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

Abstract

Can farmers adapt to climate change by altering effective weather conditions on their fields? Existing technologies allow farmers to cool down plants by a few degrees during critical periods, reducing the damage from excess heat. With nonlinear effects of high temperature on yields, slight cooling can bring significant gains in many crops. We call this approach "Microclimate Engineering" (MCE), and note that it could be useful as a climate change adaptation concept. Our case study deals with California pistachios, threatened by warming daytime temperatures in the winter. A new light reflecting technology, already used in other contexts and crops, could potentially help deal with this challenge. We develop a model to analyze grower choice and market outcomes with MCE for California pistachios. The expected increase in welfare for the period of 2020-2040 is assessed at 0.49 - 1.42 billion dollars under several scenarios. Simulation results show increases in consumer surplus and total welfare when MCE is available, but decreases in aggregate grower profits. We also introduce market power to test its potential effects on the gains from MCE, finding mixed effects.h

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Climate change poses a major challenge to 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). The threat of rising temperatures for agriculture is therefore less in terms of warming average temperatures, and more about the increased probability of very hot days. As the right side tails of temperature distributions get longer and fatter, temperature which used to be considered extreme are becoming the new normal.

Technologies for targeting temperature distribution tails exist and have been used by farmers for decades. 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 straightforward: 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, raising the temperature around plants by a few degrees and preventing the frost damage. 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 the adverse effects of temperatures in the right side tail exist as well. Shading plants using nets or fabric is an existing practice, but these technologies are costly and not very flexible. Other technologies offer more nuanced implementation. One such technology, available commercially since 1999, consists of spraying plants with a reflective coat or "particle film" based on kaolin clay. Reflecting the sunlight, this technology has been shown to effectively diminish high temperature damages (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, and flexible shading.

The aforementioned technologies are examples of an approach we call "Microclimate 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. While MCE technologies have been used for decades, the economic literature has paid them little if any attention.[1] The concept of 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 from MCE for California pistachios as a case study. Specifically, pistachios are threatened by warming winter days, which could hit existing acreage within the next twenty years (2020-2040). 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, and we set to asses the potential gains from this technology. While addressing a pressing issue for an important crop in California, this article contributes to the growing literature of climate change and agricultural economics in several ways: First, while technologies for temperature adjustment are already being used by growers, an economic framework to assess their value and potential role in climate change adaptation has not been offered so far. Second, we focus on a solution for a perennial crop, facing different adaptation constraints than annuals. The annual-focused literature traditionally saw variety development and switching as the key adaptation mechanism (e.g., Olmstead and Rhode, 2011). However, variety switching costs in perennials are much higher, considering setup and opportunity costs while trees reach maturity. Alternative adaptation solutions such as MCE might be more suitable in their case. A third contribution is in exploring a climate change effect outside the flowering or bearing season. Most articles analyze the "direct" effect of heat on production by implicit stress like mechanisms. This article incorporates agronomic knowledge on bloom disruption due to high "off season" winter temperatures, a mechanism that has received less attention in the economic literature. As our results show, the potential damage from changes in winter temperature patterns can be as bad as the changes in summer, or even worse. A fourth contribution is integrating market power considerations with production models in a full market simulation to analyze the potential effects of climate change and adaptation. With increasing concentration and complexity of food supply chains, we find this intersection of agricultural economics, industrial organization, and climate change studies worthy of further research.

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 pistachios 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, the 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 can begin (CPRB, 2009).

The climate 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). Pistachios, like other fruit and nut trees, shed their leaves and go dormant for the winter. Trees need to time their spring bud breaking, and do so using environmental signals. One signal involves the trees experiencing cold temperatures for a certain amount of time. Several agronomic models have been developed to understand this signal, and the Dynamic Model (see Fishman, Erez, and Couvillon, 1987b,a; Erez et al., 1989) seems to be the most precise in predicting bloom in many temperate areas such as California (Luedeling, 2012). This model uses a metric of chill portions, which are calculated with a vector of hourly temperatures. Roughly speaking, when temperatures rise above 6^oC, buildup of chill portions slows down. When temperatures exceed 15^oC, the count reverses, quickly rounding down to the last integer portion that has been "banked." Failure to attain chill portion thresholds can lead to virtually zero yields. 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. For the areas covered in this study, chill portions are strongly (and negatively) correlated with the 90^{th} temperature percentile ($R^2 = 0.91$) between November and February, the dormancy season for pistachios. Insufficient chill can be conceptualized as a temperature tail effect in the winter, comparable with similar 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).

Climate and Damage Predictions

Chill in most of California has been declining in the past decades, and is predicted to decline further. 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 a valuable crop (Doll, 2017; Jarvis-Shean, 2017). At the same time, 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).

We create downscaled temperature maps, interpolated on a 1km grid in pistachio growing areas, to assess the potential effects of insufficient chill on California pistachios. This high granularity allows us to explore the heterogeneity in chill distributions – current and future ones – between counties or even within them. The damage from insufficient chill is non-linear, and small variations in chill portions can generate large differences in potential climate risks and MCE gains. A detailed map can inform us which counties are predicted to fare better than others, and help assess the economic value of MCE technologies more accurately. The pistachio growing areas are identified by satellite (Boryan, Yang, and Willis, 2014). We use two sources for temperature data. 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 in agricultural areas, making them especially adequate for this purpose. Data from a total of 27 stations is used. Future temperature predictions come from the Community Climate System Model verion 4 (CCSM4) published through the Centre for Environmental Data Analysis CEDA (2016). These predictions use the Representative Concentration Pathway 8.5 (RCP8.5) scenario (IPCC, 2013), currently considered a "business as usual" scenario (e.g., Burke, Hsiang, and Miguel, 2015; Crane-Droesch et al., 2019). More details on the climate data processing can be found in a supplementary appendix online.

What is the effect of chill portions on yields? Trilnick (2019) uses a panel of California county yields from 1984 to 2016, and the heterogeneity in chill portions within counties, to estimate a logistic loss function with location (mean) of 46.63 and scale 7.18.[2] This estimate concurs with the above mentioned agronomic observations of a threshold around 54-58 portions.

With climate predictions and a loss function from insufficient chill, we can predict the potential future damages from climate change. In 2000-2018, the average chill portion count in the pistachio growing areas was 69 portions, and the average loss rate 6.5%. In 2020-2040, that average chill count is predicted to drop to 61 portions, and the average loss rate would be 16.3%. Looking beyond these state averages over decades, we see heterogeneity both in space and time. Different growing areas experience different chill already, and some will be more likely than others to suffer losses due to insufficient chill in the future. These above mentioned averages also include years with sufficient chill, where losses would be minimal in most areas. However, when looking at the warmest 1/4 years, the predicted average chill portion count in 2020-2040 drops to 51, and the loss rate increases to 35.3%. Figure 1 shows these averages of chill and damage rates in the 1/4 warmest years in different growing areas of the five main growing counties in California.

Modeling Microclimate Engineering in Pistachios

In this section we develop a model to assess the gains from MCE. This is a single year, short run market model, solving for price and quantity under different winter chill realizations.[3] Equilibrium price and quantity are used to calculate welfare outcomes such as grower profits, consumer surplus, and the total welfare. For each weather 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 act optimally. MCE gains are to be interpreted as the difference in welfare measures between a world with MCE and a world without it.

Growers

The individual grower model draws from the pest control literature (reviewed in Sexton et al. 2007; Waterfield and Zilberman 2012). Growers are small, see the same prices for inputs and output, are risk neutral, and have full information about the prices and climatic conditions on all California plots. Following the damage control approach (Lichtenberg and Zilberman, 1986), we model growers with a production function $H(z)$, increasing in input z. The function $H(z)$ is referred to as the *potential output* function in ideal weather. Growers also face a damage or loss function $L(c) \in [0, 1]$. This loss depends on the local chill realization c. 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. When MCE is available, a separate MCE input is used as well, and growers optimize the levels of both inputs.

We aggregate California growers while taking climate heterogeneity into account. Our climate information is location specific, with 2,165 weather interpolation points of the same pixel size (1 Km^2) in the pistachio growing areas. Each of these pixels can be though of as one grower or orchard. However, solving numerically for the supply of 2,165 distinct growers is computationally unfeasible. Moreover, we only have production and yield data for counties to calibrate our functions with. We therefore represent each county with five agents. Each agent has 20% of the county's acreage and potential output, and experiences a quintile of the chill realizations within the county. Agents in the same county, while having the same potential output function, may therefore choose different MCE levels. The total market supply is calculated as the sum of the supplied quantities by the representative agents. The choice of five agents per county balances the desire to include climate heterogeneity into consideration with computational efficiency. Modeling with county quintiles offers a good compromise, given that a higher resolution (e.g. using chill deciles rather than quintiles) often results in many identical agents per county in terms of chill realizations. Using quintiles captures most of the chill heterogeneity while minimizing redundancies.

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:

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

Without loss of generality, we 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 with the input price:

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

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 potential supply for the grower. Linear supply has traditionally been used in multiple settings, including on the returns from agricultural R&D (Norton and Davis, 1981; Alston et al., 2009).[4] Together with the damage component, the supply function is as follows:

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

As expected, with higher price and/or higher net-of-loss rates, supply increases.

We use two equations to calibrate the parameters α and β^2/p_z. The first is equation (3) itself, where we also use the market price, county quantities, and chill measured in 2016. The second equation is the definition for elasticity of supply with our production function, where we assume an elasticity to solve for the parameters.[5] 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 we 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.[6] We take this as a starting point for the pistachio own price short run supply elasticity and use it in the main specifications. We later show results with other elasticities as well.

The total supply without MCE is the total sum of these county supplies:

$$Q(p) = \sum_j \sum_{k=1}^{5} q_{j,k}(p) = \sum_j \sum_{k=1}^{5} [1 - L(t_{j,k})] \cdot \left[\alpha_{j,k} + \frac{\beta_{j,k}^2}{p_z} \cdot (1 - L(t_{j,k})) \cdot \frac{p}{2}\right] \tag{4}$$

where j are counties an k are the quinitiles.

Supply with MCE

When MCE is available, the grower can also adjust the loss due to adverse 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 other useful properties (e.g. some pest control capabilities and lowering water requirements), these properties are not very useful at the time of tree dormancy.

An internal solution for the grower problem is derived 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.[7] We combine equations (7) and (10) to get a necessary conditions for profit maximization:

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

This is an implicit function of x^*, given the relative prices and other parameters. To better understand the concept of MCE as a solution for climate challenges, let us differentiate equation (11) w.r.t. the output price p and the optimal MCE input x^*. We get (after some simplification):

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

where regularity conditions assure 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. However, a significant increase requires a large marginal MCE effect, i.e. $L_x(x^*) \gg 0$ in the numerator. When $L_x(x^*) \to 0$, either because the weather is adequate or MCE level reached satiation, an increase in price will result in very little increase in MCE input x^*. Rather, the grower would respond by changing z^*.

To specify a loss function with MCE, we 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/acre.[8] In practice, there would be a limit to the potential cooling effects of kaolin clay. Applying more of the 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, we take these costs and effects as linear for the model. The total required "extra" chill portions, seems feasible with weekly applications starting early in the winter. For a more conservative estimate, and to take into account potential higher MCE prices in a warm year, we run the simulations with double the estimated price, setting $p_x = \$110/acre$.

Once the optimal x^* has been established by solving equation (11), a solution for the regular input level z^* can be calculated directly (for the algebra details see the supplementary appendix online). This results in an implicit supply function for a grower with MCE:

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

Note that the $\beta_{j,k}$ terms cancel out, and we are left with an expression of the coefficients we calibrated before. That is, given the input prices p_x and p_z, and the chill realization for the grower, we have the supplied quantity for a given pistachio price.

The supply function is not quasi-concave over its entire support. Rather, given the weather realization, the grower uses no MCE under some critical price, and a positive amount above it (see Figure 2 for an illustration). This threshold behavior is common in pest control models (e.g. Moffitt, 1988). We verify that the shape of the loss function, combined with the linear supply forms, guarantees a unique solution to the grower's profit maximizing solution (either internal or a corner solution).

Market Demand

In empirical demand estimations, such as the ones we cite below, we usually find either linear or iso-elastic specifications. Linear demand allows for a choke price (i.e., a price where zero units are wanted) and demand elasticity that varies with the price, which seems more realistic when modeling large supply disruptions. The demand function in our model is therefore linear:

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

where p is the grower price and δ are added costs down the supply chain. To calibrate the demand function, we use the total output and price in 2016 together with a demand elasticity estimate. This allows to solve equation (14) by tying a and b together, in a similar way to our calibration of the supply function.[9] Most estimates for demand elasticity for pistachios are between -1 and -2. Demand for pistachio is considered elastic because 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 we 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 (standard error) 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 (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. Our elasticity of choice for the model is a weighted average of the latter (more recent) two estimates, given that 2/3 of pistachios are exported. The result of combining these two normally distributed estimates is $\varepsilon_D \sim N(-1.61, 0.23^2)$. We assume an elasticity of $\varepsilon_D = -1.61$ and later show results with other elasticities as well. For δ, the added costs down the supply chain to the consumer, we take the lowest consumer price per ounce registered in Cheng et al. (2017), and calculate the difference from the grower price.[10]

Alternate Bearing Considerations

Alternate bearing is a biennial yield pattern where trees alternate "on" (high yield) and "off" (low yield) years. Pistachios are perceived as having a relatively strong alternate bearing pattern (Rosenstock et al., 2010). The actual effects of alternate bearings are subject for further research,[11] but the observable yield fluctuations could potentially change the gains from MCE in our model. We emulate an alternate bearing pattern based on existing state yields. Looking at the distribution of the ratio between yields and their lags, the median ratio is close to one (0.96), and the average for ratios below the median (i.e., ratios where the current yield is lower than the previous) is 0.65. Therefore, we include "off' years in our model, where the agent capacity coefficients are multiplied by 0.65, a loss which cannot be compensated by MCE. Furthermore, we set the first (and least discounted) year in our analysis (2020) to be an "off" year. This reduction in baseline yield can have opposite effects on the gains from MCE: on one hand, as capacity in the "off" years is reduced by a third, the gains from MCE would be lower. On the other hand, higher prices in the "off" year, resulting from lower supplied quantity, increase gains and present a stronger incentive to use MCE when needed.

Market Clearing and Welfare Outcomes

The total market supply is the aggregated supply of all the growers. We have 30 representative growers, each responsible for one fifth of a county. A solution is obtained by solving the quantity supplied by each representative grower, while at the same time equating the sum of their supply to demand at an equilibrium price. That is, a solution vector has a market price and the output for each representative grower. With this solution, and the rest of the model assumptions, we calculate consumer surplus, grower profits, and total welfare.

In each simulation, the model is solved twice: once with the option to use MCE and once without it. The gains from MCE are the outcomes with MCE minus the outcomes without. Note that the expansion of supply by MCE is guaranteed to result in (weakly) positive gains from MCE in terms of total welfare and consumer surplus: the equilibrium price is lower and quantity is higher. As for the growing sector, it does enjoy higher revenues with increased quantities, but the resulting lower price also decreases its profits from the output that would have been produced without MCE. Therefore, one cannot tell *a priori* if grower profits increase or decrease when MCE is available. The sign and magnitude will need to be determined in the simulations, given the parameters and functional forms.

For a given set of model parameters and climate predictions for 2020-2040, the model is solved twice for each year in this range. The consumer, grower, and welfare gains are calculated for each year using these two simulations. We calculate the Net Present Value (NPV) of the MCE gains in 2019 using a discount rate of 7%. This rate is the "base case" for social analysis of federal programs, where it serves as "an estimate of the average before-tax rate of return for private capital in the U.S. economy" (OBM, 1994). A pistachio cost and return study from 2015 (Brar et al., 2015) quotes a nominal interest rate of 5.75%, at a time when the Federal Reserve rate targets were 0.25-0.5%. With the latter rates now about one percent point higher, a discount rate of 7% seems reasonable for an approximation of the alternative costs of investment in MCE technologies.

Capacity Growth Scenarios

Before we present the simulated welfare gains, there is one more piece in the puzzle. The model is calibrated using 2016 production statistics. Production capacity is likely to change through 2020-2040, mainly by change in acreage. To give some bounds on the expected gains, we run the simulations with four different capacity growth scenarios, each specifying a different pistachio capacity growth path until 2040. These scenarios are meant to give bounds to acreage change due to population growth, international market dynamics, and the role of the US as a major exporter of pistachios. In all cases, a county's modeled production capacity grows by the same rate as its acreage.

All scenarios assume some growth path until 2030, when acreage stabilizes and stays fixed through 2040. The first scenario is "No Growth", meaning that 2020-2040 climate predictions are cast over the 2016 acreage. This should give a lower bound for gains, as acreage is predicted to grow and not shrink. 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. This assumes that we are on the brink of a dynamic equilibrium in growth, and therefore no new acres will be planted in California. This scenario should give estimates that are higher than the “No Growth” scenario, but still rather conservative. The third scenario is “High Growth.” This scenario sets the growth rate until 2022 at 14.6%, the average rate since 2010, and then lets pistachio acreage follow the historic path of almonds in California (total acreage growth of 260%). That is, the growth rate of almonds when they had the corresponding pistachio acreage. This very optimistic growth prediction makes the “High Growth” scenario our upper bound for gains from MCE. One potential concern with acreage and capacity 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 as 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). This last scenario is, in our opinion, the most plausible in terms of MCE gain magnitudes. A summary of the growth rates is depicted in Figure 3. In all scenarios, the modeled demand grows by the total rate of acreage growth. Results from all scenarios are reported below.

Simulations Results

For each capacity growth scenario, we run this procedure for 100 independent draws of 2020-2040 prediction paths. For each draw, an entire simulation is run to produce a sum of NPVs for the gains. For each growth scenario, we report the Expected NPV (ENPV) and standard errors of the outcomes from these 100 simulations. More details on the numerical solution of the model can be found in the supplementary appendix online.

We present the Expected NPV of the MCE gains in our simulations in Table 1. The total welfare gains from MCE technologies are positive, for the market as a whole and for consumers specifically. ENPVs of the total welfare gains are between \$0.49 billion in the "No Growth" scenario to \$1.42 billion in the "High Growth" scenario. Consumer surplus gains range from \$0.73 billion to \$2.06 billion for the same scenarios. The gains from MCE for growers turn out negative, ranging from $-\$0.24$ billion dollars in the "No Growth" scenario to $-\$0.63$ billion in the "High Growth" scenario.

The average loss for growers is not the result of a distortion. Growers in the model make optimal decisions given the market conditions. Rather, the increase in production costs is higher than the increase in revenues, lowering the total grower profit. This is true not only for the ENPV calculation, but in general for almost every predicted year and acreage growth scenario. Moreover, this is true for almost every representative agent, even the ones most susceptible to yield losses due to insufficient chill. Climate heterogeneity seems not to play a major role in the outcomes, mainly because MCE in our case is cheap compared to other costs and market prices.

Introducing Market Power

So far, we assumed that consumers buy directly from growers, and the market is competitive. In fact, pistachios are processed and marketed by intermediaries, and it has been reported that about half of California's pistachio 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. Therefore, it is interesting to examine the gains from MCE under some degree of market power in the supply chain.

Market power on the supply side is often modeled as a large supplier limiting the supplied quantities, so as to increase the equilibrium price and its total profits. The effects of MCE on total welfare should be positive in this case as well. We have two main questions on our mind. First, we want to know if these effects are stronger or weaker with grower market power, compared to the initial specification. Second, as the grower gains from MCE in our competitive market specification are negative, we want to know if they can be positive under a reasonable measure of market power.

To include market power in the model, we use a flexible framework with an intermediary or middleman which can have market power on consumers (see Sexton and Zhang, 2001; Just, Hueth, and Schmitz, 2005, p. 386-388).[12] This intermediary manipulates the market quantity 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:[13]

$$p^{CONSUMER} = \left(p^{GROWER} + \delta\right) \times \left(1 + \frac{\psi}{\varepsilon_D}\right)^{-1} \tag{15}$$

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 parameter ε_D is the price elasticity of demand, which is negative, making the term in parenthesis smaller than one.[14] δ are added costs in the supply chain from grower to consumer.

The actual measure of market power ψ for pistachios is unknown. We believe an upper bound of 0.5 is reasonable, and run simulations with $\psi = 0.5$ and $\psi = 0.25$ for a middle point between the upper bound and the competitive market simulations reported above.

Applying market power means limiting supplied quantities. This might increase or decrease "raw" grower profits while creating positive profits for the intermediary. To get a sense of the total oligopsonist gains, we add both the grower and intermediary gains together, resulting in "Agribusiness" gains. Table 2 shows the results from these simulations, for the "High North" scenario. For the mid range value $\psi = 0.25$, the total welfare gains from MCE in pistachios in our main specification are \$2.48 billion, a \$1.43 billion increase from the competitive market outcome, attributable almost entirely to increase in consumer surplus. From $\psi = 0$ to $\psi = 0.25$, the loss for growers from reduced output roughly cancels out with the excess revenues from higher prices, resulting in a slight increase in agribusiness profits. However, at $\psi = 0.5$, the total welfare gains grow to \$5.9 billion, while agribusiness gains from MCE turn positive, \$0.68 billion. Therefore the answer to our first question, on the relationship between market power and MCE gains, is that they are positively related. However, this might not always be the case, as we explain in the discussion section. As for our second question, is there a point where a large grower sees positive gains from MCE, our results do show that at the upper value of ψ the answer is positive. A quadratic interpolation of the results reveals that the indifference point (zero MCE gains) is located at $\psi = 0.35$. This point, as the rest of the model outcomes, also depends on the elasticities. Figure 4 depicts the average simulation results under alternative assumptions on elasticities. We use the values $\varepsilon_S = 0.1, 0.19, 0.3$ and $\varepsilon_D = -1.1, -1.61, -2$. As expected, consumer surplus and total welfare gains from MCE increase when supply is more elastic and demand is less elastic. In a competitive market setting (i.e. $\psi = 0$) the total welfare gains are relatively stable. As ψ increases, so does the magnitude of MCE impact.

Discussion and Conclusion

We model the pistachio market and assess the potential welfare gains from an MCE technology that lowers the effective temperatures in orchards. We estimate the welfare gains from this technology in 2020-2040 in the range of \$0.49 - \$1.42 billion. These gains are fully attributed to consumer surplus gains, as the total gains for growers are negative. The latter result is not unheard of in agricultural settings, where a negative supply shock can actually increase grower profits. For example, Carter et al. (1981) show that the 1979 labor strikes in California actually increased revenues and profits for some lettuce growers. Our simulation results shows the flip side of this phenomenon: solving a weather generated supply shock can lower grower profits.

While less tangible (and taxable) than actual registered profits, consumer surplus gains are real economic gains 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, let us assume that Californians still enjoy half of the consumer surplus gains from MCE (and the entire the grower gains). Adjusting Table 1, the total welfare gains in California are smaller but still positive. Note that this analysis stops at the farm gate. Other local economic gains, such as value added and multiplier effects down the supply chain, are not modeled or accounted for in this study.

Our main findings hold under a range of model parameters, and also when introducing market power. Grower profits see a negative impact from MCE, but a positive impact on consumer surplus makes the discounted welfare gains greater than \$0.5 billion in the "High North" growth scenario for all the parametric combinations tested.

Total welfare gains from MCE could theoretically decrease or increase with market power. On one hand, a large grower might under-utilize an MCE technology, setting the supplied quantity at a lower level than the competitive market optimal benchmark. Therefore, at higher degrees of market power, we would see lower welfare gains from MCE. On the other hand, when market power is stronger, the initial non-MCE equilibrium is set at a point where demand is more elastic and prices are higher than the benchmark. This increases both the incentive to recover output by using MCE and the potential gains from MCE in terms of consumer surplus. It is hard to tell *a priori* which effect will be dominant, and it may depend on the non-MCE benchmark output. We actually observe both effects being dominant in different simulations: in our main specification, including the alternate bearing impacts on potential output, welfare gains from MCE are higher when market power is higher. It turns out that when "off" years (lower yield on a biennial cycle) and "bad" years (insufficient natural chill) coincide, market conditions are such that the gains from MCE increase with market power. When there are no "off" years to decrease the potential output, the first effect is dominant, and the relation is opposite. Table 2 has the results from simulations with and without the alternate bearing component. The online appendix include a version of Figure 4 for results without alternate bearing.

Beyond the potential gains from MCE on an "intensive margin" (how much MCE would be used in different cases), there is also an extensive margin of MCE technology development. Generally speaking, a world with market power would probably see less demand for MCE use. Incentives for investment in R&D to tackle a climate challenge, either by a large grower or private innovators, would be reduced. Additionally, some MCE solutions, like the the kaolin technique for pistachios, are actually adaptations of existing technologies. Returns for research investment in such solutions could be hard to monetize by investors, further hindering the development of MCE technologies. Considering these points, and with social returns from MCE exceeding private ones, research of new MCE technologies is a good candidate for prioritizing in public research fund allocation (Alston, Norton, and Pardey, 1995, p. 491).

What might be the implications of MCE technologies in a broader sense? One could imagine, with further agronomic research, more MCE technologies applied to other fruit and nut crops. Perennial crops are natural candidates for MCE applications, as the setup costs make adaptation by crop switching and migration more expensive. For example, the setup costs for an acre of pistachio trees is about $16,000, not including the opportunity cost in the 7-10 years while trees reach maturity (Brar et al., 2015). Eventually, MCE technologies might even help deal with climate change challenges for annuals such as corn or soybeans. Another 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 as they get warmer. MCE might be a key adaptation concept on both geographic frontiers of climate change. Looking at the global view, we also think MCE technologies could change the distribution of climate change damage incidence. For example, the kaolin application on pistachios is not very expensive in US terms, but might not be affordable for growers in other parts of the world. If everyone is facing similar climate challenges, US growers could increase their share of the world market.

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 employing various scenarios to produce a reasonable bounds for our results, basing our parameter ranges on values found in the relevant literature, and choosing conservatively when possible, we believe to have gotten a reasonable range for the potential gains from MCE in California pistachios. Gains are in the hundreds of millions of dollars for one California crop. We believe this shows a great potential of MCE technologies for climate change adaptation in general.

Tables

Scenario	Consumer	Grower	Welfare
No Growth	0.73 (0.12)	-0.24 (0.06)	0.49 (0.08)
Low Growth	1.21 (0.21)	-0.39 (0.09)	0.82 (0.14)
High North	1.55 (0.27)	-0.49 (0.12)	1.05 (0.18)
High Growth	2.06 (0.341)	-0.63 (0.15)	1.42 (0.23)

Table 1: Expected net present value of MCE in billions of US dollars. Yearly gains in the years 2020-2040 are discounted at 7% yearly and summed to calculate ENPV in 2019. The values presented are the mean (standard deviation) from 100 simulations.

Alt. Bearing	ψ	Agribusiness	Consumer	Grower	Welfare
Yes	0.00	-0.49 (0.12)	1.55 (0.27)	-0.49 (0.12)	1.05 (0.18)
	0.25	-0.32 (0.15)	2.80 (0.36)	-1.02 (0.16)	2.48 (0.35)
	0.50	0.68 (0.35)	5.22 (0.50)	-2.20 (0.23)	5.90 (0.68)
No	0	-0.98 (0.16)	2.24 (0.35)	-0.98 (0.16)	1.26 (0.21)
	0.25	-0.24 (0.07)	1.24 (0.26)	-0.46 (0.11)	1.00 (0.20)
	0.50	0.08 (0.03)	0.47 (0.16)	-0.13 (0.08)	0.55 (0.16)

Table 2: Expected net present value of MCE in billions of US dollars, for three levels of monopolistic market power parameter (ψ) in the High North scenario and the elasticity parameters in our main specification ($\varepsilon_D = -1.61$ and $\varepsilon_S = 0.19$). Results are presented with and without alternate bearing activated for the simulations. Yearly gains in the years 2020-2040 are discounted at 7% yearly and summed to calculate ENPV in 2019. The values presented are the mean (standard deviation) from 100 climate prediction bootstraps.

Figures

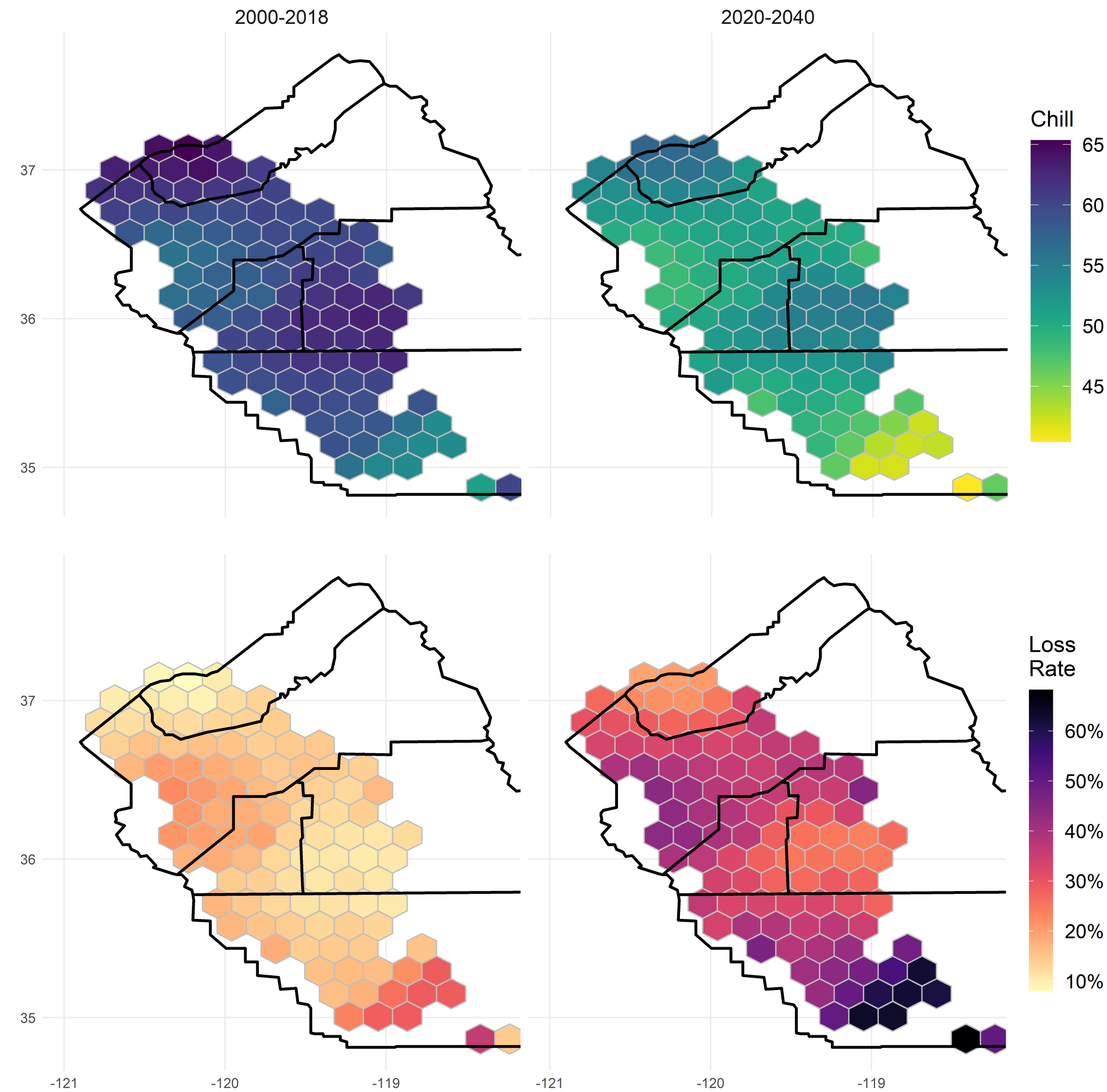

Figure 1: In the top row: average local chillon the 1/4 warmest years in 2000-2018 (observed) and 2020-2040 (predicted). In the bottom row: estimated damage from insufficient chill on the 1/4 warmest years. Color codes represent the average measure in pistachio points in each hexagon. Past climate data is processed from CIMIS (2018), climate predictions from CEDA (2016).

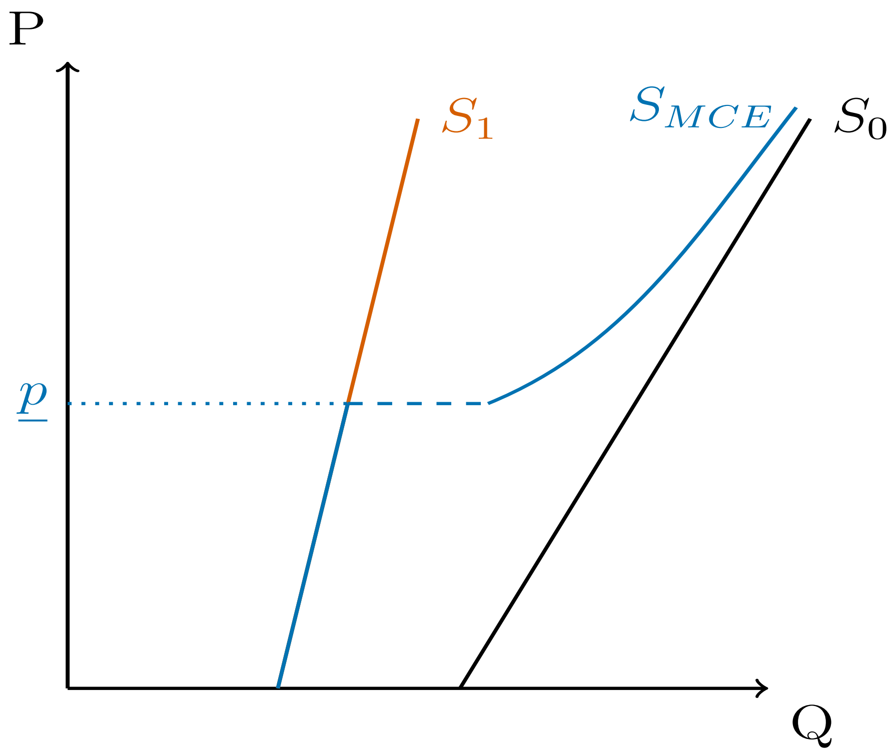

Figure 2: Sketch of the grower's supply function. S_0 is the supply curve under perfect weather. S_1 is the supply curve in a warm year, when productivity is impaired and supplied quantity at every price is lower. S_{MCE} is the supply with Microclimate Engineering (MCE). Even when MCE is available, the grower will not use it when the output price falls below $\underline{p}$. In that range, equation (11) has no solution (in rare cases, no positive solution), because the relative price p_x/p is too high to justify any level of MCE input x. The marginal productivity of x is bounded by the damage function. At price $\underline{p}$ or above it, x^* jumps from zero to a positive number, and z^* increases as a consequence. This results in the discontinuity of S_{MCE}.

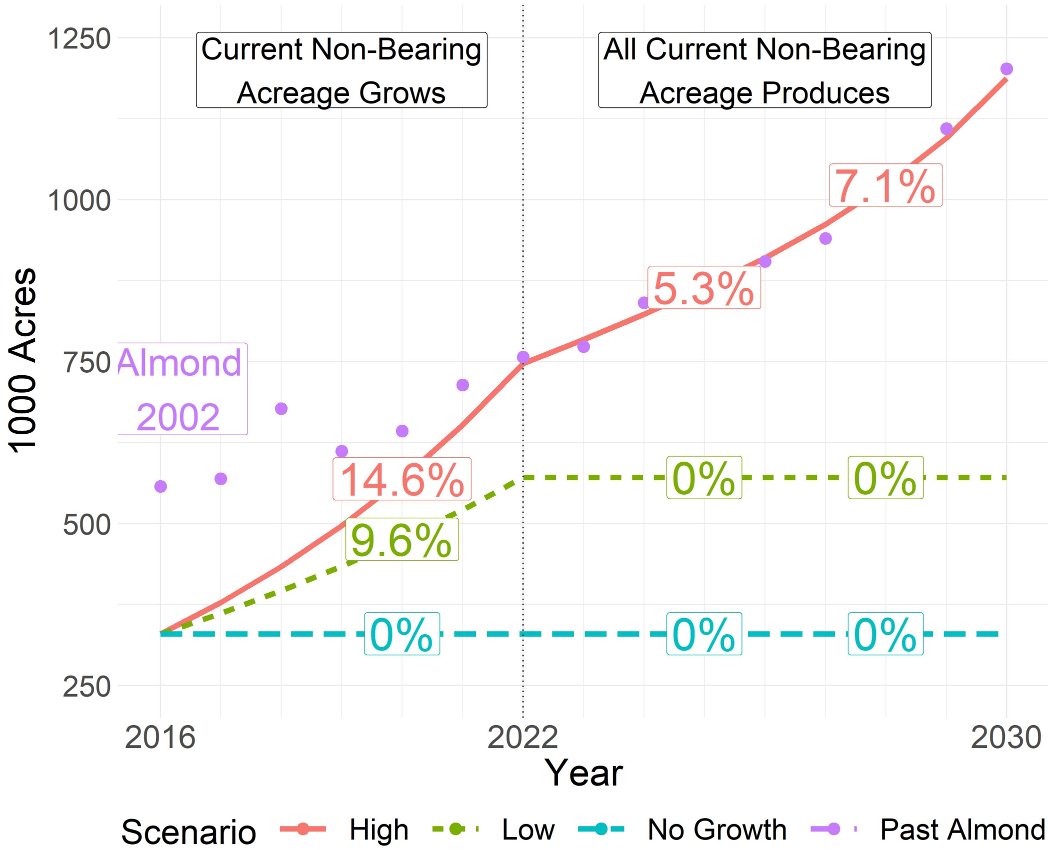

Figure 3: Growth rate development for different scenarios. Rates are based on past pistachio acreage growth rates in California (CDFA, 2018)

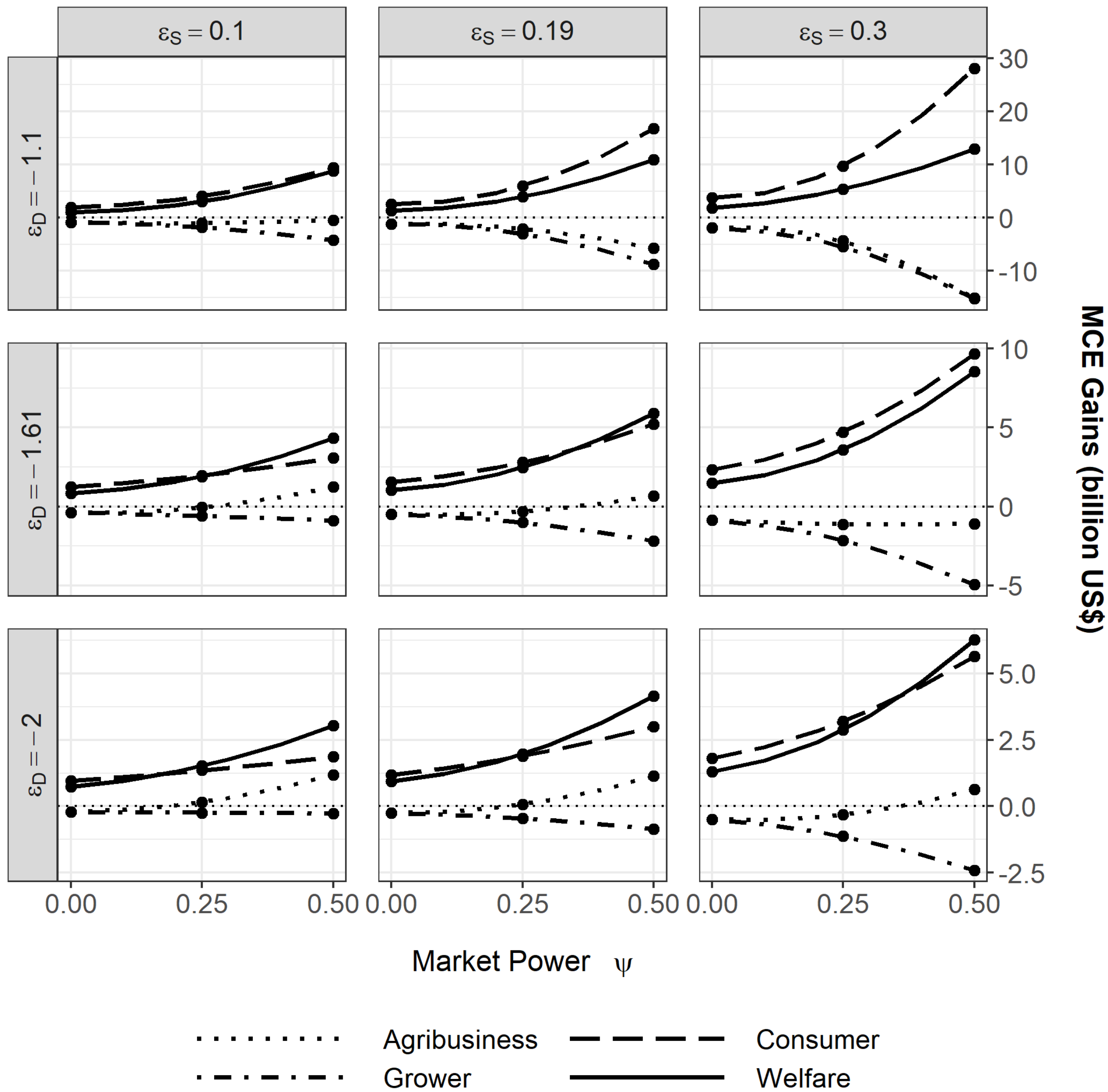

Figure 4: Expected Net Present Value (ENPV) for gains from MCE in 2020-2040 under various parametric combinations. Each point is the average of 100 simulation outcomes. The various panels show the results for combinations of elasticity of supply (ε_S) and demand (ε_D). The horizontal axis represent the measure of market power (ψ), where zero is a competitive market and one is monopoly. The curves are interpolated by a quadratic equation. Our main specification results are in the center panel. Note the scale changes of the vertical axis between panel rows.

Notes

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.

2. The loss function, returning the percent loss, is $Loss(chill) = 1/\left(1 + exp(\frac{46.63 - chill}{7.18})\right)$

3. We 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.

4. A more recent review on the impact of biofuel demand on commodity prices matched estimates from the literature with estimates generated by a model with linear supply and demand and given elasticities. It turns out this simple model can give good approximations for the impact estimates generated by the more intricate models in the literature (Persson, 2015).

5. The combined equations is:

$$\frac{\beta_j^2}{2 \cdot p_z} = \frac{\varepsilon_s}{\sum 1 - L(t_{j,k}^{2016})} \cdot \frac{q_{j,2016}}{p_{2016}} \implies \alpha_j = q_{j,2016} - \frac{\beta_j^2}{2 \cdot p_z} \cdot p \cdot \sum \left(1 - L(t_{j,k}^{2016})\right)$$

6. This estimate is not statistically significant (p-value = 0.2)

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

8. We 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) We assume a weekly rain event during winter washes off the treatment, which needs to be applied again

9. adding the condition $\varepsilon_D \cdot p_{2016} = -b \cdot (a - b \cdot p_{2016})$

10. We use the lowest price, \$6400/ton, for several reasons: first, some of the output is sold in bulk for processing, and some is exported, probably at a lower price than the average consumer price. Second, a smaller δ minimizes the effect of market power (discussed in the results section) and the resulting gains from MCE are conservative in that case.

11. In fact, Rosenstock et al. (2010) analyze a yield panel of 4,288 pistachios and find that 42% of the trees do not exhibit statistically significant patterns of alternate bearing. Looking at state yield in 1983-2017 and using a similar statistical methodology, we fail to reject a null hypothesis of a random yield pattern.

12. 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, we only use the monopolistic market power part.

13. 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)

14. This number is greater than zero since we are assuming elastic demand.

A Climate and Pistachio Location 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, we 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, we use temperature predictions of a CCSM4 model from CEDA (2016). These predictions use an RCP8.5 scenario. This scenario assumes a global mean surface temperature increase of $2^o C$ between 2046-2065 (from a baseline of 1986-2005) (IPCC, 2013).

The data are available with predictions starting 2006, and include daily maximum and minimums on a 0.94 degree latitude by 1.25 degree longitude grid. To interpolate hourly temperatures from the predicted daily extremes, we use a procedure involving the latitude and date (coded in R by Luedeling, 2017).

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, we calculate winter chill portions for each each point season. Erez and Fishman (1997) produced an Excel spreadsheet for chill calculations, which we obtain from the University of California division of Agriculture and Natural Resources, together with instructions for growers (Glozer, 2016). For speed and ease of calculations, we translated the spreadsheet to an R function (available at https://github.com/trilnick/miniChill).

B Results Without Alternate Bearing

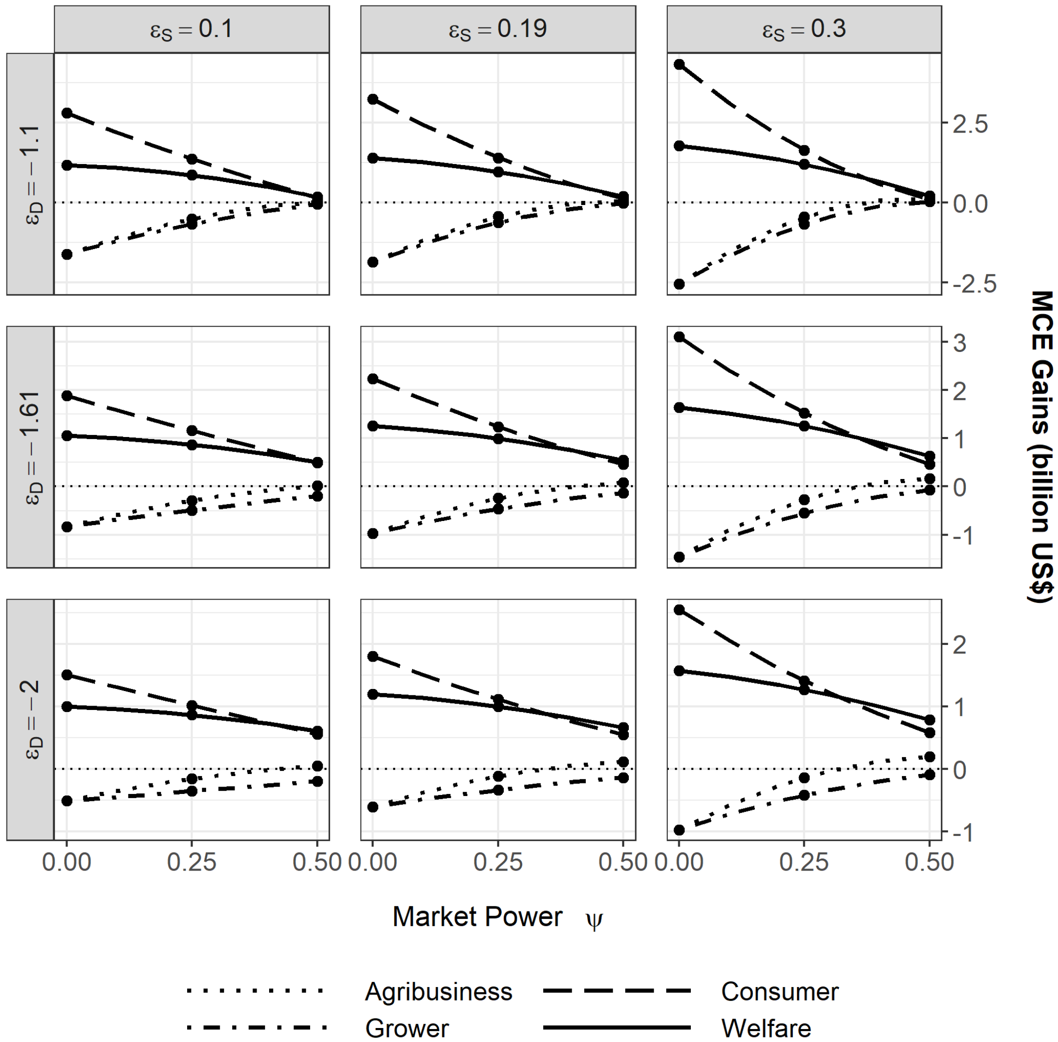

Figure 5: Mean model outcomes (sum of discounted gains from MCE in 2020-2040) for various parametric combinations in simulations without the alternate bearing component. Each point is the average of 100 simulation outcomes. The various panels show the results for combinations of elasticity of supply (ε_S) and demand (ε_D). The horizontal axis represent the measure of market power (ψ), where zero is a competitive market. The curves are interpolated by a quadratic equation. Our main specification results are in the center panel. Note the scale changes of the vertical axis between panel rows.

C Model Details

Getting an expression for z^*

The representative county grower maximizes profit. γ_i represent capacity growth for the grower by the simulated year, 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:

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

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

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

Note that, later on, 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.

Details For Numerical Solution

We model the entire supply with 30 growers: five for each of the six counties. Each of these five represents a county chill quintile realization. The total market supply is the sum of these supplies. When simulating without MCE, the linear supply functions can be added directly, and only a market clearing equation needs to be solved.

Simulating the model with MCE is more complicated, as the implicit supply functions of our 30 representative growers are not additive. We have 30 equations such as equation (11) to determine the equilibrium quantity of MCE input x^*_{cd} for each county-quintile. These values are then used to calculate the county-quintile supplied quantities, such as in equation (13). The sum of this quantity is equated with demand to clear for a price. This system of 31 equations is numerically solved for one price and 30 levels of x^*_{cd}, which translate to supplied quantities. A solution for this system is the market equilibrium. The consumer surplus is calculated, as before, using the area under the linear supply curve. For grower profits, we need the area under a supply curve, or sum of areas under the 30 supply curves. However, these supply functions are implicit, and we cannot directly integrate them. We approximate this integral by solving for each grower's output for a range of 20 equally distanced prices from zero to the equilibrium price. We then create rectangles using these points, and sum them to approximate for the grower profits.

The model is run for each year in 2020-2040, and net present value is calculated. This procedure produces one simulation result for each set of pre-defined parameters. However, the yearly predictions we use are not intended to forecast the weather in specific years (e.g. predicting the chill in 2035), but rather present the climate trend and variation around it. Our climate predictions are therefore a stochastic input, making the otherwise deterministic market model and simulations stochastic as well. We are interested in the expected gains from MCE, given the predicted climate. To do this on a "moving target" (as climate has a trend), we regress the future chill predictions on a third degree polynomial of years, plus a dummy variable for counties. The residuals from this regression should be free of the climate trend, and are plausibly *i.i.d.* We use 100 bootstraps of these residuals, adding them to the predicted climate trend, to create weather draws for 2020-2040.

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