ABSTRACT

HAN, JUNG HOON. Adapting to a Changing Environment: Three Essays on Food, Nutrition, and Controlled Environment Agriculture (Under the direction of Drs. Xiaoyong Zheng and Daniel Tregeagle).

This dissertation discusses the effects of changing environments. Chapter 1 analyzes the effects of climate change on nutrient demand. We construct a unique dataset of weather, food purchases, and nutrient information at the household and week level. We then estimate the effects of weekly change in temperature and precipitation on nutrient demand using a fixed effects estimator. We find that rising temperature has a negative effect on consumers' demand for calories, sugar, saturated fat, and sodium, while precipitation has a positive effect on the demand for calories, saturated fat, and sodium. The estimated effects are heterogeneous across households with larger effects for those with a smaller share of females, relatively young, a higher income, a larger size and a higher demand for calories. Using the estimated effects, we calculate how climate change (temperature and precipitation changes over long horizons) affects nutrient demand. Our results show that climate change has the unintended benefit of leading to an improvement in consumers' diet quality. Specifically, as temperature and precipitation increase over long horizons, household weekly nutrient demand per person decreases up to 118.36kcal (0.81%) for calories, 3.66g (0.39%) for sugar, 2.01g (0.93%) for saturated fats, and 0.17g (0.82%) for sodium.

Chapter 2 examines the economics of adopting Controlled Environment technology in the US strawberry nursery industry. Currently, the strawberry nursery industry in California is facing challenges such as risks of plant diseases and high costs. The use of Controlled Environment (CE) technology has been receiving attention as a potential breakthrough to overcome the difficulties. However, applying CE to the California strawberry nursery industry is still on the

early stages compared to other crops or European cases. Although there have been efforts in the horticulture science field to examine the effects of CE on the plant production, economic research on the strawberry nursery industry is very limited. We examine potential opportunities and challenges of CE in the strawberry nursery industry in California. We adopt a case-study approach to collect and organize limited information about the industry.

Chapter 3 evaluates the welfare effects of Controlled Environment propagation in the strawberry nursery industry. We construct a structural model to describe the strawberry nursery industry in California using EDM framework. A Multistage production system is considered to explain the market. We then simulate changes in the surplus of producers of field and CE nursery plants, consumer surplus of strawberry consumers as well as total surplus using the quasi-random sampling method with the Halton sequence. We perform sensitivity analysis to compensate for the weaknesses of EDM due to unknown parameter values and scarcity of data on the industry and technology. Our results reveal that field plants producer surplus decreases whereas CE plants producer surplus, consumer surplus, and the total surplus increase when there is a 10% price reduction in CE plants. Magnitudes of the surplus depend on market penetration rates. CE plants producer surplus and the total surplus will be increased with larger use of CE technology. Based on our calculations, total surplus will increase by 40.35 million dollars if quantity produced of nursery plants using CE technology accounts for half of total nursery plants and price of CE drops by 10%. This conclusion can serve as an important basis for the need to introduce CE technology in the strawberry nursery industry.

Adapting to a Changing Environment: Three Essays on Food, Nutrition,
and Controlled Environment Agriculture

by
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DEDICATION

I dedicate my dissertation work to my family for their unconditional support.

BIOGRAPHY

Jung Hoon Han was born in Seoul, South Korea. He received his Bachelor and Master of Arts degree in Economics from Korea University, Seoul. After graduation, he participated in research projects in the agricultural economics field at Korea Rural Economic Institute. After that, he began his Ph.D. in Economics at North Carolina State University.

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CHAPTER 1

The Effects of Climate Change on Nutrient Demand

1.1. Introduction

Over the past several decades, overweight and obesity have become one of the major public health issues worldwide. According to Cawley et al. (2021), adult obesity in the United States was responsible for $260.6 billion in medical expenditures in 2016, while Okunogbe et al. (2021) report that obesity costs as a percentage of GDP in 2019 were 1.74% in Australia, 2.11% in Brazil, 0.80% in India, 2.05% in Mexico, 2.42% in Saudi Arabia, 1.58% in South Africa, 2.09% in Spain, and 1.27% in Thailand, respectively. What kind of food and nutrients people eat plays an important role in the overweight and obesity epidemic. Consumption of unhealthy food, which are high in added sugars, calories, and saturated fats, are found to be associated with developing overweight and obesity conditions (Askari et al. (2020)).

People's demand for and consumption of nutrients are affected by various factors. Weather is one such factor. Typically, in the developing country context, research in the literature (e.g. Yu and Babcock (2010); Zhang, Zhang, and Chen (2017); Kuwayama et al. (2019); Darwin (2004); Hasegawa et al. (2014)) have studied the effects of weather and climate change on crop production and food price, which in turn impact food and nutrients availability and affordability and the risk of hunger. However, there may be another channel through which climate change affects consumers' demand for nutrients. When weather and climate change, consumers may choose to eat different kinds of food items even if there is no change in food availability and affordability. For example, consumers eat more ice cream during summer months and drink more hot chocolate during cold weather. Unlike the climate change and food availability and affordability channel, this pathway through which climate change affects nutrients demand can be at work in both developed and developing countries. Surprisingly, to the best of our knowledge, no study has investigated this issue.

To fill this gap in the literature, in this paper, we measure the impact of climate change on consumer's nutrients demand, following the approach of Deschênes and Greenstone (2007). Specifically, we first estimate the impact of short-run variations in temperature and precipitation on household nutrients demand and then multiply them by the predicted change in climate to infer the impact of climate change on nutrients demand. To achieve our goal, we compile a novel panel dataset on household food purchases, the nutrients these food items contain and weather information for where the households reside at the household and week level. We then estimate a panel data fixed effects regression model for each of the four nutrients, calories, sugar, saturated fat and sodium, to measure the impact of week-to-week variation in temperature and precipitation on nutrients demand. The regression includes multiple sets of fixed effects, which control for a large set of potential confounders.

Our regression estimation results show that there is an inverse relation between temperature and consumers' nutrient demand. Specifically, consumers' weekly nutrient demand for calories, sugar, saturated fat, and sodium decrease by 36.47kcal, 1.11g, 0.62g, and 0.05g, respectively, as the average temperature rises by 1℃. Also, our results reveal that nutrient demand for calories, saturated fat, and sodium is increased as precipitation increases. Weekly household nutrient demand per person for calories, saturated fat, and sodium are increased by 5.98kcal, 0.10g, and 0.02g, respectively, when there is a 1mm increase in the average precipitation. We checked the robustness of the estimation results through different ways. We confirmed that the results of robustness check using different temperature variables (Bin variables, Degree days) are consistent with the baseline results. Also, we conducted heterogeneity analysis to examine how the weather effects on nutrient demand differ by different characteristics of households. The results reveal that the effects are stronger for households with smaller share of females, younger household members, a higher income, a larger size, and a higher demand for calories. Using the marginal effects of temperature and precipitation on each nutrient demand, we calculate the predicted change in nutrient demand due to climate change in the future. The results show that there will be a reduction in nutrient demand as temperature and precipitation increase in the future. More specifically, household's nutrient demand per person for calories is predicted to decrease by up to 118.36kcal (0.81% of the sample mean), sugar by 3.66g (0.39%), saturated fat by 2.01g (0.93%), and sodium by 0.17g (0.82%) when temperature and precipitation increase over long horizons.

First and foremost, our paper contributes to the literature on the effects of weather on household food purchases and nutrients consumption. Bhattacharya et al. (2003) investigated whether poor American families had lower food expenditures and worse nutritional intake during cold-weather periods when they needed to pay more for heating costs, using data from the Consumer Expenditure Survey and National Health and Nutrition Examination Survey. They found that the winter resource shift induced statistically significant reductions in caloric intake among both children and adults in poor families, but no statically significant differences were found for the prevalence rates of vitamin deficiencies and anemia. Hou (2010) used data from the Mexican PROGRESA program to evaluate the impact of drought on total calorie availability and found drought reduced total food expenditures but increased the total availability of calories. Carpena (2019) investigated the impacts of droughts on food expenditure and macronutrient consumption among rural Indian households and found for a median dry shock, households spent

1% less per capita per month on food and consumed up to 1.4% fewer calories, protein, and fat. Our study is different from these studies in four important aspects. First, these studies focused on poor households (often in a developing country context) and the impacts of weather on undernutrition, while we study the impacts of weather on households in the US and the problem of overnutrition. Second, while previous studies examined the effects of short-run weather changes, we use our estimates to further calculate the effects of long-term change in climate on nutrient demand. Third, while these studies in the literature examined the effects of weather on consumption of calories and vitamins only, we also study the effects of weather and climate change on other nutrients such as sugar, saturated fat and sodium. Fourth, we also examine how the effects of weather and climate change on nutrients consumption vary across households with different demographic characteristics such as gender, age, income and household size, while previous studies either study all households in their samples as a whole or only examined differences along the income dimension. These differences make our article a more comprehensive study of the effects of weather and climate change on household nutrient demand.

More broadly, our study also contributes to the large literature on the relationships between food consumption and climate change. One strand of this literature examines how different diets and consumption of different foods affect climate change and greenhouse emissions in particular (e.g. Berners-Lee et al. (2012); Heerwagen et al. (2014); Auestad and Fulgoni III (2015); Hyland et al. (2017)). Our study differs from this strand of literature by studying the other direction of the causality, that is, how climate change affects nutrient demand. Another strand of this literature investigates the effects of weather and climate change on crop production, food price and hence on food consumption and risk of hunger (e.g. Yu and Babcock

(2010); Zhang, Zhang, and Chen (2017); Kuwayama et al. (2019); Darwin (2004); Hasegawa et al. (2014)). Our study advances this strand of literature by studying a new channel through which climate change can affect nutrient demand.

The rest of the paper is organized as follows. In the next section, we describe three different datasets used in the construction of our sample. Section 3 provides the empirical strategy for the estimation of the weather effects on nutrition Demand. Estimation results across alternative model specifications and their interpretation are presented in Section 4. Section 5 describes how the weather effects on nutrient demand differ by household's characteristics. The impacts of climate change on nutrient demand are demonstrated in Section 6. Concluding remarks are discussed in the final section.

1.2. Data

To investigate the effects of weather on nutrients consumption, we assembled a unique dataset on household food purchases, nutrition information for the food products purchased, and weather information from the locations where the households reside. These data come from various sources and the fact that a novel data set was created by merging data from these sources is a contribution of this study to existing studies. Below are the details.

1.2.1. Household Food Purchase Data

The household food purchase data comes from the Nielsen Academic Dataset, provided by the Kilts Center for Marketing at University of Chicago. In particular, household (Home Measurement System or HMS) scanner data for the period of 2004-2019 is used for the analysis. At any point in time, approximately 60,000 American households report to Nielsen detailed information on their consumer-packaged goods purchases, including purchase quantity, date and locality. Their purchases are recorded at home using hand-held scanning devices or mobile apps. The HMS data provides us information on which food items and how many units of these food items households purchase in each week.

In this dataset, a product corresponds to a unique Universal Product Code (UPC). The UPCs in the dataset are grouped into 12 categories.[1] We excluded UPCs in four non-food categories.[2] We also excluded some UPCs in the food categories but are not related to consumers' nutrients intake such as pet food, ice, vitamins, etc. In the end, the dataset includes a total of 362,994 UPCs. Of these, 244,640 (67.40%) were Dry Grocery, 46,111 (12.70%) were Frozen Foods, 37,309 (10.28%) were Dairy, 12,461 (3.43%) were Packaged Meat, 11,483 (3.16%) were Deli, 10,966 (3.02%) were Fresh Produce, and 24 (0.01%) were Magnet.

There are a total of 194,470 households in the dataset. The states with the greatest number of households are California (16,589 households, 8.53%), Texas (15,131 households, 7.78%), Florida (13,133 households, 6.75%), New York (9,777 households, 5.03%) and Ohio (9,110 households, 4.68%). Demographic information reported in the dataset includes household income, household size, age, employment status and the education level of the household head, as well as geographic information such as in which 5-digit zip code area and hence in which county a household resides.

[1] These are 0 (Health & Beauty Care), 1 (Dry Grocery), 2 (Frozen Foods), 3 (Dairy), 4 (Deli), 5 (Packaged Meat), 6 (Fresh Produce), 7 (Non-food Grocery), 8 (Alcoholic Beverages), 9 (General Merchandise), 99 (Magnet Data), and 9999 (Unclassified). The Magnet category includes products that do not use standard UPCs such as fruits, vegetables, meats, and in-store baked-goods.

[2] These are 0 (Health & Beauty Care), 7 (Non-food Grocery), 8 (Alcoholic Beverages), 9 (General Merchandise), and 9999 (Unclassified).

1.2.2. Nutrition Data

The nutrition data used in this study comes from Cengiz and Rojas (2024), who merged the Nielsen scanner data with the Syndigo nutrition data.[3] The merging process of the two datasets was a sophisticated one. Only 18% of the total UPCs were direct matches. However, the matching rate was improved significantly through a reliable proxy method based on common product attributes between matched and unmatched UPCs.[4] The final product of their merging process is a UPC level data containing nutrition information such as number of calories and amounts of various nutrients for each UPC in two years, 2007 and 2015.

For all the years in our sample, we merged our household scanner data with the nutrition data from Cengiz and Rojas (2024) based on the UPC information. For a particular UPC, if its nutrition information exists in both the nutrition data of 2007 and 2015, the 2015 information was used. If the UPC only exists in either the 2007 or 2015 nutrition data, we used the nutritional data for the year in which they exist. On average, nutritional information was matched to 85.2% of the UPCs in the household scanner data during the sample years. We then computed the total amounts of calories, sugar, saturated fat, and sodium for the food items each household purchased in each week. A number of studies including Neuhouser (2019) and Dötsch-Klerk et al. (2022) have warned that excess intake of sugar, saturated fat and sodium may lead to chronic diseases such as heart diseases, high blood pressure, type 2 diabetes, and obesity. The 2020-2025 Dietary Guidelines provided by the U.S. Department of Health and Human Services recommend an eating pattern low in added sugar, saturated fats, and sodium and include recommended upper tolerable intake amounts for these nutrients.

[3] Syndigo, formerly Gladson, is one of the leading providers of nutrition database for groceries.

[4] More details can be found in their study.

1.2.3. Weather Data

Our weather data comes from Schlenker and Roberts (2009).[5] This dataset was constructed based on the PRISM weather dataset[6] and gives daily minimum and maximum temperature as well as total precipitation on a 2.5×2.5-mile grid for the contiguous United States from 1900-2019.

Using this dataset, we created weather variables for each county in each week. More specifically, we first calculated the mean temperature for each grid on each day by averaging the minimum and maximum temperatures reported in the dataset. Then, average temperature and precipitation for a given county in a given week was computed by averaging the mean temperatures and precipitation across all grids in the county and all days in the week. We then merged the weather data with our household scanner data based on the household location (county) information.

1.2.4. Summary Statistics

After merging the three datasets discussed above, we have a total of 35,215,971 observations. The unit of observation is one household in one week. The final dataset comes from 362,994 UPCs, 194,470 households and 2,982 counties exist in the merged data.

The average temperature and precipitation during the sample period across all counties are 13.89℃ and 2.88mm, respectively. Over the sample period, the temperature increased by 0.01% per week, while the precipitation decreased by 0.02% per week. Based on the weekly average temperature across all counties, the coldest week was the week of 2017-12-31 to 2018-01-06, and the average temperature during this week was -4.69 ℃. The hottest week was the week of 2011-07-17 to 2011-07-23, with the average temperature of 26.8℃. The week with the

[5] https://www.columbia.edu/~ws2162/links.html
[6] https://prism.oregonstate.edu/.

highest weekly average precipitation across all counties was 2011-09-04 to 2011-09-10, which recorded an average precipitation of 6.50mm. The weekly average precipitation during the week of 2006-12-03 to 2006-12-09 was 0.48mm and it was the lowest during the sample period. The coldest county in the sample is Hinsdale, Colorado. The weekly average temperature across all weeks during the sample period in Hinsdale was 0.49℃. The hottest county is Miami-Dade county, Florida. Its weekly average temperature across all weeks in the sample period was 24.53℃. Tillamook county, Oregon is the county with the highest average weekly precipitation across all weeks in the sample period, whereas Imperial county, California recorded the lowest average weekly precipitation. The average weekly precipitation in both counties was 8.57mm and 0.19mm, respectively.

For nutrition variables, different households have different numbers of household members as well as different age compositions of these members. As a result, the amounts of nutrients purchased by different households in a week can be quite different. To make the nutrition variables comparable across different households, we follow Dubois, Griffith, and Nevo (2014) and compute the amounts of nutrients each household purchases on an adult equivalent scale (AES) during each week.[7] Weekly average of calories demand per AES across all households during the sample period is 14,690.4kcal. Weekly average demand of sugar, saturated fat and sodium per AES are 930.6g, 217.0g, and 20.5g, respectively. Figure 1.1 to Figure 1.4 present the time series plots for each nutrient demand. Demand for calories, sugar, and sodium decreased during the sample periods. The average growth rates of calories, sugar, and sodium were −0.018%, −0.024%, and −0.036% per week, respectively. But the demand for

[7] Please see the Appendix for the definition of AES and details of the computation procedure.

saturated fat slightly increased (at the rate of 0.009% per week). Summary statistics of the weather and nutrition variables are presented in Table 1.1.

1.3. Empirical Strategy

We estimate the weather effects on consumer weekly nutrients demand using the panel data fixed effects approach. In particular, we estimate the following equation,

$$y_{nit} = \beta_0 + \beta_1 Temp_{c(i)t} + \beta_2 {Temp_{c(i)t}}^2 + \beta_3 Precp_{c(i)t} + \beta_4 {Precp_{c(i)t}}^2 + \theta_{cy} + \theta_i + \theta_t + \epsilon_{nit} \quad (1)$$

where y_{nit} is the demand of nutrient n by household i in week t for a particular nutrient (calories, sugar, saturated fat, and sodium) divided by AES. $Temp_{c(i)t}$ is the average temperature in county c of household i's residency in week t. $Precp_{c(i)t}$ is the average daily precipitation in county c of household i's residency in week t. We follow the convention in literature (e.g. Deschênes and Greenstone (2007)) and model the climatic variables with linear and quadratic terms. β_1, β_2, β_3 and β_4 are the parameters of interest.

We include three sets of fixed effects in the regression to control for a large number of potential confounders. θ_{cy} captures the unobserved county-level year-specific factors that can affect consumer demand for nutrients such as change in income, opening and closing of grocery stores, local health promotion campaigns, etc. θ_i is the household fixed effect, controlling for the time-invariant unobserved characteristics of an individual household such as race, country of origin, preference for certain kinds of food, etc. θ_t is the week fixed effects, capturing unobserved characteristics that vary over time but not across different households in a given week. These factors include changes in overall food prices, national and international events related to food consumption, other macro shocks, etc.

Identification of the parameters of interest β_1, β_2, β_3 and β_4 comes from the following facts. First, weather is a natural event and hence weather variables are exogenous by construction. Second, temperature and precipitation vary across different weeks in the same location and across different locations during the same week. Indeed, Figure 1.5 and Figure 1.6 show the distributions of the residuals from the regressions of temperature and precipitation on all three sets of fixed effects. It can be clearly seen that there are still significant variations left in the weather variables after the control variables are partialed out.

1.4. Estimation Results

1.4.1. Main Results

Estimation results for (1) are reported in Table 1.2. Since we use a quadratic specification for the weather variables, direct interpretation of the coefficients for these variables is difficult. Therefore, we compute the marginal effects of temperature and precipitation and report them in the last two rows of Table 1.2. These marginal effects are functions of the weather variables and we evaluate them at the sample means of the weather variables. Results show that household's demand per person for calories, sugar, saturated fat, and sodium will decrease by 36.47kcal, 1.11g, 0.62g, and 0.05g per week, respectively when the average temperature increases by 1℃. These estimates are statistically significant. These results are consistent with the well-known fact that more energy expenditure is required when the weather is cold. Many studies in the physiology literature such as Langeveld et al. (2016), Chen et al. (2013), Wijers, Saris, and Lichtenbelt (2010), and Wijers, Saris, and van Marken Lichtenbelt (2007) find that exposure to cold increases energy expenditure and hence it can stimulate appetite and cause people to eat more. At the same time, we note that the magnitudes of the estimates are small. Compared with the sample means, these correspond to a reduction of 0.25% in calories, 0.12% in sugar, 0.29% in saturated fat, and 0.25% in sodium per 1℃ increase in the average temperature. This might be due to the fact that our data comes from the US. Air conditioning and heating are widely available in the US and hence consumers in the US are much less exposed to huge variations in temperature in their living environments than consumers in many other countries. Therefore, we could potentially see a larger impact if data from other countries were used.

Turning to precipitation, results show that precipitation has a positive and statistically significant effect on demand for calories, saturated fat and sodium. Its effect on sugar, however, is negative but not statistically significant. These results are consistent with the interpretation that consumers spend more time at home when it rains outside. As a result, they eat more at home. Since we use grocery purchase data for our analysis, we find a positive effect of precipitation on purchase of nutrients. In terms of the magnitudes, for all nutrients, the effects are very small, about ten times smaller than the effects from average temperature. When the average daily precipitation increases by 1mm, household's demand per person for calories, sugar, saturated fat, and sodium will only change by 5.98kcal (0.04%), -0.18g (-0.02%), 0.10g (0.05%), and 0.02g (0.10%) per week, respectively.

1.4.2. Robustness Checks

1.4.2.1. Weather Variable Bins

We next perform a robustness check to assess the stability of our main results above. First, we replace the quadratic specification for the temperature variable in (1) above with a set of weather variable bins. This is a more flexible way to capture the nonlinear effects of temperature on nutrient demand. More specifically, we create a total of fourteen bins: $(-\infty, 0$ ℃] (0℃, 3 ℃], (3℃, 6 ℃], (6℃, 9 ℃], (9℃, 12℃], (12℃, 15℃], (15℃, 18℃], (18℃, 21℃], (21℃, 24℃], (24℃, 27℃], (27℃, 30℃], (30℃, 33℃], (33℃, 36℃], and (36℃, ∞). We then count the numbers of days when the average temperature falls into these fourteen bins for each county and each week. For example, if the 7 daily average temperatures are 13℃, 15℃, 14℃, 15℃, 19℃, 12℃ and 14℃ in a week, then the numbers of days in the fifth, sixth and seventh bins are 1, 5, and 1, respectively.[8] The first bin is omitted in the regression to avoid the multicollinearity problem.

The estimation results are collected in Table 1.3. Since the first bin is omitted, the interpretation of estimated coefficients for other bins is how the nutrient demand is affected when the number of days in which the average daily temperature falls in a bin increases by one day compared to the number of days in which the average daily temperature is below 0 ℃. As we can see, the coefficient estimates for all the bins are negative. Also, with a few exceptions, the absolute values of the coefficients for the bins in the relatively low temperature range are small, whereas those for the bins in the relatively high temperature range are large. For example, demand for calories will decrease by 184.71kcal if there is one additional day in a week when the average temperature is above 36℃ compared to the number of days that the average temperature is below or equal to 0℃, while calories demand will only be reduced by 23.78kcal if there is one additional day in a week when the average temperature is in the range of 0-3℃ compared to the number of days that the average temperature is below or equal to 0℃. These results imply that consumers purchase fewer nutrients when the temperature increases. This is consistent with our main results found above.

[8] As described in subsection (1.2.3.), the raw temperature data of Schlenker and Roberts (2009) are daily maximum and minimum temperatures for each grid. After obtaining the daily average temperature for each grid by taking the average of daily maximum and minimum temperatures for each grid, we further averaged this average temperature across all grids in a county to obtain the daily average temperature at the county level.

On the other hand, we find average daily precipitation has a statistically significant and positive effect on the purchase of calories, saturated fat and sodium and its effect on sugar is not statistically significant. In terms of magnitude, demand for calories, saturated fat, and sodium will increase by 5.27kcal, 0.08g, and 0.02g respectively, when average precipitation increases by 1mm. Again, these results are consistent with our main results above.

1.4.2.2. Degree Days

Another popular measure of how hot or how cold a place is is the degree days. For example, in the literature on the impacts of climate change on agricultural yield (e.g. Ritchie and Nesmith (1991); Schlenker and Roberts (2009); Jessoe, Manning, and Taylor (2018); Wang, Rejesus, and Aglasan (2021)), degree days are computed to measure how much a crop is exposed to specific ranges of the temperature during the growing season. Therefore, in the second robustness check, we use degree days variables as alternative measures for the temperature variable. More specifically, we create four degree days variables, ${DD^{EC}}_{c(i)d}(h_d)$, ${DD^{L}}_{c(i)d}(h_d)$, ${DD^{M}}_{c(i)d}(h_d)$, and ${DD^{H}}_{c(i)d}(h_d)$. ${DD^{EC}}_{c(i)d}(h_d)$ represents the degree days for the extreme cold temperature range and is defined as ${DD^{EC}}_{c(i)d}(h_d) = 0 - h_d$ if $h_d < 0$ and 0 otherwise. ${DD^{L}}_{c(i)d}(h_d)$ is the degree days for the low temperature range, which is defined as ${DD^{L}}_{c(i)d}(h_d) = 18.33 - h_d$ if $0 \leq h_d < 18.33$ and 0 otherwise. The threshold of 18.33℃ (approximately 65°F) comes from the concept of heating degree days. According to the National Weather Service, the concept of heating and cooling degree days is commonly used to track the energy use because heating is often turned on when the temperature is below 65°F. ${DD^{M}}_{c(i)d}(h_d)$ is the degree days for the relatively high temperature range, which is defined as ${DD^{M}}_{c(i)d}(h_d) = h_d - 23.89$ if $23.89 \leq h_d < 30$ and 0 otherwise. The threshold of 23.89℃ (approximately 75°F) comes from the fact that Americans typically turn on their air conditioning when the temperature is higher than 23.89℃. Finally, $DD^{H}{}_{c(i)d}(h_d)$ is the degree days for the very high temperature range, which is defined as $DD^{H}{}_{c(i)d}(h_d) = h_d - 30$ if $h_d \geq 30$ and 0 otherwise.

We then compute the degree days variables for the week by summing over the degree days variables over all the seven days in a week. For example, the extremely cold degree days in county c where household i resides and in week t is defined as $DD^{EC}{}_{c(i)t} = \sum_{d=1}^{7} DD_{c(i)d}(h_d)$. Other degree days variables at the week level are similarly defined. We then replace the temperature variables in the baseline specification (1) using the four degree days variables: $DD_{c(i)t}$, $DD^{EC}{}_{c(i)t}$, $DD^{L}{}_{c(i)t}$, $DD^{M}{}_{c(i)t}$, and $DD^{H}{}_{c(i)t}$.[9]

Estimation results are reported in Table 1.4. For all nutrients, the estimated coefficients for $DD^{EC}{}_{c(i)d}(h_d)$ and $DD^{L}{}_{c(i)d}(h_d)$ are positive and statistically significant. These results are consistent with our baseline results above that nutrient demand increases when the temperature is lower. For example, demand for calories, sugar, saturated fat, and sodium will increase by 6.82kcal, 0.16g, 0.11g, and 0.01g when the extreme cold degree days increases by one unit. Also, similar to our baseline results above, precipitation has a positive and statistically significant effect on the demand for calories and sodium, but it has a negative and statistically significant effect on the demand for sugar, which is different from our baseline results above. In summary, results from this robustness check are largely in line with our baseline results above.

[9] Unlike the regression with weather variable bins above, here there is no multicollinearity problem even when we include all four degree days variables in the regression.

1.5. Heterogeneity Analysis

In this section, we examine how the weather effects on nutrient demand differ by households with different characteristics. First, we group households into three categories based on the share of females in a household. Households with a low percentage of females are the ones whose share of females is less than 50%, which is the 25th percentile of the share of females variable. Households with a medium percentage of females are the ones whose share of females is higher than or equal to 50% but lower than 66.7%, the latter of which is the 75th percentile of the share of females variable. Households with a high percentage of females are the ones whose share of females is higher than or equal to 66.7%. Group dummy variables are then created and their interaction terms with the weather variables are added to the regression. Table 1.5 reports the results. In particular, the last six rows of the table report the marginal effects of temperature and precipitation for households in the three groups.

Results show that the negative temperature effects on nutrient demand are stronger for households with a low percentage of female household members. And for households with a high percentage of female household members, the effects are even positive, even though the magnitudes of the effects remain to be small. As for precipitation, we find that the baseline result that precipitation has a positive effect on nutrient demand is mainly driven by households with a high percentage of female household members, while its effects on households with a low or medium percentage of female household members are largely not statistically significant.

Next, we examine the weather effects on nutrient demand by the age of household members. Again, we define three groups. Young households are those whose average age of household members is below 38, which is the 25th percentile of the average age of household members variable. Middle-aged households are those whose average age of household members is between 38 and 65, the latter of which is the 75th percentile of the average age of household members variable. Lastly, elderly households are those whose average age of household members is higher than or equal to 65. Results from this heterogeneity analysis are presented in Table 1.6. We find that the negative temperature effects on nutrient demand are stronger for young and middle-aged households while the effects on elderly households are small and largely statistically insignificant. As for precipitation, we find that the baseline result that precipitation has a positive effect on nutrient demand is mainly driven by middle-aged households, while its effects on young and elderly households are small or not statistically significant.

We also examined the weather effects on nutrient demand by income strata. Low-income households are those with annual income lower than $35,000, which is 25th percentile of the household income variable. Medium-income households are those whose income is higher than $35,000 but lower than $100,000, the latter of which is the 75th percentile of the household income variable. High-income households are those with an income higher than $100,000. Results are presented in Table 1.7. We find that the negative effects of temperature on nutrient demand are the strongest among high-income households, followed by middle-income households and the effects are the smallest for low-income households. As for precipitation, we find that the baseline result that precipitation has a positive effect on nutrient demand is mainly driven by middle-income households, while its effects on other households are largely statistically insignificant.

Next, we examine the heterogeneity of the weather effects on nutrient demand by household size. We define small households as those with only one-person, medium households as those with two or three person and big households as those with four or more people. Results from this analysis are collected in Table 1.8. We find that unlike the baseline result above, temperature has a positive effect on nutrient demand for small households. Its effects on medium and big households remain to be negative with the effects on big households larger than those on medium households. The effects of precipitation on nutrient demand are also heterogeneous across households with different sizes. Its effect on small households are positive while its effect on big households is negative.

Finally, we conduct quantile regressions to examine how the weather effects on nutrient demand vary by households with different levels of demand for calories. Table 1.9 presents the marginal effects of temperature and precipitation on demand for calories at different quantiles of calories demand. The results show that for both temperature and precipitation, the effects are larger for households with higher calories demand.

1.6. The Impacts of Climate Change on Nutrient Demand

Based on our analysis of how changes in temperature and precipitation affect nutrient demand, we can calculate how nutrient demand will be affected by long-term climate change. There have been many attempts to predict climate change using various models. Almazroui et al. (2021) is one of the recent studies that predicted climate change. They simulated projected changes in temperature and precipitation over the United States, Central America and the Caribbean using the Coupled Model Intercomparison Project Phase 6 dataset. Specifically, they computed the predicted changes in temperature and precipitation for three future time periods (2021-2040, 2041-2060, and 2080-2099) relative to the reference period (1995-2014). The simulation was conducted using 31 models from previous studies and under the assumptions of three Shared Socioeconomic Pathways (SSPs; SSP1-2.6, SSP2-4.5, and SSP5-8.5) scenarios. We used their estimates to compute the effects of climate change on nutrient demand under several assumptions. First, because our sample is limited to the United States, we applied the average of the estimates of Western North America (WNA), Central North America (CNA), and Eastern North America (ENA) to match the consistency of regional scope with our sample. Second, for consistency in the time period of our sample, we set the reference period as the last week of 2019. Third, for ease of analysis, near future, mid future, and far future were defined as 2030, 2050, and 2090, respectively.

Calculating the average by regions and scenarios of the estimates calculated by Almazroui et al. (2021), the average temperature is expected to rise by 1.20℃ by 2030, by 2.01℃ by 2050, and by 3.26℃ by 2090. Also, average precipitation is predicted to increase by 2.34% by 2030, by 3.37% by 2050, and by 5.56% by 2090. Since the average daily precipitation of the last week of 2019 in our sample is 2.11mm, the average precipitation is expected to increase to 2.17mm by 2030, to 2.19mm by 2050, and to 2.23mm by 2090. Based on the marginal effects of temperature in our analysis, we can predict the change in nutrient demand due to temperature changes in the future. Table 1.10 represents how climate change will affect nutrient demand in the future. If temperature is increased by 1.20℃ and precipitation is increased by 2.34% by 2030, weekly household demand per person for calories, sugar, saturated fat, and sodium are decreased by 43.43kcal, 1.34g, 0.74g, and 0.06g, respectively. Those correspond to reduction of 0.30%, 0.14%, 0.34%, and 0.30% with the sample mean of each nutrient demand. If temperature rises 2.01℃ and precipitation is increased by 3.37% by 2050, weekly household demand per person for calories, sugar, saturated fat, and sodium are deceased by 72.81kcal, 2.25g, 1.24g, and 0.10g, respectively. That is, 0.50%, 0.24%, 0.57%, and 0.50% of each nutrients are decreased. If temperature is increased by 3.26℃ and precipitation is increased by 5.56% by 2090, demand for calories, sugar, saturated fat, and sodium are decreased by

118.36kcal, 3.66g, 2.01g, and 0.17g, respectively. These are reductions of 0.81%, 0.39%, 0.93%, and 0.82% of each nutrients.

1.7. Conclusion

We revealed the relation between climate change and consumers' nutrient demand by using a unique dataset of UPC-week level household's food purchases data and nutrient information of food products, and county-week level weather data. We found inverse effects of temperature on nutrient demand. Weekly household's nutrient demand per person for calories, sugar, saturated fat, and sodium decrease by 36.47kcal (0.25%), 1.11g (0.12%), 0.62g (0.29%), and 0.05g (0.25%), respectively, as the average temperature rises by 1℃. Precipitation has positive effects on nutrient demand. When precipitation is increased by 1mm, nutrient demand for calories, saturated fat, and sodium are increased by 5.98kcal (0.04%), 0.10g (0.05%), and 0.02g (0.10%), respectively. Robustness of the estimation result is checked through different ways. Heterogeneity analysis results shows that inverse temperature effects on nutrient demand are stronger for households with less females, younger age, higher income, larger household size, and higher calories demand. Using the marginal effects of temperature and precipitation on each nutrient demand, we predicted changes in nutrient demand due to climate change in the future. Due to increases in temperature and precipitation in the far future, household's weekly demand per person for calories, sugar, saturated fat, and sodium is predicted to decrease by up to 118.36kcal, 3.66g, 2.01g, and 0.17g, respectively.

Our estimation results can convey several implications for policy makers. For instance, our estimation result reveals vulnerable consumers to weather changes. Based on the heterogeneity analysis result, a household with less females, younger household member, a higher income, a larger household size is more vulnerable to the temperature changes. Also, temperature changes have a greater impact on a household with higher calories demand. In particular, households in the top 25% of calorie demand are highly affected by temperature changes. This means that the more obese people are more likely to change their nutrient demand due to weather. This fact can be an important clue for policy makers in the future when setting up countermeasures for changes in nutrition demand due to climate change. Also, our results may deliver a message that weather is a significant factor when consumers purchase food items to policy makers. That is, policy makers may need to consider weather when they design nutrition assistance policy. Currently, USDA Food and Nutrition Service has implemented Supplement Nutrition Assistance Program (SNAP) to provide food benefits to low-income household. In many states including North Carolina, the benefits are issued on an Electronic Benefit Transfer (EBT) card monthly based on the number of household members. Based on our results, it might be better to assign different amount of benefits based on temperature. For instance, it may be more effective to issue relatively large amount of benefits during cold periods from November to January whereas to give relatively small amount of benefits during hot periods from June to August. Our analysis also can suggest a marketing strategy for food companies. Food producers can use a strategy to differentiate the nutrition content of products based on temperature. For example, food companies can produce and sell relatively low-calorie products in summer and high-calorie products in winter to meet the consumer’s different demand according to the temperature.

Our study has limitations. A household’s nutrient demand is calculated based on the amount of food purchased from the shopping trips. Nutrients obtained from food consumption other than grocery purchases (e.g. delivery and eating out) were not considered in this model. It is also important to bear in mind that nutrient demand does not equal to nutrient consumption as households may waste some of the food items they purchase.

The results of this study might be extended to further research. For instance, a new research may expand the scope of the nutrients studied. Based on the results of this study, temperature effects on sodium demand are the biggest among four different nutrients, calories, sugar, saturated fat, and sodium. To the extent data are available, if more nutrient variables are used, we might reveal which nutrient intakes are most affected by the weather changes.

Figure 1.1. The Trend of Calories Demand

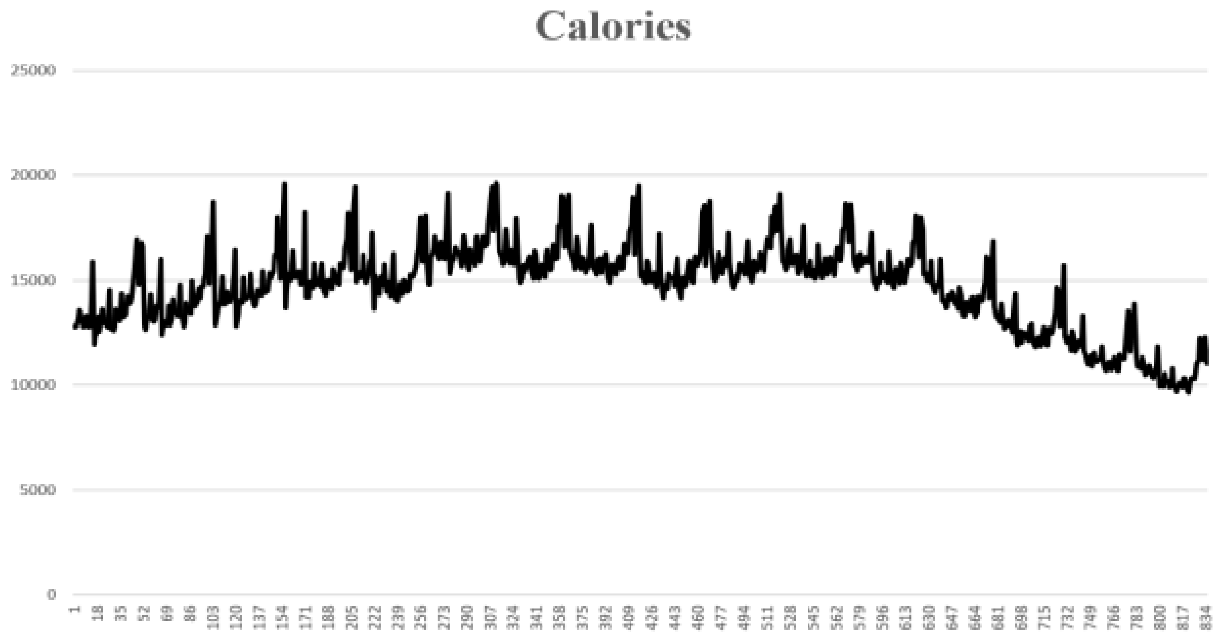

Figure 1.2. The Trend of Sugar Demand

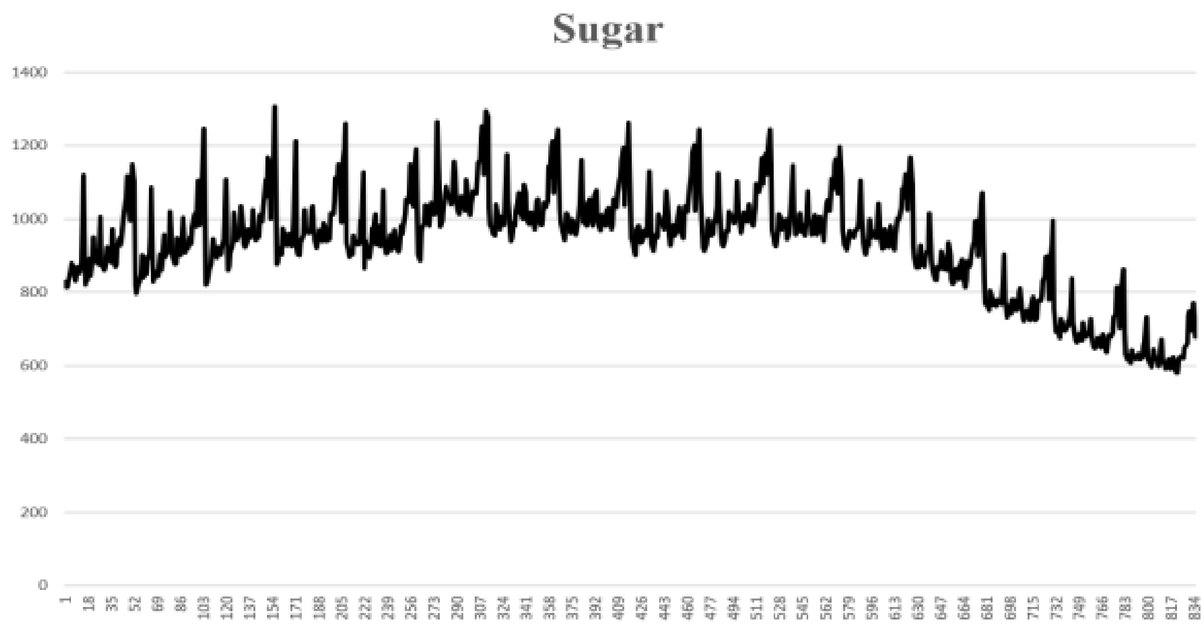

Figure 1.3. The Trend of Saturated Fat Demand

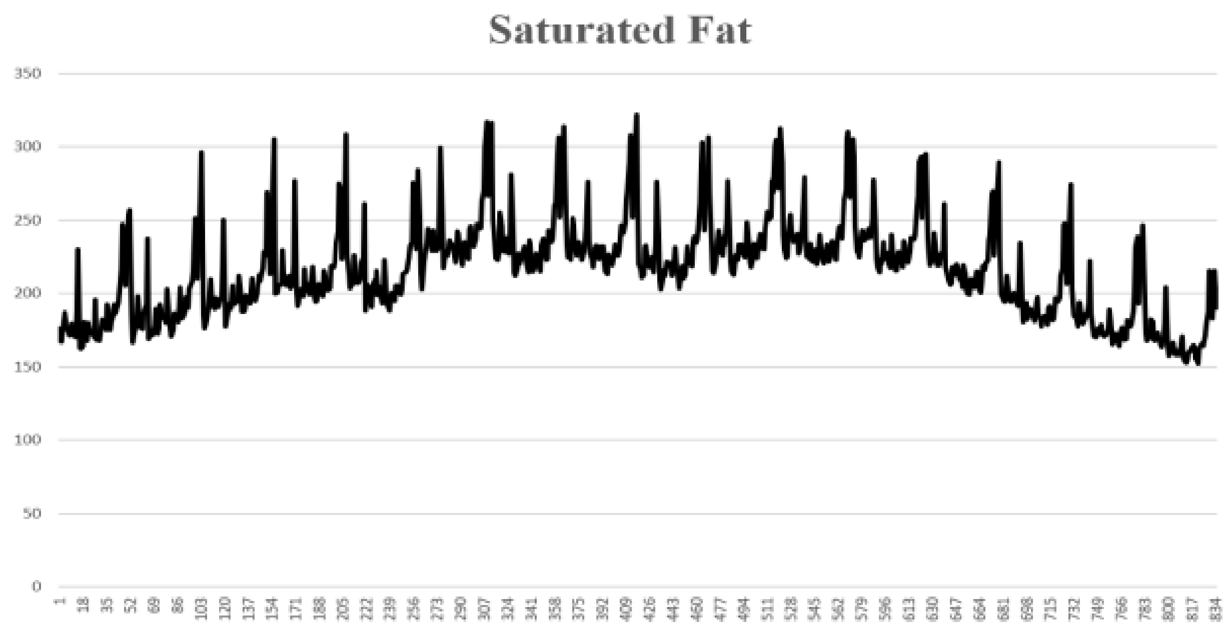

Figure 1.4. The Trend of Sodium Demand

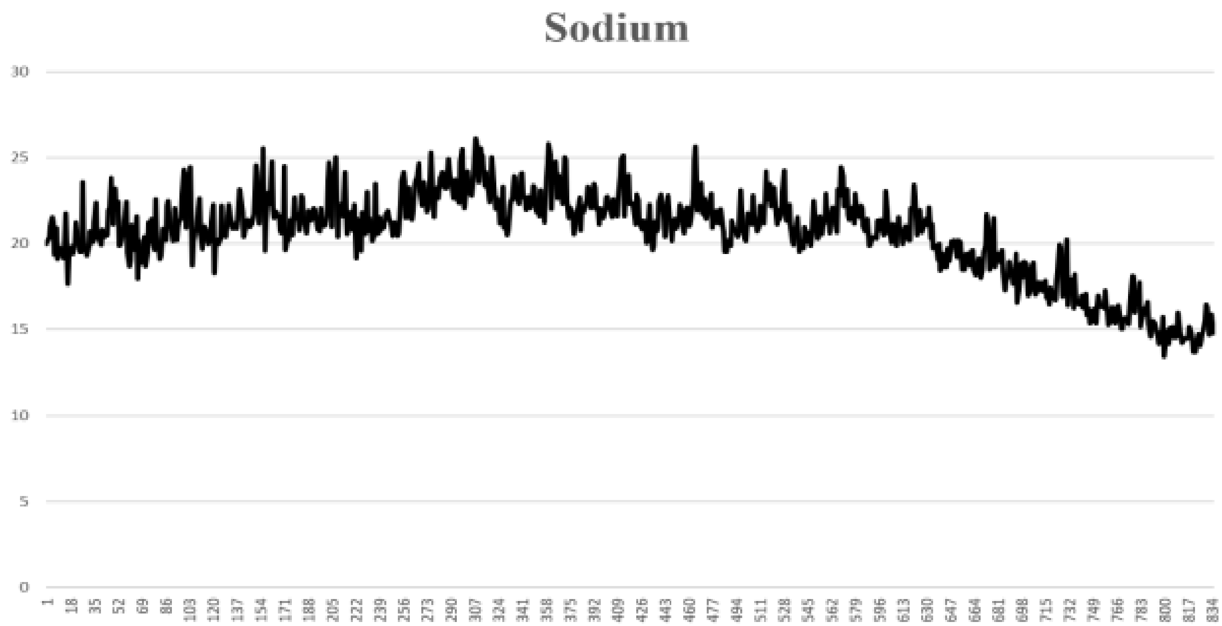

Figure 1.5. Variation in Temperature Residuals

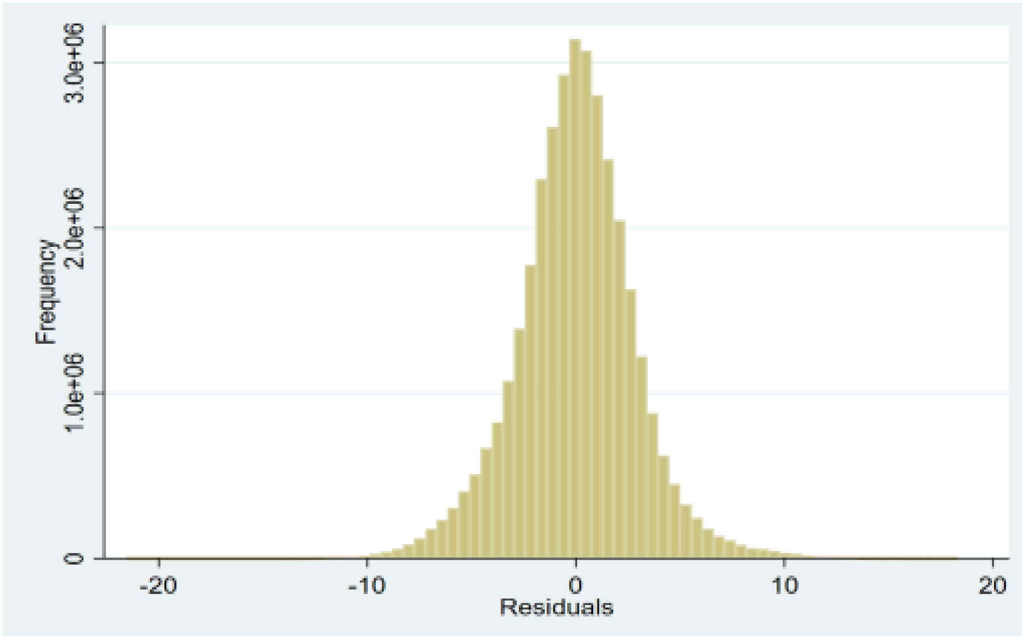

Figure 1.6. Variation in Precipitation Residuals

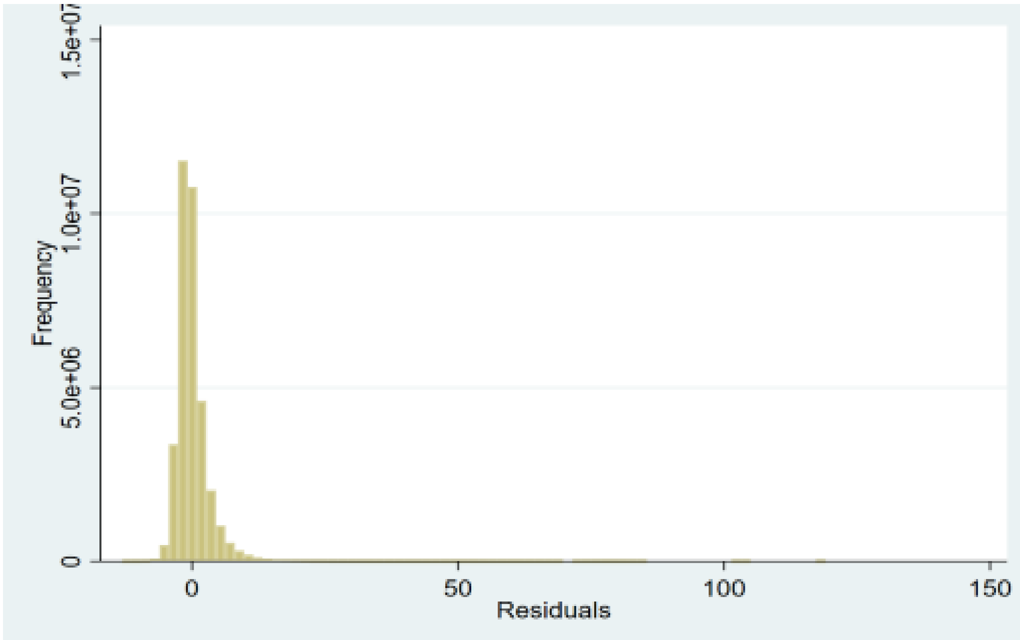

Figure 1.7. The Trend of Weekly Average Temperature

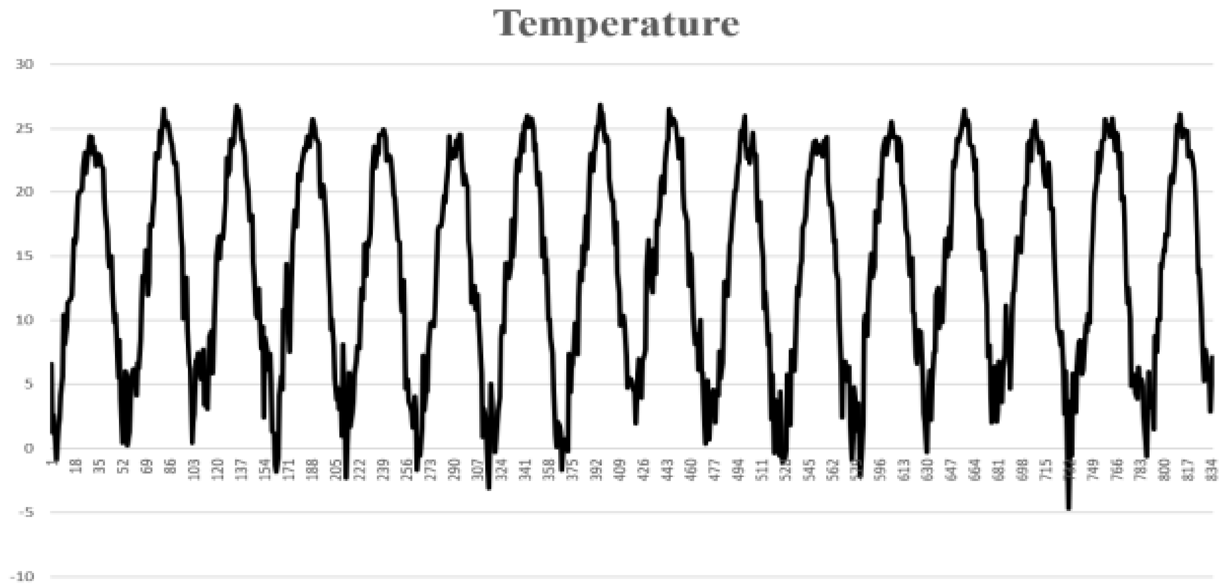

Figure 1.8. The Trend of Weekly Precipitation

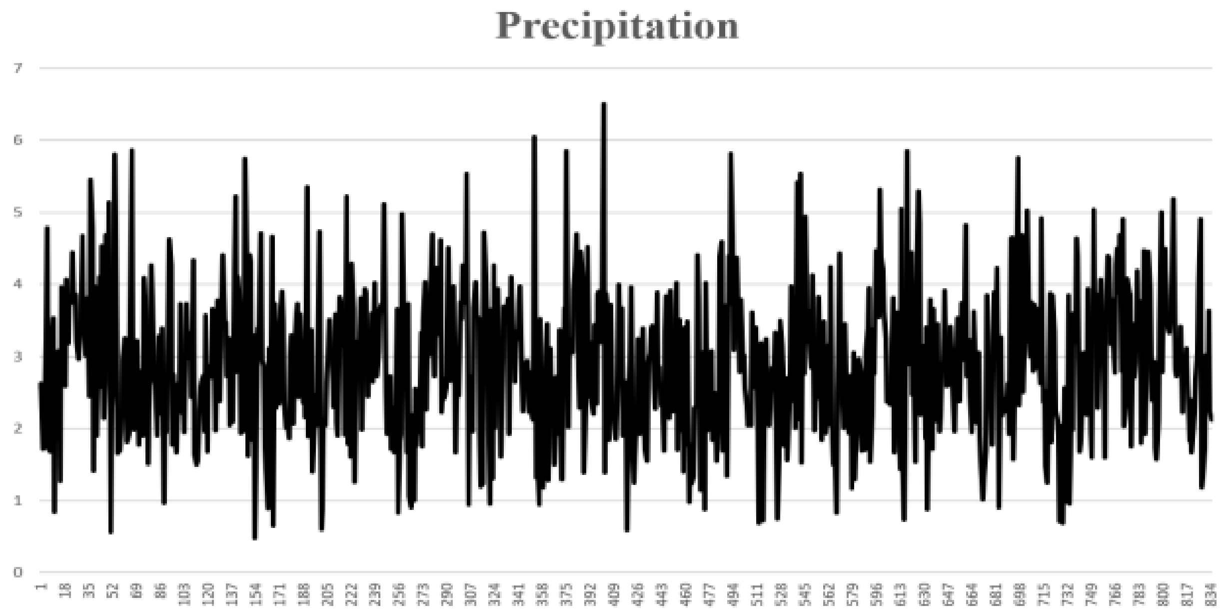

Table 1.1. Summary Statistics of Weather and Nutrition Variables

Variable	Mean	Std.Dev	Min	Max
Temperature (avgtp) (℃)	13.89	9.89	-27.18	37.03
Precipitation (avgpp) (mm)	2.88	3.39	0.00	127.30
Calories (kcal)	14,690.37	14,560.81	0.00	151,705.70
Sugar (g)	930.61	1,102.97	0.00	9,715.28
Saturated Fat (g)	216.98	267.52	0.00	2,265.05
Sodium (g)	20.52	50.90	0.00	28,376.32

Notes: Unit of Observation: one household in one week. The number of observations is 35,215,971.

Table 1.2. Weather Effects on Nutrient Demand: Baseline

	Calories	Sugar	Saturated Fat	Sodium
$avgtp$	-24.644***	-1.544***	-0.398***	-0.087***
	(5.6675)	(0.4260)	(0.1194)	(0.0161)
$avgtp^2$	-0.135	0.005	-0.003	0.0004
	(0.0713)	(0.0056)	(0.0014)	(0.0002)
$avgpp$	6.840**	-0.191	0.116**	0.024***
	(2.1111)	(0.1491)	(0.0374)	(0.0071)
$avgpp^2$	-0.150	0.002	-0.003	-0.0006
	(0.0995)	(0.0055)	(0.0017)	(0.0003)
Time Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.227	0.209	0.204	0.061
Marginal Effects of $avgtp$	-36.474***	-1.114***	-0.619***	-0.052***
	(2.0808)	(0.1624)	(0.0347)	(0.0007)
Marginal Effects of $avgtp$	5.978***	-0.1778	0.098**	0.020***
	(1.7286)	(0.1281)	(0.0304)	(0.0058)

Notes: Standard Errors in parentheses are two-way clustered at county and week. The number of observations is 35,215,971. * p<0.05, ** p<0.01, *** p<0.001.

Table 1.3. Weather Effects on Nutrient Demand: Weather Variable Bins

	Calories	Sugar	Saturated Fat	Sodium
b2 (0-3℃)	-23.776***	-0.048	-0.247	-0.091***
	(6.7624)	(0.5311)	(0.1358)	(0.0174)
b3 (3-6℃)	-53.851***	-2.149***	-0.823***	-0.144***
	(5.9095)	(0.4374)	(0.1173)	(0.0183)
b4 (6-9℃)	-53.037***	-1.728***	-0.834***	-0.145***
	(6.0200)	(0.4630)	(0.1251)	(0.0174)
b5 (9-12℃)	-80.446***	-3.148***	-1.375***	-0.168***
	(5.7598)	(0.4279)	(0.1127)	(0.0176)
b6 (12-15℃)	-88.102***	-3.514***	-1.563***	-0.188***
	(6.4603)	(0.4830)	(0.1243)	(0.0204)
b7 (15-18℃)	-113.416***	-4.456***	-1.954***	-0.223***
	(7.4874)	(0.5173)	(0.1256)	(0.0213)
b8 (18-21℃)	-129.639***	-4.649***	-2.203***	-0.246***
	(6.9234)	(0.5360)	(0.1287)	(0.0231)
b9 (21-24℃)	-148.059***	-5.217***	-2.490***	-0.234***
	(7.4972)	(0.6084)	(0.1343)	(0.0230)
b10 (24-27℃)	-156.162***	-5.044***	-2.594***	-0.260***
	(8.4588)	(0.6941)	(0.1488)	(0.0271)
b11 (27-30℃)	-163.899***	-5.092***	-2.816***	-0.270***
	(9.7121)	(0.7779)	(0.1700)	(0.0320)
b12 (30-33℃)	-162.700***	-4.542***	-2.724***	-0.377***
	(11.4390)	(0.8513)	(0.2135)	(0.0387)
b13 (33-36℃)	-188.464***	-5.999***	-3.537***	-0.302***
	(15.0566)	(1.1694)	(0.2164)	(0.0469)
b14 (above 36℃)	-184.706*	-5.314*	-3.818**	-0.443***
	(74.4937)	(2.2626)	(1.2807)	(0.1192)
$avgpp$	5.976**	-0.245	0.099**	0.024***
	(2.0578)	(0.1480)	(0.0371)	(0.0071)
$avgpp^2$	-0.123	0.003	-0.003	-0.0006*
	(0.0925)	(0.0053)	(0.0017)	(0.0003)
Time Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.227	0.209	0.204	0.061
Marginal Effects of $avgpp$	5.268**	-0.225	0.083**	0.020***
	(1.7144)	(0.1280)	(0.0305)	(0.0058)

Notes: Standard Errors in parentheses are two-way clustered at county and week. The number of observations is 35,215,971. * p<0.05, ** p<0.01, *** p<0.001.

Table 1.4. Weather Effects on Nutrient Demand: Degree Days

	Calories	Sugar	Saturated Fat	Sodium
DD_{EC}	6.816***	0.162**	0.107***	0.011***
	(0.8242)	(0.0517)	(0.0171)	(0.0021)
DD_L	2.964***	0.095***	0.055***	0.001
	(0.3365)	(0.0223)	(0.0072)	(0.0010)
DD_M	1.122	0.279***	0.021	0.006
	(1.0373)	(0.0705)	(0.0206)	(0.0035)
DD_H	-0.067	0.372	-0.051	-0.018
	(2.7059)	(0.1938)	(0.0577)	(0.0094)
$avgpp$	4.975*	-0.325*	0.076*	0.022**
	(2.1729)	(0.1507)	(0.0385)	(0.0071)
$avgpp^2$	-0.105	0.006	-0.002	-0.0005
	(0.0943)	(0.0051)	(0.0016)	(0.0003)
Time Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.227	0.209	0.204	0.061
Marginal Effects of $avgpp$	4.369*	-0.292*	0.063	0.019**
	(1.8326)	(0.1313)	(0.0324)	(0.0058)

Notes: Standard Errors in parentheses are two-way clustered at county and week. The number of observations is 35,215,971. * p<0.05, ** p<0.01, *** p<0.001.

Table 1.5. Weather Effects on Nutrient Demand by Share of Females in a Household

	Calories	Sugar	Saturated Fat	Sodium
$avgtp$	-51.300***	-3.144***	-0.762***	-0.106***
	(5.9670)	(0.4397)	(0.1215)	(0.0165)
$avgtp^2$	-0.161*	0.003	-0.003	0.0004
	(0.0751)	(0.0058)	(0.0015)	(0.0002)
$avgtp$ × medium % of females among HH member	12.767***	0.703***	0.170***	0.0006
	(1.4308)	(0.1028)	(0.0219)	(0.0030)
$avgtp$ × high % of females among HH member	97.047***	5.973***	1.335***	0.091***
	(2.7925)	(0.1837)	(0.0416)	(0.0054)
$avgpp$	-1.684	-0.724**	-0.030	0.016
	(3.0183)	(0.2258)	(0.0523)	(0.0097)
$avgpp^2$	-0.147	0.002	-0.003	-0.0006
	(0.1003)	(0.0055)	(0.0018)	(0.0003)
$avgpp$ × medium % of females among HH member	4.142	0.291	0.080	0.004
	(2.9510)	(0.2258)	(0.0488)	(0.0093)
$avgpp$ × high % of females among HH member	27.772***	1.678***	0.460***	0.0247*
	(6.1449)	(0.4395)	(0.1030)	(0.0122)
Time Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.230	0.210	0.206	0.061
Marginal Effects of $avgtp$ for low % females HH	-65.392***	-2.859***	-1.015***	-0.074***
	(2.2522)	(0.1777)	(0.0368)	(0.0067)
Marginal Effects of $avgtp$ for medium % females HH	-52.625***	-2.156***	-0.845***	-0.074***
	(2.2471)	(0.1698)	(0.0364)	(0.0067)
Marginal Effects of $avgtp$ for high % females HH	31.655***	3.114***	0.321***	0.017*
	(3.0470)	(0.2175)	(0.0483)	(0.0064)
Marginal Effects of $avgpp$ for low % females HH	-2.534	-0.710***	-0.048	0.013
	(2.8003)	(0.2143)	(0.0488)	(0.0087)
Marginal Effects of $avgpp$ for medium % females HH	1.608	-0.419*	-0.077*	0.017*
	(2.2369)	(0.1634)	(0.0376)	(0.0066)
Marginal Effects of $avgpp$ for high % females HH	25.238***	0.968**	0.412***	0.037***
	(4.6735)	(0.3226)	(0.0768)	(0.0107)

Notes: Standard Errors in parentheses are two-way clustered at county and week. The number of observations is 35,215,971. * p<0.05, ** p<0.01, *** p<0.001.

Table 1.6. Weather Effects on Nutrient Demand by Age of Household Members

	Calories	Sugar	Saturated Fat	Sodium
$avgtp$	-71.321***	-4.659***	-1.036***	-0.155***
	(6.0739)	(0.4377)	(0.1236)	(0.0165)
$avgtp^2$	-0.072	0.009	-0.002	0.0005*
	(0.0762)	(0.0058)	(0.0015)	(0.0002)
$avgtp \times$ middle aged households	59.067***	3.875***	0.799***	0.087***
	(1.5519)	(0.1046)	(0.0242)	(0.0027)
$avgtp \times$ elderly aged households	87.111***	5.929***	1.208***	0.127***
	(2.2525)	(0.1472)	(0.0346)	(0.0043)
$avgpp$	-6.467*	-0.853***	-0.088	0.010
	(3.2657)	(0.2116)	(0.0557)	(0.0078)
$avgpp^2$	-0.130	0.004	-0.003	-0.0005
	(0.0964)	(0.0053)	(0.0017)	(0.0003)
$avgpp \times$ middle aged households	22.250***	1.196***	0.332***	0.031***
	(4.2969)	(0.2757)	(0.0724)	(0.0092)
$avgpp \times$ elderly aged households	15.902**	0.532	0.270**	-0.0009
	(5.8969)	(0.3820)	(0.1027)	(0.0116)
Time Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.229	0.210	0.205	0.061
Marginal Effects of $avgtp$ for young aged households	-77.598***	-3.854***	-1.181**	-0.113***
	(2.3109)	(0.1711)	(0.3988)	(0.0065)
Marginal Effects of $avgtp$ for middle aged households	-71.321***	0.021	-0.382	-0.026***
	(2.0334)	(0.1599)	(0.3985)	(0.0067)
Marginal Effects of $avgtp$ for elderly aged households	9.514**	2.075***	0.027	0.014
	(2.8979)	(0.2097)	(0.3996)	(0.0075)
Marginal Effects of $avgpp$ for young aged households	-7.219*	-0.832***	-0.105*	0.007
	(3.0959)	(0.2001)	(0.0530)	(0.0069)
Marginal Effects of $avgpp$ for middle aged households	15.032***	0.364	0.227***	0.037***
	(2.6720)	(0.1879)	(0.0456)	(0.0083)
Marginal Effects of $avgpp$ for elderly aged households	8.684*	-0.300	0.165*	0.006
	(4.0723)	(0.2865)	(0.0712)	(0.0102)

Notes: Standard Errors in parentheses are two-way clustered at county and week. The number of observations is 35,215,971. * p<0.05, ** p<0.01, *** p<0.001.

Table 1.7. Weather Effects on Nutrient Demand by Income

	Calories	Sugar	Saturated Fat	Sodium
$avgtp$	-8.280	-0.440	-0.162	-0.070***
	(5.8032)	(0.4340)	(0.1200)	(0.0163)
$avgtp^2$	-0.152*	0.004	-0.003	0.0004
	(0.0726)	(0.0057)	(0.0015)	(0.0002)
$avgtp \times$ middle income households	-20.081***	-1.367***	-0.288***	-0.019***
	(1.1204)	(0.0771)	(0.0179)	(0.0024)
$avgtp \times$ high income households	-29.496***	-1.961***	-0.431***	-0.032***
	(1.4726)	(0.0987)	(0.0232)	(0.0034)
$avgpp$	6.191	-0.334	0.123*	0.020*
	(3.2306)	(0.2227)	(0.0548)	(0.0103)
$avgpp^2$	-0.142	0.003	-0.003	-0.0006
	(0.0981)	(0.0054)	(0.0017)	(0.0003)
$avgpp \times$ middle income households	1.583	0.215	-0.004	0.004
	(3.3514)	(0.2192)	(0.0532)	(0.0107)
$avgpp \times$ high income households	-1.845	0.133	-0.047	0.007
	(3.9295)	(0.2554)	(0.0690)	(0.0116)
Time Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.228	0.209	0.204	0.061
Marginal Effects of $avgtp$ for low income HH	-21.621***	-0.113	-0.405***	-0.037***
	(2.1770)	(0.1644)	(0.0362)	(0.0069)
Marginal Effects of $avgtp$ for middle income HH	-41.702***	-1.480***	-0.693***	-0.056***
	(2.1539)	(0.1670)	(0.0350)	(0.0064)
Marginal Effects of $avgtp$ for high income HH	-51.107***	-2.075***	-0.836***	-0.070***
	(2.2474)	(0.1774)	(0.0387)	(0.0065)
Marginal Effects of $avgpp$ for low income HH	5.372	-0.318	0.105*	0.017
	(2.9885)	(0.2090)	(0.0497)	(0.0094)
Marginal Effects of $avgpp$ for middle income HH	6.955***	-0.103	0.101**	0.021**
	(2.0442)	(0.1469)	(0.0345)	(0.0070)
Marginal Effects of $avgpp$ for high income HH	3.527	-0.185	0.058	0.024**
	(2.6217)	(0.1798)	(0.0496)	(0.0089)

Notes: Standard Errors in parentheses are two-way clustered at county and week. The number of observations is 35,215,971. * p<0.05, ** p<0.01, *** p<0.001.

Table 1.8. Weather Effects on Nutrient Demand by Household Size

	Calories	Sugar	Saturated Fat	Sodium
$avgtp$	91.829***	5.883***	1.226***	0.076***
	(7.6678)	(0.5341)	(0.1415)	(0.0172)
$avgtp^2$	0.073	0.018*	0.0004	0.0007**
	(0.0983)	(0.0071)	(0.0017)	(0.0002)
$avgtp \times$ medium size households	-157.278***	-9.976***	-2.197***	-0.218***
	(2.3255)	(0.1465)	(0.0357)	(0.0048)
$avgtp \times$ big size households	-239.895***	-15.467***	-3.331***	-0.341***
	(3.4378)	(0.2137)	(0.0511)	(0.0061)
$avgpp$	43.346***	1.927***	0.634***	0.064***
	(6.7111)	(0.4264)	(0.1033)	(0.0141)
$avgpp^2$	-0.109	0.005	-0.003	-0.0005
	(0.0896)	(0.0051)	(0.0016)	(0.0003)
$avgpp \times$ medium size households	-43.843***	-2.595***	-0.613***	-0.046***
	(7.1555)	(0.4534)	(0.1085)	(0.0139)
$avgpp \times$ big size households	-69.391***	-3.964***	-1.002***	-0.085***
	(11.0806)	(0.7005)	(0.1692)	(0.0171)
Time Fixed Effects	Yes	Yes	Yes	Yes
Household Fixed Effects	Yes	Yes	Yes	Yes
County-Year Fixed Effects	Yes	Yes	Yes	Yes
Adjusted R^2	0.239	0.217	0.211	0.063
Marginal Effects of $avgtp$ for small size HH	98.259***	7.491***	1.258***	0.136***
	(3.6103)	(0.2473)	(0.0553)	(0.0086)
Marginal Effects of $avgtp$ for medium size HH	-59.018***	-2.485***	-0.939***	-0.081***
	(2.5380)	(0.1862)	(0.0406)	(0.0068)
Marginal Effects of $avgtp$ for big size HH	-141.636***	-7.976***	-2.073***	-0.205***
	(2.5751)	(0.1830)	(0.0428)	(0.0068)
Marginal Effects of $avgpp$ for small size HH	42.716***	1.956***	0.619***	0.061***
	(6.5371)	(0.4184)	(0.0997)	(0.0133)
Marginal Effects of $avgpp$ for medium size HH	-1.127	-0.639***	0.006	0.015*
	(2.2177)	(0.1624)	(0.0392)	(0.0068)
Marginal Effects of $avgpp$ for big size HH	-26.67***	-2.009***	-0.383***	-0.024**
	(5.3040)	(0.3480)	(0.0828)	(0.0081)

Notes: Standard Errors in parentheses are two-way clustered at county and week. The number of observations is 35,215,971. * p<0.05, ** p<0.01, *** p<0.001.

Table 1.9. Marginal Effects of Temperature and Precipitation by Different Quantiles of Demand for Calories

Quantile of Calories Demand	Marginal Effects of Temperature on Calories Demand	Marginal Effects of Precipitation on Calories Demand
25% Quantile	-21.756***	3.932***
	(0.5799)	(0.5897)
50% Quantile	-33.661***	5.364***
	(0.7419)	(0.7773)
75% Quantile	-52.017***	7.573***
	(1.2821)	(1.3558)

Notes: Standard Errors in parentheses. The number of observations is 35,215,971. * p<0.05, ** p<0.01, *** p<0.001.

Table 1.10. The Impact of Climate Change on Nutrient Demand

1) If temperature is increased by 1.20℃ and precipitation is increased by 2.34% by 2030

	Calories	Sugar	Saturated Fat	Sodium
Change in nutrients demand	-43.43kcal	-1.34g	-0.74g	-0.06g
Percentage change	-0.30%	-0.14%	-0.34%	-0.30%

2) If temperature is increased by 2.01℃ and precipitation is increased by 3.37% by 2050

	Calories	Sugar	Saturated Fat	Sodium
Change in nutrients demand	-72.81kcal	-2.25g	-1.24g	-0.10g
Percentage change	-0.50%	-0.24%	-0.57%	-0.50%

3) If temperature is increased by 3.26℃ and precipitation is increased by 5.56% by 2090

	Calories	Sugar	Saturated Fat	Sodium
Change in nutrients demand	-118.36kcal	-3.66g	-2.01g	-0.17g
Percentage change	-0.81%	-0.39%	-0.93%	-0.82%

CHAPTER 2

The Economics of Adopting Controlled Environment Technology in the US Strawberry Nursery Industry: A Case Study

2.1. Introduction

Strawberries are an important fruit in the US in terms of both production and consumption aspects. California is the most important state for the strawberry industry in the US. The majority of US-grown strawberries come from California. Strawberries are grown on approximately 35,000 acres along the California coast. Strawberry production in this state averages about 50 thousand pounds per acre each season. It means that more than 200 million trays of fresh strawberries are harvested each year, equivalent to about 1.8 billion pounds of strawberries (California Strawberry Commission).[10]

Strawberry nursery industry provides a key input to produce strawberry fruit. Although there are various inputs for the production of strawberry fruit, nursery plant is one of the irreplaceable inputs. Every year, strawberry growers in the US rely on new plants from a limited number of strawberry nurseries in California, North Carolina and Canada. Strawberry nursery plants are important not only as an essential input for fruit production, but also in terms of the scale of the industry itself. In the US, more than one billion plants are produced every year, adding an estimated 200 to 300 million dollars to strawberry farm gate value (USDA Current Research Information System).[11]

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[10] https://www.californiastrawberries.com/.
[11] https://cris.nifa.usda.gov/cgi-bin/starfinder/0?path=fastlink1.txt&id=anon&pass=&search=R=94312&format=WEBLINK

The strawberry nursery industry faces significant challenges. Stable production of nursery plants is threatened by the occurrence of plant diseases, and potential phase-out of Methyl Bromide also acts as a potential threat to the nursery industry. Another difficulty that the industry is facing is securing labor. The strawberry industry experiences a labor shortage due to various factors. Additionally, the strawberry seed industry is exposed to risks such as high transportation costs and increased risk of plant pathogens due to its long and complicated supply chain.

Controlled Environment (CE) technology is a proposed response to these challenges. CE technology manipulates environmental factors such as light, temperature, CO_2, etc. to produce disease-free nursery plants and achieve a stable production year-round (USDA Current Research Information System). In fact, in Europe, CE technology has been successfully utilized in the strawberry nursery industry. Efforts are also being made in North America to introduce CE technology in the strawberry nursery industry. Precise Indoor Propagation - Coordinated Agricultural Project (PIP-CAP) has been investigating and developing protocols for US and North American context.

This paper seeks to review, qualitatively, the opportunities/challenges, costs/benefits of CE as a response to the challenges. Lack of data is a major difficulty in evaluating CE in the strawberry nursery industry. Contrary to the strawberry fruit industry, data for the strawberry nursery industry is very limited. We use case-study methods to collect and organize information from published study, scientific expertise from PIP-CAP and observations from California field trip in 2022.

The paper is structured as follows. In the next section, we introduce case-study research methodology. In Section 3, we provide an overview of the strawberry nursery industry.

Difficulties in the strawberry nursery industry are explained in Section 4. Section 5 provides information on Controlled Environment technology in the strawberry nursery industry. Potential opportunities and challenges of Controlled Environment technology are presented in Section 6. Section 7 is the concluding remarks.

2.2. Methodology

We adopt case-study research methodologies to investigate in detail the strawberry nursery industry. According to Yin (2018) and Boland (2020), exploratory case-study is a condensed case-study to gather basic data that could be used to identify a particular question for a larger study. Our study uses exploratory case-study. There are still many unknowns about the California strawberry nursery industry, so it is meaningful to collect and organize as much information as possible about it. We collect information about the strawberry nursery industry from previous studies and existing data. There is limited published research for the US strawberry nursery industry. However, limited previous research for the European strawberry nursery case exists. To make up for the problem of insufficient prior information about the industry, we visited California in June 2022. Experts in various fields, including plant physiology, genetics, economics, and field evaluation, accompanied the California field tour from June 26 to July 1, 2022. We visited San Luis Obispo, Salinas, Watsonville, and Macdoel in California and met with industry members and experts from California strawberry center, prominent strawberry nursery firms, low elevation nursery & high elevation nursery, and USDA-ARS. Various information of the CA strawberry nursery industry including the industry overview, practice of conventional propagation system, plant quality, and the current strawberry plant supply chain was obtained through the trip. Conversations and observations from the trip were organized in the form of notes by team members from various fields. In case-study, observational evidence is useful to provide information about the topic (Yin (2018)). Information that is not otherwise cited is coming from this note.

2.3. Overview of Strawberry Nursery Industry

This paper focuses on the California strawberry nursery industry. According to the USDA National Agricultural Statistics Service, 89.1% of total strawberry production in the US is from California. Since the majority of all strawberry production in the US is accounted by California, studying the California strawberry nursery industry is significant. The California strawberry nursery industry is a very specialized process. Figure 2.1 represents the strawberry nursery process in the US. The entire process of strawberry propagation and production in California takes multiple years in multiple locations. It usually takes 5 years. The first 1.5 years of the process takes place in the tissue culture. Selection, identification, heat treatment, and disease testing of the mother plant are performed. Then, the tips are harvested from the mother plant. A meristem isolated from the tips grows in a tube. Before going out into the field, plants go through an 'acclimatization' process inside the greenhouse, which is a process of adapting to the external environment. The next 1.5 to 3 years of the process takes place in a low elevation nursery. The healthiest plants selected by growers in the screenhouse are planted in the nursery's field. Then the plants are propagated via runner in the propagation fields. The next 3 to 4 years of the process are held in a high elevation nursery. The plants are shipped to the high elevation nursery to get chilling hours. Different chilling hours are required based on cultivars. Plant harvest in nurseries is driven by amount of received chilling hours. In the high elevation nurseries, the covers are removed and the plants are mowed. Bare roots are processed and either frozen or shipped to fruit growers. In year 5, fruit growers are planting strawberry plants (plug plants or fresh, semi-dormant, or frigo bare roots) in farm fields.

Although there is no publicly available data on the total value of California's strawberry nursery industry, it can be indirectly estimated using existing data. According to the recent cost returns study by UC Davis, cost per each strawberry plant is 0.15 dollars.[12] Given the fact that about one billion strawberry plants are produced every year by USDA Current Research Information System, the total value of the strawberry nursery industry in CA is approximately 15 million dollars. In California, there are a small number of nursery firms which are very heterogeneous. A high degree of coordination exists between the nursery industry and fruit growers. Some fruit growers visit nurseries before receiving plants to ensure conditioning specifications are met. However, fruit growers and nurseries do not necessarily have a 1:1 contract. A fruit grower typically orders plants from 2-4 different nurseries to hedge risks such as procurement and disease. From a fruit grower's perspective, there are around 300 strawberry growers in California. Most of the growers are located in five areas, Watsonville, Salinas, Santa Maria, Oxnard, and Orange County (California Strawberry Commission).

In Europe, CE technology has already been introduced in the strawberry nursery industry. The use of CE technology has mainly focused on controlling temperature and atmosphere. In the Netherlands, controlled atmosphere and temperature treatment (CATT) has been used as an alternative to Methyl Bromide to control disease and pests. In contrast, California's strawberry nursery industry is still in the early stages of introducing CE technology. Although research is being actively conducted to develop and introduce CE technology, almost all nursery plants produced in California are still produced in open fields.

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[12] SAMPLE COSTS TO PRODUCE AND HARVEST STRAWBERRIES Central Coast Region - Santa Cruz & Monterey Counties - 2021

2.4. Challenges in the Strawberry Nursery Industry

One of the main challenges in the strawberry nursery industry is a plant disease problem. Various plant disease problems occur in the current open field nursery system. Diseases of strawberry plants can be detected in a fruit production field after the plants are delivered to fruit growers. Various pathogens are associated with transplants. Soil-borne and foliar plant pathogens are frequently introduced into fruit production areas through infected nursery plants. Diseases and pathogens including *Phytophthora* crown rot, *Botrytis cinerea* (Disease: gray-mold), *Xanthomonas fragariae* (Disease: angular leaf spot), *Podosphaera phanis* (Disease: Powdery mildew), *Anthracnose*, and *Neopestalotiopsis* fruit rot result in significant damages to fruit production fields. They can be traced back to nurseries. For instance, *Anthracnose* was traced back to nurseries over 150 cases over the past decade in North Carolina, Flolida, and California's south coast.[13] Some pathogens cannot be completely controlled by current control systems. For instance, diseases such as Botrytis fruit rot often show pesticide resistance. Therefore, hedging disease risk is a very important task for the strawberry nursery industry (USDA Current Research Information System). So far, the strawberry nursery industry has relied on the use of MB to produce disease-free plants. However, dependency on Methyl Bromide (MB) might be a potential threat in the strawberry nursery industry. Methyl bromide is a fumigant used to control pests in agriculture and shipping (US Environmental Protection Agency).[14] In the 1960s, scientists proved that fumigation with two chemicals, MB and Chloropicrin, is effective to control verticillium wilt. The strawberry industry widely accepted this practice, leading to a significant improvement in productivity. Increase in productivity was a huge, that is, from 3-5

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[13] https://strawberries-pip.cals.ncsu.edu/

[14] https://www.epa.gov/ods-phaseout/methyl-bromide

tons per acre to 20-30 tons per acre (Guthman (2019)). However, concerns were raised that MB could cause skin cancer through ozone layer destruction, and the Montreal Protocol in 1991 eventually mandated the phaseout of MB. The United States also agreed to gradually reduce the production and import of MB and completely stop it by 2005 (Guthman (2019)). Although strawberry nursery industry in the US still use MB under the "Quarantine and Preshipment Exemption", alternative propagation technology will be needed to prepare the potential phaseout of MB. Currently, virtually all open-field strawberry nurseries in the US use a mix of MB and Chloropicrin as soil fumigant to each open-field operation. Although fumigation costs approximately 5,000 dollar per acre, use of MB has contributed to effectively reducing the risk of soilborne diseases such as *Nematode*. However, the possibility of the phase-out of MB is a threat in the strawberry nursery industry (USDA Current Research Information System). Phase-out of MB in the strawberry nursery industry would result in increase of soil-borne pathogens such as *Phytophthora ssp.*, *Pythium ssp.*, *Rhizoctonia spp.*, *Fusarium oxysporum*, and *Macrophomina phaseolina*. It will lead to additional costs of screening transplants.[15] Given this threat, strawberry nursery industry will need to develop cost-effective alternative tools for soil disinfestation (USDA Current Research Information System).

Another major difficulty that the strawberry industry is facing is a labor problem. A majority of strawberry growers experience labor shortages. More staffs and field pickers are needed for the growers. Labor shortage and higher labor costs had driven some growers out of business (Guthman (2019)). The shortages of labor come from various factors including decrease in labor migration to California due to immigration policy and labor competition with other crops (Guthman (2019)). For strawberry growers, difficulties with labor availability lead to loss of

[15] https://strawberries-pip.cals.ncsu.edu/

production. One industry representative insisted that difficulties in accessing labor result in a 10 to 20% loss at certain times of the year. Growers can mitigate the losses by hiring a temporary guest worker through the H-2A visa program, however, using the program costs a lot for growers because of pay and housing requirements (HsuFlanders, Gallagher, and Wilson (2019)). The reason labor is a big threat to the strawberry industry is not only the difficulty in securing it, but also the high cost. Labor cost is the most expensive part of all of the costs. Labor cost accounts for 75% of the production cost, including picking as well as transplanting.

Another challenge faced by the California strawberry industry arises from characteristics of the process. The supply chain of strawberry nursery industry is long and complicated. Strawberry transplant process in California is a multi-year and multi-location operation. As explained in the introduction section, the transplant production process for strawberries usually takes 5 years from tissue culture to supplying the plants to fruit growers. Nursery plants are transported between several different locations including screen house, increasing blocks and propagation fields in the low elevation nursery, conditioning field in the high elevation nursery to be propagated for 5 years before they are sold to fruit production location (USDA Current Research Information System). For instance, plants are harvested in high elevation nurseries from September to November and they are harvested in low elevation nurseries from January to March. High elevation nurseries are located at 5000 ft elevation in Northern California (Macdoel, CA). Low elevation nurseries are located in the northern Central Valley at less than 100 ft elevation (Manteca, CA). This multi-year and multi-location process results in problems such as increased transportation costs, higher fixed costs for duplicative infrastructure and equipment, etc. Also, virtually all the nursery firms in California are operating open-field nurseries. Open-field locations are threatened by various weather events including droughts, run-off, floods, and wildfires.[16]

2.5. Controlled Environment Technology

Environmental factors such as light, temperature, and humidity are one of the important factors to determine plant productivity and quality. Controlled environment technologies such as protected cultivation, greenhouses, Controlled Environment Plant Production Systems (CEPPS), plant factories, etc., reduce damage caused by the external environment by controlling microenvironmental conditions and enables stable plant production throughout the year (Ting, Lin, and Davidson (2016)). The need for CE technology has been recognized in various agricultural fields, and research on it has been actively conducted. In fact, through examples of many crops such as potatoes, tomatoes, carrots, and lettuce, it has been proven that the use of CE technology is effective in producing high-quality crops. For instance, well controlled lack of water under controlled environment might improve the fruit quality, flavor and taste (sweetness) of tomatoes (Geilfus (2019)).

Some CE technologies have already been applied to the strawberry nursery industry in Europe. In understanding the strawberry nursery industry in Europe, it is necessary to focus on the Netherlands case. The Netherlands has favorable climatic conditions for the propagation of strawberry plants, including temperature, precipitation, abundant chilling, and fertile sandy soils. In addition, the Netherlands exports strawberry plants throughout Europe, including Germany, Scandinavia, the UK, and Eastern-European countries, based on its geographical advantage of being located in the center of Western-Europe. Strawberry propagation accounts for more than

[16] https://strawberries-pip.cals.ncsu.edu/

half of the strawberry industry in the Netherlands, and the professional certified nursery area has increased more than 13 times in the 30 years since 1980. There are about 30 officially registered strawberry nurseries in the Netherlands. Over the past 25 years, an innovative strawberry nursery industry has been established in the Netherlands (Lieten (2012)). In the Netherlands, strawberry nursery industry CE technology is mainly applied to production of pest and disease-free mother plants. Until 2008, fumigation of mother plants using MB was a common method to remove tarsonemids. After the ban on the use of MB, the Netherlands introduced the controlled atmosphere and temperature treatment (CATT), a non-chemical method, as an alternative. The effectiveness of this method was proven through Van Kruistum et al. (2009). Through the CATT process, mother plants are subjected to high CO_2 levels at 35-38°C for 48 hours. This process may have some negative effects on plant vigor compared to conventional MB fumigation, but in addition to tarsonemic mites, it can also effectively eliminate spider mites and nematodes. The CATT technology, after several years of optimization, is now applied to all EE (Extra Elite) mother plants produced in the Netherlands (Lieten (2012)).

Additionally, in the Netherlands, not only field propagation such as fresh bare-root plants, waiting bed plants, and cold stored runner plants, but also substrate propagation such as plugplants and trayplants are used. Substrate propagation is effective in preventing infection of runners by soilborne pathogens by planting mother plants in containers 2 to 3 meters above the ground. Substrate propagation technology is expected to become more sophisticated in the future. Technological improvements will mainly be in the production of marketable runners and improvements in plant morphology. The Netherlands strawberry nursery industry aims to isolate nurseries from production fields and shorten the transfer time of disease-free plants from nurseries to fruit producers to less than one year in order to minimize risks of pest and diseases

(Lieten (2012)). However, the Netherlands strawberry nursery industry does not insist on the controlled environment for all processes of plants production. In order for a new cultivar to be selected in the Netherlands, a high level of inspection and certification is required. In this process, certification is required through complete natural propagation, not propagation through a controlled environment. This is different from most other countries that are certified through micropropagation (Lieten (2012)).

In the US, there have been various attempts to apply CE technology in the strawberry nursery industry. Some previous studies have shown how CE technology could be implemented in the strawberry nursery industry. Shi, Hernández, and Hoffmann (2021b) proved that adjusting runner removal intervals through a controlled environment improved optimal production of daughter plants. Xu and Hernandez (2020) found that optimizing the light intensity using a precision indoor propagation (PIP) system had a significant impact on improving plant growth and reducing propagation cost. They revealed that propagation of strawberry plants in a controlled environment could address some challenges of conventional strawberry propagation. Also, CE has been used to identify factors to affect flower production. Shi, Hernández, and Hoffmann (2021a) revealed how fertilizer solutions affected production of flower and daughter plant using an experiment in a greenhouse container system.

Although the application of CE technology in the California strawberry nursery industry lags somewhat compared to Europe, this does not mean that CE technology is not used at all. CE is used in some ways at the top of the supply chain of strawberry nursery industry in California. For instance, controlling the quality of plants in a screen house is a form of CE technology. The future task will be to discover parts of the supply chain of the strawberry nursery industry that can improve productivity and quality of plants through the introduction of CE technology and study the effects and problems that may arise in this process.

2.6. Opportunities and Challenges of CE in the CA Nursery Industry

Currently, CE technology is of limited use in the early stages of the strawberry nursery industry supply chain, but applications are expected in more phases of the supply chain. For instance, CE technology could be applied in the propagation stage. A research project has been conducted to make an innovation of strawberry plant propagation through CE systems such as indoor farms and greenhouses.[17] It is expected that the use of CE technology in the propagation stage could increase propagation rate and improve propagation uniformity (USDA Current Research Information System). Another important benefit of CE technology is to reduce the risk of disease. Strawberry production is exposed to the risk of pests and diseases. This is evidenced by the fact that strawberries are the most agrochemical-intensive crop of all crops grown in California. Even without soil fumigants, strawberries have the highest pesticide residues of any fresh fruit or vegetable (Guthman (2019)). Strawberry production is sensitive to various environmental factors such as temperature, humidity, solar irradiance, etc (Li et al. (2010); Palencia et al. (2013); Pathak et al. (2016)). In addition to the direct damage caused by weather conditions such as flooding to strawberry plants, temperature and humidity can also damage strawberry production through causing plant disease. Some strawberry diseases are promoted by high temperatures, low temperatures, and humidity. For instance, warm dry weather causes mite infestations and powdery mildew occurs in warm weather (Elias, Anderson et al. (2015)). Fungicide cannot be a perfect solution to control disease and pest problems. Only a small part of

[17] https://units.cals.ncsu.edu/cea/research/

it can be controlled through scientists' technology. Much of strawberry production is beyond the realm of scientists (Guthman (2019)). In addition, one of the difficulties of using a fungicide is timing. Fungicide application in appropriate timing might be a challenge for strawberry growers when weather changes quickly. Using fungicide at the wrong time leads to additional labor and chemical costs (Hsu-Flanders, Gallagher, and Wilson (2019)). Currently, pests and diseases that can occur during the production of strawberry plants are being controlled through the use of MB, but it is time to prepare for the potential phase-out of MB. Propagation through CE technology can be an effective alternative that can reduce dependence on MB. In the long term, if the adoption of CE technology by nursery partners increases, it is expected that the occurrence of diseases during strawberry production can be significantly reduced (USDA Current Research Information System).

Another potential opportunity of CE technology is that it minimizes risks of weather variation. Strawberries are one of the fruits that are sensitive to climatic conditions. In California, strawberries are produced year-round due to favorable climatic conditions for strawberry production, but in most regions of the world, strawberries are a fruit that can only be produced for a few weeks in late spring (Guthman (2019)). Strawberry production can vary greatly depending on the environment, such as temperature, precipitation, solar radiation, wind, air pollution, and carbon dioxide (CO_2). As weather changes become more severe, strawberry growers face greater uncertainty when making decisions related to strawberry production. The bigger problem is that strawberry growers are unaware of the extent to which weather risks affect their strawberry production and what strategies are needed to reduce risks (Morton et al. (2017)). Furthermore, in the field of horticulture, it has already been confirmed that strawberry mother plants are greatly affected by light or nutrition controlled through CE. This means that strawberries are very suitable candidates for CE propagation (USDA Current Research Information System). Therefore, if favorable environmental conditions for strawberry production can be maintained through CE technology, it is expected that the strawberry nursery industry will be able to minimize risks due to weather fluctuations and achieve stable production.

However, potential difficulties exist in introducing CE technology at the propagation stage. First of all, in order to maximize propagation yield and increase affordability, more research should be conducted on how strawberry plants respond to changes in various factors such as light, CO_2, photoperiod, temperature, substrate, nutrition and systems on propagation yields. Since the success of the strawberry industry largely depends on whether high-quality plant materials can be supplied, more studies will be needed on how to control the environment for plant production.[18]

Also, the cost issue cannot be overlooked. In the long run, application of CE technology may be more cost-effective than the conventional open-field system. It is expected that costs such as infrastructure, equipment, labor and transportation due to multi-year and multi-location supply chain can be reduced in the long term (USDA Current Research Information System). However, initially, the cost of constructing a green house or indoor system and research costs to investigate an effective CE technology will be required. In general, CE production requires investment and high operation cost. For instance, establishing a CE hydroponics vegetation operation requires 10 million dollars of investment.[19] This cost problem might be a challenge for the introduction of CE technology in the strawberry nursery industry. There has not yet been active research on how much cost the introduction of CE technology will incur in the strawberry

[18] https://units.cals.ncsu.edu/cea/research/
[19] Controlled Environment Agriculture Market – Forecast (2023 to 2029) (maximizemarketresearch.com)

nursery industry. In order to emphasize the need to introduce CE technology, a careful investigation of costs will be needed.

Additionally, securing skilled labor is also one of the expected difficulties. In order to increase the effectiveness of CE technology, personnel who have a high understanding of the technology and can operate the facility are required. To achieve this, training in the use of CE technology will be needed, which can be a potential barrier to the introduction of CE technology.[20]

2.7. Conclusion

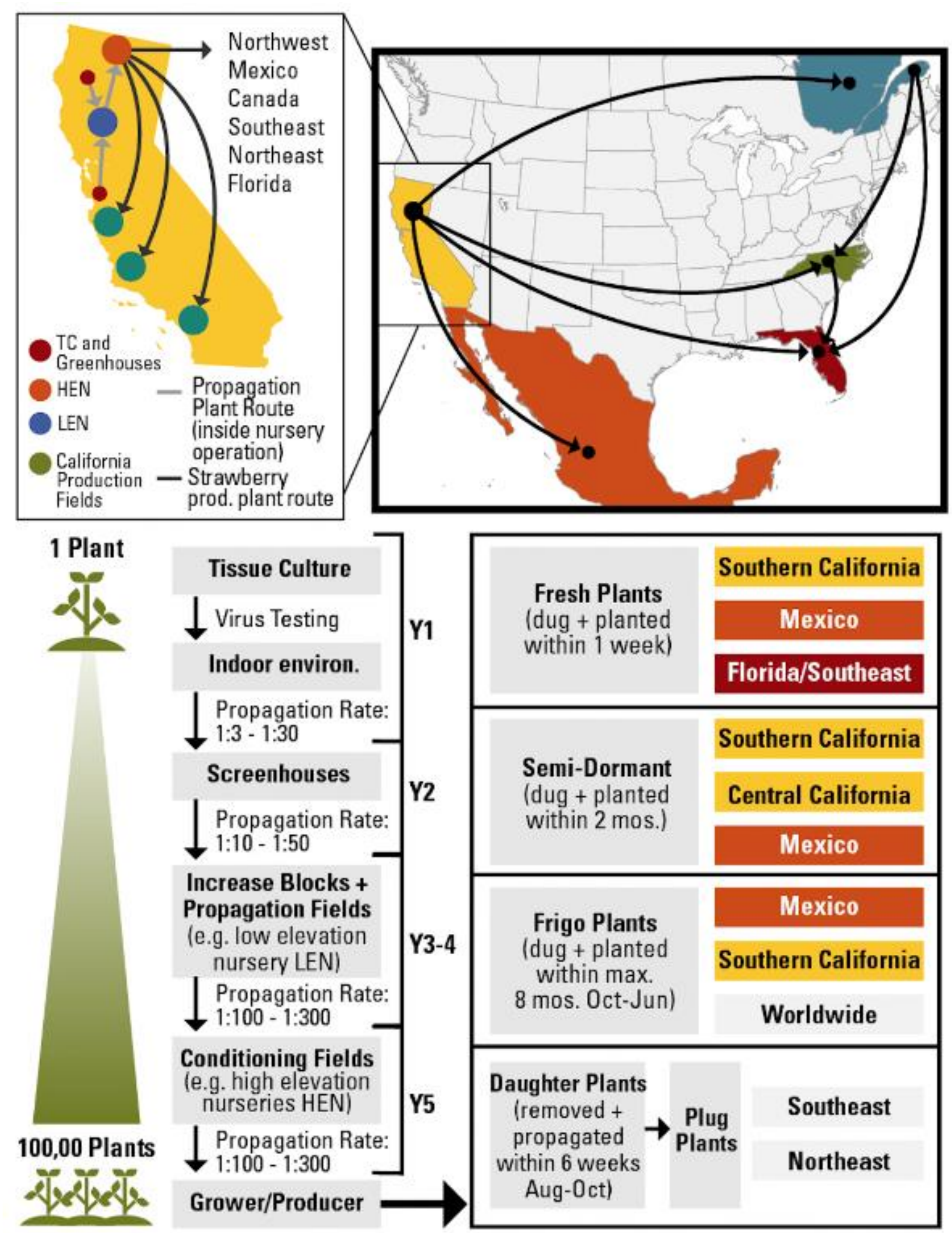
Most of the strawberries in the United States are produced in California, and nursery plants are one of the essential inputs for strawberry production. Virtually all the strawberry plants in California are produced in an open-field nursery system. The conventional propagation process is multi-year and multi-location. This characteristic of the nursery process leads to several problems including risk of disease and high cost. Moreover, the potential phase-out of Methyl Bromide might be a threat to the California strawberry nursery industry. Given this situation, applying controlled environment technology to the nursery industry is considered as an alternative to the conventional propagation system. Thus, examining the opportunities and challenges of CE in the California nursery industry is important. However, there is very limited economics research on the California strawberry nursery industry. This paper aims to collect and organize the limited information about the industry and to suggest the potential opportunities and challenges of applying CE to the industry. We adopt a case-study approach to explain the results qualitatively.

[20] Controlled Environment Agriculture Market – Forecast (2023 to 2029) (maximizemarketresearch.com)

Other crops and vegetables such as potatoes, tomatoes, carrots, and lettuce have already been applied CE technology to their production process to achieve high quality products. There have been efforts to apply CE technology in the strawberry nursery industry as well. In particular, the European strawberry nursery industry has been using CE technology, especially in the Netherlands. In the California strawberry nursery industry, research is continuously being conducted to develop and introduce CE technology, and some CE technology is being applied in the early stages of the supply chain. However, there is still room for CE technology to be introduced in more parts of the strawberry nursery process. For instance, CE technology could be used in the propagation phase. A higher propagation rate and improved propagation uniformity could be achieved through strawberry plant propagation using indoor farms and greenhouses. Also, CE technology in the propagation stage could reduce risks of plant diseases and weather variations. However, there could be challenges using CE technology such as examination on the effects of controls of environmental factors, high initial investment costs on infrastructure, and requirement of skilled labor to operate CE facilities.

Economics research on the California strawberry nursery industry has not been conducted actively so far. There are still unknown parts for the strawberry nursery industry. Especially, quantitative information on costs and benefits of introducing CE technology is not revealed yet. More research examining the economics of CE technology in the strawberry nursery industry will be needed to overcome existing problems in the industry.

Figure 2.1. The Strawberry Nursery Process in the US



Source: https://strawberries-pip.cals.ncsu.edu/

CHAPTER 3

The Welfare Effects of Controlled Environment Propagation in the Strawberry Nursery Industry

3.1. Introduction

3.1.1. Strawberry Nursery Industry

The supply chain of strawberry industry from seed planting to consumer's table goes through several stages. The nursery industry spans the first few steps of the entire strawberry supply chain. In the strawberry industry, fruit growers usually receive strawberry seedlings from a nursery and transplant them rather than propagating them by themselves (Hsu-Flanders, Gallagher, and Wilson (2019)). The pre-production stage, a stage from nursery to fruit growers, is crucial for the strawberry production process. There are lots of inputs in the strawberry production process. Strawberry plant is one of the irreplaceable inputs for strawberry fruit production. Most of strawberry growers in the United States depend on strawberry plant from limited nurseries in California, North Carolina, Canada, etc. Strawberry plant is produced through strawberry nursery propagation system. The strawberry nursery process begins with tissue culture, and it goes through screenhouse, propagation fields, conditioning fields, etc. The plants are finally sold to strawberry fruit growers. The strawberry nursery system is a highly complex process. The whole process from tissue culture to fruit growers usually takes about 5 years and the plants are moved to multiple locations during the process. Strawberry nursery is a significant market not only as an input for strawberries, but also as an industry itself. Strawberry nurseries in the United States produce more than a billion plants every year, and they generate an additional 200-300 million dollars to the strawberry farm gate value (USDA Current Research

Information System).[21] The current production system of strawberry plants is as open-field nurseries. Strawberry growers produce the fruit all year-round using the plants provided from nurseries. Most of the strawberries produced in California are shipped to other states.

Unlike the active research for the strawberry fruit, there is very limited published research for the strawberry nursery industry. Limited information about the strawberry nursery industry exists in the European country case. Martínez-Treceño et al. (2009) investigated the strawberry nursery industry in Spain. They presented a brief explanation of strawberry nursery production and the strawberry cultivar registration process in Spain. Lieten (2012) examined the strawberry nursery industry in the Netherlands. Cultivars, certification, pest and disease control, propagation process of strawberry nursery in the Netherlands are presented. However, there is very limited published information similar to the upper studies for North America. Impacts of CE technology on welfare gains in the US strawberry nursery industry is unknown with the information gap between strawberry fruit and strawberry nursery, also, the information gap between Europe and North America. Also, although those two studies examined the European strawberry nursery industry, they did not analyze the welfare effects of new technologies. In this respect, our study can be a novel contribution.

Although the strawberry nursery is an essential input in strawberry fruit production, the nursery industry is encountering several constraints. First, the strawberry nursery industry requires a specific geographic condition. Plants are needed to move to multiple locations during the multi-year nursery process under the current open field propagation system. This leads to a significant cost. Second, the strawberry nursery industry is relying on disease-free plants. Propagation material of strawberry plants can be a symptomless carrier of plant pathogens and

[21] https://cris.nifa.usda.gov/cgi-bin/starfinder/0?path=fastlink1.txt&id=anon&pass=&search=R=94312&format=WEBLINK

pests.[22] It might not be discovered at the nursery inspection stage but might be later discovered during the fruit production process after the plants are delivered to growers. Third, relying on Methyl Bromide (MB) is also a constraint of strawberry nursery industry. MB is an odorless, colorless gas used to control a wide variety of pests in agriculture and shipping, including fungi, weeds, insects, nematodes (or roundworms), and rodents (United States Environmental Protection Agency (EPA)).[23] In the strawberry industry, MB was used as a major tool to combat diseases. Fumigation with a combination of chloropicrin and methyl bromide lead to a significant increase of strawberry productivity in 1960s by controlling Verticillium wilt (Guthman (2019)). However, MB was recognized as a public health threat which potentially causes skin cancer through ozone depletion. Montreal Protocol in 1991 mandated the phaseout of methyl bromide. The United States agreed to stop producing and importing MB by 2005 (Guthman (2019)). However, unlike the strawberry industry where the use of MB is prohibited, strawberry nurseries have avoided phase-out under the 'quarantine pre-shipment exemption'. Thus, in the nursery industry, MB has been used during the plant propagation process in both screen house and open fields (Guthman (2019)). However, if MB has been phased-out, this, combined with the frequent emergence of new nursery-borne pathogens and the increasing resistance of major pathogens to pesticides, can pose a serious risk to strawberry supply chain resilience (USDA Current Research Information System). Therefore, the nursery industry will need to devise a cost-effective and environmentally acceptable alternative to MB in preparation for potential stricter regulation of fumigants.

As a solution to this problem, the strawberry nursery industry began to take interest in Controlled Environment (CE) technology. There have been remarkable technological leaps in the

[22] https://strawberries-pip.cals.ncsu.edu/
[23] https://www.epa.gov/ods-phaseout/methyl-bromide

field of CE technology, such as greenhouses and precise indoor propagation systems, over the past decade (USDA Current Research Information System). It enables to produce disease-free plants year-round by controlling environmental factors such as light, temperature, and CO_2. As a result, it presents a possible solution to existing problems in the strawberry nursery industry by reducing costs incurred due to multiple nursery locations, improving propagation rates, and improving uniformity in the propagation and fruiting processes. Above all, the biggest promise of the new technology is that a stable amount of plants can be produced free from external climatic environmental factors and disease threats. In contrast to Europe, US CE is still in the early research stages. Many aspects, including costs, benefits, quality, and scale, have not yet been closely studied.

This study evaluates the welfare impacts of an improvement in the CE technology on the industry. Specifically, we investigate changes in producer and consumer surplus in the strawberry nursery and fruit industry when there is a shift in CE plants supply using an Equilibrium Displacement Model (EDM) framework.[24] EDMs are logarithmic differential equations explaining a movement in market equilibrium resulting from a change in one or more of the parameters of the equation system (Wohlgenant (2011)). To construct the EDM, parameters are obtained and assumed through existing data and previous literature.

Under the EDM framework, structural equations are constructed to describe each market stage. We derive changes in market equilibrium in each stage by taking logarithmic

[24] We focus on the California strawberry nursery industry. Since strawberry production in California accounts for the majority of all strawberry production in the United States, it is meaningful to specify the scope of the study to California. According to the USDA National Agricultural Statistics Service data, based in 2022, acres harvested of strawberry in California was 79.8% of total acres harvested of strawberry in the US. Production measured in CWT, production measured in dollar of strawberry in California were 89.1% and 84.0%, respectively, of total strawberry in the US.

approximation of the structural equations, and the calculated changes in market equilibrium are used to estimate the welfare effects.

3.1.2. Literature Review

EDM is an appropriate methodology to evaluate the impact of CE technology. There have been many studies that used EDM to evaluate specific policy effects. Muth (1964) is one of the pioneering studies in the EDM approach. Muth (1964) was the first attempt to construct reduced form for a system of supply and demand functions. Muth's model describes how exogenous supply and demand shifters lead to a relative change in equilibrium of single-product two-factors market. Gardner (1975) applied Muth's framework to examine how the farm-retail price spread responded to changes in supply and demand in food industry. After early attempts to study the EDM, studies were actively attempted to analyze how government policies affect the market using the EDM framework. Perrin and Scobie (1981) estimated the effects of market intervention policies on nutrient intake of low-income households in Colombia using EDM. They calculated percentage change in calorie consumption in response to different food market policies such as subsidy and direct income transfer. Sumner and Wohlgenant (1985) examined the impacts of a cigarette tax increase on the cigarette and tobacco industries using the EDM. They simulated quantitative effects of a change in cigarette tax on the domestic market price, quantities, revenue, and producers' economic rents. Lusk and Anderson (2004) examined the effects of Country-of-Origin Labeling (COOL) on meat industry using EDM. They simulated changes in market equilibrium and economic surplus in beef and pork industry resulting from COOL. Keller, Boland, and Çakır (2022) evaluated the impacts of an increase in the federal or state minimum wage on the egg industry using EDM. A two-output (table eggs and processed eggs) and three-input (hens, labor, and all other inputs) model was constructed to represent the Iowa egg industry. Zhai and Kuusela (2022) estimated the welfare effects of export tax and subsidies in log and lumber markets in Oregon using EDM. They constructed equations representing the vertical linkages between lumber production (output) and the market for two input factors, logs and processing services.

EDM has been widely used in the field of agricultural economics. Perrin (1980) examined the impacts of component pricing on soybeans and milk industry using EDM. He estimated percentage equilibrium displacement from component pricing of soybeans and milk. Lemieux and Wohlgenant (1989) evaluated the impacts of biotechnology on the U.S. port industry using EDM. They estimated changes in market equilibrium and economic surplus of pork industry due to adoption of Porcine Somatotropin by different adoption rates and lengths of run for supply and demand shifts. Gotsch and Burger (2001) was one of the attempts to reflect the biological characteristics of agricultural commodity to the model. They assessed the welfare effects of technical change in relation to a perennial crop. They addressed dynamic aspects of supply responses. To reflect the biological characteristics of perennial crops, they suggested the vintage model to represent the distribution of tree age. Jiang, Cassey, and Marsh (2017) constructed the dynamic EDM framework which explained the intermediaries within the industry. They simulated welfare from various shocks for the U.S pear industry. Their model covered the tree fruit packing and processing intermediaries.

To the best of our knowledge, no study has examined the impact of CE technology on the welfare in the strawberry nursery industry. Of course, research related to strawberry fruit has been actively conducted. Several studies have analyzed the demand for strawberries (You, Epperson, and Huang (1996); You, Epperson, and Huang (1998); Lin et al. (2009); Sobekova, Thomsen, and Ahrendsen (2013)). Also, studies on consumer food safety have been conducted for the strawberries (Henneberry, Piewthongngam, and Qiang (1999); Richards and Patterson (1999)). In addition, there are several studies that have analyzed the impact of banning MB on the strawberry industry (Carter et al. (2005); Norman (2005)).

The rest of this study is organized as follows. Section 2 outlines the EDM conceptual framework to describe the multi-stage strawberry nursery market. Parameters for the estimates of welfare effects and the process for calculating them are presented in Section 3. Section 4 provides changes in economic surplus of producers and consumer in each different stage. Results of sensitivity analysis are reported in Section 5. Conclusion is discussed in the last section.

3.2. Model Framework

The EDM began with the concept of elasticity. Allen (1938) and Hicks (1963) firstly expressed in quantitative terms of the elasticity by the industry-derived demand for a factor. Afterwards, the concept of total elasticity was first introduced to agricultural economics by Buse (1958). Based on the concept of elasticity, Muth (1964) firstly discussed the reduced form for a supply and demand system and exogenous shifts. Gardner (1975) studied implications of shifts in supply and demand using Muth's framework (Wohlgenant (2011)). Since then, a wide variety of studies using EDM have been conducted in the field of agricultural economics.

3.2.1. Equilibrium Displacement Model (EDM)

Equilibrium Displacement Model (EDM), also termed linear elasticity models, is a widely used technique to estimate changes in prices and quantities resulting from exogenous shocks. We can calculate consequent changes in endogenous variables from exogenous shocks for a given set of demand and supply, and elasticity of substitution of inputs and factor shares using EDM. EDM is also widely used to estimate changes in producer and consumer surplus arising from exogenous shocks and to quantify the impacts of shocks across multiple markets (Brester, Atwood, and Boland (2023)). EDM enables researchers to use estimated elasticities from existing studies without re-estimating all the equations. This allows researchers to focus on policy implications of the model rather than concerning about functional forms and data availability (Wohlgenant (2011)).

Estimation of changes in economic surplus through EDM can be explained by three steps. First, we construct structural equations to describe supply and demand of each market stage. Second, we derive elasticity form equations by taking total differentials of structural equations. Lastly, we calculate changes in market equilibrium by solving the simultaneous equation system of elasticity form equations. For this new equilibrium, the changes in producer and consumer surplus are calculated.

The example below, adapted from Wohlgenant (2011), explains how to calculate producer and consumer surplus using EDM.

Suppose the simplest EDM example in the form of a single input with one market. First, assume that linear demand and supply equations are given by equation 1 and 2 where P is price of good, ϵ_D and ϵ_S represent shifters in demand and supply, respectively.

$$Q_D = f(P; \epsilon_D) \tag{1}$$

$$Q_S = g(P; \epsilon_S) \tag{2}$$

Structural equations for supply and demand can be converted into the elasticity form equations. Equation 3 represents a relative change in demand where E is relative change (e.g., $EQ = \Delta Q/Q \cong \Delta\log(Q)$), η is the price elasticity of demand, and δ is relative change in demand due to any exogenous shock other than own price change ($\delta = \gamma_{Q_d\epsilon_D} E\epsilon_D$ where $\gamma_{Q_d\epsilon_D}$ is elasticity of demand with respect to ϵ_D). Equation 4 is a relative change in supply where ε is the price elasticity of supply, and k is the relative change in supply due to any exogenous shock other than own price change ($k = \gamma_{Q_S\epsilon_S} E\epsilon_S$ where $\gamma_{Q_S\epsilon_S}$ is elasticity of supply with respect to ϵ_S).

$$EQ_D = \eta EP + \delta \tag{3}$$

$$EQ_S = \varepsilon EP + k \tag{4}$$

Since $Q_D = Q_S$ at the equilibrium, $EQ_D = EQ_S$. Then, relative changes in market price (EP) and market quantity (EQ) can be obtained by using equation 3 and 4 as follows.

$$EP = \frac{\delta - k}{\varepsilon - \eta} \tag{5}$$

$$EQ = \frac{\varepsilon\delta - \eta k}{\varepsilon - \eta} \tag{6}$$

For given value of initial price (P_0) and quantity (Q_0), changes in consumer and producer surplus can be calculated using equation 7 and 8 as below.[25] We assumed linear supply and demand equations and parallel shift of supply and demand curves.

$$\begin{aligned} \Delta CS &= AREA\ (ABP_1F) \\ &= -(\Delta P - \delta P_0)(Q_0 + 0.5\Delta Q) \qquad (7) \\ &= -P_0 Q_0 (EP - \delta)(1 + 0.5EQ) \end{aligned}$$

$$\begin{aligned} \Delta PS &= AREA\ (P_1FCG) \\ &= -(\Delta P - kP_0)(Q_0 + 0.5\Delta Q) \qquad (8) \\ &= -P_0 Q_0 (EP - k)(1 + 0.5EQ) \end{aligned}$$

[25] Shifts in supply-demand are depicted in Figure 3.3.

This is the simplest example of EDM structure. We may develop more complex structural equations based on this conceptual framework to reflect the real market. For example, more structural equations will be needed if there are multiple market stages (Wohlgenant (1993)). Also, alternative formulas will be needed to calculate changes in producer and consumer surplus if we relax linear demand and supply equations and parallel shifts (Zhao, Mullen, and Griffith (2005)).

3.2.2. Multi-Stage Markets Framework

Initial EDM model framework by Muth (1964) began with a single stage model. Changes in market equilibrium of a single stage with a single output and two input factors were studied using the system of supply and demand equations. However, a series of processes organized by different sets of decision makers are required in modern agriculture (Freebairn, Davis, and Edwards (1982)). Holloway (1989) pointed out that a single stage has a limitation to represent the sequential nature of agrimarketing operations. For this reason, multistage production system has been widely used to describe a specific industry in agricultural field. Multiple market stages such as input supply stage, farm stage, marketing stage, processing stage, and distribution stage have been applied in several previous literature using EDM framework (Freebairn, Davis, and Edwards (1982); Holloway (1989)). Our model is also based on a multi-stage market framework. The strawberry industry is a market that has multiple stages including nursery market stage, fruit market stage, and retail market stage. Additionally, it is meaningful to estimate how the welfare of stakeholders at each stage changes due to the introduction of CE technology. This is a reason why our study models a multi-stage market framework.

Indeed, research on the distribution of welfare gains in multi-stage markets has been actively discussed. Freebairn, Davis, and Edwards (1982) examined the effects of research on economic surplus in a multistage agricultural production system. Alston and Scobie (1983) added comments to Freebairn, Davis, and Edwards (1982) that elasticities of factor substitution is important in determining the distribution of research benefits between the stages. Holloway (1989) presented a multi-stage production framework by disaggregating Muth's single-stage model into two sequential stages: 'processing' and 'distribution'. Multiple inputs in multiple market stages are assumed to be substitutable. Wohlgenant (1993) analyzed distribution of gains from research and promotion in the U.S. beef and pork industries. He found that producer gains from research on farm-level production would be larger than benefits from research on marketing services and promotion. Chung and Kaiser (1998) pointed out that the results from Wohlgenant (1993) were limited to the case of parallel shifts in demand and supply. They revealed that producers would benefit more from promotion than research under the assumption of pivotal shift.

3.2.3. Assumptions for Modeling the Strawberry Nursery Industry

We construct a multi-stage markets framework to describe the strawberry nursery and fruit industry. Our model follows Holloway (1989) in that the output of the previous market stage becomes the input to the next market stage, and substitutability exists between the inputs of each market. To construct a multi-stage model, several assumptions are required. First, we abstract away from several important details of the long-run supply responses and models it with a net supply. Gotsch and Burger (2001) examined a dynamic supply response and welfare effects of technological change on perennial crops. They took into account changes in trees and cultivated areas to measure the effects of new planting material. However, our paper is not incorporating modeling details explicitly as Gotsch and Burger (2001) did. For instance, it is hard to define what the length of run we are referring to is, because true supply elasticity is unknown. Thus, since we don't know short- and long-run elasticity of supply, we use essentially a net supply response elasticity. Second, we assume that the marginal cost of CE technology is higher than that of the field system. Although there are some benefits including lower disease risk, lower weather risk, and potentially lower labor requirement, the marginal cost of CE plants is higher than the existing system at the transition as CE becomes the early to medium stages of its adoption by the industry. Our welfare analysis examines changes in surplus if the marginal cost of CE were to be lowered. If CE technology matured, the cost of CE plants lowered which causes a shift in supply of CE nursery plants.[26] Third, we assume homogeneous fruits. Our model does not consider different cultivars of strawberries. In our model, fruit growers produce identical strawberries, and retailers purchase the identical strawberries. This might be a strong assumption. California strawberry growers produce various cultivars such as Albion, Camarosa, Monterey, etc. The impacts of adopting new technology might vary depending on different cultivars. However, the purpose of our study is to measure the changes in producer and consumer surplus for the entire strawberry nursery and fruit industry rather than by cultivars. Therefore, homogeneous fruit assumption might be useful to make a simpler model and calculation process. Fourth, we assume that the intermediary markets are perfectly competitive. That is, we assume that there are many strawberry fruit growers and retailers in the strawberry industry. It might not be a very strong assumption. Because, according to California Strawberry Commission, there are

[26] Our model does not consider fixed costs explicitly. In the welfare measurement for the producer, the fixed costs are regarded as sunken costs. For instance, a farm rents land and pays a rental fee at the beginning of the season. That rents will not be affected by any policy changes imposed on the producer (Just, Hueth, and Schmitz (2005)).

approximately 300 strawberry growers in California. Also, although the exact number is not known, it is reasonable that there are numerous retailers supplying strawberries retail products throughout the United States.

We assume that the strawberry nursery and fruit industry is a form of a multi-stage market as depicted in Figure 3.4. There are three different stages in the model. Stage 1 is nursery plant market. Nursery plant producers produce the strawberry plants and supply them to the fruit growers. Stage 2 is strawberry fruit market. Strawberry growers produce the fruit using nursery plants from the stage 1 and supply the fruit to retailers. The assumptions of stages 1 and 2 are based on what the actual strawberry industry looks like. Strawberry fruit growers receive strawberry seedlings from a nursery and transplant them rather than doing the propagation themselves. (Hsu-Flanders, Gallagher, and Wilson (2019)) Stage 3 is retail market. Retailers produce retail products using the fruit from stage 2 and supply the retail products to consumers. Assumption of stage 3 may reflect the real strawberry industry. Usually, strawberry growers do not sell the fruits to consumers directly. As many previous studies have revealed (Kelly et al. (2019); Parajuli, Matlock, and Thoma (2022); Baghizadeh et al. (2022)), there is a retail stage between fruit growers and consumers in the strawberry industry. Growers and shippers are distinct in the California strawberry industry. It is true that historically, many of the shippers are originated from growers' cooperatives. However, they have become separate market stages. Because marketing is a distinct task from farming, typically, it is not easy for growers to have marketing capabilities. Strawberries are moved to distant markets with dedicated cooling, packing, and shipping facilities to address issues of fragility and perishability. It is more economical for retailers, rather than growers, to take charge of this process. (Guthman (2019))

The important idea in our model is the quality differentiation of nursery plants. The main hypothesis in our model is that the nursery plants using CE technology have different quality with different cost. We assume that there are two types of nursery firms in stage 1. Type 1 is a group of nursery firms that use traditional field propagation methods. Type 2 is a group of nursery firms that use controlled environment propagation technologies. Type 1 and type 2 nursery firms produce different types of plants. Thus, fruit growers have two different types of inputs. The two inputs are not identical and not perfect substitutes.

The purpose of our model is to estimate the change in consumer and producer surplus when there is an exogenous shock in the strawberry plant supply. Especially, our model targets to measure 1) change in surplus of type 1 nursery plant at stage 1, 2) change in surplus of type 2 nursery plants at stage 2, 3) change in consumer surplus at the last stage, and 4) change in total surplus. Our model follows the multi-stage market framework, however, there is no need to compute any surplus in the intermediary stages because of zero profit condition from perfectly competitive intermediary market assumption. This might be a limitation of our model. We may extend the logic to cases where there are imperfect competitions in the intermediary market stages. As Brester, Atwood, and Boland (2023) pointed out, higher output prices, lower input prices, and reduced quantity produced are resulted if an output market is imperfectly competitive. The effects of imperfect competition can be measured by a wedge between consumer and producer prices in the output market. However, from another perspective, even assuming a perfectly competitive intermediary market, there may not be a significant difference in estimated welfare effects compared to the case with existence of market power. Wohlgenant and Piggott (2003) examined the distribution of gains from research and promotion when market intermediaries have market power in the retail market. They revealed that the results with market power are indistinguishable from those obtained under perfect competition. Rather, input substitutability was more important to affect the distribution of gains. If we can apply this logic to our model, even if we assume that strawberry fruit industry is perfectly competitive, the estimated welfare changes in producer and consumer surplus might not be much affected by the assumption. Also, there are many strawberry fruit growers and retailers in California and in the US, which might support the assumption.

3.2.4. Structural Model

We construct the structural equations to describe the strawberry nursery markets. Since there are four different markets (input 1, input 2, stage 2, and stage 3), eight equations are specified: supply and demand for the nursery plants from type 1 (field plants), supply and demand for the nursery plants from type 2 (CE plants), supply and demand for the strawberry fruit, and supply and demand for the retail products.

$$P_{N1} = S_{N1}(Q_{N1}, \epsilon_{SN1}) \tag{9}$$

$$P_{N1} = P_F g_{N1}(Q_{N1}, Q_{N2}, \epsilon_{SF}) \tag{10}$$

Equations 9 and 10 represent inverse supply of type 1 nursery plants and inverse derived demand of type 1 nursery plants respectively, where P_{N1} is price of nursery plants of type 1, Q_{N1} is a production of nursery plants of type 1, and ϵ_{SN1} is supply shift in type 1 nursery plants, P_F is price of strawberry fruit, g_{N1} is marginal products of inputs(nursery plants from type 1) in the production of strawberry fruit, Q_{N2} is a production of nursery plants of type 2, and ϵ_{SF} is supply shift in strawberry fruit.

$$P_{N2} = S_{N2}(Q_{N2}, \epsilon_{SN2}) \tag{11}$$

$$P_{N2} = P_F g_{N2}(Q_{N1}, Q_{N2}, \epsilon_{SF}) \tag{12}$$

Equations 11 and 12 are inverse supply of type 2 nursery plants and inverse derived demand of type 2 nursery plants respectively, where P_{N2} is price of nursery plants of type 2, ϵ_{SN2} is supply shift in type 2 nursery plants, and g_{N2} is marginal products of inputs(nursery plants from type 2) in the production of strawberry fruit.

$$Q_F = g(Q_{N1}, Q_{N2}, \epsilon_{SF}) \tag{13}$$

$$P_F = P_R f_F(Q_F, \epsilon_{SR}) \tag{14}$$

Equations 13 and 14 indicate supply of strawberry fruit and inverse derived demand of strawberry fruit respectively, where Q_F is quantity produced of strawberry fruit, P_R is price of strawberry retail products, f_F is marginal product of strawberry fruit in the production of retail products, and ϵ_{SR} is production function shifter in the retail production.

$$Q_R = f(Q_F, \epsilon_{SR}) \tag{15}$$

$$Q_R = D_R(P_R, \epsilon_D) \tag{16}$$

Equations 15 and 16 are supply and demand of retail products where Q_R is quantity produced (demanded) of retail products and ϵ_D is retail demand shifter. Eight structural equations from 9 to 16 can be converted into elasticity form equations by taking log differential where $*$ represents percentage change. (i.e., $x^* = \frac{dx}{x}$)

$$P_{N1}^* = \frac{1}{\eta_{N1}} Q_{N1}^* + \gamma_{P_{N1}\epsilon_{SN1}} \epsilon_{SN1}^* \tag{9.1}$$

$$P_{N1}^* = P_F^* + \frac{S_{N2}}{\sigma_F} Q_{N1}^* + \frac{S_{N2}}{\sigma_F} Q_{N2}^* + \gamma_{g_{N1}\epsilon_{SF}} \epsilon_{SF}^* \tag{10.1}$$

Equations 9.1 and 10.1 are elasticity form equations of 9 and 10 where η_{N1} is own price elasticity of supply of type 1 nursery plants, $\gamma_{P_{N1}\epsilon_{SN1}}$ is elasticity of supply of type 1 nursery plants with respect to supply shock in type 1 nursery plants (ϵ_{SN1}), S_{N2} is cost share of type 2 nursery plants, σ_F is elasticity of substitution between inputs (Q_{N1} andQ_{N2}) in the fruit production, and $\gamma_{g_{N1}\epsilon_{SF}}$ is elasticity of marginal product of type 1 nursery plants with respect to ϵ_{SF}.

$$P_{N2}^* = \frac{1}{\eta_{N2}} Q_{N2}^* + \gamma_{P_{N2}\epsilon_{SN2}} \epsilon_{SN2}^* \tag{11.1}$$

$$P_{N2}^* = P_F^* + \frac{S_{N1}}{\sigma_F} Q_{N1}^* + \frac{S_{N1}}{\sigma_F} Q_{N2}^* + \gamma_{g_{N2}\epsilon_{SF}} \epsilon_{SF}^* \tag{12.1}$$

Equations 11.1 and 12.1 represent elasticity form equations of 11 and 12 where η_{N2} is own price elasticity of type 2 nursery plants supply, $\gamma_{P_{N2}\epsilon_{SN2}}$ is elasticity of supply of type 2 nursery plants with respect to supply shock in type 2 nursery plants (ϵ_{SN2}), S_{N1} is cost share of type 1 nursery plants, and $\gamma_{g_{N2}\epsilon_{SF}}$ is elasticity of marginal product of type 2 nursery plants with respect to ϵ_{SF}.

$$Q_F^* = S_{N1} Q_{N1}^* + S_{N2} Q_{N2}^* + \gamma_{Q_F\epsilon_{SF}} \epsilon_{SF}^* \tag{13.1}$$

$$P_F^* = P_R^* + \gamma_{f_F Q_F} Q_F^* + \gamma_{f_F\epsilon_{SR}} \epsilon_{SR}^* \tag{14.1}$$

Equations 13.1 and 14.1 are elasticity form equations of 13 and 14 where $\gamma_{Q_F\epsilon_{SF}}$ is elasticity of fruit supply (Q_F) with respect to ϵ_{SF}, $\gamma_{f_F Q_F}$ is inverse elasticity of fruit demand (Q_F) with respect to marginal product of fruit (f_F), and $\gamma_{f_F\epsilon_{SR}}$ is elasticity of marginal product of fruit (f_F) with respect to ϵ_{SR}.

$$Q_R^* = S_F Q_F^* + \gamma_{Q_R\epsilon_{SR}} \epsilon_{SR}^* \tag{15.1}$$

$$Q_R^* = \eta_R P_R^* + \gamma_{Q_R\epsilon_D} \epsilon_D^* \tag{16.1}$$

Equations 15.1 and 16.1 represent elasticity form equations of 15 and 16 where S_F is cost share of fruit, $\gamma_{Q_R\epsilon_{SR}}$ is elasticity of retail products supply (Q_R) with respect to ϵ_{SR}, η_R is own price elasticity of retail products demand, and $\gamma_{Q_R\epsilon_D}$ is elasticity of retail demand (Q_R) with respect to ϵ_D.

3.3. Parameters in the Model

Since the results may vary depending on the values of parameters in EDM, choosing parameters is crucial to estimate precise results. The values of parameters are usually obtained in one of the three ways: (i) arbitrarily assumed; (ii) borrowed from existing studies; or (iii) estimated (Brester, Atwood, and Boland (2023)). There are many parameters in our model. Some of them are non-shock parameters which are exogenously determined whereas some are shock parameters which explain change in endogenous variables. Even in a situation where there was very little information on parameter values for the nursery industry, we specified parameter values or ranges based on reasonable inference and general problems in specialty crop supply.

Table 3.1 shows parameters in our model. η_{N1} and η_{N2} represent own price elasticity of type 1 and type 2 nursery plants, respectively. Since there is no information about price elasticity of nursery plants supply, we use supply elasticity of strawberry fruit as a proxy following the approach of Cembali et al. (2003). Supply elasticity of strawberry was estimated by Lohr and Park (1995). In their study, the short- and long-term supply elasticity of strawberries was estimated to be 0.32, 0.56, 1.59, and 0.68 depending on the estimation period. We adopt these estimates for η_{N1} and η_{N2}.

We need to know values of cost shares of nursery plants, S_{N1}, for the analysis. Seven strawberry production cost information over the past two decades were obtained from UC Davis Cost & Return Studies website.[27] We calculate the ratio of material cost related to plant among the total operating cost from each information. Cost share of field plants for the strawberry fruit production ranges from 0.051 to 0.093. We use these data as S_{N1}.

[27] https://coststudies.ucdavis.edu/archived/commodities/strawberries

Also, relative price of CE nursery plants compared to field nursery plants is needed to calculate the welfare changes. Relative price, α, is equal to $\frac{P_{N2}}{P_{N1}}$ by definition. Given the information on P_{N1}, we can get P_{N2} and S_{N2} using α. We assumed that the price of CE nursery plants is 100% to 300% of the price of field nursery plants. That is, the range of α is 1 to 3.

In our model, we assume that fruit growers choose a combination of field nursery plants and CE nursery plants to produce the strawberry fruit. Fruit growers prefer multiple sources of plants to reduce risk. The two inputs are substitutable by a specific rate. This may reflect the real strawberry industry. Because open field propagation and CE technology propagation are not completely separate. Fruit growers in California may choose both ways especially at the initial technology introduction stage. Estimates of economic surplus vary depending on the elasticity of substitution between two inputs (Q_{N1} and Q_{N2}) in the fruit production. We assume that elasticity of substitution (σ_F) is from 1 to 5 because the two inputs are not close to complementary goods.

To get the information on cost share of fruit (S_F), we collected the percentage of farm price over the retail price of strawberries in the past two decades from USDA ERS data.[28] From the dataset, we get the information that cost share of fruit ranges 0.31 to 0.45.

We also need to know own price elasticity of retail strawberry demand (η_R). We collect the elasticities from the literature; Ferguson and Padula (1994), You, Epperson, and Huang (1996), You, Epperson, and Huang (1998), Henneberry, Piewthongngam, and Qiang (1999), Richards and Patterson (1999), Tronstad (2008), Lin et al. (2009), and Sobekova, Thomsen, and Ahrendsen (2013). These eight studies estimated own price elasticity of U.S. strawberry demand using retail price. From the literature, we obtain the information that η_R is from -2.8 to -0.2753.

[28] https://www.ers.usda.gov/data-products/price-spreads-from-farm-to-consumer/

In addition, initial price and quantity of field nursery plants, CE plants, and retail product is needed. Using the information from the recent cost returns study by UC Davis, we obtain strawberry plant quantity per acre and trays produced per acre.[29] Given the information that 200 million trays are produced in a year, we can calculate the total acre. We then multiply strawberry plants quantity per acre by the total acre to calculate the total quantity of nursery plants.[30] Given the fact that total quantity of plants is fixed, we assume five different market penetration ratios, 10%, 20%, 30%, 40%, and 50%. That is, quantity of plants produced using CE technologies accounts for each percentage of total quantity of plants. Initial price of field nursery plants is 0.15 dollar per each plant.[31] We can get P_{N2} using P_{N1} and α by definition. Also, we find out initial market price (P_R) and quantity (Q_R) at the retail stage. Initial price of retail products (P_R) is 4.225 dollar per pound, which is from USDA data.[32] Initial quantity of retail products (Q_R) is 2,665 million pounds from USDA data.[33]

Lastly, the most important parameter, change in price of CE nursery plants caused by shift in CE nursery plants supply ($\gamma_{P_{N2}\epsilon_{SN2}}\epsilon^*_{SN2}$), is assumed to be 10% price reduction.

3.4. Welfare Effects

Before we discuss the welfare effects of CE technology, it is needed to clarify the concept of welfare. 'Welfare' in this study refers to economic surplus. The concept of 'economic surplus', invented and popularized by classical economists such as Dupuit and Marshall, has been used

[29] SAMPLE COSTS TO PRODUCE AND HARVEST STRAWBERRIES Central Coast Region - Santa Cruz & Monterey Counties – 2021
[30] The total quantity of nursery plants here is closer to the lower bound. Because it does not include the amount of plants transporting to Mexico, Florida, North Carolina, and Canada.
[31] SAMPLE COSTS TO PRODUCE AND HARVEST STRAWBERRIES Central Coast Region - Santa Cruz & Monterey Counties - 2021
[32] https://data.ers.usda.gov/reports.aspx?ID=17850
[33] https://www.ers.usda.gov/data-products/fruit-and-tree-nuts-data/fruit-and-tree-nuts-yearbook-tables/

and analyzed in a variety of ways in many subsequent studies. Boulding (1945), one of the classic studies that discussed the concept of economic surplus, defined consumer surplus as ‘the difference between the total amount actually paid by consumers (buyers) and the total amount which they would have been willing to pay’. In the same way, producer (seller) surplus can be defined as ‘the difference between the total amount that the sellers receive and the total amount which they would have been willing to sell’. If we assume a linear supply and demand curve, consumer surplus can be measured as the triangle area between the demand curve and the market price, and producer surplus can be measured as the triangle between the market price and the supply curve. We adopt this classical concept of economic surplus to measure the welfare changes. Consumers we want to analyze in this study are defined as people who purchase retail product at the last stage. Thus, consumer surplus can be measured as the difference between the amount actually purchased for a retail product of strawberry fruit and the amount willing to purchase. Producers in this study are defined as producers of type 1 nursery plant and type 2 nursery plant at the first stage. Therefore, producer surplus can be measured as the difference between the amount actually received for type 1 and 2 plants from fruit growers and the amount willing to sell. Total surplus can be defined by sum of consumer surplus and producer surplus. Thus, total surplus in our model is sum of consumer surplus, surplus of type 1 producer, and surplus of type 2 producer.

Change in market equilibrium at each stage can be calculated by solving the simultaneous elasticity form equations, (9.1) to (16.1). After that, we measure the change in welfare gains by using the parameters including market price and quantity, change in market equilibrium, and elasticity of substitution, etc. Parameters we used are listed in Table 3.1. We estimate the change in two producer surplus at the 1st stage, (change in surplus of type 1 nursery plant at the 1st stage and change in surplus of type 2 nursery plant at the 1st stage) and change in consumer surplus at the last stage. The calculation of welfare effects in this study follows partial equilibrium approach in Zhao, Mullen, and Griffith (2005).[34] Change in surplus of type 1 nursery plant at the 1st stage is graphically depicted by Figure 3.5 where P_{N1} and Q_{N1} are initial price and quantity of type 1 nursery plants respectively, and P'_{N1} and Q'_{N1} are price and quantity of type 1 nursery plants after shocks respectively. Type 2 plant becomes cheaper at any given price and quantity, then the demand builds, there will be a substitution from type 1 towards type 2. Thus, there is an inward shift of demand for type 1 nursery plant. Change in surplus of type 1 nursery plants can be computed by equation 17 where $P^*_{N1} = \frac{P'_{N1} - P_{N1}}{P_{N1}}$ and $Q^*_{N1} = \frac{Q'_{N1} - Q_{N1}}{Q_{N1}}$.

$$\begin{aligned} \Delta PS_{N1} &= -AREA\ (P_{N1}E_0E_1P'_{N1}) \\ &= P^*_{N1}Q_{N1}P_{N1}\left(1 + \frac{1}{2}Q^*_{N1}\right) \end{aligned} \tag{17}$$

Change in surplus of type 2 nursery plant at the 1st stage is described by Figure 3.6 where P_{N2} and Q_{N2} are initial price and quantity of type 2 nursery plants respectively, P'_{N2} and Q'_{N2} are price and quantity of type 2 nursery plants after shocks respectively, and ϵ is price change of type 2 nursery plant due to technological shock. Since relative price of type 2 nursery plants become cheaper than that of type 1 nursery plants, there will be a substitution from type 1 towards type 2. Thus, type 2 demand outward shifts because fruit growers want more type 2 nursery plants than type 1 plants. Change in surplus of type 2 nursery plants is derived by equation 18 where $P^*_{N2} = \frac{P'_{N2} - P_{N2}}{P_{N2}}$ and $Q^*_{N2} = \frac{Q'_{N2} - Q_{N2}}{Q_{N2}}$.

$$\Delta PS_{N2} = -AREA\ (CE_1AB)$$

[34] The welfare effects are calculated based on the assumptions of linear supply & demand functions, and parallel shifts of supply curve. The errors are small even if the true functions are not linear as long as the exogenous shift is marginal. (Zhao, Mullen, and Griffith (2005)).

$$= P_{N2}Q_{N2}(P_{N2}^{*} - \frac{\epsilon}{P_{N2}})(1 + \frac{1}{2}Q_{N2}^{*}) \tag{18}$$

Change in consumer surplus at the last stage is represented in Figure 3.7 where P_R and Q_R are initial price and quantity of retail products respectively, and P_R' and Q_R' are price and quantity of retail products after shocks respectively. Supply of retail products outward shifts because fruit price, which is input price of retail products, is decreased. Change in consumer surplus is computed by equation 19 where $P_R^{*} = \frac{P_R' - P_R}{P_R}$, $Q_R^{*} = \frac{Q_R' - Q_R}{Q_R}$, and $\eta = \frac{Q_R^{*}}{P_R^{*}}$.

$$\Delta CS_R = -AREA\ (P_R E_0 E_1 P_R')$$

$$= -P_R Q_R P_R^{*}(1 + \frac{1}{2}\eta P_R^{*}) \tag{19}$$

3.5. Sensitivity Analysis

Calculated welfare effects using EDM are point estimates and vary depending on the parameters in the model. As we discussed in the previous section, researchers generally adopt parameter values from previous studies and/or assume them based on existing data. Limitation of EDM is resulted from this process. Since the parameters from previous studies, especially elasticities, are unique values obtained through specific data, time periods, and estimation strategies, the results of EDM vary depending on which parameter values are used. (Brester, Atwood, and Boland (2023)) There have been many attempts to overcome this shortcoming of EDM. Davis and Espinoza (1998) suggested a strategy to overcome the limitation of sensitivity analysis by including the researcher’s entire subjective prior distributions on the structural elasticities. Posterior distributions for change in market equilibrium can be generated based on the prior distributions, and confidence intervals and p-values can also be generated using the central tendencies and dispersion. Zhao et al. (2000) used a simulation approach to conduct sensitivity analysis. They specified hierarchical distributions for the parameters, and derived mean sensitivity elasticities to individual parameters from various scenarios.

This paper examines how the welfare effects vary depending on distribution of parameters using the quasi-random sampling method with the Halton sequence by Saltelli et al. (2008). We follow the example of this method by Tregeagle and Zilberman (2023). We construct random parameter values for each parameters. Upper bounds and lower bounds of each parameters are based on existing data. We draw 1,000 random values from each uniformly distributed parameters scaled by a Halton sequence. Extracting random numbers from Halton sequence point sets allows us to obtain accurate estimates while reducing computation costs by requiring a relatively small number of simulations (Le, McRoy, and Diop (2018)). We use seven non-shock parameters for the sensitivity analysis: own price elasticity of nursery supply from field nursery firms (η_{N1}), own price elasticity of nursery supply from CE nursery firms (η_{N2}), cost share of nursery plants from field nursery firms for the strawberry fruit production (S_{N1}), relative price of CE nursery plants compared to field nursery plants (α), elasticity of substitution between two inputs in the strawberry fruit production (σ_F), cost share of strawberry fruit for the production of retail products (S_F), and own price elasticity of retail demand (η_R). Using MATLAB, we simulate the changes in producer surplus of field nursery firms, CE nursery firms, consumer surplus of retail products, and total surplus using different parameter combinations. One thousand welfare effects are estimated for 1,000 different parameter sets. Table 3.2 represents the welfare effects of a 10% reduction in the price of CE technology. Change in producer surplus of field nursery plants and CE nursery plants, consumer surplus, and total surplus are the averages of 1,000 welfare effects using 1,000 random values for each parameter. Decrease in field plants producer surplus due to a 10% price reduction in CE plants is larger with a higher market penetration. That is, surplus of producer using a conventional system decreases more as CE technology is more widely used. On the other hand, increases in CE plants producer surplus and total surplus are larger with a higher market penetration. When quantity of CE plants accounts for half of total plants quantities, CE plants producer surplus and total surplus are increased to a maximum of 7.49 million dollars and 40.35 million dollars, respectively, due to the 10% price reduction in CE plants. Consumer surplus is increased by 32.92 million dollars when there is a 10% price reduction in CE plants but it does not change by different market penetration rates.[35] Market penetration is defined by the allocation between the initial field plants quantity and the initial CE plants given constant total amount of nursery plants. Since changes in market equilibrium in each stage are calculated in the equation system before the initial price and quantity are defined, changes in price and quantity due to the supply shock on CE remain the same regardless of the market penetration. Therefore, the only reason the results in Table 3.2 differ across market penetration rates is because the initial allocations are different. Unlike the case of producer surplus of field and CE plants, equation for the consumer surplus is not a function of the initial quantities of field and CE plants. Therefore, change in consumer surplus due to the 10% price reduction in CE plants is the same regardless of the different market penetration.

Meanwhile, welfare effects resulting from the introduction of CE technology vary depending on relative prices. Figure 3.8 shows the relationship between relative price of CE plants compared to field plants and welfare effects of CE technology. Our welfare analysis starts with calculating the initial market equilibrium given all parameters as fixed. We then estimate

[35] Equation of consumer surplus is a function of Q_R (initial quantity of retail product), P_R (initial price of retail product), and P_R^* (percentage change of retail product price). Q_R and P_R are exogenously given. P_R^* is endogenous but does not change by different market penetration rates.

the welfare surplus using a new market equilibrium with a 10% price reduction in CE plants. As we can see in Figure 3.8, at the initial technology introduction stage where the relative price of CE is much higher than the existing system, a 10% price reduction in CE plants leads to a larger substitution effect from field to CE plants. However, at the next stage where the relative price of CE to field plants becomes small and the quantities of field and CE plants are almost same, substitution effects from field to CE would be smaller than the initial stage. Therefore, the increase in CE producer surplus, field producer loss, consumer surplus, and the total surplus due to a 10% price reduction in CE plants is greater for higher relative price.

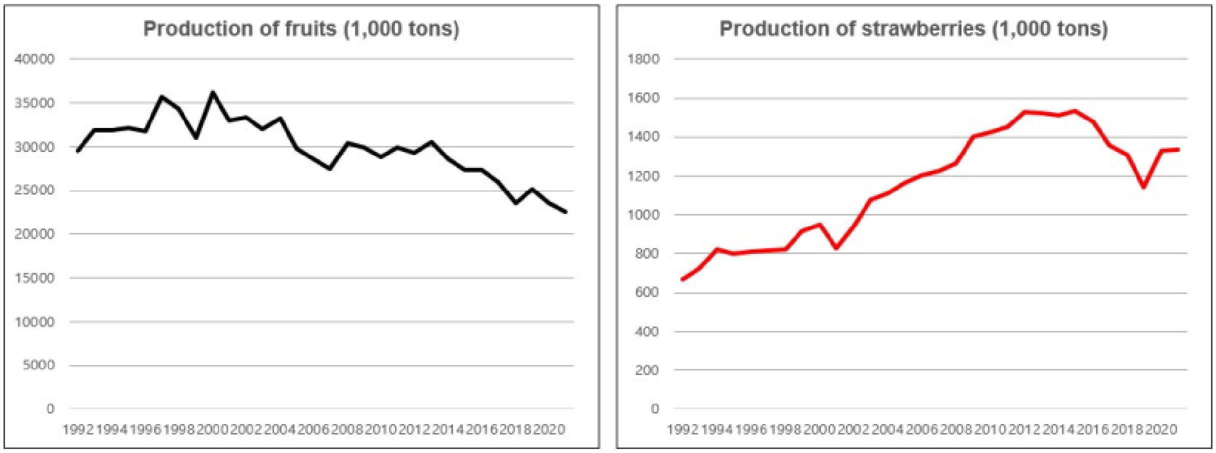
3.6. Conclusion

Strawberry nursery industry in California is facing challenges including cost problem from conventional field propagation system, dependency on disease-free plants, and potential threats of phase out of Methyl Bromide. Controlled environment propagation technology might be a solution for these problems. However, unlike active research on strawberry fruit industry, study on the strawberry nursery industry is limited. There is no research evaluating the economic effects of introducing CE technology to the California strawberry nursery industry. This study is significant in that it provides evidence for the economic benefits of CE technology by estimating the welfare effects of CE technology. We constructed a structural model to describe the strawberry nursery industry in California using EDM framework. We performed sensitivity analysis to compensate for the weaknesses of EDM due to unknown parameter values and scarcity of data on the industry and technology. Our results reveal that CE propagation technology will result in significant welfare benefits on CE plants producer surplus, consumer surplus as well as total surplus. Based on our calculations, total surplus will increase by 40.35

million dollars if quantity produced of nursery plants using CE technology accounts for half of total nursery plants and price of CE drops by 10%. This conclusion can serve as an important basis for the need to introduce CE technology in the strawberry nursery industry.

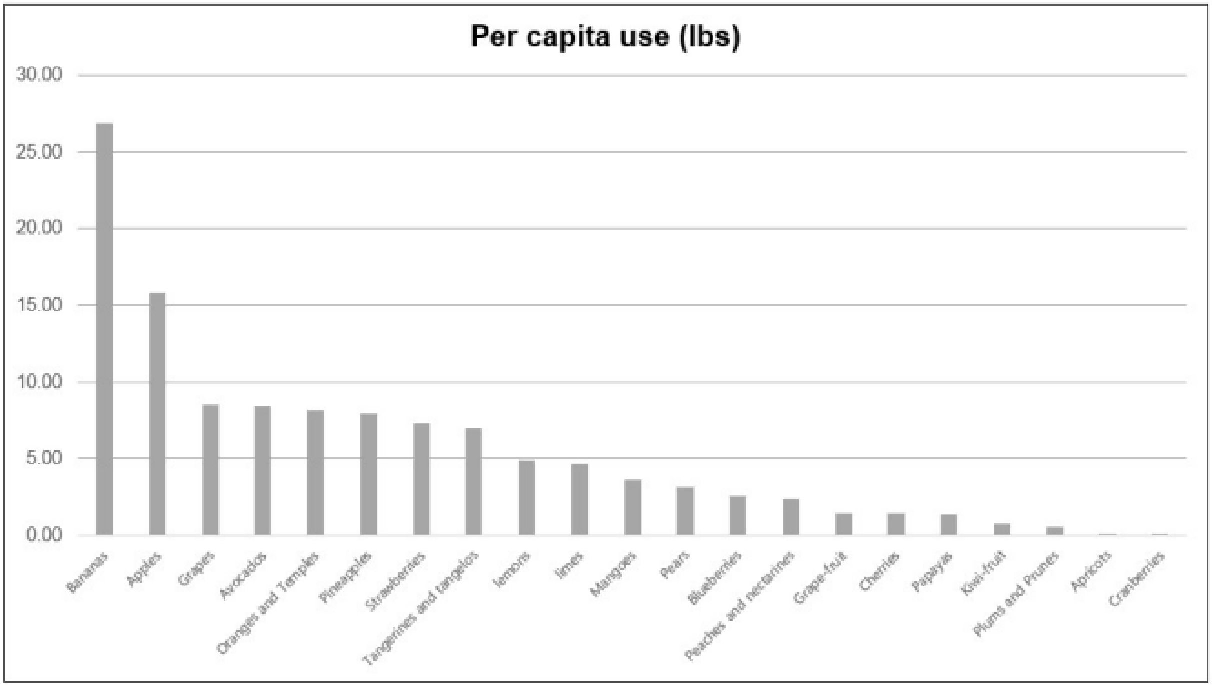
Additional research should be conducted to improve this study. Currently, virtually all strawberries are grown in open-field. In other words, the quantity of strawberry nursery plants produced using the CE technology is close to zero except in meristem stage. Therefore, to accurately reflect the current strawberry market situation, the welfare effects must be analyzed for the case when the quantity of nursery plants produced using CE technology goes from 0 to a certain positive value. Those effects explain the short-run effects of the initial introduction of CE technology on the strawberry industry. However, the EDM framework is appropriate to estimate the effects of marginal shocks. That is, the EDM is effective when there are small changes in exogenous and endogenous variables (Wohlgenant (2011)). Changes in nursery quantity from 0 to a certain positive value are non-marginal changes rather than marginal changes to an already established CE system. Therefore, examining welfare effects based on the current model is limited. This paper discusses the long-run effects of CE technologies from small positive initial CE nursery plants quantity to larger positive nursery plants quantity after the shock. This is not an initial effect of technology introduction and is therefore a limitation of this study. This limitation can be compensated for through additional research.

Figure 3.1. Production of Fruits and Strawberries



Sources: Fruit and Tree Nuts Yearbook Table from USDA Economic Research Service (ERS)

Figure 3.2. Consumption per capita by Fruits Commodities



Note: This is the data of per capita use in the U.S. in 2021.
Sources: USDA Economic Research Service (ERS) calculations

Figure 3.3. Changes in Producer and Consumer Surplus in the Simplest EDM Example

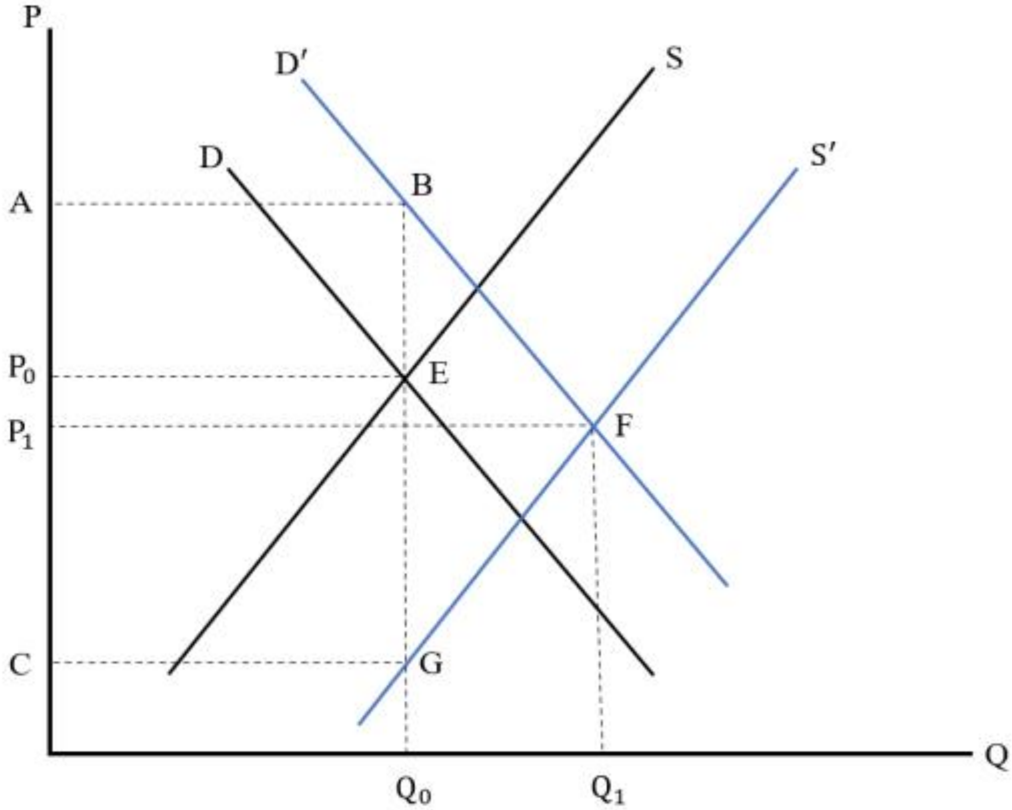


Figure 3.4. Multi-Stage Market Framework

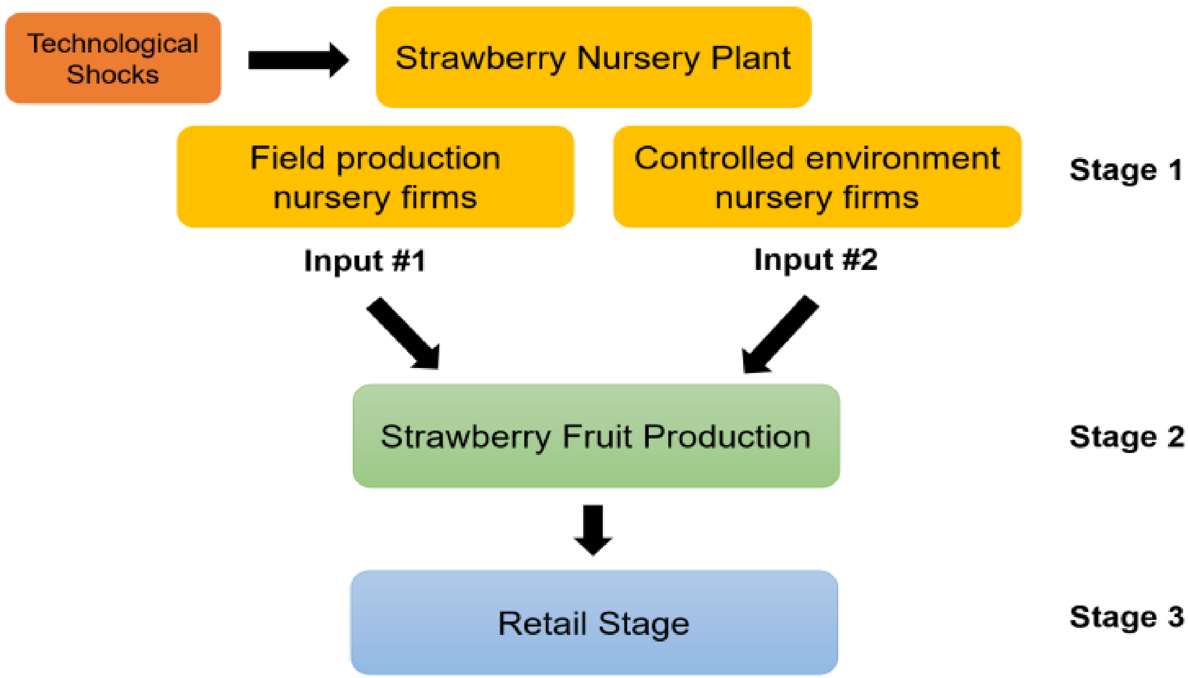


Figure 3.5. Change in Surplus of Field Nursery Plants at the 1st Stage

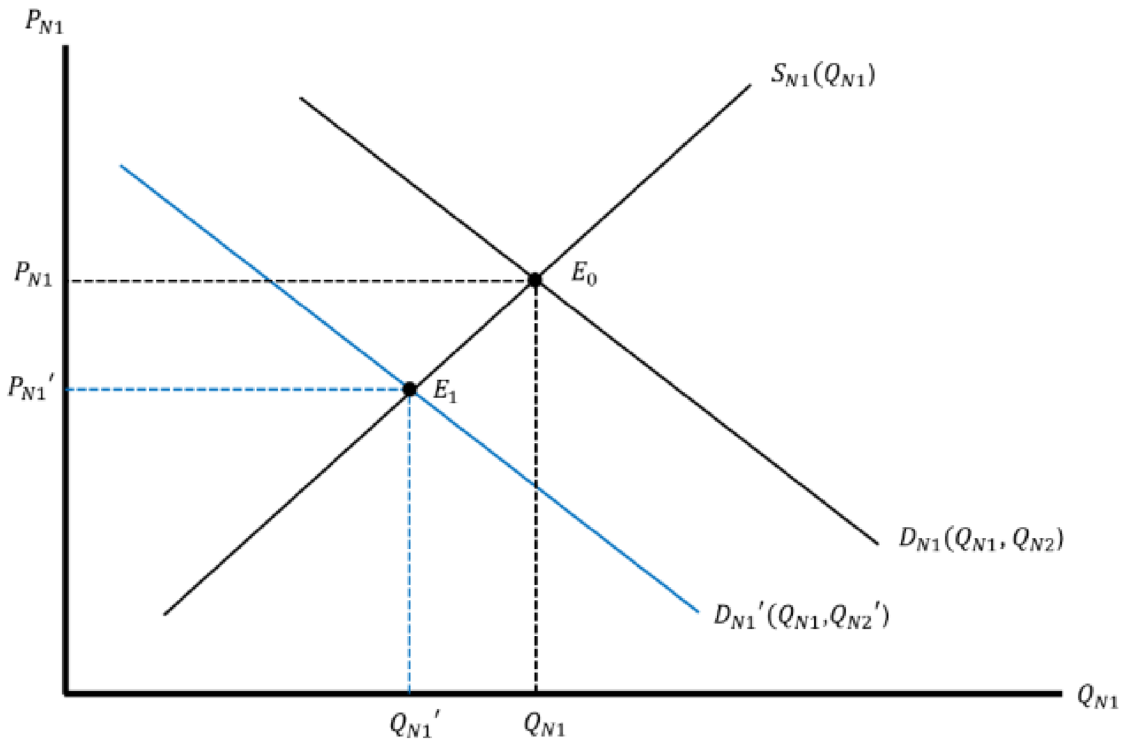


Figure 3.6. Change in Surplus of CE Nursery Plants at the 1st Stage

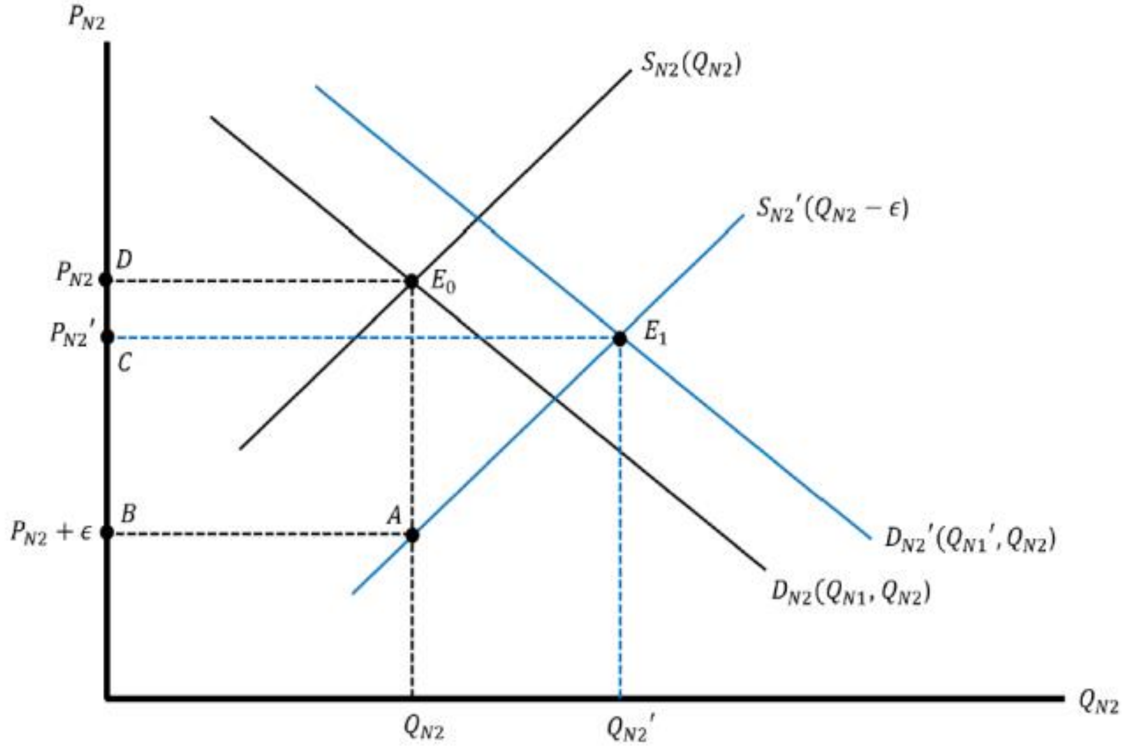


Figure 3.7. Change in Consumer Surplus at the Last Stage

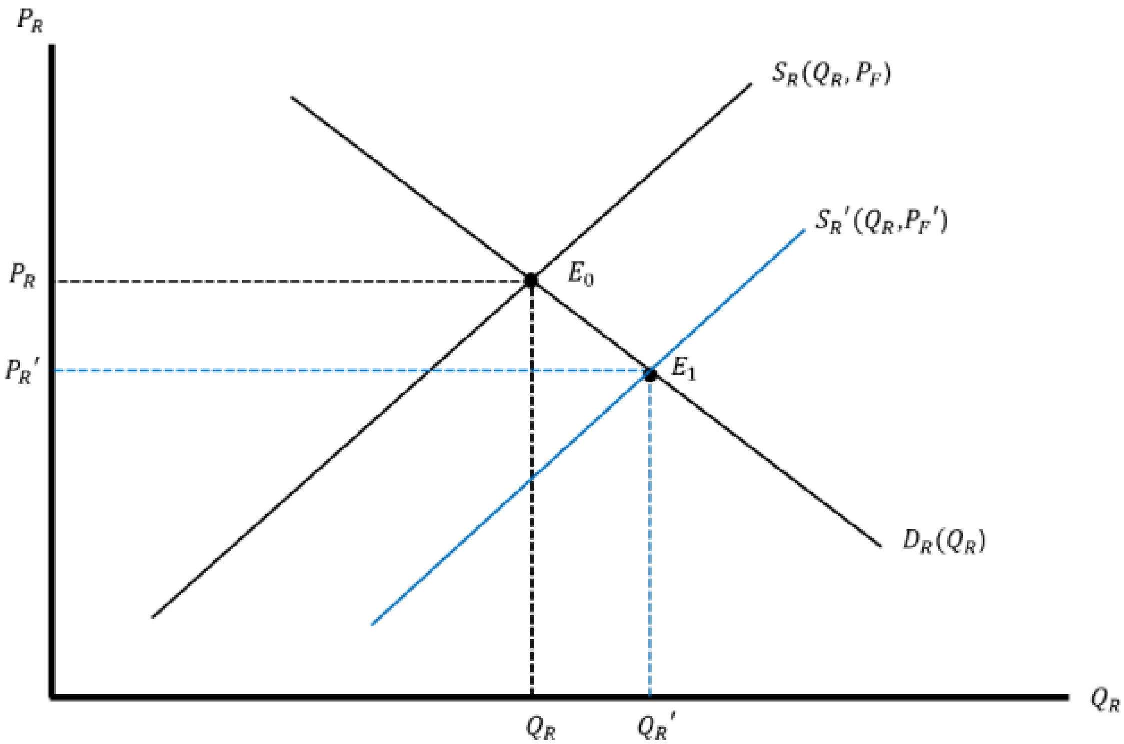


Figure 3.8. Relationships between Relative Prices and the Welfare Effects

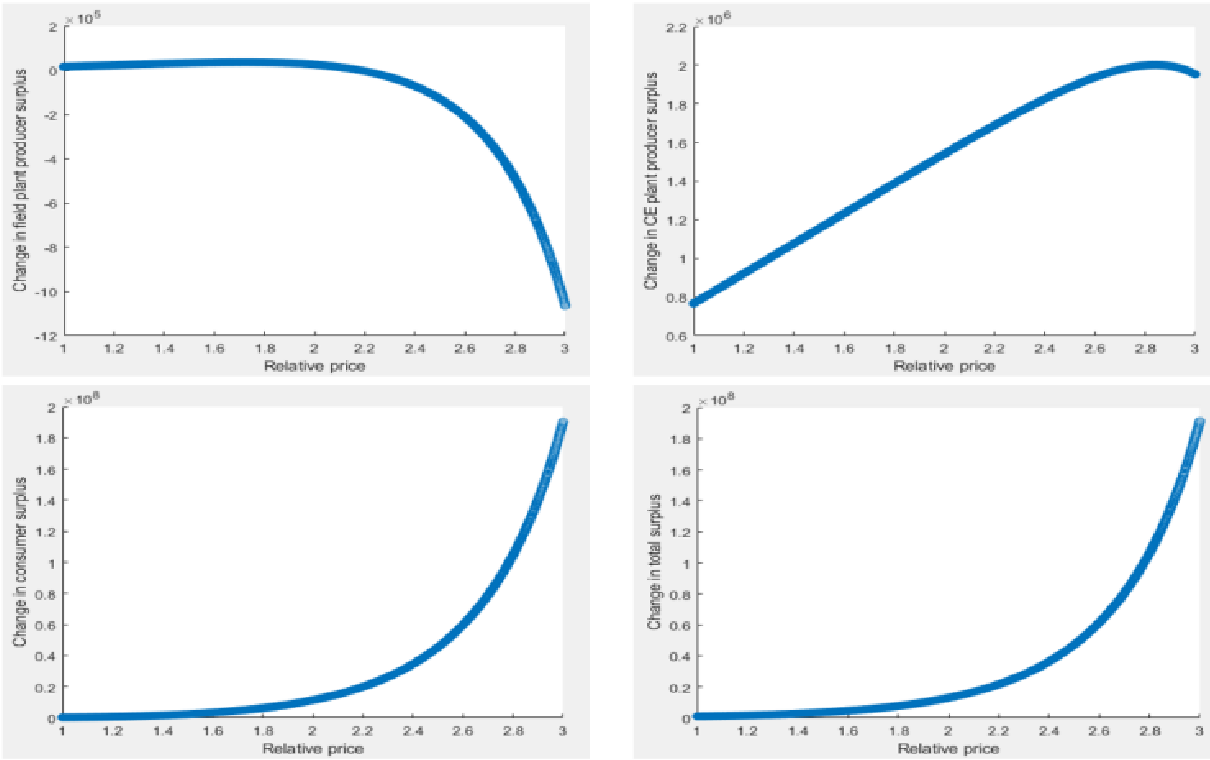


Table 3.1. Parameters in the Model

Non-Shock Parameters	Description	Range (or value)
η_{N1}	Own price elasticity of field nursery plants	0.32 to 1.59
η_{N1}	Own price elasticity of field nursery plants	0.32 to 1.59
S_{N1}	Cost share of field nursery plants	0.051 to 0.093
α	Relative price of CE nursery plants compared to field plants	1 to 3
σ_F	Elasticity of substitution between two types of plants	1 to 5
S_F	Cost share of fruit	0.31 to 0.45
η_R	Own price elasticity of retail products	-2.8 to -0.2753
P_R	Initial price of retail products (dollar per pound)	4.225
Q_R	Initial quantity of retail products (million pounds)	2,665
Q_{N1}	Initial quantity of field nursery plants (million plants)	254.10 to 457.38
P_{N1}	Initial price of field nursery plants (dollar per plant)	0.15
Q_{N2}	Initial quantity of CE nursery plants (million plants)	50.82 to 254.10
P_{N2}	Initial price of CE nursery plants (dollar per plant)	0.15 to 0.45
Shock Parameters	**Description**	**Range (or value)**
$\gamma_{P_{N1}\epsilon_{SN1}}\epsilon^*_{SN1}$	Change in price of type1 nursery plants caused by shift in type1 nursery plants supply	NA
$\gamma_{g_{N1}\epsilon_{SF}}\epsilon^*_{SF}$	Change in marginal product of type1 nursery plants caused by shift in fruit supply	NA
$\gamma_{P_{N2}\epsilon_{SN2}}\epsilon^*_{SN2}$	Change in price of type2 nursery plants caused by shift in type2 nursery plants supply	-10%
$\gamma_{g_{N2}\epsilon_{SF}}\epsilon^*_{SF}$	Change in marginal product of type2 nursery plants caused by shift in fruit supply	NA
$\gamma_{Q_F\epsilon_{SF}}\epsilon^*_{SF}$	Shift in fruit supply	NA
$\gamma_{f_F Q_F}Q^*_F$	Change in marginal product of fruit caused by fruit supply	NA
$\gamma_{f_F\epsilon_{SR}}\epsilon^*_{SR}$	Change in marginal product of fruit caused by shift in retail supply	NA
$\gamma_{Q_R\epsilon_{SR}}\epsilon^*_{SR}$	Shift in retail supply	NA
$\gamma_{Q_R\epsilon_D}\epsilon^*_D$	Shift in retail demand	NA

Table 3.2. The Welfare Effects of a 10% Reduction in the Price of CE Technology

Market penetration rate	Change in field plants producer surplus	Change in CE plants producer surplus	Change in consumer surplus	Change in total surplus
10%	-0.11	1.50	32.92	34.31
20%	-0.10	3.00	32.92	35.82
30%	-0.09	4.50	32.92	37.33
40%	-0.07	6.00	32.92	38.84
50%	-0.06	7.49	32.92	40.35

Notes: The results are the average of 1,000 outputs derived based on 1,000 random values of each parameter. Unit is one million US dollars.

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APPENDICES

Appendix A: Appendix for Chapter 1

Computing Nutrients Purchased on an Adult Equivalence Scale (AES)

To make the amounts of nutrients purchased comparable across different households, we compute the nutrients purchased per AES. The computation procedure is best explained by going through an example. For example, suppose there is a household with four household members. The household members are male (40 years old), female (38 years old), male (11 years old), and female (4 years old). Table 11 contains the daily nutrient goals for different age-sex groups set by the USDA Dietary Guidelines for Americans 2015-2020. Using calories as an example, the calorie needs of this household can be computed as 2,200+1,800+1,800+1,200=7,000kcal, according to this table. We then define an adult as a male between 19 and 50. According to Table A.1 of the Dietary Guidelines for Americans 2015-2020, the calorie need for such an adult is 2,500kcal, which is the average for a person with a sedentary lifestyle and a person with a moderately active lifestyle. Therefore, this household of four in our example is equivalent to a household with 7,000/2,500 = 2.8 adults. Now suppose this household purchases foods with a total of 19,500kcal of calories, the calories purchased per AES is then 19,500/2.8 = 6,964kcal. The amounts of sugar, saturated fat and sodium purchased per AES are computed similarly. Our computation procedure is similar to that of Dubois, Griffith, and Nevo (2014).

Table A.1. Daily Nutritional Goals by Age-Sex Groups

Age	Calories (kcal)		Sugar (g)		Saturated Fat (g)		Sodium (g)	
	Male	Female	Male	Female	Male	Female	Male	Female
1-3	1,000	1,000	25.0	25.0	11.1	11.1	1.5	1.5
4-8	1,500	1,200	37.5	30.0	16.7	13.3	1.9	1.9
9-13	1,800	1,600	45.0	40.0	20.0	17.8	2.2	2.2
14-18	2,733	1,800	68.3	45.0	30.4	20.0	2.3	2.3
19-30	2,666	2,000	66.7	50.0	29.6	22.2	2.3	2.3
31-50	2,200	1,800	55.0	45.0	24.4	20.0	2.3	2.3
51+	2,000	1,600	50.0	40.0	22.2	17.8	2.3	2.3

Note: Calorie levels of male 4-8, male 14-18, and male 19-30 are the averages of calorie levels of each age range from Table A7-1 on page 97 of the Dietary Guidelines for Americans 2015-2020.

Note: According to the Dietary Guidelines for Americans 2015-2020, daily intake of added sugar is needed less than 10% of calories for all age-sex groups. Since 1g of sugar approximately contains 4kcal, we converted kcal to gram by dividing the number of kcal by 4.

Note: According to the Dietary Guidelines for Americans 2015-2020, daily intake of saturated fatty acids is needed less than 10% of calories for all age-sex groups. Since 1g of saturated fat approximately contains 9kcal, we converted kcal to gram by dividing the number of kcal by 9.

Appendix B: Appendix for Chapter 3

Background of Strawberry

Strawberries are an important fruit in the US. According to the Fruit and Tree Nuts Yearbook Tables from USDA Economic Research Service (ERS)[36], utilized production of strawberries in 2022 was about 2.78 billion lbs, which accounted for 5.7% of utilized production of total fruits. Value of production of strawberries in 2022 was 3.2 billion dollars, which was 12% of value of production of total fruits. Over the past three decades, utilized production of total fruits has declined by an annual average of 1%, while strawberry production has increased by an annual average of 2.2%. Even in terms of value of production, total fruits have increased by an annual average of 3.3%, while value of the strawberries have increased by an annual average of 5.3%.

Strawberries are also an important in terms of consumption side. Per capita availability of strawberries in 2022 was 7.62 lbs, which was 6.5% of per capita availability of total fruit. Even more noteworthy than the consumption itself is its increasing trend. Over the past 40 years, per capita availability of strawberries has grown at an average annual rate of 3.01%, and over the recent 20 years it has recorded 3.13%. This is a more steady and steep increase compared to the increases of 0.62% and 0.74%, respectively, based on the total fruit. Nutritional aspects have contributed significantly to the increase in strawberry consumption. Majority of nutritionists agree on the fact that fresh fruits and vegetables are crucial to consumers' diet (Guthman (2019)). And among the recommended fruits, berries are rated as particularly beneficial.[37] As various statistics prove, strawberries are one of the most important fruit products in the US.[38]

[36] https://www.ers.usda.gov/data-products/fruit-and-tree-nuts-data/fruit-and-tree-nuts-yearbook-tables/
[37] Guthman (2019) pointed out that not only consumers recognize that strawberries are rich in nutrients, but also that consumption of strawberries by kids had a positive effect on the increase in consumption. Parents love to purchase strawberries because it is one of the few fruits and vegetables that don't require too much cajoling.
[38] Trend of production and consumption of strawberries in the US is depicted in Figure 3.1 and Figure 3.2.

Derivation of Elasticity Form Equations

$$P_{N1} = S_{N1}(Q_{N1}, \epsilon_{SN1})$$

$$dP_{N1} = \frac{\partial P_{N1}}{\partial Q_{N1}} dQ_{N1} + \frac{\partial P_{N1}}{\partial \epsilon_{SN1}} d\epsilon_{SN1}$$

$$\frac{dP_{N1}}{P_{N1}} = \frac{\partial P_{N1}}{\partial Q_{N1}} \frac{Q_{N1}}{P_{N1}} \frac{dQ_{N1}}{Q_{N1}} + \frac{\partial P_{N1}}{\partial \epsilon_{SN1}} \frac{\epsilon_{SN1}}{P_{N1}} \frac{d\epsilon_{SN1}}{\epsilon_{SN1}} \tag{9}$$

$$P_{N1}^{*} = \frac{1}{\eta_{N1}} Q_{N1}^{*} + \gamma_{P_{N1}\epsilon_{SN1}} \epsilon_{SN1}^{*}$$

where η_{N1} is own price elasticity of type 1 nursery plant supply and $\gamma_{P_{N1}\epsilon_{SN1}} = \frac{\partial P_{N1}}{\partial \epsilon_{SN1}} \frac{\epsilon_{SN1}}{P_{N1}}$: inverse elasticity of shift in nursery supply with respect to type 1 nursery plants price.

$$P_{N1} = P_F g_{N1}(Q_{N1}, Q_{N2}, \epsilon_{SF})$$

$$dP_{N1} = \frac{\partial P_{N1}}{\partial P_F} dP_F + \frac{\partial P_{N1}}{\partial g_{N1}} dg_{N1}$$

$$dP_{N1} = \frac{\partial P_{N1}}{\partial P_F} dp_F + \frac{\partial P_{N1}}{\partial g_{N1}} \left(\frac{\partial g_{N1}}{\partial Q_{N1}} dQ_{N1} + \frac{\partial g_{N1}}{\partial Q_{N2}} dQ_{N2} + \frac{\partial g_{N1}}{\partial \epsilon_{SF}} d\epsilon_{SF} \right) \tag{10}$$

$$\frac{dP_{N1}}{P_{N1}} = \frac{dP_F}{P_F} + \frac{\partial g_{N1}}{\partial Q_{N1}} \frac{Q_{N1}}{g_{N1}} \frac{dQ_{N1}}{Q_{N1}} + \frac{\partial g_{N1}}{\partial Q_{N2}} \frac{Q_{N2}}{g_{N1}} \frac{dQ_{N2}}{Q_{N2}} + \frac{\partial g_{N1}}{\partial \epsilon_{SF}} \frac{\epsilon_{SF}}{g_{N1}} \frac{d\epsilon_{SF}}{\epsilon_{SF}}$$

By Gardner (1975), we know $f_{aa} = \frac{b}{a} \frac{f_a f_b}{\sigma X}$. Therefore,

$$\frac{\partial g_{N1}}{\partial Q_{N1}} = \frac{Q_{N2}}{Q_{N1}} \frac{\partial Q_F}{\partial Q_{N1}} \frac{\partial Q_F}{\partial Q_{N2}} \frac{1}{\sigma_F} \frac{1}{Q_F}$$

$$\frac{\partial g_{N1}}{\partial Q_{N1}} \frac{Q_{N1}}{g_{N1}} = \frac{Q_{N2}}{Q_{N1}} \; g_{N1} g_{N2} \frac{1}{\sigma_F} \frac{1}{Q_F} \frac{Q_{N1}}{g_{N1}}$$

$$= \frac{\partial Q_F}{\partial Q_{N2}} \frac{Q_{N2}}{Q_F} \frac{1}{\sigma_F}$$

$$= \frac{P_{N2}}{P_F}\frac{Q_{N2}}{Q_F}\frac{1}{\sigma_F}$$

$$= S_{N2}\frac{1}{\sigma_F}$$

And by Gardner (1975), we know $f_{ab} = \frac{f_a f_b}{\sigma X}$. Therefore,

$$\frac{\partial g_{N1}}{\partial Q_{N2}} = \frac{\partial Q_F}{\partial Q_{N1}}\frac{\partial Q_F}{\partial Q_{N2}}\frac{1}{\sigma_F}\frac{1}{Q_F}$$

$$\frac{\partial g_{N1}}{\partial Q_{N2}}\frac{Q_{N2}}{g_{N1}} = g_{N1}g_{N2}\frac{1}{\sigma_F}\frac{1}{Q_F}\ Q_{N2}\frac{1}{g_{N1}}$$

$$= \frac{\partial Q_F}{\partial Q_{N2}}\frac{Q_{N2}}{Q_F}\frac{1}{\sigma_F}$$

$$= \frac{P_{N2}}{P_F}\frac{Q_{N2}}{Q_F}\frac{1}{\sigma_F}$$

$$= S_{N2}\frac{1}{\sigma_F}$$

Therefore,

$$P_{N1}^* = P_F^* + S_{N2}\frac{1}{\sigma_F}\ Q_{N1}^* + S_{N2}\frac{1}{\sigma_F}Q_{N2}^* + \gamma_{g_{N1}\epsilon_{SF}}\epsilon_{SF}^*$$

where S_{N2} is cost share of CE nursery plants, σ_F is elasticity of substitution between inputs in the fruit production, and $\gamma_{g_{N1}\epsilon_{SF}}$ is elasticity of marginal product of nursery plants from type 1 (g_{N1}) with respect to ϵ_{SF}.

$$P_{N2} = S_{N2}(Q_{N2}, \epsilon_{SN2})$$

$$dP_{N2} = \frac{\partial P_{N2}}{\partial Q_{N2}}dQ_{N2} + \frac{\partial P_{N2}}{\partial \epsilon_{SN2}}d\epsilon_{SN2}$$

$$\frac{dP_{N2}}{P_{N2}} = \frac{\partial P_{N2}}{\partial Q_{N2}}\frac{Q_{N2}}{P_{N2}}\frac{dQ_{N2}}{Q_{N2}} + \frac{\partial P_{N2}}{\partial \epsilon_{SN2}}\frac{\epsilon_{SN2}}{P_{N2}}\frac{d\epsilon_{SN2}}{\epsilon_{SN2}} \tag{11}$$

$$P_{N2}^{*} = \frac{1}{\eta_{N2}} Q_{N2}^{*} + \gamma_{P_{N2}\epsilon_{SN2}} \epsilon_{SN2}^{*}$$

where η_{N2} is own price elasticity of type 2 nursery plant supply and $\gamma_{P_{N2}\epsilon_{SN2}} = \frac{\partial P_{N2}}{\partial \epsilon_{SN2}} \frac{\epsilon_{SN2}}{P_{N2}}$: inverse elasticity of shift in nursery supply with respect to type 2 nursery plants price.

$$P_{N2} = P_F g_{N2}(Q_{N1}, Q_{N2}, \epsilon_{SF})$$

$$dP_{N2} = \frac{\partial P_{N2}}{\partial P_F} dP_F + \frac{\partial P_{N2}}{\partial g_{N2}} dg_{N2}$$

$$dP_{N2} = \frac{\partial P_{N2}}{\partial P_F} dp_F + \frac{\partial P_{N2}}{\partial g_{N2}} \left(\frac{\partial g_{N2}}{\partial Q_{N1}} dQ_{N1} + \frac{\partial g_{N2}}{\partial Q_{N2}} dQ_{N2} + \frac{\partial g_{N2}}{\partial \epsilon_{SF}} d\epsilon_{SF} \right) \tag{12}$$

$$\frac{dP_{N2}}{P_{N2}} = \frac{dP_F}{P_F} + \frac{\partial g_{N2}}{\partial Q_{N1}} \frac{Q_{N1}}{g_{N2}} \frac{dQ_{N1}}{Q_{N1}} + \frac{\partial g_{N2}}{\partial Q_{N2}} \frac{Q_{N2}}{g_{N2}} \frac{dQ_{N2}}{Q_{N2}} + \frac{\partial g_{N2}}{\partial \epsilon_{SF}} \frac{\epsilon_{SF}}{g_{N2}} \frac{d\epsilon_{SF}}{\epsilon_{SF}}$$

By Gardner (1975),

$$\frac{\partial g_{N2}}{\partial Q_{N1}} = g_{N1} g_{N2} \frac{1}{\sigma_F} \frac{1}{Q_F}$$

$$\frac{\partial g_{N2}}{\partial Q_{N1}} \frac{Q_{N1}}{g_{N2}} = g_{N1} g_{N2} \frac{1}{\sigma_F} \frac{1}{Q_F} \frac{Q_{N1}}{g_{N2}}$$

$$= \frac{P_{N1}}{P_F} \frac{Q_{N1}}{Q_F} \frac{1}{\sigma_F}$$

$$= S_{N1} \frac{1}{\sigma_F}$$

And by Gardner (1975),

$$\frac{\partial g_{N2}}{\partial Q_{N2}} = \frac{Q_{N1}}{Q_{N2}} g_{N1} g_{N2} \frac{1}{\sigma_F} \frac{1}{Q_F}$$

$$\frac{\partial g_{N2}}{\partial Q_{N2}} \frac{Q_{N2}}{g_{N2}} = \frac{Q_{N1}}{Q_{N2}} g_{N1} g_{N2} \frac{1}{\sigma_F} \frac{1}{Q_F} \frac{Q_{N2}}{g_{N2}}$$

$$= \frac{P_{N1}}{P_F} \frac{Q_{N1}}{Q_F} \frac{1}{\sigma_F}$$

$$= S_{N1} \frac{1}{\sigma_F}$$

Therefore,

$$P_{N2}^* = P_F^* + S_{N1} \frac{1}{\sigma_F} \ Q_{N1}^* + S_{N1} \frac{1}{\sigma_F} Q_{N2}^* + \gamma_{g_{N2}\epsilon_{SF}} \epsilon_{SF}^*$$

where S_{N1} is cost share of field nursery plants and $\gamma_{g_{N2}\epsilon_{SF}}$ is elasticity of marginal product of nursery plants from type 2 (g_{N2}) with respect to ϵ_{SF}.

$$Q_F = g(Q_{N1}, Q_{N2}, \epsilon_{SF})$$

$$dQ_F = \frac{\partial Q_F}{\partial Q_{N1}} dQ_{N1} + \frac{\partial Q_F}{\partial Q_{N2}} dQ_{N2} + \frac{\partial Q_F}{\partial \epsilon_{SF}} d\epsilon_{SF} \tag{13}$$

$$\frac{dQ_F}{Q_F} = \frac{\partial Q_F}{\partial Q_{N1}} \frac{Q_{N1}}{Q_F} \frac{dQ_{N1}}{Q_{N1}} + \frac{\partial Q_F}{\partial Q_{N2}} \frac{Q_{N2}}{Q_F} \frac{dQ_{N2}}{Q_{N2}} + \frac{\partial Q_F}{\partial \epsilon_{SF}} \frac{\epsilon_{SF}}{Q_F} \frac{d\epsilon_{SF}}{\epsilon_{SF}}$$

Since $P_{N1} = P_F \frac{\partial Q_F}{\partial Q_{N1}}$ and $P_{N2} = P_F \frac{\partial Q_F}{\partial Q_{N2}}$, $\frac{\partial Q_F}{\partial Q_{N1}} \frac{Q_{N1}}{Q_F} = \frac{P_{N1}}{P_F} \frac{Q_{N1}}{Q_F}$ and $\frac{\partial Q_F}{\partial Q_{N2}} \frac{Q_{N2}}{Q_F} = \frac{P_{N2}}{P_F} \frac{Q_{N2}}{Q_F}$.

Therefore,

$$Q_F^* = S_{N1} Q_{N1}^* + S_{N2} Q_{N2}^* + \gamma_{Q_F \epsilon_{SF}} \epsilon_{SF}^*$$

where $\gamma_{Q_F\epsilon_{SF}}$ is elasticity of Q_F with respect to ϵ_{SF}.

$$P_F = P_R f_F(Q_F, \epsilon_{SR})$$

$$dP_F = \frac{\partial P_F}{\partial P_R} dP_R + \frac{\partial P_F}{\partial f_F} df_F$$

$$dP_F = \frac{\partial P_F}{\partial P_R} dP_R + \frac{\partial P_F}{\partial f_F} \left(\frac{\partial f_F}{\partial Q_F} dQ_F + \frac{\partial f_F}{\partial \epsilon_{SR}} d\epsilon_{SR} \right) \tag{14}$$

$$\frac{dP_F}{P_F} = \frac{dP_R}{P_R} + \frac{\partial f_F}{\partial Q_F}\frac{Q_F}{f_F}\frac{dQ_F}{Q_F} + \frac{\partial f_F}{\partial \epsilon_{SR}}\frac{\epsilon_{SR}}{f_F}\frac{d\epsilon_{SR}}{\epsilon_{SR}}$$

$$P_F^* = P_R^* + \gamma_{f_F Q_F} Q_F^* + \gamma_{f_F \epsilon_{SR}} \epsilon_{SR}^*$$

where $\gamma_{f_F Q_F}$ is inverse elasticity of fruit demand with respect to marginal product of fruit and $\gamma_{f_F \epsilon_{SR}}$ is elasticity of marginal product of fruit with respect to shift in supply of retail product.

$$Q_R = f(Q_F, \epsilon_{SR})$$

$$dQ_R = \frac{\partial Q_R}{\partial Q_F} dQ_F + \frac{\partial Q_R}{\partial \epsilon_{SR}} d\epsilon_{SR}$$

$$\frac{dQ_R}{Q_R} = \frac{\partial Q_R}{\partial Q_F}\frac{Q_F}{Q_R}\frac{dQ_F}{Q_F} + \frac{\partial Q_R}{\partial \epsilon_{SR}}\frac{\epsilon_{SR}}{Q_R}\frac{d\epsilon_{SR}}{\epsilon_{SR}} \tag{15}$$

$$Q_R^* = S_F Q_F^* + \gamma_{Q_R \epsilon_{SR}} \epsilon_{SR}^*$$

where S_F is cost share of fruit and $\gamma_{Q_R \epsilon_{SR}}$ is elasticity of Q_R with respect to ϵ_{SR}.

$$Q_R = D_R(P_R, \epsilon_D)$$

$$dQ_R = \frac{\partial Q_R}{\partial P_R} dP_R + \frac{\partial Q_R}{\partial \epsilon_D} d\epsilon_D$$

$$\frac{dQ_R}{Q_R} = \frac{\partial Q_R}{\partial P_R}\frac{P_R}{Q_R}\frac{dP_R}{P_R} + \frac{\partial Q_R}{\partial \epsilon_D}\frac{\epsilon_D}{Q_R}\frac{d\epsilon_D}{\epsilon_D} \tag{16}$$

$$Q_R^* = \eta_R P_R^* + \gamma_{Q_R \epsilon_D} \epsilon_D^*$$

where η_R is own price elasticity of demand of retail products and $\gamma_{Q_R \epsilon_D}$ is elasticity of retail demand with respect to ϵ_D.