MCE in California pistachios by 2030, in varying scenarios, is assessed at 153 - 540 million US dollars. Market power increases the total potential gains from MCE, but could also lower the incentive to invest in MCE technologies.

1 Introduction

Climate change poses a major challenge for agriculture, as predicted shifts 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.

To what extent can farmers adapt to these changes in temperature? A body of literature tries to examine the evidence for ongoing adaptation. The findings usually show low, if any, adaptation patterns. Yields-responses to adverse weather shocks do not seem to attenuate with time, even when shocks become more likely or severe (Dell, Jones, and Olken, 2014). Lack of evident adaptation might be attributed to many factors, but a prominent one could be the entailed costs. Adaptation mechanisms are usually thought of in terms of crop or variety switching, change in inputs, and change of the growing times (Zilberman et al., 2004). These mechanisms could be expensive, considering that agricultural practices optimize over time given a specific climate. Sadly, these high costs might be preventing adaptation that is required for dealing with relatively small changes in the tails of temperature distributions. 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 - 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 and remains still, causing plants to freeze. Using large fans, or in some cases helicopters, the cold air is mixed with the warmer air on top of it. This raises the temperatures around plants, 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 (**?**Lu et al., 2018).

Solutions for right side temperature tails exist as well. There are products that reflect sunlight and lower plant exposure to excess heat. 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).

Farmers are now able to tweak the tails of temperature distributions in their fields and orchards, an approach I 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. The economic literature has paid little, if any, attention to MCE technologies[1]. Yet, the concept of MCE could have significant consequences for climate change adaptation, 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 by the year 2030. Specifically, pistachios are threatened by warming winter days. 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 cost 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 summer. 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. However, incorporating agronomic knowledge can broaden our perspective on the effects of climate change on agriculture.

Scientists at the University of California Cooperative have been experimenting with kaolin clay applications, 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, I 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 my simulations under varying market conditions. Section 5 concludes.

[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" return no results.

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 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 the pistachio crop 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 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 varieties, leads to low and non-uniform bud breaking, which is linked to low yields at harvest. Thus, a small change in the chill portion count could make a large difference in the eventual yield. This is critical for growers, especially in warmer areas where the chill constraint might be binding. 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 portions are calculated with a vector of hourly temperatures. The formula is sequential, and chill portion build up depends on temperatures 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. In fact, for the areas covered in this study, chill portions are strongly (and negatively) correlated with the 90^{tth} temperature percentile (Q90) between November and February. In essence, chill portions linearly increase when Q90 temperature decreases. The correlation is very strong, with a goodness of fit of about 0.91. This means that insufficient chill is actually a right side temperature tail effect, comparable with other similar effects in the climate change literature.

2.1 Climate and Damage Predictions

Chill in most of California has been declining in the past decades, and is predicted to decline 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 (±2.9) chill portions in the year 2000 to estimates ranging between 50.6 (±3.8) and 54.5 (±3.6) (climate change scenario depending) in the years 2045-2060. Agronomists in California recognize this as a threat to existing varieties of pistachio (Doll, 2017; Jarvis-Shean, 2017). Together with increasing 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, 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 from 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 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. The literature does not offer a precise estimate for critical chill for California pistachios, or the shape of the response function around it. Using a panel of California county yields from 1984 to 2016, and the heterogeneity in chill portions within counties, I estimate the following loss function:

$$Loss(chill) = \frac{exp(6.49 - 0.14 \cdot chill)}{1 + exp(6.49 - 0.14 \cdot chill)} \in [0, 1]$$

Which is a logistic function with location 46.63 and scale 7.18. More details on the estimation are in Appendix B. Figure 2 shows the calculated damages from the observed and predicted 1/4 warmest years in the data.

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, used to solve for price and quantity in different winter chill realizations[2]. Equilibrium price and quantity allow 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.

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. $H(z)$ is sometimes referred to as the *potential output* function, where z is an input vector unrelated to the potential weather damage.

[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 unfeasible.

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 realistic, 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 Grower 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 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. I treat each of my 2,165 interpolation points as a grower, all with the same acreage and non-weather related conditions. Ideally, each one would have the same coefficients $alpha$ 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 grower. Solving for 2,165 growers would make this solution computationally very cumbersome. For this reason, and since the available yield reporting is at the county level, I aggregate for county chill-deciles. 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 points 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 function, I also need a slope for supply. I use an estimated supply elasticity of $\varepsilon_S = 0.19$[3] in my main specification, and later show results with other estimates 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:

$$\frac{\beta_c^2}{2 \cdot p_z} = \frac{\varepsilon_s}{\sum 1 - L(t_{c,d}^{2016})} \cdot \frac{q_{c,2016}}{p_{2016}} \implies \alpha_c = q_{c,2016} - \frac{\beta_c^2}{2 \cdot p_z} \cdot p \cdot \sum \left(1 - L(t_{c,d}^{2016})\right) \quad (4)$$

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:

$$Q(p) = \sum q_{c,d}(p) = \sum [1 - L(t_{c,d})] \cdot \left[\alpha_{c,d} + \frac{\beta_{c,d}^2}{2 \cdot p_z} \cdot (1 - L(t_{c,d})) \cdot p\right] \quad (5)$$

3.1.2 Grower with MCE

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

$$\max_{x,z} \pi = p \cdot [1 - L(x, c)] \cdot H(z) - p_z \cdot z - p_x \cdot x \quad (6)$$

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 can be found with the two first order conditions, equating the value of marginal productivity of each input to its price:

[3] Short term elasticity in agricultural goods is usually considered very low on the short run (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 (Gray et al., 2005, e.g.), yet I think it is more realistic to take a positive one, at least in a short run model, 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. This estimate is not statistically significant (p-value = 0.2), but seems like a good starting point.

$$p \cdot [1 - L(x)] \cdot H_z(z) = p_z \tag{7}$$
$$p \cdot [L_x(x)] \cdot H(z) = p_x \tag{8}$$

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

$$\frac{p_z}{p_x} = \frac{1 - L(x^*)}{L_x(x^*)} \cdot \frac{H_z(z^*)}{H(z^*)} \tag{9}$$
$$= \frac{x^*}{\delta(x^*)} \cdot \frac{\eta(z^*)}{z^*} \tag{10}$$
$$\implies z^* = x^* \cdot \frac{\eta(z^*)}{\delta(x^*)} \cdot \frac{p_x}{p_z} \tag{11}$$

where η is the elasticity of potential output in z, and δ is the elasticity of (net-of) loss ratio in x[4]. This can be plugged in a FOC to get a necessary conditions for profit maximization:

$$p \cdot L_x(x^*) \cdot H\left(z^*(x^*)\right) = p_x \tag{12}$$

That is, the value of marginal productivity of the MCE input x has to be equal to its price. This condition will be part of the model. To better understand the concept of MCE as a solution for climate challenges, let us differentiate the FOC w.r.t. the price p and the optimal MCE input x^*. We get (after some simplification):

$$\frac{\Delta x^*}{\Delta p} = \frac{L_x(x^*) \cdot H\left(z^*(x^*)\right)}{-L_{xx}(x^*) \cdot H\left(z^*(x^*)\right) + L_x(x^*) \cdot H_z(z^*(x^*)) \cdot z^*_x(x^*)} \tag{13}$$

Where regularity conditions ensure us this ratio is positive (concavity of production function means second derivative of loss function is negative). 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. 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[5]. 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 wash off with winter rain, I take these costs and effects as linear

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

[5]I thank Donald Stewart from UCANR's Agricultural Issues Center for data on material and deployment costs. Pounds per acre ratios from (Doll, 2015) to calculate total cost per acre.

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 in the no-MCE case, an explicit solution for z^* can be found (see Appendix C for the algebra). The supply of a grower with MCE is

$$q_{c,d} = \left(\alpha_{c,d} + \beta_{c,d} \cdot \frac{-\alpha_{c,d} + \sqrt{\alpha_{c,d}^2 + 2 \cdot \frac{\beta_{c,d}^2}{p_z} \cdot \frac{1-L(x)}{L_x(x)} \cdot p_x \cdot Acres_{c,d}}}{2 \cdot \beta_{c,d}}\right) \tag{14}$$

Note that the $\beta_{c,d}$ terms cancel out, and we are left with an expression which we can calculate. This is the supplied quantity at a some price p, where equation (12) solves for the MCE level x^*. The numerical solution thus solves equation (12) first for all county-deciles, then calculates their supplied quantity.

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. First, 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. Second, there might not be an internal solution at all. In this case, Appendix C has a proof that this is due to p_x being too high for any level of x, and therefore the grower is again set to supply the no-MCE quantity. Third, there might be more than one solution for x^* which solves the grower FOC. In this case, Appendix C proves there are up to two solutions, and the highest one is a local maximum and the profit maximizing one. In the numerical solution, I make sure to choose the higher one when there are two.

Market Demand

Demand is modeled as linear in price and elastic. Estimates for 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.

$$D(p) = a - b \cdot p \tag{15}$$

The coefficients for the demand are calibrated with the 2016 market outcomes (total supply and price) and an elasticity of demand $\varepsilon_D = -1.61$ [6].

[6] 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. The earliest demand elasticity estimate I found is from the 1970's (Dhaliwal 1972, in Nuckton 1978, estimated -1.5). Awondo and Fonsah (2014) try to calculate demand elasticity by using total production and averaging consumption

4 Simulations Results

The model is run on the climate predictions for 2020-2040, trying to get an expected climate in 2030. These predictions are not supposed to pinpoint the forecast for a specific year, but rather to present the climate trend and variation around it. The expected gains from the model are therefore an average of model outcomes under the chill predictions in this period. 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, my model does not include endogenous growth. To give some bounds on the expected gains, I run the simulations with four different acreage growth scenarios.

The first scenario is "No Growth", meaning that 2020-2040 climate predictions are cast over the current acreage. The second scenario is "Low Growth", which sets the yearly growth of harvested acres until the year 2022 at 9.6%, the average rate since 2000, and then sets zero growth (total acreage growth of 75%). The growth until 2022 is attributed to currently planted but not yet bearing acres. 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.

Table 1 presents the gains in each scenario, averaged over all years between 2020 and 2040. These can be seen as the yearly expected gains over the climate distribution[7]. I

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 choose to combine the latter (more recent) two estimates, given that 2/3 of pistachios are exported. The combined elasticity distribution is $\varepsilon^D \sim N(-1.61, 0.23^2)$

[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

interpret these averages as the expected value of having the technology, before knowing a year's weather outcome. The total grower profit gains are negative in all scenarios. Ranging from -68 million dollars in the "No Growth" scenario to -218 million in the "High Same" scenario, growers seem to lose from MCE in our case. This is true not only on average, but in general in almost every predicted year and scenario. Yearly expected consumer surplus and welfare gains are, as theory would suggest, positive: ranging between 0.48 to 1.57 billion dollars and 0.29-1.09 billion dollars respectably.

The average loss for growers is not the result of a distortion. Growers in my model make optimal decisions given the market conditions. MCE expands supply and lowers prices, and the gains in revenue seem to be completely offset by the price drop[8]. 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 and overall gains for consumers and total welfare are higher. However, the increase in grower losses is more moderate than the increase in total consumer and welfare gains. Growers losses form MCE increase by 12-75%, while consumer surplus gains increase by about 150%.

Grower losses are generally negative for all growers, as weather draws are correlated. However, in the "High North" scenario there are enough pistachio acres, unaffected by climate change, to break this correlation. Figure 4 shows the average grower profits by county. Usually, they are all negative. However, in the "High North" scenario the gains for Fresno, Kern and Kings are positive. MCE expands these counties' supply, but that induces a smaller price decrease (relative to other scenarios) that still makes this move profitable for them. This points to a general point: climate heterogeneity means climate change heterogeneity. Therefore, there could be winners and losers from MCE.

Another observation on grower profit outcomes is that, while the losses from MCE are greater as potential loss is higher (i.e. there is more potential correction with MCE), there are some losses even in the cooler years. This could stem from the loss function, which -as estimated above- attributes small loss ratios even at moderate chill portions. That is, even in moderate chill years, some growers might want to use MCE at the current price. This, in fact, should hold not only in the future. There is probably a positive level of optimal MCE use for some growers even in the present.

My main specification takes certain values of elasticities for supply and demand, as well as a price for unit of MCE per acres. How do gains from MCE respond to changes in these parameters? I run the simulations with different values to find out. For my main specification 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. As

error of these 300 average gains is the reported standard error

[8] This is not a new phenomenon in agricultural settings. For example, Carter et al. (1981) show that labor strikes actually increased revenues and profits for lettuce growers in 1979.

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 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 35% 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.

So far, the model has been very simple in terms of the supply chain. Mainly, the assumption has been that consumers buy directly from growers, and the market is competitive. In fact, it has been reported that about half of output is marketed by one firm (Blank, 2016). 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. Moreover, with MCE exacerbating climate change losses for growers, there would be even higher incentives to try and hold prices higher than a competitive benchmark. Therefore, it is interesting to see the gains from MCE under some degree of market power in the supply chain. The purpose of is 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 questions are: what would be the gains from MCE if market power exists? Are there scenarios where we would expect some under-utilization of MCE, below the social optimum?

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]:

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

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. ε^D is the price elasticity

[9]In fact, the model can also accommodate market power on the growers (monopsonistic power). 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)

of demand, and the whole term will be smaller than one since it is negative. Note that the whole term inflates the consumer price, as demand will be modeled as elastic. δ are added costs in the supply chain from grower to consumer.

The actual measure of market power ψ is unknown. Since the supplied quantity and 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). No clear source for such variation can be traced in recent years, and this type of study is beyond the scope of the paper. Moreover, market conditions could change by 2030, and current estimates of market power might not be relevant by then. However, it is useful to think of a reasonable upper bound for market power, 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)[11]. 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.

Basically, 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 gains and the intermediary gains together, resulting in "Agribusiness" gains. This is the sum of industry gains rather than the gains for a large grower-processor with market power. However, the Agribusiness gains are correlated with profit gains, which means that -to some extent- smaller growers might be better off as well when market power is exercised. In fact, this is the standard result in a dominant firm type setting, and the sign of the effect of market power on Agribusiness gains is likely to be indicative of the whole industry.

It turns out that, while Agribusiness total profits increase with market power, Agribusiness gains from MCE behave differently. In most scenarios, the demand needs to be on the elastic side, and supply on the inelastic side, for the Agribusiness sector to see some positive gains from MCE. For example, in the "Low Growth" scenario with price of MCE $p_x = 55$, the maximum Agribusiness gains are \$1,822 million (for a very hot year in the predictions, 2025). These gains are attained when the monopolistic power measure is at the highest, $\psi = 0.5$. However, the demand is elastic ($\varepsilon_D = -1.61$) and the supply as inelastic as I allow ($\varepsilon_S = 0.1$). In fact, for that same weather prediction, the lowest MCE gains for Agribusiness are also attained at $\psi = 0.5$: -\$1,669 million. However, this minimum is attained with the

[11]To be clear, this is not an identified estimation but rather an imputation exercise.

most inelastic demand ($\varepsilon_D = -1.1$) and most elastic supply ($\varepsilon_S = 0.1$). This could indicate that the utilization of MCE would depend on the weather realization of each year, and even more on the general market conditions. While consumer and total welfare gains are always positive, and increase with the degree of market power, some constellations of market power and elasticities turn the Agribusiness gains from MCE to negative. This means that, in some cases under market power, MCE might be under-utilized.

To get a sense of the effect of all variables on the gains from MCE, Figure 5 shows the "ceteris paribus" picture for gains under the "High Same" scenario. This plot shows the outcomes from running the model on various parameter combinations, drawn independently. The slope of the trendline can show the effect of changes in the relevant parameter, a sort of empirical derivative (averaged over the entire range of variables). I only keep the points where Agribusiness gains are positive (i.e. MCE would be used), or cases where there is no market power. The Agribusiness gains, in elasticity constellations where they are positive, increase with market power. When this happens, consumer and total welfare gains from MCE increase with market power as well.

5 Discussion and Conclusion

MCE could help overcome a climate challenge for California pistachios. I estimate 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 my main specifications are negative. While less tangible (and taxable) than actual registered profits, consumer surplus gains are real economic gains enjoyed by the public[12].

The scope of consumer surplus gains brings me 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 funds allocation (Alston, Norton, and Pardey, 1995, p. 491). Moreover, if market power is being exercised in pistachios, there might be a stronger case for public research on MCE. First, since consumer gains from MCE are higher in the presence of some monopolistic power. Second, as there is a real possibility that MCE is actually not profitable for a large grower holding some market power. Innovations in the private sector are likely to come from the industry itself: a large growing company would have the resources and access to enough

[12]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, local consumers still enjoy an expected gain from MCE in the hundreds of millions of dollars on a hot year, more than offsetting the grower losses.

pistachio acreage to run experiments and develop new MCE solutions. If this large company is also exercising some market power, and sees negative gains from MCE, investment in these solutions might fall below the social optimum.

What could be the implications of MCE technologies in a broader sense? One could imagine, with some more research, other MCE technologies applied to other crops such as corn, rice, and soybeans. Of course, these are less profitable than pistachios, but they face similar challenges, and MCE solutions are not necessarily very expensive. One can think of more extensions of this framework. For example, who can adapt using MCE? Technologies might only be available (and affordable) to growers in countries better off financially, further exacerbating the disparities in climate change damage incidence around the world. Another extension would look at the potential of MCE to accelerate 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. MCE might be a key element in transitioning to an agriculture adapted to a changing climate.

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. I expect to find more examples of MCE for dealing with climate change in California and other parts of the world in the coming years.

Tables

Scenario	Profits	Consumer	Welfare
No Growth	-68.0 (3.2)	221.4 (10.5)	153.3 (9.5)
Low Growth	-113.1 (5.6)	376.3 (18.1)	263.3 (16.5)
High North	-180.0 (7.8)	500.8 (24.5)	320.7 (19.3)
High Same	-217.9 (11.3)	757.5 (37.0)	539.6 (34.1)

Table 1: Average gains from MCE in 2020-2040 with price $55 per acre chill portion.

Scenario	Profits	Consumer	Welfare
No Growth	-77.8 (6.2)	539.3 (25.0)	461.5 (27.7)
Low Growth	-128.6 (10.7)	924.1 (43.1)	795.5 (48.0)
High North	-315.6 (11.1)	1,259.4 (60.1)	939.4 (55.3)
High Same	-244.3 (22.4)	1,886.0 (89.0)	1,641.7 (99.7)

Table 2: Average gains from MCE in warm years of 2020-2040 with price $55 per acre chill portion

	$\varepsilon_D = -2.0$	$\varepsilon_D = -1.61$	$\varepsilon_D = -1.1$	$\varepsilon_D = -0.5$
$\varepsilon_S = 0.10$	-64.2 ; 346.7	-136.5 ; 424.7	-300.6 ; 601.9	-838.6 ; 1,183.3
	282.5	288.2	301.2	344.7
$\varepsilon_S = 0.19$	-99.1 ; 414.6	**-180.0 ; 500.8**	-355.8 ; 688.4	-866.5 ; 1,235.5
	315.5	**320.7**	332.5	369.0
$\varepsilon_S = 0.30$	-193.6 ; 585.3	-294.3 ; 688.9	-499.5 ; 901.7	-1,018.7 ; 1,445.9
	391.8	394.6	402.2	427.2

Table 3: Yearly expected gains from MCE under varying elasticities. “High North” scenario. Figures in million US$. Top left is grower gains, top right is consumer gains, bottom is total welfare gains. The emphasized numbers correspond to the main specification.

Figures

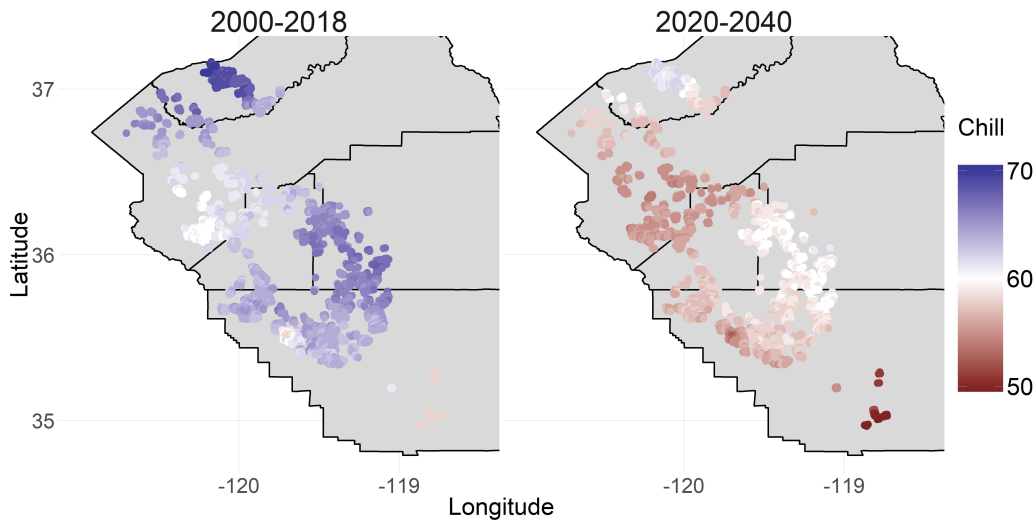

Figure 1: Chill of 1/4 warmest years in pistachio growing counties

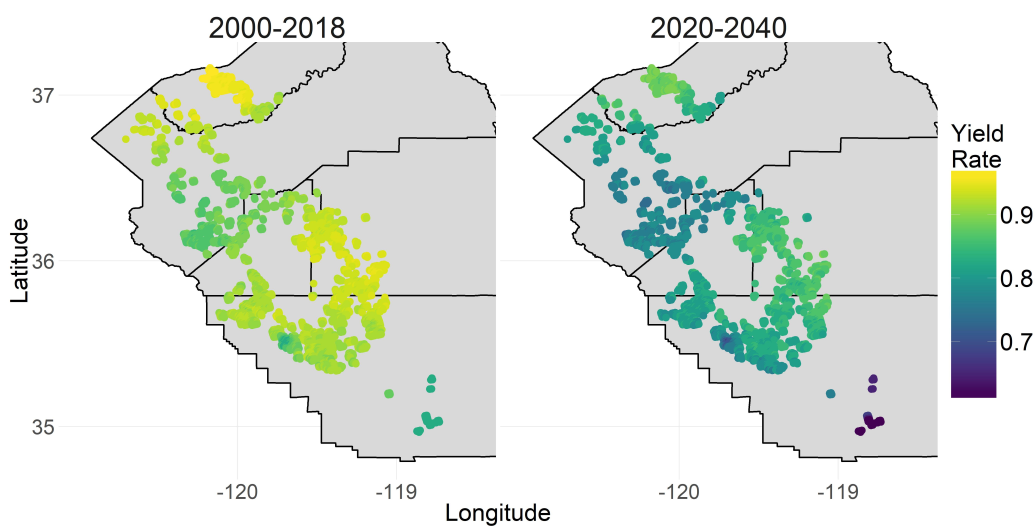

Figure 2: Damage in the 1/4 warmest years in pistachio growing counties

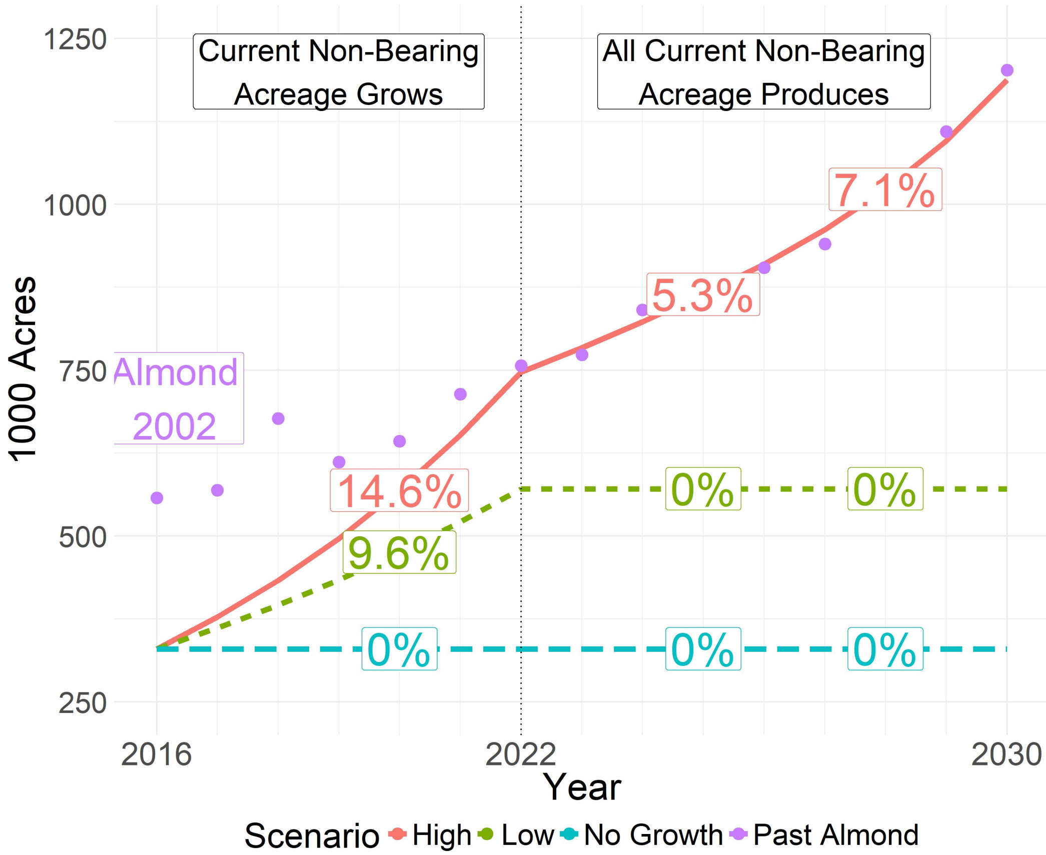

Figure 3: Growth rate development for different scenarios

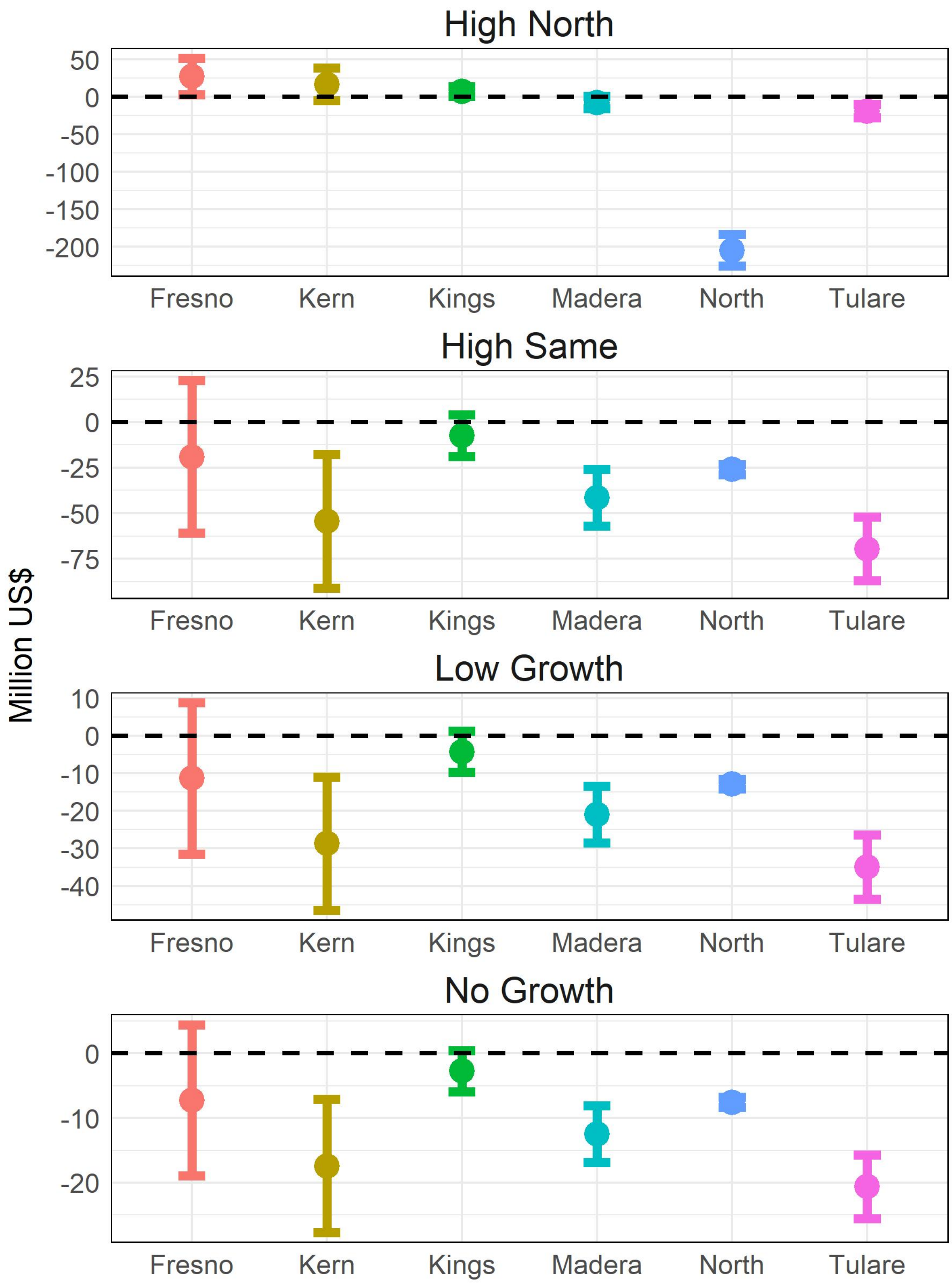

Figure 4: Mean and 95% CI for county profit gains from MCE.

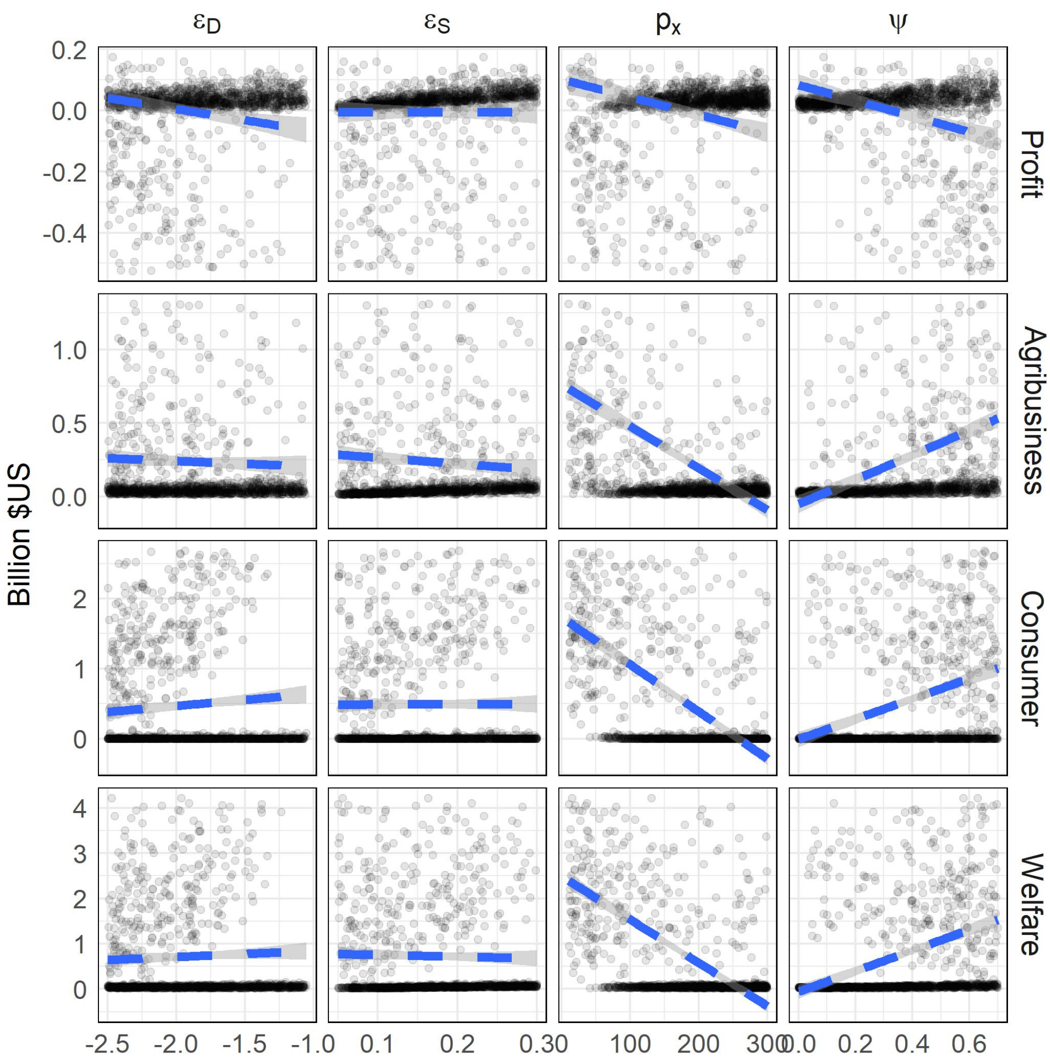

Figure 5: Effect of model variables on MCE gains

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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, I 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 I 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, I code them in $C++$ embedded 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 where chill was below 59 portions in one of the locations, bloom was uneven. Yields were observed, and while no statistical inference was made using 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 stems 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".

Ideally, with enough orchard observations and sufficient variation across a range of winter chill counts, we 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. My setup considers the yield data in my panel as a county average of yields across the county pistachio growing areas, weighted by the distribution of chill realizations. Each chill realization has a share of the county that experienced it, and I estimate the yield effects using this these shares.

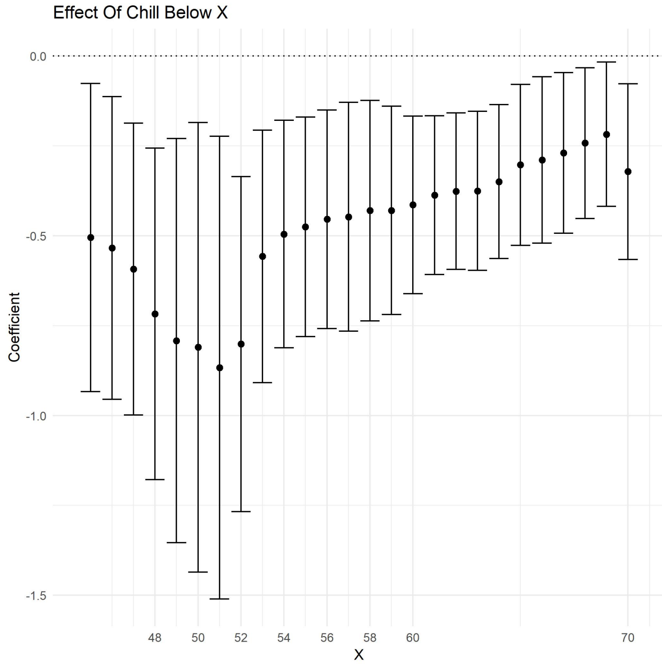
The first instinct for an empirical researcher is probably to try and estimate a flexible model on the panel, regressing yields on county shares of each chill portion count, in the following way:

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

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 more than one chill 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:

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

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.2 Main 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, we can take logs and get:

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

Since I don't have the yields of orchards, my panel consists of the county yields in 1984-2016 for Kern, Kings, Fresno, Madera, and Tulare counties. These county-year yields are matched with the shares of each county growing areas, exposed to chill portions between 38 (the lowest) and 86 (the highest). 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:

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

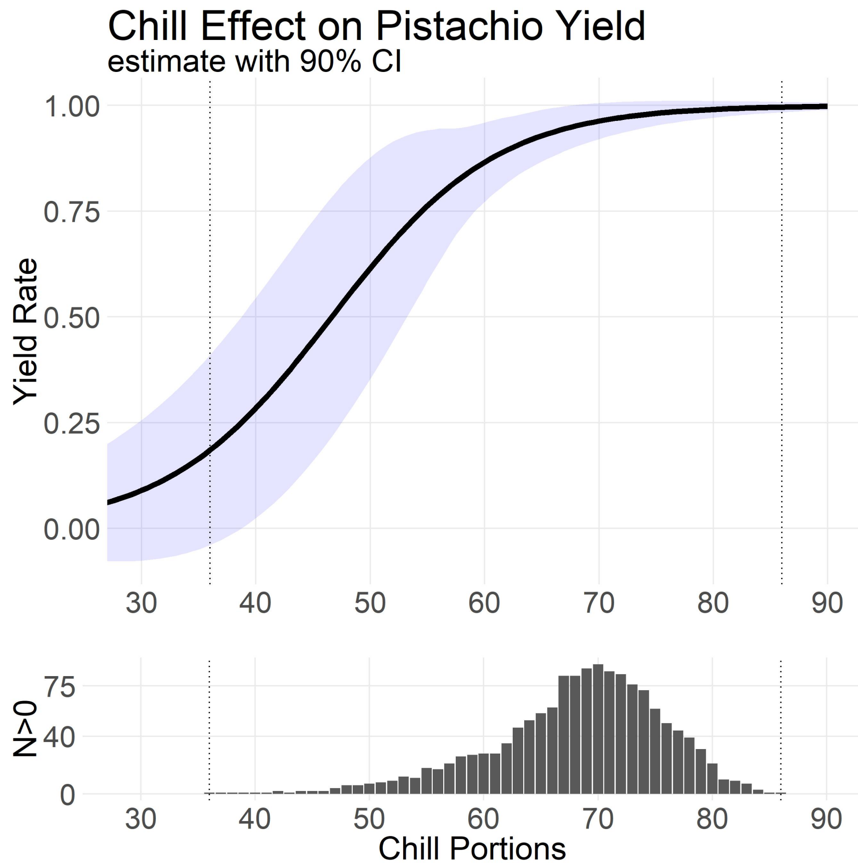
From here, we can isolate $f(Chill_{i,t} \mid \delta)$ and try to estimate it the parameter vector δ, assuming some functional form. I'll assume this to have a shape derived from a logistic function. This function is bounded between zero and one, and has a threshold behavior which is expected by agronomists. 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:

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

The resulting output is below. The first estimate is for the location parameter, and the second is for the scale. We 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:

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

Combining them:

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

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, we only consider the positive solution.

C.2 Checking That An Internal Solution Is a Local Maximum

When is a FOC of a grower with MCE a local maximum? Our production function is:

$$G(x, z) = \left[\frac{exp(m + n \cdot x)}{1 + exp(m + n \cdot x)}\right] \cdot \left[\alpha + \beta \cdot \sqrt{z}\right] \tag{6}$$

for ease of notation, the net-of loss function will be in linear parameter. Translating from the common notation of location and scale:

$$
\begin{aligned}
m + n \cdot x &= \frac{x-\mu}{s} \\
n &= \frac{1}{s} > 0 & s = 7.1 \implies n = 0.141 \\
m &= \frac{-\mu}{s} < 0 & \mu = 46.6 \implies m = -6.56
\end{aligned}
$$

The partial derivatives are:

$$
\begin{aligned}
G_x &= \left[n \cdot \frac{exp(m+n\cdot x)}{(1+exp(m+n\cdot x))^2} \right] \cdot \left[\alpha + \beta \cdot \sqrt{z}\right] > 0 \\
G_z &= \left[\frac{exp(m+n\cdot x)}{1+exp(m+n\cdot x)} \right] \cdot \frac{\beta}{2\cdot\sqrt{z}} > 0
\end{aligned}
$$

The first derivative is always positive if we assume $\alpha,\ \beta > 0$. The latter is usually true for production functions (as z should be an input), but the former is only true for inelastic supply. Which is out case in most agricultural settings (at least on the short run), but in other cases we would need to check the sign. If supply were elastic, i.e. $\alpha < 0$, one would need to verify that the output price actually results in a positive output. The Hessian is:

$$
\begin{pmatrix} G_{xx} & G_{xz} \\ G_{zx} & G_{zz} \end{pmatrix} = \begin{pmatrix} \frac{n^2}{(1+t)^3} \cdot (1-t) \cdot [\alpha + \beta \cdot \sqrt{z}] & \left[n \cdot \frac{t}{(1+t)^2} \right] \cdot \frac{\beta}{2\cdot\sqrt{z}} \\ \left[n \cdot \frac{t}{(1+t)^2} \right] \cdot \frac{\beta}{2\cdot\sqrt{z}} & \frac{t}{1+t} \cdot \frac{-\beta}{4\cdot(z)^{1.5}} \end{pmatrix}
$$

where $t = exp(m+n\cdot x) > 0$. Note that $G_{xx} < 0$ if and only if $t > 1$, which actually happens when x is greater than the location (center) parameter. Hence, a necessary condition for a local maximum is that x is greater than the location $(= -m/n)$. We also have $G_{zz} < 0$. The determinant of the Hessian is:

$$
\begin{aligned}
det(H) &= \frac{n^2 \cdot t}{(1+t)^4} \cdot (1-t) \cdot \left[\alpha + \beta \cdot \sqrt{z}\right] \cdot \frac{-\beta}{4 \cdot z^{1.5}} - \left[n^2 \cdot \frac{t^2}{(1+t)^4} \right] \cdot \frac{\beta^2}{4 \cdot z} \\
&= \frac{n^2 \cdot t}{(1+t)^4} \cdot \frac{\beta}{4z} \left[(t-1) \cdot \frac{\alpha + \beta \cdot \sqrt{z}}{\sqrt{z}} - t \cdot \beta \right]
\end{aligned}
$$

Let's try to see when the bracketed term is positive:

$$
\begin{aligned}
(t-1) \cdot \frac{\alpha + \beta \cdot \sqrt{z}}{\sqrt{z}} - t \cdot \beta &> 0 \\
\frac{t-1}{t} &> \frac{\beta\sqrt{z}}{\alpha + \beta\sqrt{z}}
\end{aligned}
$$

and this is verifiable in the simulations. In fact, it never fails in the simulations.

C.3 One Solution For Grower With MCE

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 bounded above.*

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 $\lim\limits_{x\to\infty} VMPx = 0$ and $\lim\limits_{x\to-\infty} VMPx = 0$. 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, 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 upper bound of VMPx. Hence VMPx is positive and bounded above. □

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. □

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

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

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

Proof. Two internal solutions means that p_x intersects $VMPx$ at two points. Recall that the latter is unimodal, so this intersections creates an interval between the intersection points, where $VMPx > p_x$. 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. $\square$

In the code, I make sure to verify that the higher solution is chosen if more than one exists. However, note that the left one is in an area convex in x, which creates an equilibrium but not a steady state in market outcomes. The numerical solution, which includes a market clearing equation, seems to always reach the higher root anyway.

Proof of proposition 1. If there is no internal solution, or if the solution is negative (not feasible), then the grower in fact sees the the no-MCE problem which has only one solution. If there is an internal solution, the FOC will give us up to two solutions, and one of them results in higher profits than the other. Thus there is only one profit maximizing solution for the grower problem. $\square$

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:

$$p^{RETAIL} \cdot \left(1 + \frac{\psi}{\varepsilon^D}\right) = p^{GROWER} \cdot (1 + \phi) \tag{7}$$

$$\implies \psi = \left[\frac{1+\phi}{\frac{p^{RETAIL}}{p^{GROWER}}} - 1\right] \cdot \varepsilon^D \tag{8}$$

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 these 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 phi_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.

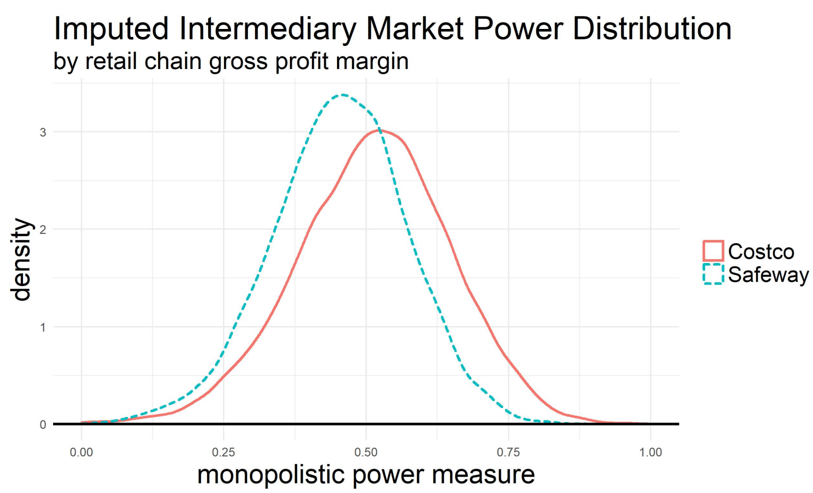
Both Walmart and Costco sell a variety of products besides food items. For example, only 55% of Costco's net sales in 2017 were from "foods", "sundries", and "fresh foods" categories (pistachio sales probably fall under the first two, either as ingredients in other food items or snacks). Unfortunately, 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. Importantly, labor and administrative costs are generally not included in costs of sales, so they mostly represent the purchasing costs. 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.



Imputed Intermediary Market Power Distribution
by retail chain gross profit margin
density
3
2
1
0
0.00
0.25
0.50
0.75
1.00
monopolistic power measure
Costco
Safeway