THREE ESSAYS ON ORGANIC AGRICULTURE

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Abstract

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This dissertation contains three pieces of empirical research in organic agricultural economics. The first essay examines the factors that influence farmers to direct market their product, rather than sell into the wholesale market, and estimates the impact of direct marketing on farm performance, considering farms' locational environment and spatial interaction between farmers' choice of marketing strategy. Results from the endogenous treatment model show that variables of geographic location and spatial interaction have significant influence on marketing strategy choice, and some of geographic variables are associated with farm sales. Also, it is found that a direct marketing penalty exists on the average, while for the smaller farms, the amount of the difference in expected sales is not significant across the marketing strategies, implying that direct marketing may be a viable strategy for some smaller farms.

The second essay investigates a number of scenarios that represent pest or disease outbreak due to climate change. I constructed a dynamic model of the U.S. apple industry that is separated into organic and conventional industries to better measure the impacts on producers and consumers. Findings in this study suggest that there would be heterogenous impacts of the outbreaks between organic and conventional industries and by type of shock since production systems and growers and consumers' responses to shock could differ widely across industry.

The third essay investigates the supply response of organic apples to price. This study estimates an econometric model of land adjustment and yields to determine how the elasticity of supply depends on the market-level organic premium versus farm-level prices. To my knowledge, it is the first paper in the partial adjustment literature to measure supply response with farm-level crop prices. The aggregate-level results show that supply responses to price premiums and/or own prices are positive as expected, while the long-run production and yield elasticities are inelastic relative to acreage responses. The farm-level results suggest that a farm's yield responds to the average market price more than the prices they received, and that organic apple producers depend on the organic premiums rather than organic prices when they invest in organic apple acres.

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CHAPTER ONE

Spatial effects, marketing strategies, and farm success: evidence from farms growing organic products

1.1 Introduction

One of key policy questions in the field of applied microeconomics (agricultural economics) centers on the determinants of success of firms (farms). As some firms continue to grow and account for a larger share of total production, whereas others remain small and struggle to survive. Understanding the determinants of success is beneficial for firms to identify pathways to profitability and enhance the chance of success. Nowadays, it is widely acknowledged that spatial aspects should be regarded as having an influence on the performance of firm as well as firms' characteristics, following the theories dating back to Marshall (1890) that point out the advantage of location of firms within a geographically concentrated area. Glaeser et al. (1992) also suggest that location and proximity matter for firms since knowledge spillovers take place within a spatially bounded region. As the impacts of geographic location have gained prominence, some empirical studies have provided evidence for the existence of knowledge spillover in a geographically bounded region (Jaffe, 1989; Jaffe et al., 1993; Audretsch and Feldman, 1996). The relationship between locational impacts and firm performance, in terms of firm employment growth, has also been paid attention by Audretsch and Dohse (2007) and Hoogstra and Van Dijk (2004). In the field of agricultural economics, most studies have employed regional dummy variables as a location variable (Park, 2015; Uematsu and Mishra, 2011; Detre et al., 2011), while there has been less attention on the impact of detailed geographic location on farm performance and growth.

Theoretically a firm would choose its location to maximize profits (Ellison and Glaeser, 1997), but the optimal location may change over time due to the dynamics in the economic environment. However, firms cannot move frequently as the optimal location shifts, since relocation may be more expensive than staying. Therefore, firms will stay in sub-optimal locations until they approach the spatial margins of profitability (Van Dijk and Pellenbarg, 2000). Meanwhile, firms would continue to make decisions in order to maximize profits at their locations. In agricultural economics, one such strategy for farmers is the choice of marketing channel to sell their products. The locations of farms would influence the decisions of marketing strategy, which affects the performance of individual farms accordingly. Location would affect firm's performance through the choice of marketing strategy. Direct marketing can generate much higher prices for farms than selling into the wholesale market, although demand is potentially more limited and uncertain, and prices may be more volatile. Previous studies, however, looking at the choice of marketing channel have only considered the characteristics of farm and farmers as the significant factors that drive the marketing strategy selection, while they have overlooked the impacts of spatial factors on marketing strategy choice. There are a few studies in which they used the distance to paved highway and the distance to the nearest city in order to account for specific locational effects on direct marketing channel choices (Hernandez et al.; 2007, Uematsu and Mishra, 2011; Park et al., 2018).

When farms who are located close to each other make their decisions on marketing strategy, it may be affected by the same unobserved factors and/or influenced by the behavior and opinions of their neighbors. The former represents spatial heterogeneity that can be estimated by locational variables, such as spatial dummy variables (Park et al., 2018) or distance to city (Hernandez et al., 2007; Park et al., 2018), while the latter depicts spatial dependence between farms. Ignoring this dependence will lead to biased or inconsistent estimates when spatial interdependence really exists. Although the literature in agricultural economics quantifying spatial dependence in discrete choice models is growing in technology adoption (Case, 1992; Langyintuo and Mekuria, 2008), the choice of agricultural system (Seo, 2011), the adoption of management practices for water protection (Yang and Sharp, 2017), adoption decisions of organic farming (Wollni and Andersson, 2014; Läpple and Kelley, 2014; Schmidtner et al., 2011; Lewis et al. 2011), and land use choice. (Li et al., 2013; Munroe et al. 2002; Robertson et al. 2009), it has yet to be explored in the area of marketing strategy. This study will build on the growing literature quantifying spatial dependence in discrete choice models by explicitly taking into account the neighborhood effects in the decisions of farms to marketing strategies as well as the influences of geographic locations of farms.

The objective of this study is to identify the factors that influence farmers to choose direct marketing and estimate the impacts of direct marketing on farm performance, considering farms' locational environment and spatial interaction between farmers' choice of marketing strategy. This paper departs from previous studies in two ways. First, none of the previous studies have focused on the impact of the spatial environment on both marketing strategy and farm success. We use georeferenced data of certified organic farms in Washington State which are able to capture spatial heterogeneity in socioeconomic and environmental conditions and spatial interaction between farms, and thus it will allow us to estimate the direct impacts of spatial aspects on farms' performance and the indirect impacts through marketing strategy. Also, we explicitly address self-selection problems for the empirical analysis in order to account for selection bias and endogeneity that are likely to be caused by correlations between farms' outcomes and the decisions on marketing channels, which allows us to get unbiased and accurate estimates of determinants of the decision of marketing strategy.

This paper is organized as follows: The next section starts with the discussion on marketing channels of farms in the U.S. and a literature review in which the relationship between marketing strategies and farm success and why spatial effects are important in this relationship are discussed. Section 3 describes the data set and discusses the variables used in the estimations. Section 4 explains the empirical methods to test the impact of spatial aspects and marketing strategies on farm success. In Section 5, the results of empirical analysis are presented. Finally, this paper concludes with Section 6 in which the main findings and policy implications are suggested.

1.2 Marketing strategy and farm success

The marketing channel is one of the most important strategies that firms (farms) choose to maximize their profits and manage business risks. Following Gilg and Battershill (2000), it could enhance the sustainability of farm systems to precisely evaluate the economic impacts of marketing practices. The marketing strategies are divided by two main channels, traditional wholesale channel and direct sales channel. Wholesale channels typically have the ability to move large quantities of produce quickly and at a lower price, while direct channels not only allow consumers to have access to locally grown fresh products, but also enable farmers to have the opportunity to develop their competitiveness by reducing marketing costs. Producers are faced with the decision on marketing channel with different advantages of each strategy.

In the United states, direct marketing channels increasingly have been recognized as a viable strategy. According to the 2017 Census of Agriculture, 130,056 farms sold $2.8 billion fresh edible agricultural products directly to consumers in 2017, which account for 6.4 percent and 0.7 percent of total number of farms and total sales, respectively. The value of direct sales is growing, up from $1.2 billion dollars in 2007, but it remains to be a small portion of the total sales in the U.S. This is in large part due to the fact that the majority of farms selling fresh edible products directly to consumers are small. Within the category of fresh fruit and vegetables, as well as organic, the percent of sales would be much higher, although USDA does not break-out this specific categorization. They do report a separate number for small farms. According to the USDA, a small farm is defined as an operation with gross cash farm income under $250,000, and these small farms represent a large share of farms that sell directly – around 90 percent of farms selling directly to consumer were small operations in 2017.

Farmers sell products directly to consumers in a variety of ways – through farmers markets, roadside stands, pick-your-own operations, community supported agriculture (CSA) arrangements, and other efforts (USDA, 2014). Direct marketing of farm products through farmers' markets also continues to be an important sales outlet for agricultural producers nationwide in the U.S, mostly due to the growing consumer interest in obtaining fresh products directly from the farm. According to USDA's Agricultural Marketing Service, 8,687 farmers' markets operated in 2017, up from 2,746 in 1998.

Along with the growth of the direct sales market, direct marketing has turned into a survival strategy for a large number of small farms that cannot compete with the large farm conglomerates in the market. While most U.S. farms are small (less than $250,000 of annual sales)– 69 percent of farms according to the Census of Agriculture in 2017, large farms ($250,000 and above) account for about 89 percent of the market value of agricultural production in 2017. Moreover, the number of small farms, as well as their share of sales, has shrunk over time. Production is shifting to larger farms because economies of scale reduce costs in production system, and thus small farms may need different marketing channels, such as direct marketing through local retailers and markets, that may be typically not something that makes sense for really large farms whose production far outstrips local demand. For these reasons, agricultural policy makers have promoted for small farmers to adopt direct marketing strategy, suggesting that it allows farmers to develop their competitiveness and the likelihood of survival. Also, consumers are increasingly interested in buying products directly from farmers. Some consumers are driven towards direct marketing not only for the fresh products directly from the farm but to support small farmers. Chang and Lusk (2009) shows that consumers exhibit altruistic preferences toward small farms. Therefore, examining the impacts of adopting a direct marketing strategy, and whether the direct marketing strategy really improves the likelihood of farms' success and survival, has become an important research question.

In the past, most studies on direct marketing mainly focused on the consumer side rather than the producer side. Some of them have examined the characteristics of consumers who purchase products through direct marketing channels (Eastwood et al., 1987; Schatzer et al., 1989; Govindasamy and Nayga, 1997; Wolf, 1997; Kezis et al., 1998).

There are some recent studies that have focused on the producer side from two different perspectives. One is the factors that influence marketing strategy choice (Brown et al., 2006; Monson et al., 2008; Adanacioglu, 2017; Capt and Pierre, 2014; Park et al., 2014; Park et al., 2018; Uematsu and Mishra, 2011; Detre et al. 2011; Corsi et al., 2014), and the other is the impacts of marketing strategy on firms' performance (Park, 2015; Park et al., 2014; Park et al., 2018; Uematsu and Mishra, 2011; Hernandez et al., 2007; USDA, 2015; Detre et al. 2011).

There is often a perception that direct marketing is not feasible on a larger scale, and thus large farms do not need to rely on the direct marketing channel. However, according to Ostrom and Jussaume (2007), when the effects of location and farm type are taken into account, farm size becomes a less significant factor. They show that while a greater percentage of farms that have less than $25,000 per year in sales market directly than do farms that have more than $250,000 a year in sales, these differences are not statistically significant and that the characteristics that best explain whether a farm utilized direct marketing are the type of farm product and the location of farm. Some other studies have also tried to find the factors affecting the choice of marketing strategies. Brown et al. (2006) identifies that factors such as median housing value, population density, and proximity to D.C. have a positive impact on direct marketing sales, but their study is limited to county-level analysis. Monson et al. (2008) and Adanacioglu (2017) conclude that farm characteristics such as farm size, farming experience, and types of production are significant determinants of direct marketing outlets. On the other hand, Capt and Pierre (2014) focus on external factors (local market characteristics) that influence the propensity to sell directly to consumers as well as farms' internal factors. Also, Park et al. (2014) and Park et al. (2018) employ management and marketing skills and the use of internet access as key variables influencing on the choice of marketing channel, respectively. In order to test the hypothesis that small farms are obligated to rely on the direct marketing, while it is not feasible for large farms and identify the factors affecting the marketing strategy choice, this study also employ various independent variables including locational, spatial dependence variables.

In addition to identifying the factors affecting the choice of marketing channel, some studies have assessed the impact of marketing channel strategies — results are mixed. Detre et al. (2011) show that farmers who have adopted a direct marketing strategy while growing organic crops can increase gross sales. USDA (2015) analyzes the impacts of direct sales on farm survival, and suggests that farms selling local food through DTC (Direct-To-Consumer) marketing channels were more likely to remain in business over 2007-12 than farms not using DTC marketing channels. While some studies show the positive relationships between direct marketing strategy and the outcome of farms, the others suggest the negative impacts of direct marketing efforts. Uematsu and Mishra (2011) point out that the intensity of direct marketing strategy adoption has no significant impact on farm income and that participation in farmers' markets is negatively correlated with farm income. Park et al. (2014) and Park et al. (2018) confirm that there exists the direct marketing penalty, suggesting that direct marketing is associated with farm sales declines. Park (2015) employ the unconditional quantile regression model and show that the impacts of direct marketing are uniformly negative across all the quantiles. Also, according to Ostrom and Jussaume (2007), many small- to mid-sized (farm receipts of less than $250,000) Washington vegetable growers employ a combination of marketing strategies as a way of capturing added value and reducing risk, while Park (2015) suggests that smaller farms are more severely impacted when they participate in direct marketing and the declines in sales tend to grow smaller as sales increase. These conflicting results from previous studies suggest that farms could either benefit from direct sales or face a direct sales penalty, and the impacts of marketing strategy may be different across the size of farms (e.g. small vs. large farms). This motivates our empirical approach to consider whether direct marketing benefits or hurts producers, and to assess whether the impacts vary across different sizes of farms.

As discussed previously, spatial effects, including both spatial heterogeneity and spatial dependence, have been proven to have a significant influence on firm performance. However, studies on the relationship between marketing strategy and farm performance have up to now paid little attention to the possible impact of spatial aspects. Only a few studies have focused on the influence of geographic location on marketing channel choice and the outcome of farms. Corsi et al. (2014) and Detre et al. (2011) use regional dummy variables to estimate the effects of location on the adoption of marketing strategy, while Hernandez et al. (2007), Uematsu and Mishra (2011), and Park et al. (2018) employ more specific locational variable such as distance to paved highway or the nearest city. Also, some research estimates the impacts of location on farms' performance with regional dummies (Park, 2015; Uematsu and Mishra, 2011; Detre et al., 2011). Although some studies have considered geographic location as a determinant of marketing strategy choice and farm success, none of the previous studies have focused on the spatial dependence between individual farms.

Including spatial aspect variables in our analysis would develop the predictive power of estimation in two ways. First, locational variables would represent the unobserved factors which cannot be explicitly included in the model. We will include variables of detailed geographic location in order to estimate the impacts of location on marketing strategy choice and farm performance. Another point is to consider spatial interaction between farms over the choice of marketing channel. Spatial dependence considers whether there is positive spatial interaction between farmers' choice. By evaluating this possibility, we will be able to confirm whether direct marketing can benefit or hurt farmers and how different the impacts are across different sizes of farms, which will be useful for policy makers or agricultural experts to properly suggest to initiate or expand direct marketing activities to farmers.

1.3 Data and Variables

This study analyzes data of certified organic farms in Washington state – the second largest producer of organic products in the U.S.; earning $515 million in 2014 (USDA 2014 Organic survey), which are derived from the database of all WSDA certified organic farms and the renewal forms covering the 2009–2012 production years. Our farm-level data also include a breakout of sales by direct marketing versus wholesale for each year for most farms, which lead to two types of marketing strategies from which farmers can choose.

There are 588 unique farms, combined over the four years (2009-2012). An observation in the underlying data set specifies farm-year, and there are a total of 1,767 observations. By year, there are 400, 437, 463, and 467 farms, respectively. We specify farms as direct sales farms if they sell equal to or more than half of their products directly to consumers in terms of total sales. Since most of the farms only choose either direct sale or wholesale channel, and the others, 483 observations, are evenly distributed over the proportion of direct sales, our classification may not have a great influence on the analysis. Of all observations, 591 and 1,176 observations choose direct marketing channel and wholesale channel to sell their crop products, respectively. By year, 121, 161, 156, and 153 farms employ direct marketing strategy, respectively. Descriptive statistics of key variables used in the analysis are presented in Table 1. Table 2 compares descriptive statistics by marketing channel – direct and wholesale sales channels.

The variables of farm acres, farm age, and owner's gender are used to represent farm's characteristics. To account for the impacts of the degree of diversification, we also include a version of the Herfindahl index of farm diversification as an explanatory variable. We use specified grouping of crops including tree fruits, berry, grape, other fruits, vegetables, mixed horticulture, herbs, lavender, mint, hay, hops, corn, cereal, nut, pasture, pulse, and seed other than herb. The index proposed by Gollop and Monahan (1991) is used as:

$$d = \left(1 - \frac{1}{n}\right) + \sum_{i} \left(\frac{1}{n^2} - s_i^2\right)$$

where n is the number of crops, and s_i is the share of the crop i in total sales. The first term is the number property which increases as the number of crops marketed grows. The second term represents the distribution component. It takes a zero value when the n products are equally distributed, whereas it takes increasingly negative values as the distribution of sales across crops becomes more unequal.

To represent urban proximity variables, we include an urban dummy variable. Also, we employ the georeferenced data which allows us to derive spatial heterogeneity based on the driving distances from each farm to nearby cities with a population of 50,000 or more. Two variables, distance to nearest city and average distance to 3 nearest cities, are included to measure the effects of location of farms. Since many farms with direct marketing rely on farmers' markets[1], we also include the number of farmer's markets around each farm as an explanatory variable.

[1] In the U.S., of the $3 billion in direct-to-consumer sales, farmers' markets accounted for $711 million, or 23 percent in 2015, and the number of farms utilizing farmers' market outlet was 41,156, about 36 percent of total number of farms selling directly to consumer.

1.4 Empirical method

1.4.1 Endogenous treatment model

This section outlines the endogenous treatment model used in the article. Following Trost and Lee (1984), the estimation is likely to be underestimated when a selectivity problem is neglected. Farmers may endogenously self-select marketing channel, and thus decisions are likely to be influenced by unobserved factors that may be correlated with the outcomes of interest such as the value of farm sales and farm growth. Using the endogenous treatment model, we explicitly address self-selection problems for the empirical analysis in order to address selection bias and endogeneity that are likely to be caused by correlations between farms' outcomes and the decisions on marketing channels, which allows to us to get unbiased and accurate estimates of outcomes of marketing strategies.

The endogenous treatment regression model is composed of an equation for the outcome y_j (the value of farm sales and growth rates of sales) and an equation for the endogenous treatment t_j (the marketing strategy choice of farms). It allows for a specific correlation structure between the unobservables that affect the treatment (decision on marketing strategy) and the unobservables that affect the potential outcomes (the value of farm sales and farm growth). If the error term of treatment equation and that of outcome equation are not independent, the estimates of OLS regression may be biased due to self-selection problem. In this case, the endogenous treatment regression model enables us to get consistent and efficient estimates while controlling for selection bias. The endogenous treatment model is divided by two different models, constrained and unconstrained treatment models.

1.4.1.1 Constrained model

The constrained form of the model is given by:

$$y_j = X_j\beta + \delta t_j + \epsilon_j$$

$$t_j^* = w_j\gamma + u_j$$

$$t_j = \begin{cases} 1, & if \quad t_j^* > 0 \\ 0, & otherwise \end{cases}$$

where y_j is the outcome variable (e.g. the values of farm sales), X_j are the covariates used to model the outcome equation, representing farm characteristics and geographical variables. The variable of t_j is a binary-treatment variable that is assumed to stem from an unobservable latent variable, t_j^*, and $w_j = \{z_j, \omega t_j\}$ are the covariates used to model treatment assignment, where z_j represents the variables of farm characteristics and location, ω is the spatial weight matrix based on the distances between farms. We assign the weights by use of an inverse distance function, where d_{ji} equals the distance between farm *i* and *j*. Beyond some distance, the effect of marketing strategy choice of other farms might no longer affect farm's decision making. An upper distance is chosen as a point beyond which all weights equal zero. Following the results of Moran's *I* statistics in Table 3, we set a spatial weights matrix with an upper distance of 30km since it shows the largest positive relationship between farms' choice, although the results are quite robust to the particular weights matrix chosen. The error terms ϵ_j and u_j are bivariate normal with mean zero and covariance matrix as:

$$\begin{bmatrix} \sigma^2 & \sigma\rho \\ \sigma\rho & 1 \end{bmatrix}.$$

The treatment is exogenous if $\rho = 0$, in this case, therefore, endogenous treatment model may not be appropriate, and the standard OLS regression may be more preferable. On the other hand, when $\rho \neq 0$, ignoring the correlation between error terms may lead to biased estimates, and it would be reasonable to have the endogenous treatment model be applied.

The likelihood function for this model is given by Maddala (1986). The following is the log likelihood for observation *j*:

$$lnL_j = \begin{cases} ln\Phi\left\{\frac{w_j\gamma + (y_j - X_j\beta - \delta)\rho/\sigma}{\sqrt{1-\rho^2}}\right\} - \frac{1}{2}\left(\frac{y_j - X_j\beta - \delta}{\sigma}\right)^2 - ln(\sqrt{2\pi}\sigma) & if\ t_j = 1 \\ ln\Phi\left\{\frac{w_j\gamma + (y_j - X_j\beta)\rho/\sigma}{\sqrt{1-\rho^2}}\right\} - \frac{1}{2}\left(\frac{y_j - X_j\beta}{\sigma}\right)^2 - ln(\sqrt{2\pi}\sigma) & if\ t_j = 0 \end{cases}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.

1.4.1.2 Unconstrained model

Unlike the constrained model, the unconstrained model does not explicitly include treatment effects as an explanatory variable, but it allows for individuals with different treatment selections to have different coefficient estimates for outcome equations. Here, farms engaging in direct sales have different outcome equations from farms with a wholesale strategy. The unconstrained form of the endogenous treatment model is represented by:

$$y_{0j} = X_j\beta_0 + \epsilon_{0j} \quad if\ \ t_j = 0$$

$$y_{1j} = X_j\beta_1 + \epsilon_{1j} \quad if\ \ t_j = 1$$

$$t_j^* = w_j\gamma + u_j$$

$$t_j = \begin{cases} 1, & if \quad t_j^* > 0 \\ 0, & otherwise \end{cases}$$

where y_{0j} is the outcome that individual *j* obtains if treatment 0 (wholesales strategy) is selected, while y_{1j} is the outcome that individual *j* obtains if treatment 1 (direct sales strategy) is selected. We never observe both y_{0j} and y_{1j}, only one or the other. Therefore, we can observe:

$$y_j = t_j y_{1j} + (1 - t_j) y_{0j} \, .$$

In the unconstrained model, the vector of error terms $(\epsilon_{0j}, \epsilon_{1j}, u_j)'$ is a mean zero trivariate normal distribution with covariance matrix as:

$$\begin{bmatrix} \sigma_0^2 & \sigma_{01} & \sigma_0\rho_0 \\ \sigma_{01} & \sigma_1^2 & \sigma_1\rho_1 \\ \sigma_0\rho_0 & \sigma_1\rho_1 & 1 \end{bmatrix}.$$

The likelihood function for this model is given by Maddala (1986) as:

$$lnL_j = \begin{cases} ln\Phi\left\{\dfrac{w_j\gamma + (y_{1j} - X_j\beta_1)\rho_1/\sigma_1}{\sqrt{1-{\rho_1}^2}}\right\} - \dfrac{1}{2}\left(\dfrac{y_{1j} - X_j\beta_1}{\sigma_1}\right)^2 - ln(\sqrt{2\pi}\sigma_1) & if\ t_j = 1 \\ ln\Phi\left\{\dfrac{w_j\gamma + (y_{0j} - X_j\beta_0)\rho_0/\sigma_0}{\sqrt{1-{\rho_0}^2}}\right\} - \dfrac{1}{2}\left(\dfrac{y_{0j} - X_j\beta_0}{\sigma_0}\right)^2 - ln(\sqrt{2\pi}\sigma_0) & if\ t_j = 0 \end{cases}$$

where $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution.

1.4.2 Average treatment effect on the treated (ATET)

Unlike the constrained model, in the unconstrained model, the treatment effects are not explicitly estimated. Rather, we can estimate average treatment effect on the treated (ATET) which is the average difference of the treatment potential outcomes and the control potential outcomes on the treated population. We compare expected values of outcomes of direct marketing strategy adopters ($t_j = 1$) and nonadopters ($t_j = 0$) in actual and counterfactual scenarios. The conditional means of potential outcomes of adopters with adoption is:

$$E(y_{1j} | t_j = 1) = X_j\beta_1 + \rho_1\sigma_1\phi(w_j\gamma)/\Phi(w_j\gamma).$$

The conditional means of potential outcomes of direct marketing adopters had they decided not to adopt (counterfactual) is given by:

$$E\left(y_{0j}\middle|t_j = 1\right) = X_j\beta_0 + \rho_0\sigma_0\phi(w_j\gamma)/\Phi(w_j\gamma).$$

Finally, the ATET is calculated by:

$$E\left(y_{1j} - y_{0j}\middle|t_j = 1\right) = E\left\{E\left(y_{1j} - y_{0j}\middle|X_j, w_j, t_j = 1\right)\right\}$$

$$= E(X_j(\beta_1 - \beta_0) + (\rho_1\sigma_1 - \rho_0\sigma_0)\phi(w_j\gamma)/\Phi(w_j\gamma) \mid t_j = 1)$$

1.4.3 Model specification

When using the selection models including the endogenous treatment model, one of the important questions might be the selection of variables that can be included in selection and outcome equations, including the question of which variables included in the treatment assignment should also be included in the outcome equation. In order to determine the specification of endogenous treatment model, we refer to the following results of simple probit and OLS regression and then employ the significant variables as explanatory variables in the endogenous treatment model.

1.5 Analysis

1.5.1 Spatial autocorrelation between marketing strategy selection

To confirm the existence of the pattern of spatial autocorrelation between marketing strategy selection, we first check global spatial autocorrelation with the statistics of Moran's *I* and Geary's *C*. Table 3 shows that there is positive spatial autocorrelation between marketing channel selections of farms. For distance-based spatial weight matrix, upper distances are set to

30km, 40km, and 50km. An upper distance is chosen as a point beyond which all weights equal zero. We also use 15, 25, and 35 nearest neighbors for K-nearest neighbor criteria. The statistics confirm the existence of significant spatial dependence between farms' decisions on marketing channel selection with various criteria. Also, the spatial correlation is represented to be positive as Moran's I statistics are positive and Geary's C statistics are less than 1.

In addition to the statistics of global spatial autocorrelation, we also estimate bivariate K_d function in order to show the distributional pattern of the two types of marketing channel. Bivariate K_d is calculated for *r* between 0 and 70 kilometers. The calculated function is shown in Figure 1, analyzing

the locations of farms with direct marketing in a neighborhood of *r* meters of farms with wholesale sales channel. The result shows that the observed K_d values lie below the lower confidence band, representing that a repulsion would be detected between direct marketing farms and wholesale farms at all distance.

Taken together, therefore, we hypothesize that there may exist positive spatial interaction and social network effects between farms' choice of sales outlets rather than spatial competition, and thereby account for the influence of neighborhood's marketing strategy decisions to estimate the propensity to participate in direct marketing in the following estimation.

1.5.2 Choice of direct marketing strategy

Table 4 reports estimated coefficients from the probit model of marketing channel selection. Note that the base group for comparison is the farmers with wholesale marketing outlet. The results are presented with and without spatial lagged variable of dependent variable. By distinguishing between the two models, we can explore the effects of including and ignoring spatial interdependence on the influence of explanatory variables on the adoption of direct marketing strategy as well as estimate the neighborhood effects on the choice of marketing strategy.

Since it is more convenient to interpret the marginal effects on the choice of marketing strategy, we focus on average marginal effects which are presented in Table 5. Note that the marginal effects of all explanatory variables differ only slightly between the two specifications, but all the effects are smaller except for the interaction term, Urban*distance to nearest city, when controlling for neighborhood effects of spatial lagged variable.

In the results of spatial model of column (2), all of the explanatory variables are highly statistically significant. Results indicate that gender affects the choice of marketing outlet. Female farmers are more likely to direct market than male farmers by 13%. According to USDA (2013), about 61 percent of women principal operators have education beyond high school, compared with only 47 percent of male principal operators in 2007. A plausible explanation in female farmers with higher likelihood of adoption of direct marketing may be that women farm operators are more highly educated, and thereby allowing them to keep better understanding of consumer preferences and to easily extract benefits from direct marketing. Another explanation is that knowledge spillovers between female farmers are stronger than male farmers, and thus neighboring female-owned farms may be more likely to share information and strategies that are much more important in direct marketing than wholesale marketing.

Farm size, as measured by acres, is negatively related with the adoption of direct sales. A 1% increase in farm size in terms of total farm acres reduces the probability of adopting direct marketing channel by 4%. The finding here is consistent with the general understanding that compared to large farms, smaller farms tend to rely more on direct marketing strategies, and also consistent with the results from previous literatures (Monson et al. 2008; Detre et al. 2011; Uematsu and Mishra, 2011). It would be beneficial for small farms since even if competition exists in the field of direct marketing, it is often among farms of the same size, rather than between large-scale and small-scale farms (ATTRA, 2016). Also, direct marketing through local retailers and markets may not be typically something that makes sense for really large farms whose production far outstrips local demand. Thus, the strategy of direct marketing of certified organic food may fits smaller farms well.

On the other hand, the marginal effect of diversification on adoption of direct marketing strategy is found to be positive, indicating that farms with more diversified crops are more likely to direct market. Diversified farms, usually coupled with smaller farm size, get benefits from economies of scope rather than economies of scale that larger and non-diversified farms can achieve. It may be difficult for diversified farms to compete with larger and non-diversified farms in wholesale market outlet since they are less likely to be competitive in production costs and the prices of products. For these reasons, farmers with a greater diversity of crops may tend to choose direct marketing strategy.

The coefficients that are related to the farm age show a negative relationship, but with a decreasing rate, between farm experience and the probability of adopting direct marketing. Some studies have suggested that beginning farmers are more likely to choose direct marketing outlet (Park et al., 2014; Detre et al., 2011). On the other hand, our results show that farms with longer experiences are less likely to choose direct sales strategy until 9.38 years of farm experiences, while the experience of farms has a positive effect on the adoption of direct marketing strategy after operating farms for 9.38 years. This finding suggests that very beginning farmers may be more educated and are more likely to be innovative, which lead them to engage in direct market outlet that needs better understanding of the system of direct marketing and consumer preferences. On the other hand, the reason that more experienced farms over 9.38 years are likely to adopt direct sales strategy may be due to skills and abilities needed for direct marketing, which is developed by their work experiences. This supports the argument of Uva (2002) that a direct marketing strategy requires a special set of skills and abilities.

Geographic attributes also have statistically significant effects on the probability of adoption of direct sales channel. An interesting finding is in the driving distances to nearest city and the average distance to three nearest cities. Results in Table 5 show that the coefficient of distance to nearest city is negative while that of average distance to three nearest cities is positive, which has robust results when we use average distance to five nearest cities instead of three nearest cities and Euclidean distances instead of driving distances. A 10 km decrease in distance to nearest city increases the likelihood of adopting direct marketing strategy by 1.6%, while A 10 km decrease in average distance to 3 nearest cities associated with decreasing probability of adoption by 2.9%. This suggests that the likelihood of adoption of direct marketing increases with better accessibility to one big city rather than multiple cities. In Figure 2, for example, consider two different farms who are located different locations. The distances from Farm (a) to Seattle, Tacoma, and Vancouver are 180, 150, and 250 km, respectively, and thus the distance to nearest city is 150 km and the average distance to three cities is 193km, while the distances from Farm (b) are 300, 250, and 70 km, respectively, and the distance to nearest city is 70 km and the average distance to three cities is 206 km. In this example, Farm (b) is more likely to choose direct sales strategy than Farm (a), even if Farm (a) has better accessibilities to two cities, Seattle and Tacoma, than Farm (b). Taken together with the estimated coefficients, Farm

(b) may be more likely to adopt direct marketing strategy by 16.57 percent (0.16*80+0.29*13=16.57) than Farm (a) due to distances to cities.

We also included urban dummy variable and the interaction term, Urban*distance to nearest city, in the model. The variable of Urban*distance to nearest city is included to capture the different influences of proximity to big city on marketing strategy between urban and rural areas. Results show that farms located in urban county tend to choose direct sales strategy by 8 percent, and their decisions on marketing strategy are more influenced by distance to nearest city compared to those located in rural county. When a farm locates in urban county, a 10 km decrease in distance to nearest city increases the probability of adoption by 1.8%, while, for a farm in rural county, 10 km decrease increases the probability by 1.6%.

Results from urban proximity variables suggest that farms located near an urbanized city are more likely to participate in direct marketing. It would be easier for farmers to reflect the preferences of local consumers on the types and prices of crops they grow if they are located near big city. Also, when farms' operation can take place literally in the customer's backyards, this high visibility in a populated area can attract customers. Therefore, customers living in urban cities may more rely on local products produced near their living area, and their propensity to consume local products through direct market outlet may grow with shorter distance from farm to city. For these reasons, farms located near urban area may tend to take opportunities of direct marketing.

As we expected, another geographic variable, the number of farmer's markets within 200 km from each farm, is also positively related to the probability of adoption of direct sales. An increase in the number of farmers' markets is associated with increasing probability of adoption by 0.6%. Selling directly to consumers through farmers' market is one of the most popular form of direct marketing, and moreover it is growing and accounted for 23 percent of direct-to-consumer sales in 2015 (USDA, 2015). Therefore, it stands to reason that farmers having more farmers' markets around their farms have a lot of access to them and therefore more likely to engage in direct marketing through farmers' markets.

Finally, the coefficient of spatially lagged dependent variable (ϕ) is positive after controlling for various important geographic variables, which confirms the existence of spatial dependence in marketing channel selection among farmers. Results are quite robust when using different spatial lagged variable with different criteria. The result in Table 5 suggests that for each farm, adoption of direct sales strategy is positively influenced by the adoption of the same strategy of near farms within 30 km, which is consistent with the results from global autocorrelation tests represented by Moran's I and Geary's C in Table 3. Result implies that there may be positive spatial dependence and social network effect on the selection of sales outlet between farms rather than spatial competition in the same marketing outlet. Farms interested in direct marketing strategy may readily get the information about direct sales from neighboring farms having engaged in it, and therefore it might be easier for them to start direct sales than other farms.

Following the significant effects of the variables on the marketing strategy choice, we include all of the variables used in the probit model in the selection equation of the endogenous treatment model.

1.5.3 Impacts of marketing choices on farm sales

Table 6 shows estimation results of OLS regression with the natural logarithm of the value of sales per acre as a dependent variable. Results represent that there exists negative impacts of direct marketing adoption and urban proximity on the farm sales. To confirm the robustness of the results when considering the endogeneity, we use the endogenous treatment model with the significant variables in Table 6 as explanatory variables. We also employ the significant variables used in the probit model (Table 4) for selection equation in the endogenous treatment model.

Table 7 compares the estimation results of the constrained and unconstrained treatment regression models with the natural logarithm of the value of sales per acre as a dependent variable. In the constrained model, all farms have the same estimated coefficients regardless their choice of marketing strategy, while farms with different marketing strategies have different coefficients in the unconstrained model. First, note that the correlations between error terms in the selection equation and outcome equation (ρ and ρ_1) are significant in the constrained and unconstrained treatment models, implying that the estimates from OLS regression may be biased due to self-selection problem. In this case, therefore, treatment regression models may be more reliable and preferable than standard OLS regression to estimate the impacts of marketing strategies and other covariate variables. However, the results of the endogenous treatment model are not much different from the estimation results of the OLS regression reported in Table 6. We also confirm that the estimates for the marketing strategy in Table 7 have similar coefficients to those of marketing strategy choice equation using the standard probit model in Table 4, thereby we focus on the results of outcome equation of the endogenous treatment model in this part.

Our key findings for the analysis are in the estimated coefficients on direct marketing strategy. In the constrained model, farms that adopt direct marketing have farm sales per acre that are 75.74 percent (exp(-1.4162)=0.2426) lower. Although, in the unconstrained model, the impact of direct marketing strategy is not directly estimated, we can estimate average treatment effect on the treated (ATET) which is the average difference of the treatment potential outcomes and the control potential outcomes on the treated population. The average effect of a direct marketing strategy on farm sales per acre estimated by ATET is -1.2562 (0.2952). Following the result of unconstrained model, if farms choose direct marketing outlet, their farm sales per acre would be reduced by 71.53 percent (exp(-1.2562)=0.2847), which is lower than the estimates from the constrained model. The OLS regression model assumes that marketing strategy decision is exogenous and predicts that sales decline due to direct marketing outlet is smaller than treatment regression models as 65.05 percent (exp(-1.0513)=0.3495). Results present that there is a statistically significant sales decline when farmers choose direct sales outlet, which is robust to inclusion of geographic variables and is consistent with the previous empirical results (Park et al. 2014; Park, 2015; Park et al. 2018).

However, this effect is not constant for every farm. Figure 3 shows the expected value of farm sales per acre by sales strategy, and farm acres. For very small farms, in terms of farm acres, there is not a significant difference in the expected values of sales between farms with different marketing channels, while the effects of marketing strategy become bigger as farms size increases. It is also presented by negative coefficients of farm acre variable, indicating that an increase in farm acres exacerbates the farm sales decline due to direct marketing strategy. In the unconstrained model, the negative effects of farm acres on sales are larger for the direct sales farms than those with wholesale channel. Still, the impacts of direct marketing adoption are negative for farms regardless their farm size. Farms may continue to participate in direct markets despite its negative impact. One possible explanation would be that direct marketing strategy is used as a risk management tool rather than strategy for higher outcome. Direct marketing may allow farms to make product changes faster reflecting consumer preferences and get to market faster without retail interruptions. Also, start-up costs in direct selling are typically low. Some types of direct marketing, such as farm or roadside stands, would be easiest way for small farmers to start selling their products, while it may be difficult for smaller farms to enter wholesale market with their small amount of production.

On the other hand, farm age has significantly positive effects on farm sales, and moreover the estimated coefficients are larger for the farmers with direct marketing channel in the unconstrained model. These results indicate that although participation in direct marketing is related to lower farm sales, farmers with more farm experiences may be able to limit the amount of the sales decline. In the unconstrained model, one-year increase in farm age reduces the sales decline of direct marketing farms by about 9.71 percent (exp(0.0927)=1.0971). This result is consistent with the argument of Uva (2002) that a direct marketing strategy requires a special set of skills and abilities which may be acquired by farm experiences, suggesting that direct sales fits farms with longer experience well.

Since three geographical variables, average distance to three nearest cities, urban dummy, and interaction term of urban*distance to nearest city, have noticeably different coefficients across farms with different marketing strategies, we focus on the unconstrained model to interpret the results of those variables. Total sales per acre of direct sales farms are significantly affected by those two urban proximity variables, the variables of urban and urban*distance to nearest city. Results show that their sales per acre reduce as the direct farm locates in urban area and locates closer to big city. Direct marketing farms located near big urban cities may be influenced by either positive external benefits generated by spatial concentration of businesses and households or the negative externality. There may be more demand for crop products within local market near urban area, leading to success of farms, whereas urban proximity could also generate negative externalities, which is due to competition between direct marketing farms. As shown in the estimation results of marketing choice equation, farmers are more likely to be involved in direct marketing in urban region, which may lead the direct market to be highly competitive. Therefore, urban proximity would have positive influences on farms' success if positive externalities overwhelm negative externalities, or vice verca. Our results imply that there exist overwhelming negative externalities which leads reduced sales of farms with direct marketing strategy in urban area. One the other hand, the sales of wholesale sales farms are significantly influenced by average distance to nearest three cities. As they locate near urban cities, the sales per acre of farms with wholesale channel increase. If it is easier for wholesale sales farms to access to several big urbanized cities, they would be able to reduce the costs from farm to wholesale market (e.g. transportation costs), and thus their benefits from urban location would contribute to increase their farm sales.

The number of farmers' markets also have conflicting effects between direct and wholesale sales farms. While one farmers' market increase around the farm increases direct marketing farm sales by 1.32 percent (exp(0.0131)=1.0132), it decreases farm sales with wholesale channel by 1.65 percent (exp(-0.0166)=0.9835). Since direct marketing of farm products through farmers' markets is one of the most popular sales outlets for agricultural producers in the U.S., an increase in the number of farmers' markets could lead farmers with direct marketing strategy to have an easier access to farmers' markets and consumers who prefer to purchase products directly from farmers. This may allow direct marketing farms to reduce sales decline due to direct marketing. On the other hand, the sales of farms with wholesale channel would be lower as more farmers' markets exist around them, since parts of demand for products would be taken away from the direct marketing farms who sells their products in the farmers' markets.

1.6 Conclusion

The U.S. Department of Agriculture launched the "Know your farmer, know your food" initiative in 2008 to promote local, sustainable agriculture. According to the USDA, it is designed to support local farmers and community food groups, strengthen rural communities and help schools connect with locally grown foods, and the initiative will also enhance direct marketing. As such, the direct marketing option increasingly have been recognized as a feasible strategy for farmers as well as local economy. This leads to the requirement of information on how the choice of marketing outlets impacts on the farm performance and which determinants are important for producers to involve in the marketing strategies.

The primary objective of this study was to estimate the relationship between the adoption of direct marketing and farm performance, with considering spatial aspects. We employed two types of the endogenous treatment regression models in the form of constrained and unconstrained models, which explicitly address self-selection problems that are likely to be caused by correlations between farms' outcomes and the decisions on marketing channels. Our results showed that there exists the direct marketing penalty even after various spatial variables were included. When farms adopt direct marketing channel, their farm sales per acre would decrease. However, for very small farms, in terms of farm acres, there was not significant difference in the expected values of sales between farms with different marketing channels and those with wholesale channel. This suggests that direct marketing strategy could be a viable option for small farms to succeed.

Another interesting finding was in the results of geographic variables, in which the effects of geographic variables on farm sales were opposite between farms with different marketing strategies. Results represented that their sales per acre reduce as the direct sales farm locates in urban area and locates closer to big city, which may due to that direct markets are highly competitive in urban area. One the other hand, the sales of wholesale sales farms were found to be increased as they locate near urban cities, since they could reduce the farm to wholesale market costs (e.g. transportation costs), and thus their benefits from urban location would contribute to increase their farm sales. The number of farmers' markets also had conflicting effects between direct and wholesale sales farms. While the number of farmers' market increase around the farm increases direct marketing farm sales, it decreases farm sales with wholesale channel.

The secondary objective was to highlight the factors that influence farmers to direct market, including locational environment and spatial interaction between farmers' choice of marketing strategy. Results showed that the variables of urban proximity have significant impacts on the adoption of direct marketing. The propensity to consume local products through direct market outlet may grow with a shorter distance from farm to city since high visibility in a populated area can attract many customers. Also, it might be easier for farmers to reflect the preferences of local consumers on the types and prices of crops they grow if they are located near big city. As the farmers' market is one of the most popular way to sell products directly, the number of farmer's markets around each farm was also positively related to the probability of adoption of direct sales. Also, we considered spatial dependence between farmers' choice, which confirms the existence of positive spatial dependence and social network effect on the selection of sales outlet between farms rather than spatial competition in the same marketing outlet. There may be knowledge spillovers between neighboring farms, which allows farms to start direct sales readily with better information about direct sales from neighboring farms who engaged in it.

Our findings have important policy implications in that spatial aspects are significant factors to estimate the relationship between marketing strategies and farms' outcome. The results suggest that the impacts of marketing strategies could be different across the location of farms, and farmers are influenced by neighboring farms as well as geographic location when they choose marketing strategies. Also, the impacts of direct marketing on farm outcome are found to be different across farm size. Overall, the findings suggest that the promotion of direct marketing should consider farm size, location of farms, and spatial dependence between them in order to reduce sales decline from direct marketing and enable farmers to extract the benefits of each marketing strategy.

An important question that remains but is beyond the scope of this study is: why is direct marketing associated with lower total sales per acre? Additional analysis is needed to understand the reason, but we could anticipate that one of possible explanation may be in that direct marketing is employed by farmers as risk management tools. For example, with direct marketing, farmers would be able to rapidly respond to changing product preference, which allows them to lower the products in stock. Future research could analyze the impacts of marketing efforts on the survival of farms to show whether direct marketing is in practice used to reduce business risk by farmers. Another challenge we faced was that we could not capture the adoption of each specified direct marketing strategy which may require different skills and may be differently affected by spatial aspects. In the future, it will be addressed to explore the relationships between more specified marketing strategy and the success of farms.

TABLES AND FIGURES

Table 1.1. Summary statistics

Variable	Mean	Std. Dev.	Min	Max
Total sales	416,209	989,383	30.97	11,600,000
Direct sales	28,580	112,781	0	2,256,124
Wholesale sales	387,629	991,015	0	11,600,000
Total sales per acre	12,893	98,935	0.15	2,722,132
Acres	114.98	300.41	0.01	5,322
Direct (binary)	0.33	0.47	0	1
Diversification (Herfindahl index)	0.08	0.17	0	0.74
Farm age	7.79	6.18	0	24
Urban	0.18	0.38	0	1
Female	0.19	0.39	0	1
Distance to nearest city (km)	90.73	76.97	0.17	286.85
Average distance to 3 nearest cities (km)	123.47	71.96	7.07	317.46
Number of farmers mkt within 200km	30.05	25.65	1	81
N		1767		

Table 1.2. Summary statistics by marketing channel

Variable	Direct sales		Wholesale sales	
	Mean	Std. Dev.	Mean	Std. Dev.
Total sales	86,794	208,633	581,758	1,169,345
Total sales per acre	11,614	108,128	13,536	94,018
Acres	52.84	119.26	146.21	354.37
Diversification (Herfindahl index)	0.10	0.18	0.07	0.16
Farm age	8.06	6.96	7.65	5.75
Urban	0.28	0.45	0.13	0.33
Female	0.33	0.47	0.12	0.32
Distance to nearest city	85.90	74.09	93.16	78.30
Average distance to 3 nearest cities	115.46	74.82	127.49	70.17
Number of farmers mkt within 200km	43.43	28.83	23.32	20.88
N	591		1176	

Table 1.3. Global spatial autocorrelation in marketing channel selection

Upper distance	Moran's I	Geary's C
30km	0.2754***	0.7681***
	(0.0002)	(0.0003)
40km	0.2713***	0.7699***
	(0.0002)	(0.0003)
50km	0.2646***	0.7746***
	(0.0002)	(0.0003)
Knn 15	0.2550***	0.7339***
	(0.0000)	(0.0000)
Knn 25	0.2415***	0.7430***
	(0.0000)	(0.0000)
Knn 35	0.2361***	0.7427***
	(0.0000)	(0.0000)

Variance of statistics in parentheses.

Table 1.4. Estimation results of probit model

	(1)	(2)
Ln(Farm acre)	-0.1553***	-0.1527***
	(0.0246)	(0.0254)
Farm age	-0.0595***	-0.0573***
	(0.0179)	(0.0184)
Farm age^2	0.0032***	0.0032***
	(0.0008)	(0.0008)
Female	0.4871***	0.5066***
	(0.0866)	(0.0896)
Diversification	1.0079***	0.9867***
	(0.2081)	(0.2155)
Urban	0.3754**	0.3099*
	(0.1549)	(0.1586)
Distance to nearest city	-0.0070***	-0.0060***
	(0.0015)	(0.0015)
Average distance to 3 nearest cities	0.0125***	0.0111***
	(0.0018)	(0.0019)
Number of farmers mkt	0.0274***	0.0239***
	(0.0022)	(0.0023)
Urban*Distance to nearest city	-0.0057	-0.0077**
	(0.0037)	(0.0038)
ϕ		1.1504***
		(0.1040)
Constant	-1.8400***	-2.1682***
	(0.2313)	(0.2401)
Log likelihood	-881.7660	-819.2067
Pseudo R2	0.2170	0.2725
N	1,767	

Year dummy included.
Standard errors in parentheses.
Dependent var: Direct=1 if % of direct sales ≥ 0.5, 0 otherwise.

Table 1.5. Marginal effects of probit model

	(1)	(2)
Ln(Farm acre)	-0.0437***	-0.0398***
	(0.0067)	(0.0064)
Farm age	-0.0167***	-0.0150***
	(0.0050)	(0.0048)
Farm age^2	0.0009***	0.0008***
	(0.0002)	(0.0002)
Female	0.1369***	0.1322***
	(0.0237)	(0.0228)
Diversification	0.2833***	0.2574***
	(0.0574)	(0.0552)
Urban	0.1055**	0.0809**
	(0.0433)	(0.0413)
Distance to nearest city	-0.0020***	-0.0016***
	(0.0004)	(0.0004)
Average distance to 3 nearest cities	0.0035***	0.0029***
	(0.0005)	(0.0005)
Number of farmers mkt	0.0077***	0.0062***
	(0.0006)	(0.0006)
Urban*Distance to nearest city	-0.0016	-0.0020**
	(0.0010)	(0.0010)
ϕ		0.3001***
		(0.0245)

Year dummy included.
Standard errors in parentheses.

Table 1.6. OLS results of farm sales per acre

	(1)	(2)
Direct marketing	-1.0188***	-1.0513***
	(0.0937)	(0.0917)
Ln(Farm acre)	-0.9190***	-0.8983***
	(0.0979)	(0.0972)
Ln(Farm acre^2)	0.0600***	0.0584***
	(0.0127)	(0.0127)
Farm age	0.0771***	0.0568***
	(0.0206)	(0.0063)
Farm age^2	-0.0010	
	(0.0009)	
Female	-0.0678	
	(0.1036)	
Diversification	-1.6208***	-1.6207***
	(0.2398)	(0.2392)
Urban	-0.6974***	-0.7183***
	(0.1864)	(0.1860)
Distance to nearest city	0.0021	
	(0.0016)	
Average distance to 3 nearest cities	-0.0078***	-0.0054***
	(0.0019)	(0.0007)
Number of farmers mkt	-0.0131***	-0.0117***
	(0.0024)	(0.0021)
Urban*Distance to nearest city	0.0103**	0.0109**
	(0.0043)	(0.0043)
Constant	11.5115***	11.3764***
	(0.2849)	(0.2403)
R-squared	0.2563	0.2549
Adj. R-squared	0.2499	0.2498
N	1767	

Year dummy included.
Standard errors in parentheses.

Table 1.7. Regression results of farm sales per acre with the endogenous treatment model

	(1)		(2)		
	Constrained model		Unconstrained model		
	Sales per acre	Marketing choice	Direct sales per acre	Wholesale sales per acre	Marketing choice
Direct marketing	-1.4162*** (0.2237)				
Ln(Farm acres)	-0.9316*** (0.1156)	-0.1428*** (0.0272)	-1.1630*** (0.2277)	-0.7002*** (0.1596)	-0.1431*** (0.0270)
Ln(Farm acres squared)	0.0598*** (0.0152)		0.0338 (0.0356)	0.0465** (0.0185)	
Farm age	0.0575*** (0.0061)	-0.0600*** (0.0188)	0.0927*** (0.0092)	0.0315*** (0.0077)	-0.0597*** (0.0187)
Farm age squared		0.0033*** (0.0008)			0.0033*** (0.0008)
Female		0.5096*** (0.0862)			0.5032*** (0.0874)
Diversification	-1.4981*** (0.2388)	0.9689*** (0.2204)	-0.9272*** (0.3464)	-1.6519*** (0.3442)	0.9406*** (0.2177)
Urban	-0.6691*** (0.2066)	0.3049* (0.1646)	-0.5043* (0.2737)	-0.4617 (0.3118)	0.3070* (0.1641)
Distance to nearest city		-0.0030*** (0.0015)			-0.0062*** (0.0016)
Distance to 3 nearest cities	-0.0049*** (0.0007)	0.0114*** (0.0020)	0.00003 (0.0017)	-0.0044*** (0.0009)	0.0115*** (0.0020)
Urban*Distance to nearest city	0.0103** (0.0045)	-0.0077* (0.0040)	0.0179*** (0.0063)	0.0020 (0.0057)	-0.0079** (0.0040)
Number of farmers' mkts	-0.0090*** (0.0028)	0.0240*** (0.0023)	0.0131*** (0.0044)	-0.0166*** (0.0050)	0.0241*** (0.0023)
ϕ		1.1810*** (0.1043)			1.1882*** (0.1027)
Constant	11.4277*** (0.2780)	-2.2046*** (0.2585)	8.5406*** (0.5744)	11.2215*** (0.3877)	-2.2318*** (0.2595)

ρ	0.1519* (0.0775)		
ρ_1			0.3444*** (0.0971)
ρ_0			0.2395 (0.2114)
N		1767	
Log pseudolikelihood	-4151.46		-4062.74

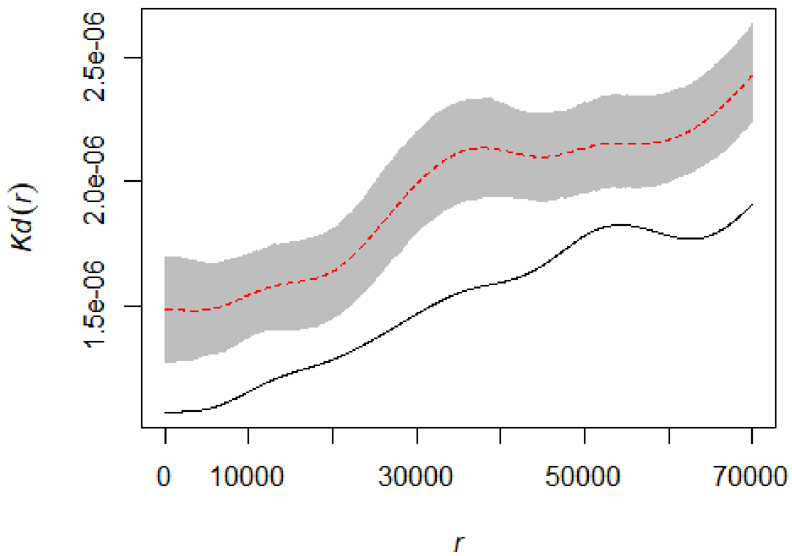

Figure 1.1. Bivariate K_d values in year 2012[2]

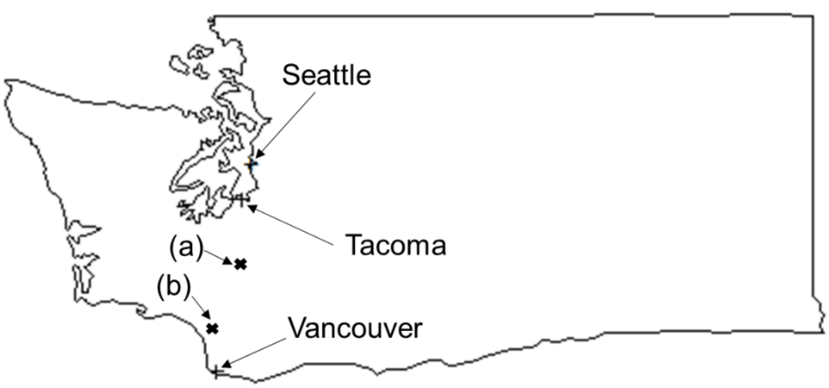

Figure 1.2. Example of locational effects

[2] The solid black curve is K_d. The dotted red curve is the average simulated value and the shaded area is the confidence envelope under the null hypothesis of random location. The risk level is 5%, and 1000 simulations have been run to build the global confidence envelope. Distances are in meters.

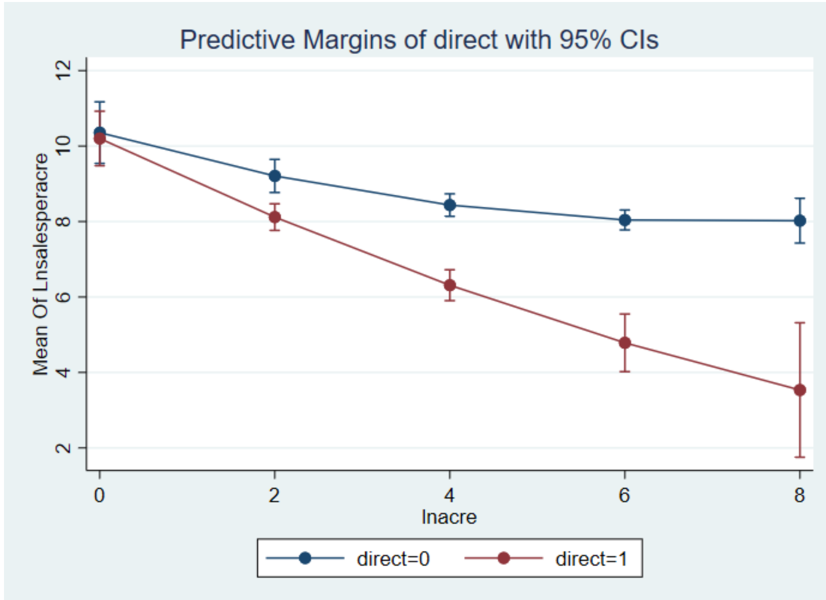

Figure 1.3. Expected farm sales per acre by sales strategy and farm acres

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CHAPTER TWO

Economic consequences of shocks due to climate change and pest and disease outbreak: Comparison of organic and conventional apple industry

2.1 Introduction

Global temperature is rising as a result of increased atmospheric concentrations of greenhouse gases. As the consequence of current and projected climate change, pests and diseases are expected to occur even more frequently and possibly to extend to previously non-affected regions. The temperature changes may strongly affect the insects' physiology and spatial distribution, especially in areas where temperatures tend to be below species optima for most of the year (Harrington et al. 2001; Yamamura et al. 2006). Many species have already responded to the warming conditions that occurred over the last century (Crozier and Dwyer 2006). What is more, the increased frequency of climate extremes can also promote outbreaks of the pest (Gan 2004). As many pests are more prevalent in warmer climates, rising global temperatures may exacerbate the risk they pose to food production. According to the U.S. Global Change Research Program, the negative impacts on agriculture are projected to increase, due to the incidence of weeds, diseases, and insect pests, affecting productivity of most crops and livestock.

The apple industry is a temperate tree fruit crop of economic importance in the United States. According to the U.S. Department of Agriculture (hereafter USDA), the value of apple production in the U.S. was 2.7 billion dollars in 2019, which was the second largest among all fruit and tree nuts production. The value of fresh apple exports was 955.8 million dollars in 2019 which accounts for 21 percent of the total value of fresh fruits exports. Since apples are one of the most valuable fruit crops, it may be vulnerable to pest or disease outbreaks. For example, the 2000 fireblight outbreak in Michigan state resulted in the removal of about 400,000 apple trees and a direct cost of $42 million (Longstroth, 2001). The rising threat of pest or disease outbreaks accompanying climate change impose potentially large costs on apple producers and other economic agents, but the impacts of shock are likely to be different between organic and conventional apple markets since the agents may respond differently to even the same shock in each market.

In order to reduce crop losses, U.S. farmers employ a range of pest management strategies. Despite improved control materials for crop protection, however, pest and disease continue to be the key problem especially in organic orchards. Organic growers may adopt pest and disease management practices that are significantly more expensive and labor intensive than conventional methods. Galinato and Gallardo (2015) found that total variable costs were different for both conventional and organic Gala apple production systems in Washington state as of 2014. In fact, the costs of chemical and fertilizer for organic were about 25% higher than those of conventional growers. Therefore, an outbreak of pest or disease may impose much larger costs on organic producers through pest control programs, and thus it could cause either some transition from organic to conventional system or an increase in organic price premium.

In addition to different aspects in production between organic and conventional apple industries, consumers also have different preferences for organic and conventional fruits. Increased consumer demand for healthier fruit and more environmentally sustainable farming has driven the development of pest management systems that use organic and integrated pest management (IPM) programs (Peck et al., 2005). In previous literature, consumers who buy organic food tend to be more concerned about human health (Demeritt, 2002; Ekelund, 1990), food safety (Goldman and Clancy, 1991; Jolly et al., 1989) and/or environmental stewardship (Grunert and Juhl, 1995; Davies et al, 1995). While U.S. acreage of apples has declined and the total production under both conventional and organic production methods, has stayed at a similar level in recent years (USDA-NASS, 1980-2019); consumer demand has spurred a fast-growing organic apple sector. The value of certified organic apples sales accounts for 17.3 percent of total apple sales in 2019, up from 6.2 percent in 2008 (USDA-NASS, 2008; 2019). This may be partly because consumers have become more conscious of food and pesticide safety issues related to pest control methods (Grunert, 2005; Simon et al, 2011; Food standard, 2011). Consumers concerned about food and pesticide safety might be more likely to purchase organic fruits when pest or disease outbreaks are expected to increase the chemical use in conventional apple industry.

The objective of this study is to measure the economic impacts of pest and disease shocks on heterogeneous agents, such as producers, intermediaries, and consumers, in the U.S. apple industry which is separated into organic and conventional production methods. We use an equilibrium displacement model that enables to measure the impacts of the above mentioned shocks in one market (e.g. organic market) on the other market (e.g. conventional market) through substitution effects. We complement the analysis by applying simulations to better understand these relationships.

Abundant research on the economics of pests and diseases have been conducted. However, most studies have focused on pest management and control systems. A number of studies analyze the economic impact of pest management strategies on productivity, yield, and product quality (Dasgupta et al., 2007; Hurd, 1994; Wetzstein et al., 1985; Bavcock et al., 1992).

Harper and Zilberman (1989) and Grogan and Goodhue (2012) pointed out that pesticide use could produce externalities that contribute to pest pressure and beneficial insects, respectively. As concerns about the sustainability of agriculture have prompted introduction of integrated pest management (IPM) which is intended to reduce ecological and health damage from chemical pesticides by using natural parasites and predators to control pest populations, the efforts have been devoted to find out the attributes that influence the adoption of IPM system (White and Wetzstein, 1995; Bechmann and Wesseler, 2003; Ricker-Gilbert et al., 2008; Greene et al., 1985; Cowan and Gunby, 1996; McNamara et al., 1991). On the other hand, Mbah et al. (2010) developed a real option framework to analyze the economically optimal timing when crop disease control measures should be taken in the presence of risk and uncertainty.

While the attention has been given to pest management and IPM literatures in economics, a number of studies on the effect of pest or disease outbreak have been conducted on the entomology and epidemiology areas. Little research attention has been paid to the economic impacts of pest outbreaks on crop production. Alam and Rolfe (2006) analyzed the government response to the disease outbreaks and estimated the loss of producers' revenue with the application of cost-benefit analysis. Chambers et al. (2010) measured revenue loss due to pest increases by incorporating supply-response adjustment of rational producers into the analysis. Mitchell et al. (2004) developed a composed-error model to estimate the variance of soybean yield loss from pest damage. Hong et al. (2019) estimated the loss of producers' profits in apple maggot quarantine areas which is caused by phytosanitary regulation. While they analyzed the economic effects on production of pest and disease, they did not show how heterogeneous agents in their industries simultaneously respond to shocks. This paper will employ a U.S. apple industry model to estimate the impacts of shock on each economic agent.

Fruit trees different from non-perennial crops can take up to 4 to 5 years to come into full bearing and require extensive horticultural management during the establishing and full production years (e.g., training, pruning, fruit thinning, spraying). Therefore, the external shocks such as outbreak of pest or disease could impose larger costs on apple industry than other crops. These features require a special model of fruit tree to estimate the impacts of shock on fruit markets. Jiang et al. (2017) constructed the model of pear industry at the national level, and explicitly included the tree fruit packing and processing intermediaries. Using this model, they measured economic impacts of disease outbreak and trade shock for heterogeneous agents along the vertical tree fruit supply chain. Although Alston et al. (2013) did not explicitly consider pest shock, they developed a model of California wine grapes to estimate the economic consequences of the termination of current disease-related policy and continuing the program.

The apple industry is the second largest tree fruit crop in the U.S. According to the USDA, the 2019 apple crop totaled just over 11 billion pounds, and the value of sales was 2.7 billion dollars. However, the number of studies on the influence of shock on apple industry is relatively limited. Willett (1993) and Roosen (1999) constructed econometric models to estimate the expected industry responses to changes in exports and domestic conditions and pesticide cancellations, respectively.

The apple industry is not as highly concentrated in a geographic region as other tree fruit. In the U.S., 32 states raise apples commercially. Thus, apple production is likely to be affected by a number of pests and diseases. Some papers have focused on the impacts of specific pest shock. Galinato et al. (2018) and Zhao et al. (2008) evaluated the impacts of apple maggot (Rhagoletis pomonella) expansion in Washington state. Zhao et al. (2008) estimated the losses in apple industry from increased pest controlling costs due to Apple maggot spread and also assessed benefits from mitigating the speed of spread. Galinato et al. (2018) estimated the costs of Apple maggot spread to the Washington state economy. They found that the impacts of Apple maggot spread on costs and outputs depends the pressure of the other pest, Codling moth. Although their model allowed to analyze the economic consequences of pest shock in a specific region, they could not explicitly address the interaction of production and demand between states. Tozer and Marsh (2018) developed regional model of apple industry to assess the economic impacts of pest and disease shocks that could occur within a specific region and studied the possibility of heterogeneous impacts of shock on regional production and welfare. They also allowed the intermediaries to be separated into two sectors (fresh and processed fruit markets) in order to capture how a shock affects the separate parts of the supply chain. However, Tozer and Marsh (2018) employed whole apple industry model and did not consider the potential for different responses to pest and disease shock between organic and conventional apple industries. As the pests and diseases are expected to occur even more frequently and possibly to extend to previously non-affected regions due to climate change, it would be more important to precisely estimate the impact of pest and disease outbreak on fruit industry. To do so, it is needed to analyze organic and conventional apple markets separately.

The organic apple industry continues to grow at a rapid pace. The 2019 Organic Survey ranked apples as the top organic produce commodity, with sales of 475 million dollars, which is increased by 45 percent from 2016 (USDA-NASS, 2016; 2019). However, most studies have developed the models of whole apple industry (Willett, 1993; Roosen, 1999; Tozer and Marsh, 2018; Zhao et al. 2008). An exception is Galinato et al. (2018). Although Galinato et al. (2018) is the only paper that studied different impacts of pest expansion between organic and conventional apple industry, they only estimated the impacts on Washington state economy. The contribution of this research is to model the U.S. apple industry by separating into organic and conventional apple sectors and measure the heterogeneous impacts of pest and disease shocks on two different apple markets by considering the interaction between two markets.

This paper is organized as follows: The next section starts with the discussion the dynamic model of the U.S apple industry separated into two types of markets, i.e. organic and conventional apple markets. Section 3 explains the Equilibrium displacement model for empirical analysis. Section 4 describes the data and scenarios used in the simulation. In Section 5, the results of simulation are presented. Finally, this paper concludes with Section 6 in which the main findings and policy implications are suggested.

2.2 Theoretical model

To estimate the economic impacts of pest and disease shocks more specifically, we develop a dynamic model of the U.S apple industry, extending Tozer and Marsh (2018) by separating apple industry into two types of production methods and markets, i.e. organic and conventional. In our model, the shock on the organic production method has effects on the conventional apple production method, and vice versa. In addition, considering the importance of export markets for the U.S. apple industry, our model includes international trade to better depict the interactions between domestic and international markets. For simplification purposes, this model only focuses on the fresh market apples. This is based on the assumption that most growers in the United States invest in apple production considering the fresh market, and the processing market is a residual market.

In our conceptual model, there are three levels of the supply chain: farm level, wholesale level, and retail level. At the farm level, total supply is determined by bearing acreage multiplied by yield per acre. We assume the bearing acreage as fixed in the short run and the maturing time for tree is needed. However, in the long run, the bearing acreage can change with the investment that is influenced by the prices that producers received and other market conditions. Apple products are distributed to the domestic and international markets through a market-clearing condition at the wholesale level. Also, imports are linked through market-clearing price conditions at the wholesale level. The quantities imported and exported apples are assumed to be determined through wholesale-level prices. At the retail level, the demand for apples is based on the retail prices of apples, retail prices of substitute product (e.g., organic apple prices for conventional apples), and household income. Finally, from the market clearing condition, domestic supply plus imports equals domestic consumption plus exports, and the market clearing prices at each level are identified through marketing margins.

The market clearing optimization model is constructed by employing the equilibrium displacement model.

2.2.1 Bearing area

The productive population of fruit tree evolves according to its biological features and to grower's decisions to adjust population stocks. Since trees requires on average 5 to 6 years to reach its full productive stage, there is a lag between investment decision and the time to efficiently bear fruit. The bearing area for each age group *j* evolves according to the following equation:

$$A_t^{j,d} = A_{t-1}^{j-1,d} - RM_t^{j,d} + A_{t-1}^{j_\tau - 1,d} \ , \qquad d = \{o, c\} \tag{1}$$

where *d*=o represents organic and c represents conventional production methods. The area of apples $A_t^{j,d}$ is a function of the area of apple in the previous year $A_{t-1}^{j-1,d}$, the area of trees removed in the current year $RM_t^{j,d}$, and area of trees planted τ years ago that have now reached a productive age $A_{t-1}^{j_\tau - 1,d}$.

Total bearing area is the sum of the areas with trees that have reached full maturity ($j \geq j_\tau$) up to age J when trees are removed due to age:

$$A_t^d = \sum_{j=j_\tau}^{J} A_t^{j,d} \tag{2}$$

And, total apple area at period *t* is described by

$$TA_t^d = \sum_{j=1}^{j<j_\tau} A_t^{j,d} + A_t^d. \tag{3}$$

The total apple area and bearing area can be represented by the change in tree area each year. The change in total apple area is:

$$\Delta TA_t^d = TA_t^d - TA_{t-1}^d \tag{4}$$

which is the net difference between new plantings NP_t^d and removals TRM_t^d, or

$$\Delta TA_t^d = NP_t^d - TRM_t^d \tag{5}$$

where $TRM_t^d = \sum_{j=1}^{J-1} RM_t^{j,d} + RM_t^{J,d}$.

Also, the change in bearing area is defined by

$$\Delta A_t^d = A_{t-1}^{j_\tau - 1,d} - \sum_{j=j_\tau}^{J} RM_t^{j,d} \tag{6}$$

or, alternatively,

$$\Delta A_t^d = NP_{t-j_\tau}^d - \sum_{j=j_\tau}^{J} RM_t^{j,d}. \tag{7}$$

For the bearing acreage, we will use the change in bearing area of organic and conventional apples since we have limited data and we cannot get the detailed data (e.g. number of trees for each age group, removal, and plating).

2.2.2 Apple production and farm-level supply

The total production of apple in each year is given by

$$TP_t^d = TA_t^d * AY_{t-1}^d * (1 + g^d), \qquad d = \{o, c\} \tag{8}$$

where AY_{t-1}^d is the yield per acre in the previous year, and g^d is the annual yield growth rate for each apple product. It is assumed that yield per acre will grow over time since the production efficiency shows the increasing trend due to the replacement of old plantings with old technologies by new orchard systems with advanced technologies and therefore increasing the yield per acre.[3] Due to the difficulties of employing data of trees or planting and removal acres, the annual growth rate of yield per acre would be most appropriate for estimating the dynamics of apple production decisions.

Farm-level supply (FD_t^d) for fresh apple is given by

$$FD_t^d = f_d * TP_t^d \tag{9}$$

where f_d is the proportion of production entered into the fresh market, which is assumed as 0.86 and 0.69 for organic and conventional industries, respectively, following by the recent trends of utilized production from 2011 to 2016 (USDA-NASS, 2011-2016).

Finally, the total supply of apple in the U.S. is given by

[3] In the U.S., the yield per acre of apples (calculated by total production divided by total bearing acres) increased by 1% annually on the average from 1980 to 2019 (USDA-NASS, 1980-2019).

$$TSA_t^d = FD_t^d + FM_t^d, \quad (10)$$

where $FM_t^d = s_t^{IM,d}(p_t^{W,d} - c_t^d)$ is the quantity of imported apple, s_t^{IM} is the imported apple function of prices and costs, $p_t^{W,d}$ is the domestic price at the wholesale level, and c_t^d is the trade costs.

2.2.3 Apple demand at the retail level

Individual demand for apple is based on the prices of organic and conventional apples, prices of substitutes, income and other potential demand shifters. The demand function is therefore:

$$q_t^d = f_t^d(p_t^{R,o}, p_t^{R,c}, I_t), \qquad \mathrm{d} = \{\mathrm{o}, \mathrm{c}\}, \quad (11)$$

where $p_t^{R,o}$ and $p_t^{R,c}$ are the retail prices of organic fresh apple and conventional fresh apple, respectively, and I_t is the income.

We assume a homothetic utility function for consumers, therefore we aggregate individual demand function to estimate total demand for apple:

$$QD_t^d = \sum_{h=1}^{H} q_{t,h}^d = q_t^d * H_t \quad (12)$$

where H is the population, and h represents individual consumers.

Finally, total demand for apple in the U.S. is represented by

$$TDA_t^d = QD_t^d + FX_t^d \quad (13)$$

where $FX_t^d = s_t^{EX,d}(p_t^{W,d} + e_t^d)$ is the quantity demanded by the international market, s_t^{EM} is the exported apple function of prices and tarriff, $p_t^{W,d}$ is the price at the wholesale level, and t_t^d

is the tariff, or the tariff equivalent of trade barriers. The quantities imported and exported apples are assumed to be determined through wholesale-level prices.

2.2.4 Intermediaries and marketing margins

In our analysis, there are two prices in the market, the farmgate price ($p_t^{F,d}$) and retail price ($p_t^{R,d}$). The farm to retail marketing margin is made up of two components, the farm to wholesale margin (MMF), and the wholesale to retail margin (MMR). Thus, the wholesale price is described by,

$$p_t^{W,d} = p_t^{F,d} + MMF_t^d \tag{14}$$

where $MMF_t^d = \gamma_i^{MMF.d} * p_t^{W,d}$, and $\gamma_i^{MMF.d}$ is the proportion of wholesale prices that is distributed to farm to wholesale margin.

The retail price is:

$$p_t^{R,d} = p_t^{W,d} + MMR_t^d \tag{15}$$

where $MMR_t^d = \gamma_i^{MMR,d} * p_t^{R,d}$, and $\gamma_i^{MMR.d}$ is the proportion of retail prices that is distributed to wholesale to retail margin.

2.2.5 Market clearing

Since the import and export decisions are made at the wholesale level, we assumed that the apple market clears at the wholesale level. Therefore, we have market clearing condition as:

$$TDA_t^d = TSA_t^d , \tag{16}$$

or

$$QD_t^d + FX_t^d = FD_t^d + FM_t^d \tag{17}$$

2.3 Equilibrium displacement model (EDM)

The farm-level supply for fresh apple is given by $FD_t^d = f_d * TP_t^d$. The total logarithmic differential equation is as follow:

$$EFD_t^d = ETP_t^d \tag{18}$$

where *E* represents total logarithmic differential of each equation.

The total demand function for domestically-grown apple is given by $QD_t^d = q_t^d * H_t$, where $q_t^d = f_t^d\left(p_t^{R,o}, p_t^{R,c}, I_t\right)$. Therefore, logarithmically differentiating the demand results in the following:

$$EQD_t^d = EH_t + \eta^{o,d} * Ep_t^{R,o} + \eta^{c,d} * Ep_t^{R,c} + \nu^d * EI_t \tag{19}$$

where $\eta^{o,d} = \frac{\partial f_t^d}{\partial p_t^{R,o}} \frac{p_t^{R,o}}{q_t^d}$ and $\eta^{c,d} = \frac{\partial f_t^d}{\partial p_t^{R,c}} \frac{p_t^{R,x}}{q_t^d}$ represent the own-price elasticities and the cross-price elasticities, and $\nu^d = \frac{\partial f_t^d}{\partial I_t} \frac{I_t}{q_t^d}$ is the income elasticity.

To depict international trade, we denoted the function of imported apples and that of exported apples by $FM_t^d = s_t^{IM,d}\left(p_t^{W,d} - c_t^d\right)$ and $FX_t^d = s_t^{EX,d}\left(p_t^{W,d} + e_t^d\right)$, respectively. Taking total logarithmic differentiation gives the following:

$$\mathrm{E}FM_t^d = \mu^{IM,d}(p_t^{W,d} - c_t^d)^{-1}(p_t^{W,d} Ep_t^{W,d} - dc_t^d) \tag{20}$$

and

$$\mathrm{E}FX_t^d = \mu^{EX,d}(p_t^{W,d} + e_t^d)^{-1}(p_t^{W,d} Ep_t^{W,d} + de_t^d) \tag{21}$$

where $\mu^{IM,d} = \frac{\partial s_t^{IM,d}}{\partial\left(p_t^{W,d} - c_t^d\right)} \frac{p_t^{W,d}}{FM_t^d}$ and $\mu^{EX,d} = \frac{\partial s_t^{EX,d}}{\partial\left(p_t^{W,d} + e_t^d\right)} \frac{p_t^{W,d}}{FX_t^d}$ are the price elasticities of imported apple and exported apple with respect to wholesale price, respectively.

The apple supply from domestic farm is given by $QS_t^d = FD_t^d + FM_t^d - FX_t^d$. The total logarithmic differential equation is as follow:

$$\mathrm{E}QS_t^d = \frac{FD_t^d}{QS_t^d} EFD_t^d + \frac{FM_t^d}{QS_t^d} EFM_t^d - \frac{FX_t^d}{QS_t^d} EFX_t^d. \tag{22}$$

The relationship between farmgate and wholesale price and between wholesale and retail price is represented by $(1-\gamma^{MMF.d})p_t^{W,d} = p_t^{F,d}$ and $(1-\gamma^{MMR,d})p_t^{R,d} = p_t^{W,d}$, respectively. Taking total logarithmic differentiation of price equations gives the following:

$$(1-\gamma^{MMF.d})Ep_t^{W,d} = \frac{p_t^{F,d}}{p_t^{W,d}} Ep_t^{F,d} + \gamma^{MMF.d} * E\gamma^{MMF.d} \tag{23}$$

and

$$(1-\gamma^{MMR,d})Ep_t^{R,d} = \frac{p_t^{W,d}}{p_t^{R,d}} Ep_t^{W,d} + \gamma^{MMR,d} * E\gamma^{MMR,d}. \tag{24}$$

Since we have market clearing condition as $TDA_t^d = TSA_t^d$, or $QD_t^d + FX_t^d = FD_t^d + FM_t^d$, the total logarithmic differentiation equation is then:

$$\begin{aligned} &EH_t + \eta^{o,d} * Ep_t^{R,o} + \eta^{c,d} * Ep_t^{R,c} + \nu_i^d * EI_t \\ &\qquad = EFD_{i,t}^d + \frac{FM_t^d}{QS_t^d}\left[\mu^{IM,d}(p_t^{W,d} - c_t^d)^{-1}(p_t^{W,d} Ep_t^{W,d} c_t^d - dc_t^d)\right] \\ &\qquad - \frac{FX_t^d}{QS_t^d}\left[\mu^{EX,d}(p_t^{W,d} + e_t^d)^{-1}(p_t^{W,d} Ep_t^{W,d} + de_t^d)\right]. \end{aligned} \tag{25}$$

Using the market clearing condition and price relationship equations, we can solve market clearing prices at different level of markets ($p_t^{W,d}, p_t^{R,d}, p_t^{F,d}$), quantities of supply and demand inside of country (FD_t^d, QD_t^d), and quantities of imports and exports (FM_t^d, FX_t^d).

2.4 Data

A dynamic model of apple market is parameterized using data from the U.S. apple industry. The fresh apple industry is separated into two different markets, organic fresh and conventional fresh markets.

We employ utilized fresh apple production from Noncitrus Fruits and Nuts and Organic Survey (USDA-NASS, 2016) as farm-level supply of apples. Imports and exports of apples are derived from the USDA-ERS. Farm-level prices of apples are also from the value of sales per pound from USDA Noncitrus Fruits and Nuts and Organic Survey (USDA-NASS, 2016). Retail prices of apples are from USDA-AMS (Agricultural Marketing Service, 2016), and we calculate the wholesale prices based on the information from Tozer and Marsh (2018). They estimated the average wholesale to retail margin is about six times of the farm to wholesale margins, respectively.

Since available data to forecast bearing acres of organic industry in the U.S. is limited, we employ Washington organic apple cultivated area in acres and F.O.B. price in $/40-lb box data by apple varieties from WSU Tree Fruit Research and Extension from 2004 to 2018 (Granatstein and Kirby, 2019). Washington is the largest apple producer and produces around 97% of the organic fresh product in the country in 2019, according to USDA-NASS (2019). For the conventional industry, we use entire apple industry (including both organic and conventional industries) data as proxy for conventional industry since we have limited data for conventional industry, and the bearing acres of conventional apples account for 95% of total apple acres in 2015 (USDA-NASS, 2015). To estimate the function of conventional bearing acres, we use bearing acres and grower price data from 1980 to 2015 from USDA Noncitrus Fruits and Nuts.

The model is then empirically calibrated as an equilibrium displacement model using the parameters in Table 1. Few studies have estimated demand elasticities for organic and conventional apples by separate. We used the estimates of Lin et al. (2009) as the retail price elasticities of fresh apples in demand model. Income elasticities for fresh apples are also from the estimates of expenditure elasticities in Lin et al. (2009).

Import and export elasticities are also needed to complete the model. Roosen (1999) reports import elasticities for fresh apples as -0.609. Seale et al. (1992) estimated demand elasticities for U.S. apples of between -0.90 to -1.62 in Canada, U.K., Singapore, and Hong Kong. Richards et al. (1997) estimated elasticities for fresh apples of -1. Given the rage of estimated results, Tozer and Marsh (2018) assumed the import and export elasticities as -1 for the U.S. fresh apples, and previous studies estimated that the elasticities for organic apples are larger than those of conventional apples (Lin et al. 2009). Following these studies, we set the export (import) elasticities at -1.3 (1.3) and -1 (1) for organic and conventional apples, respectively.

2.5 Scenarios

Given the number of potential pests and diseases outbreak, we examine a limited number of scenarios that represent pest or disease outbreak due to climate change. The baseline scenario represents economic outcomes given the environment in which consumer population annually increases by 0.09% and annual yield growth rate is 1% due to farms' strategies of planting and removal. This paper then consider several exogenous shocks to the model.

The second scenario examines a negative supply shock where 5% reduction in organic bearing area and 2% reduction in conventional apple area occur. The justification for this scenario relies on the fire blight episode in southwest Michigan in 2000, when fire blight ripped through a large portion of the region's apple orchards and caused the removal of about 400,000 apple trees covering approximately 2,000 acres which was 4% of apple bearing area in Michigan. We assume that damage on organic apple area is larger than those of conventional apples since antibiotics have been removed from the national list of allowed materials by the National Organic Standards Board in the U.S., and their use have been prohibited in organic orchards after October 2014 (Granatstein, 2019).

The third scenario represents a reduction in yields of apples, 10% reductions in organic and 5% reduction in conventional apple yields. Codling moth is nearly worldwide distributed pest and has very high potential for adaptation to season length and temperature (Stoeckli et al., 2012). Stoeckli et al. (2012) showed that under future conditions of increased temperatures (2045-2074), the present risk of below 20% for a pronounced second generation will increase to 70-100%, and the risk of an additional third generation will increase from presently 0-2% to 100%. If warming patterns are projected to cause them to live longer, it may be necessary for additional spraying of the fruit. However, recent consumers pay more attention on the issue of pesticides, and producers have limited options available to manage pest and disease (Jones et al., 2010; Simon et al., 2011), which may lead a reduction in apple yields. Under Scenario 3, a reduction in yields of organic apples is larger than those of conventional apples. This could represent the results of Simon et al. (2011) which showed that the fruit damage from pests and diseases is much more severe in organic farming system than conventional system. The fruit injuries due to pests and diseases are between 0 to 2.1%, and 0.1 to 23.7% in the conventional and organic system, respectively.

Scenario 4 would represent the phenomenon where an outcome of pests in organic apples is that producers will have to make an action, like spraying a chemical, which leads producers to no longer sell the crop as organic. This could produce some indirect effect on the supply of conventional that comes from organic apples being sold as conventional. Under the scenario 4, organic production would decrease by 5% since they cannot follow the organic standard due to pest outbreak, and therefore which cause that conventional production increases as much as organic production decreases.

Scenario 5 investigates the response of apple importing countries with pest or disease outbreaks. The spread of disease or pest is also likely to lead apple importing countries to increase their concerns on the introduction and distribution of new species in their countries. For example, China, British Columbia, and Canada require all apples shipped from the U.S. to be certified as apple-maggot-free, and Washington has implemented a quarantine program[4] to prevent apple maggot dissemination (Hong et al. 2019). Following Hong et al. (2019), apples from quarantine areas must be stored at 1°C for 40 days with the cost burden from cold treatment at $11 per 40-lbs box. Under the scenario 5, all producers would be required the implement of cold treatment to export fresh products and face the cost ($0.275 per pound) as a trade barrier.

The exogenous shocks to the system occur in 2016 under scenario 2-5, and all models were run over 10 years.

[4] Apples from quarantine areas must be stored at 1°C for 40 days with the cost burden from cold treatment at $11 per 40-lbs box.

2.6 Results

2.6.1 Bearing acres model

From the data listed above, we estimate the bearing acres model for organic and conventional industries as, respectively:

$$\Delta BA_t^o = -42.05^{***}\mathrm{t} + 0.64^{***} BA_{t-1}^o - 0.84^{***} BA_{t-2}^o + 0.32^{***} BA_{t-5}^o$$

(12.70) (0.10) (0.13) (0.09)

$$+1164.31^{***} premium_{t-2} + 459.12^{***} p_{t-2}^{F,o} - 964.06^{***} p_{t-3}^{F,o} + 711.53^{***} p_{t-5}^{F,o}$$

(323.70) (167.56) (229.56) (225.03)

$$\Delta\% BA_t^c = 0.607^{*} - 0.0007^{*}\, t - 0.046\, ^{*} lnBA_{t-1}^c + 0.769^{***} \Delta\% BA_{t-1}^c$$

(0.35) (0.0004) (0.03) (0.13)

$$+0.037^{***} \Delta\% p_{t-1}^{F,c} + 0.023^{**} \Delta\% p_{t-2}^{F,c}$$

(0.01) (0.01)

where Adj.R^2's are 0.689 and 0.706, respectively, and ***, **, and * indicate significance with 99%, 95%, and 90% confidence. $premium_t = \sum_{j=0}^{2} (p_{t-j}^{F,o} - p_{t-j}^{F,c})/3$ represents average organic price premium over three years, and $p_t^{F,d}$ represents the farmgate prices of apples where $d=\{o, c\}$.

Farms are required three years to transition from conventional to certified organic production in the U.S while there is no regulation for conventional industry. Therefore, it is reasonable that the amount of organic acres is influenced by earlier periods of prices and bearing acres. In the organic industry, the change in acres is affected by prices at lags of two, three, and five years, and the acres at a lag of one, two, and five years. Whereas, in the conventional industry, the price changes at lags of one and two years and acres change at a lag of one year have impacts on the change in bearing acres.

2.6.2 Simulation results

In the baseline scenario, the bearing area results provide evidence that the area of organic apples will grow while the area of conventional apples will continue to decrease. Annual growth rates of bearing acreage of organic and conventional apple industry are 3.4% and -1.7% on the average, respectively (see Table 2). The organic apples production distributed into fresh market increases by approximately 82% over the period of study while the conventional fresh apple produce decreases by about 10%. However, the share for conventional apples will be still larger in that the bearing acres and production of conventional industry will still account for over 90% of entire apple industry. As shown in Table 3, the prices of organic apples will be decreased gradually as the production will grow, while the prices of conventional apples will increase as the production will be reduced. Therefore, the organic price premium is expected to gradually decrease over the period of study. For the international trade, the net-trade of organic apples increases, whereas the net-trade of conventional apples decreases. This may be because decreasing prices of domestic organic products make domestic products become relatively more attractive, and therefore imports of organic products decrease, and exports increase. Whereas, domestic conventional products become less appealing to foreign consumers due to growing prices, and thus exports decrease, and imports increase.

In scenario 2 of negative supply shock on bearing acreage, all the net changes in economic surplus are negative in the organic and the conventional industry (Table 4 and Figure 1). Figure 1 shows the time paths of changes in consumer and producer surpluses. Consumers are worse off due to a supply shortage since retail prices are higher than in baseline. Domestic consumption for both apples decrease as higher prices require consumers to increase their food budget, and therefore the consumer surplus decreases with pest outbreak. On the other hand, the impacts on producer surpluses are shown as different in organic and conventional industries. In conventional industry, positive effects on producer surplus represent that the impacts of an increase in price outweigh the losses from the lower production. However, the subsequent replanting may be followed to regain the previous level of bearing area, and thus it may allow production to grow and prices to decrease, and thus producer surplus gradually decrease. On the other hand, in organic industry, huge losses due to negative shock on bearing area exceed the gain from increased prices, but producer surplus may rebound to similar level of baseline with the subsequent replanting. As the price increases, there also exists a negative net-trade effect of which imports of apples increase while exports decrease. This is because higher prices of domestic products make foreign products become relatively more attractive to domestic consumers, while domestic products become less appealing to foreign countries.

Figure 2 shows the results of changes in yields represented by scenario 3. Consumer surplus is reduced right after the yield shock, and rebounds to a positive change in the following years and then remains relatively constant over the period of analysis in both industries. This is because retail prices increase in the year of the yield decline and then decrease to the prices lower than in baseline as higher prices lead producers to produce more products. Change in producer surplus is also negative after the yield shock, but it remains below the baseline in the following years.

Figure 3 shows the welfare changes under scenario 4 of which some products from organic acreage are sold as conventional. Consumer surplus of organic apples reduced while consumer surplus from conventional apples soared right after the shock. Theses difference can be mostly explained by the changes in retail prices. For the producer surplus, organic producer surplus increases right after the shock and then decrease and remain relatively constant in the following years. On the other hand, surplus of conventional apples producer shows a downtrend relative to the baseline since an increase in produce sold as conventional decreases the prices of conventional apples, and which accordingly decreases the conventional production.

From the trade cost shock in scenario 5, organic and conventional industries show similar results to each other (Table 4; Figure 4). Cumulative net welfare changes are positive in entire industries due to increases in consumer surplus. As the trade costs are imposed to organic and conventional fresh apple markets, the exports of both apple industries decrease right after the shock. Immediately after the trade cost shock declines in exports are rerouted to domestic supply and reduce the equilibrium prices in both industries, and therefore, producer surpluses fall while consumer surpluses are better off.

2.7 Conclusion

In this study we constructed model of the U.S. apple industry that is separated into organic and conventional industries to better understand how the economic consequences of shocks are distributed. Our model is based on a dynamic change in bearing area equation for each industry and optimized to clear the markets at the wholesale level, and is designed to predict changes in economic welfare as economic agents respond to pest or disease outbreak. Though we parameterize our model using the U.S. apple industry, it is general enough to be adapted to study the impacts of various exogenous shocks on any other perennial crops.

We examine a number of scenarios that represent pest or disease outbreak due to climate change, such as reduction in bearing acreage, yield shock, and change in trade cost. Our empirical simulation results show that due to different structures between organic and conventional industries, the impacts of pests and disease shocks vary across industries, and therefore the degrees of the impacts for producer and consumer surpluses are found to be different.

Given that exogenous shock is one of the major concerns for the U.S. tree fruit industry, our model would be useful in the estimation of impacts that result from pest and disease shock due to climate change. Also, for policy makers findings in this study demonstrate that the effects of pest or disease outbreaks on producer and/or consumer welfare vary between organic and conventional industries and by type of shocks. When policy makers suggest policy responses in relation to the outbreak and examine a control strategy, for a particular type of outbreak, they should consider that apple production systems are very heterogenous between organic and conventional industries and the impacts on industries could differ widely as growers and consumers' abilities to respond to shock vary across industry.

TABLES AND FIGURES

Table 2.1. Parameter values used in simulation

Parameter	Organic apple market	Conventional apple market
Own-price elasticity of fresh apples [b]	-1.06	-0.83
Cross-price elasticity between fresh apples from different markets [b]	0.10	0.10
Income elasticity of fresh apples [b]	0.99	1.01
Export elasticity of fresh apples [c,e]	-1.3	-1
Import elasticity of fresh apples [c,e]	1.3	1
Farm to wholesale market margin rate of fresh apples [c]	0.33	0.33
Wholesale to retail market margin rate of fresh apples [c]	0.67	0.67

Sources: [b] Lin et al. (2009); [c] Tozer and Marsh (2018); [e] Assumed.

Table 2.2. Trends of bearing area and apple supply without shock, baseline

year	Area in acres		Apples distributed into fresh market (lbs)	
	Organic	Conventional	Organic	Conventional
0	15,037	313,763	448,224,954	7,261,841,653
1	14,610	308,465	439,853,159	7,210,623,485
2	14,987	302,293	455,703,057	7,136,998,489
3	16,349	296,352	502,094,400	7,066,717,787
4	18,081	290,645	560,851,890	6,999,920,806
5	19,437	285,157	608,925,099	6,936,424,976
6	20,011	279,906	633,196,569	6,876,786,171
7	19,864	274,917	634,806,607	6,821,764,742
8	19,482	270,199	628,826,120	6,771,731,752
9	19,441	265,731	633,775,258	6,726,359,071
10	20,049	261,469	660,132,976	6,684,654,210

Table 2.3. Trends of prices, exports, and imports without shock, baseline

year	Farmgate prices ($/lb)		Exports (lbs)		Imports (lbs)	
	Organic	Conventional	Organic	Conventional	Organic	Conventional
0	0.714	0.394	94,128,767	3,172,646,109	72,427,568	621,738,486
1	0.728	0.400	91,790,154	3,130,387,935	74,227,018	630,019,754
2	0.715	0.405	93,850,489	3,086,356,162	72,560,908	638,881,559
3	0.671	0.410	101,422,717	3,052,573,124	66,706,408	645,874,712
4	0.620	0.414	111,412,695	3,022,948,499	60,135,931	652,142,799
5	0.585	0.418	119,564,092	2,991,137,563	55,736,147	659,005,395
6	0.571	0.423	123,172,864	2,954,952,891	54,053,877	666,977,577
7	0.574	0.429	122,357,936	2,915,720,191	54,411,505	675,832,991
8	0.582	0.434	120,092,240	2,877,158,289	55,419,040	684,771,231
9	0.583	0.439	119,941,998	2,843,150,532	55,488,372	692,865,166
10	0.568	0.444	123,819,526	2,815,429,144	53,694,524	699,620,765

Table 2.4. Net present values of welfare impacts[5]

(a) Organic industry

Scenarios	Change in consumer surplus	Change in producer surplus	Net change in surplus
2	-114.94	-4.09	-119.03
3	48.44	-54.52	-6.08
4	14.22	-13.86	0.36
5	37.41	-12.77	24.64

(b) Conventional industry

Scenarios	Change in consumer surplus	Change in producer surplus	Net change in surplus
2	-252.86	73.70	-179.16
3	-25.40	-152.04	-177.44
4	9.14	-5.67	3.47
5	704.19	-386.43	317.77

(c) Entire industry

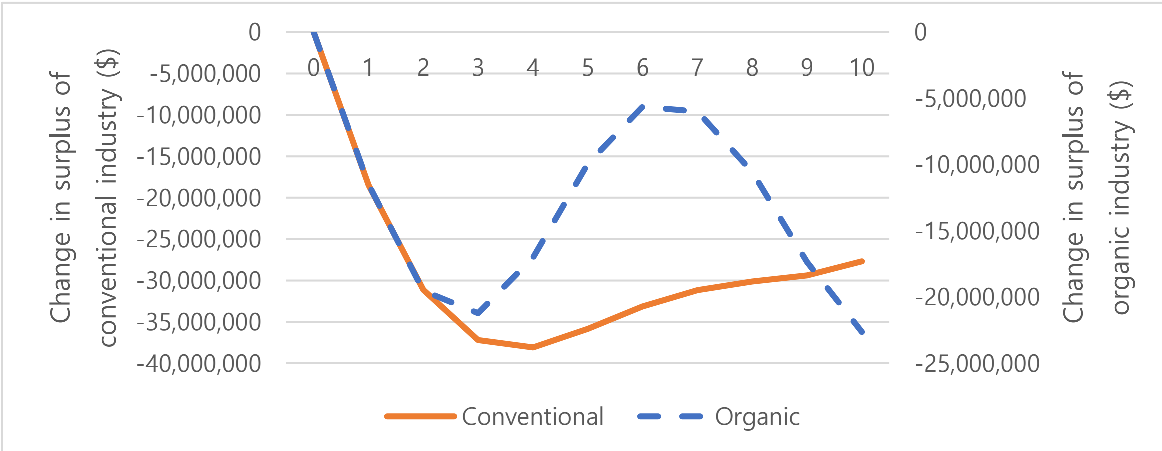
Scenarios	Change in consumer surplus	Change in producer surplus	Net change in surplus
2	-367.80	69.61	-298.20
3	23.03	-206.56	-183.53
4	23.37	-19.54	3.83
5	741.60	-399.20	342.41

All values in $US millions.

The discount rate is set as 4%.

[5] The change in surplus is the difference between surpluses in the shock scenario and baseline. Change in consumer surplus=$\int_{P1}^{x} Q_1 dP - \int_{P0}^{x} Q_0 dP = -(1+\varepsilon)^{-1} P_0 Q_0 (e^{(1+\varepsilon)EP} - 1)$. Change in producer surplus= $TP^s - TP^{baseline}$ where TP=Total revenue–Total cost. Following Taylor (2013), we assumed the costs of organic and conventional systems are \$5153/acre \$4621/acre in 2016 dollars, respectively. Net change in surplus=Change in consumer surplus +Change in producer surplus.

(a) Change in consumer surplus



(b) Change in producer surplus

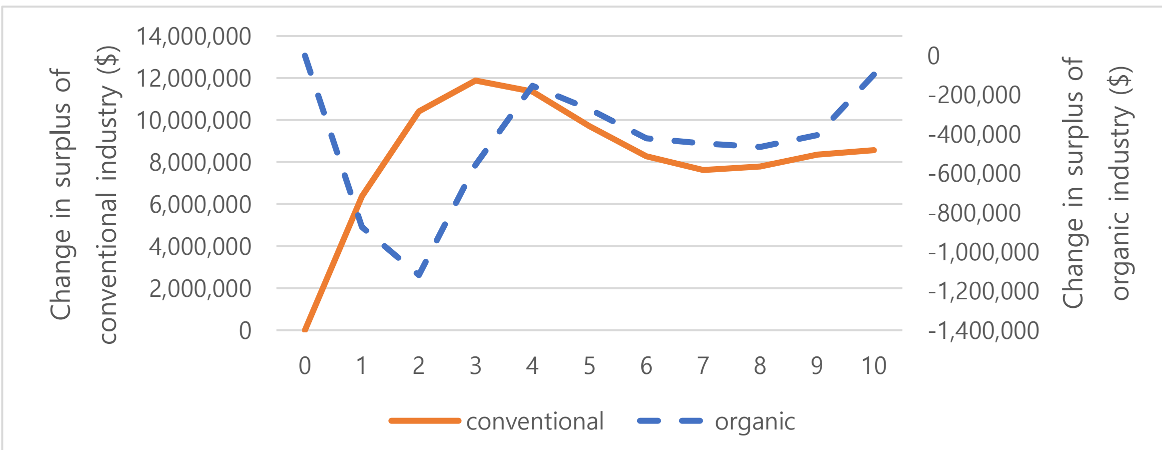
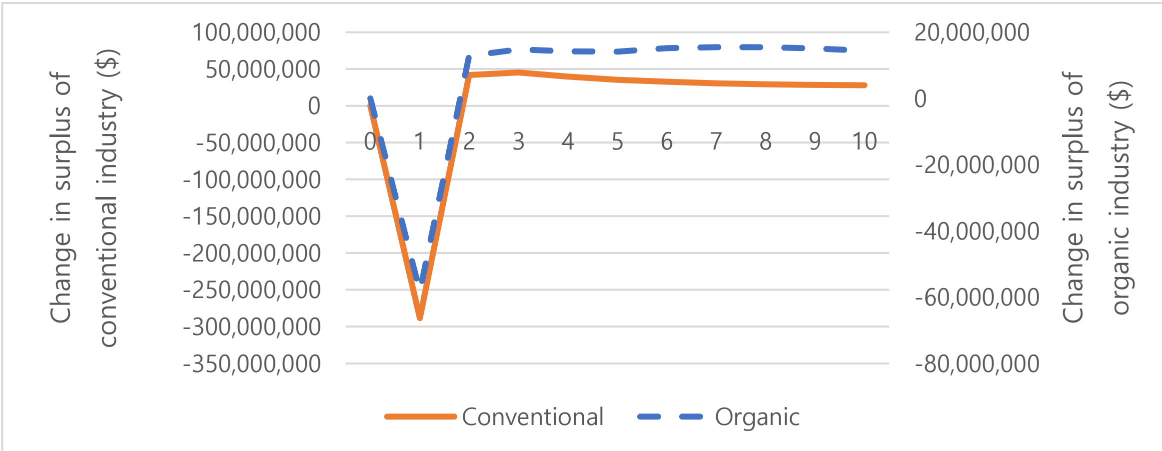


Figure 2.1. Change in economic surplus under Scenario 2

(a) Change in consumer surplus



(b) Change in producer surplus

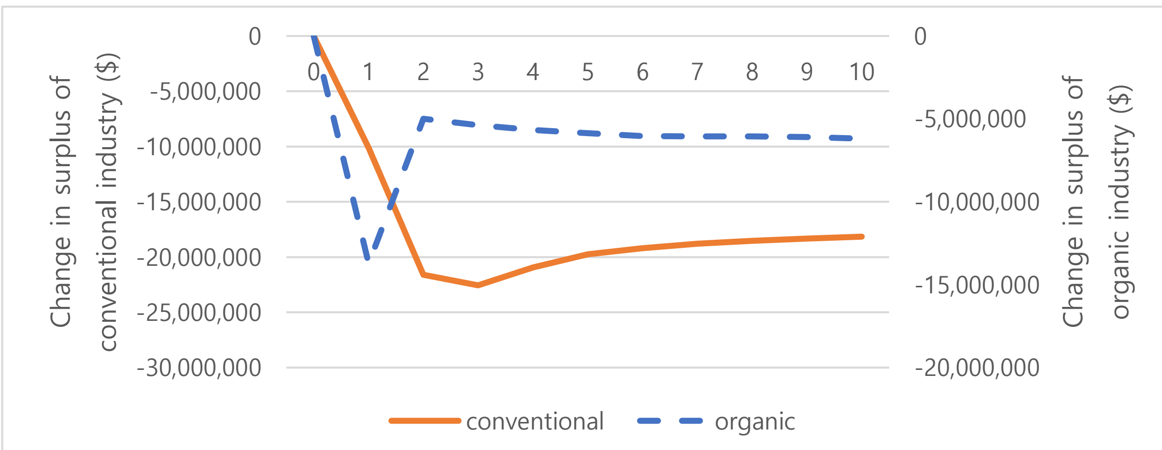
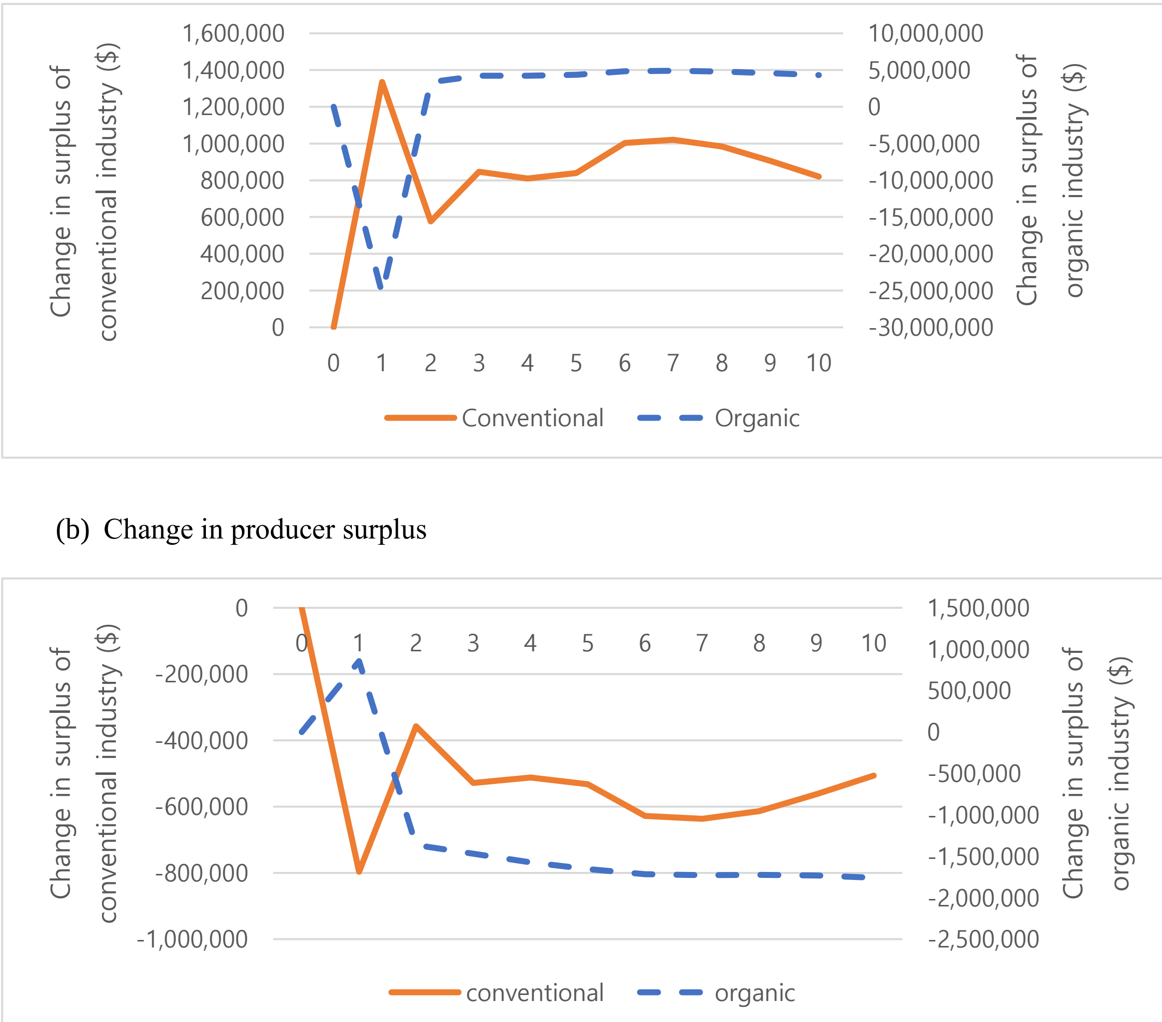


Figure 2.2. Change in economic surplus under Scenario 3

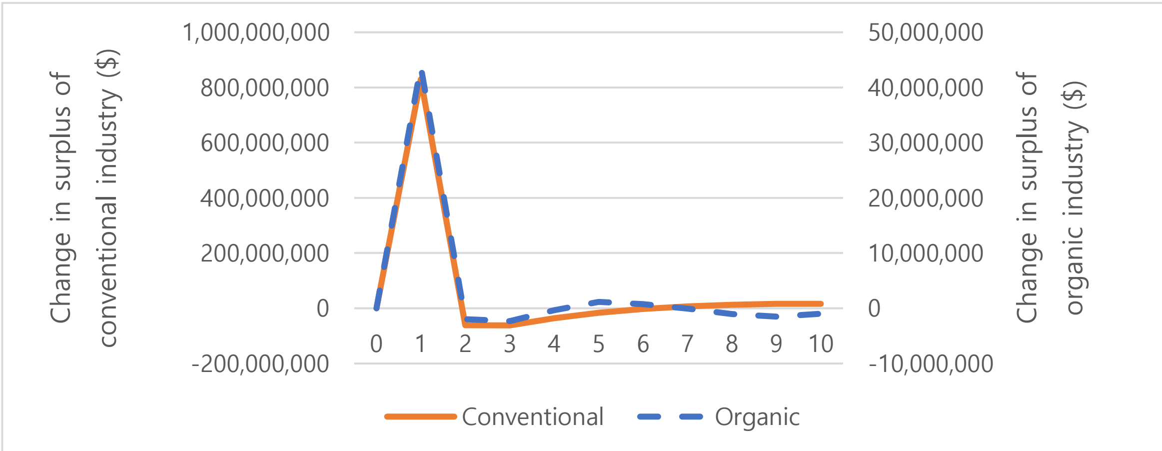
(a) Change in consumer surplus



(b) Change in producer surplus

Figure 2.3. Change in economic surplus under Scenario 4

(a) Change in consumer surplus



(b) Change in producer surplus

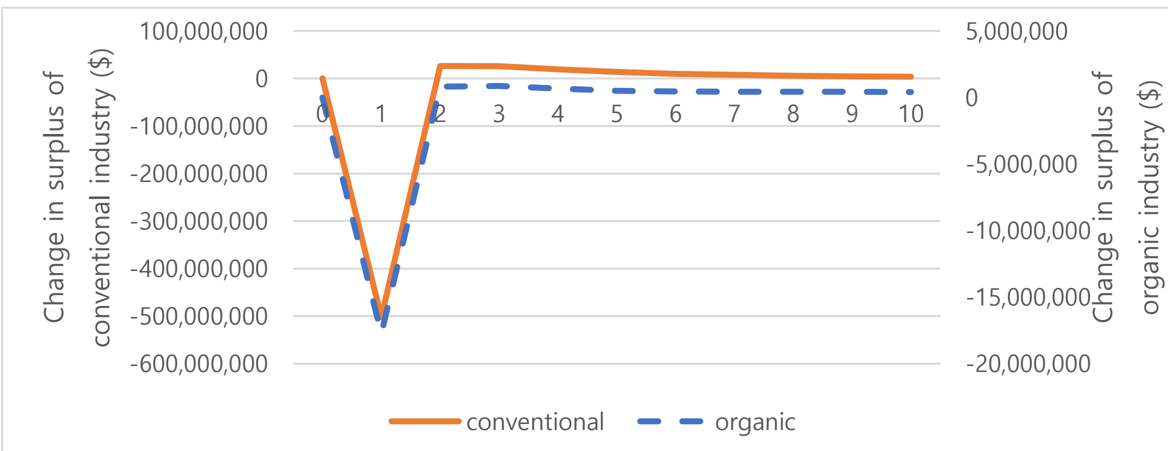


Figure 2.4. Change in economic surplus under Scenario 5

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CHAPTER THREE

Organic apple supply response to price premiums

3.1 Introduction

The organic sector continues to account for a growing share of total food purchases globally. Fresh fruit and vegetables account for a large share of total organic sales. In Washington, certified organic apple acres approximately doubled from 2013 to 2018 (Granastein and Kirby, 2019). Certified organic acres account for 14% of apple acreage in 2018, up from 7% in 2013. However, transitioning a field to certified organic status is a time consuming and costly process for a farmer. This is particularly true for perennial crops like apples that have very high establishment costs. Also, organic producers must pay for the certification fees that covers the costs of inspections and other certifier activities. In 2007, mean certification costs for apple producers were approximately 30 dollars per acer in Washington (Slattery et al., 2011). Organic premium can offset the transitioning costs and contribute to higher profits for organic farmers, and thus strong price premium can attract growers to organic production system. Over the last decade, price premiums for organic products have contributed to growth in certified organic farmland and, ultimately, market expansion (Oberholtzer et al., 2005). Therefore, it is critical to understand how the supply of organic crops responds to the price of organic relative to conventional, or the organic price premium.

There is a large literature – building from the pioneering work of Nerlove (1956) - that empirically examines the relationship between past prices, price expectations, and supply response for agricultural commodities. Compared to conventionally grown annual crops, supply response to price changes for organic crops likely has a more complex lag structure because a field must undergo a 36-month transition period. There is an asymmetric nature to this as well. An organic farmer can quickly reduce organic and transition acres when the organic price premium drops, but they are restricted in the short-run from expanding if the organic premium increases. A similar dynamic exists for conventional or organic tree fruit, which typically have about a three year establishment phase before a significant crop is harvested. This presents an interesting question for organic apples. The organic transition phase is concurrent to the establishment phase, so it may be that the time lag for organic apples is no different than conventional.

Some existing literatures identify price premium trend for a variety of crops. Oberholtzer et al (2006) shows that significant organic price premiums exist for broilers and eggs. Oberholtzer et al (2005) shows that organic price premiums for broccoli and carrots remain strong at both wholesale- and farmgate-level. Granastein and Kirby (2019) and Slattery et al. (2011) identify price premium trend for apples. The others estimate price premium for organic or specialty crops. Ankamah et al. (2016) estimate the price premium for organic salmon in Danish retail sale. Abraben et al. (2017) and Delmas and Grant (2014) identify whether the price premiums for the wines produced with organic practices exist. Weber (2011) estimate the price premium growers receive from participating in Fair Trade-organic markets.

The motivations for adopting organic agriculture have tended to change over time. While the innovators of organics were motivated by philosophical commitments like environmentalism, the recent adopters are more dependent on financial and practical incentives to cover the risks of conversion and thus need reliable access to organic price premiums (Padel, 2001; Constance and Choi, 2010). Although some existing literatures examine the price premiums for a variety of crops, the studies that analyze how the price premiums changes organic supply are limited by a lack of consistent and comparable price data. This study aims at determining the impacts of price premium on the supply of organic crops.

In this paper we analyze a rich farm-level data set of nearly every organic farm in Washington State with information on acres, yield, and prices for major varieties of organic apples for each year from 2009 to 2011. This allows for a much better understanding of the structure of organic supply response compared to what can be learned with aggregate data. Differences in scale, negotiating position with packers and processors, productivity, and product quality result in significant dispersion in prices across farms for the same type of organic apple variety. Estimating supply elasticities for organic apples is more accurate using farm and variety level price data than market level prices.

Our analysis breaks down into two parts. We first characterize the distribution of organic apple variety prices and yields across farms. We then estimate an econometric model of land adjustment and yields to determine how the elasticity of supply depends on the market-level organic premium versus farm-level prices.

We are draw from the long literature on perennial crop supply response started by French and Matthews (1971). They explain variations in output by combining changes in yields and acreage and explicitly bringing out the concept of the gestation lags between initial input and first output. Perennial crops face problems from gestation lags not ordinarily encountered in the study of annual crops. Most existing literatures on crop supply response, however, depend on the analysis with aggregate-level data (French et al.,1985; Kumar and Sharma, 2006; Devadoss and Luckstead, 2010; Laajimi et al., 2008; Kalaitzandonakes and Shonkwiler, 1992). This study focuses on how crop supply depends on the organic premium and prices using farm-level data.

Our analysis is also informed by dynamic models of adjustment in the livestock industry where it takes two to three years to adjust animal numbers in response to changes in profitability, which is similar to the organic transition time period (Rucker, Burt, and LaFrance., 1984; Foster and Burt, 1992; Mbaga and Coyle, 2003).

To properly model supply analysis, it is essential to understand both short-run and long-term decisions. Decisions made in earlier stages may affect the set of possible decisions and outcomes in later stages through the production process. Although Wickens and Greenfield (1973) note that there are two parts: potential production (long-run decision) and the proportion of potential production that is harvested (short-run decision), they estimate a single reduced form equation for the supply of coffee, a perennial crop. Most studies also resort to reduced-form models (French and Matthews, 1971; Dowling, 1979). These reduced-form specifications do not adequately capture the unique characteristics of the perennial crop supply response. In contrast, a structural model specification permits the estimation of supply decisions divided into long- and short-term responses, and thereby, determine the special features of perennial crop supply response. Our comprehensive farm-level data allows us to estimate the relevant structural equations instead of relying on a single reduced-form supply equation.

Kalaitzandonakes and Shonkwiler (1992) apply structural estimation approach of perennial new planting and replanting investment relationships to grapefruit. Devadoss and Luckstead (2010) analyze apple supply response with structural equations for new planting, removal, yield function. While they identify the detailed structural parameters, these studies only deal with state-level data. In spite of the dearth of suitable time series data for planting and removal data at farm-level, we use comprehensive farm-level data on acres, yield, and prices farms received, and focus on long- and short-term decisions by estimating the structural model specification of acreage adjustment, yields, farm-level price equations.

The objective of this study is to determine apple supply response by estimating a structural model for land adjustment, yield, and price equations. This paper is structured as follows. The next section starts with data description. Section 3 explains the estimation models and presents the analysis results at aggregate- and farm-levels. Finally, this paper concludes with Section 4 in which the main findings and policy implications are suggested.

3.2 Data description

Aggregate-level data is annual covering the years 1995 to 2020. Table 1 shows descriptive statistics of organic apple data in Washington at aggregate-level. The aggregate annual data include organic premiums, organic and conventional prices, certified and transition acres, yields, and production for seven organic apple varieties (Fuji, Gala, Granny smith, Red delicious, Golden delicious, Pink lady, and Honeycrisp). Table 2 and Figure 1 show descriptive statistics by variety and trend of variables, respectively.

Organic premium data is from WSU Tree Fruit Research and Extension, and it is calculated based on FOB prices (dollars per 40-lb box) by including all storage, grades, and sizes of apples. The organic premium is a measure of organic prices relative to conventional in percent difference. Organic apple prices are almost always higher than conventional, but the magnitude of the difference varies from year to year (Granastein and Kirby, 2019).

Transition area describes land transitioning from conventional to organic production. When land is converted to organic production, it must undergo a 36-month transition before an organic crop is harvested that creates a lag between a market signal and entering the market.

During the transition, organic practices are adopted, but products must not be labeled, sold, or represented as organic. Once the land completes the 36-month transition, the certificate is issued and the land can be used for certified organic products. Transition acres is the best measure for assessing how supply responds to changes in the organic premium. Annual change in total certified acres is not exactly equal to the one-year lag in transition acres. Producers sometimes decide to not carry through with the certification process. Also, there is always some amount of certified acres that are not recertified.

Farm-level data on production, acres, and prices by apple variety is from the years 2009, 2010, and 2011 if farms sell their products in the markets from 2009 to 2012, which are derived from the database of WSDA certified organic farms. There are 184 unique farms combined over the three years (2009-2011). By year, there are 133, 145, and 144 unique farms, respectively. An observation in the underlying data set specifies farm-variety-year, and there are a total of 1319 observations. By year, there are 430, 449, and 440 observations. Farms in the sample produced an average of 3.1 to 3.2 varieties out of a potential 9 (Fuji, Gala, Granny Smith, Golden delicious, Red delicious, Honeycrisp, Braeburn, Pink Lady, and Cameo) by year. The mode number of varieties was 1. There are 49 varieties in our data, but we focus on the 9 varieties that account for 97% of total sales and 96% of total acres. Price information is more complicated than acres and production because either that farms sometimes sell one year of production over more than one calendar year or that farms sell their product next year of production. Apples can be stored for as long as a year. We use the weighted average of prices if farms sell one year of production over more than one calendar year. We also remove the farm that has too high price. For all varieties, the average retail prices of organic apples were less than 4 dollars per pound in 2011, we drop 3 observations of a farm that has prices as about 14 dollars. Table 3 and Table 4 show descriptive statistics of farm-level data and descriptive statistics by apple variety, respectively. Each variety has 256, 251, 149, 145, 135, 124, 113, 82, and 64 observations.

3.3 Results

3.3.1 Supply elasticity estimated with aggregate data

Farms' desired area to be cultivated at time t depends on the expected prices and other explanatory variables as follows:

$$A_t^* = a_1 + a_2 P_t^* + a_3 Z_t + u_t \tag{1}$$

where A_t^* is farms' desired acreage at time t, P_t^* is the expected price, Z_t is a set of other variables determining farms' acreage, and u_t accounts for unobserved random factors affecting desired area with zero expected mean. Since a full land adjustment may not be possible in the short term and are delayed, it is necessary to apply a dynamic approach.

Nerlove (1956) assumes some relationship between desired and actual acreage as:

$$A_t - A_{t-1} = \delta(A_t^* - A_{t-1}) \tag{2}$$

where A_t is the actual acreage.

The structural form equations (1) and (2) yields the reduced form as:

$$A_t = \theta_1 + \theta_2 A_{t-1} + \theta_3 P_t^* + \theta_4 Z_t + \nu_t \tag{3}$$

with

$$\theta_1 = \delta - a_1,\ \theta_2 = 1 - \delta,\ \theta_3 = \delta a_2,\ \theta_4 = \delta a_3,\ \nu_t = \delta u_t$$

Given the abovementioned theoretical model, and assuming there are K varieties over T periods, the acreage functions can be specified as:

$$CA_{kt} = \lambda_1 + \lambda_2 CA_{kt-1} + \lambda_3 TA_{kt-1} + \lambda_4 PP_{kt} + \mu_i^{CA} + \zeta_{it}^{CA} \tag{4}$$

and

$$CA_{kt} = \lambda_1 + \lambda_2 CA_{kt-1} + \lambda_3 TA_{kt-1} + \lambda_4 PO_{kt} + \lambda_5 PC_{kt} + \mu_i^{CA} + \zeta_{it}^{CA} \quad (5)$$

where *TA* and *CA* represent transition and certified acres, respectively, PP is organic price premium and PO and PC are organic and conventional prices, respectively. We employ the lagged three-year moving average of price premiums and organic prices, and conventional prices as a proxy for expected own and competing crop prices. We also consider lagged transition acres as the variables determining farms' certified acreage since transition acres is one of the best measure for predicting certified acres.

For production and yield functions, following Nerlove (1956), expectations are assumed to be updated in proportion to the difference between the observed and expected price levels of the previous period as:

$$P_t^* - P_{t-1}^* = \gamma(P_{t-1} - P_{t-1}^*), \quad (6)$$

which then can be expressed as an infinite-order AR(p) process as follows:

$$P_t^* = \sum_{\tau=1}^{\infty} \gamma\,(1-\gamma)^{\tau-1} P_{t-\tau}. \quad (7)$$

The impact of past information on prices can be measured by substituting equation (7) in equation (3). However, this full systems estimation has a major limitation when a single misspecification in any equation leads to inconsistent estimates of all parameters in the model (Cumby et al, 1983; Shideed and White, 1989). Therefore, alternative method would be the method of quasi-rational expectations as developed by Nerlove et al. (1979) that estimates equation (7), and then in the second stage, substituting the calculated values in equation (3), which in turn, can be estimated as a single equation.

We select the first-order autoregressive process, and the specification of production and yield function is:

$$Q_{kt} = \beta_1 + \beta_2 Q_{kt-1} + \beta_3 PP_{kt-1} + \beta_4 TA_{kt-1} + \mu_i^Q + \zeta_{it}^Q \quad (8)$$

and

$$Q_{kt} = \beta_1 + \beta_2 Q_{kt-1} + \beta_3 PO_{kt-1} + \beta_4 PC_{kt-1} + \beta_5 TA_{kt-1} + \mu_i^Q + \zeta_{it}^Q \quad (9)$$

where Q is either production or yield per acre. Such specification is similar with De Menezes and Piketty (2012).

The problem with such dynamic panel data regression is that the presence of the lagged dependent variable introduces autocorrelation in the error term, which results in a dynamic panel bias when applying ordinary least squares (OLS) estimation. For transition acreage model, since the TA_{it} is a function of the fixed effect (μ_i^{TA}), it is obvious that TA_{it-1} is also a function of μ_i^{TA} and is correlated with error term. This violates the strict exogeneity assumption, and therefore it turns OLS estimator biased and inconsistent. As one of solutions to this problem, we could transform the data and apply the fixed effect (FE) estimator that wipes out μ_i. However, the lagged dependent variable remains correlated with ζ_{it-1}, and therefore the lagged dependent variable is biased downward with the FE (Roodman, 2009).

Anderson and Hsiao (1982) suggest the instrumental variable (IV) method to estimate the first difference (FD) model as an alternative to eliminate the fixed effect terms by differencing instead of within transformation. This allows to use the second lagged difference as an IV for lagged dependent variable that is strictly exogenous. Although this method leads to consistent estimates, Arellano and Bond (1991) propose a more efficient estimator than IV, difference generalized method of moments (GMM). Thus, we use the Arellano and Bond (1991) procedure to estimate a dynamic panel difference model. Also, following Roodman (299), we collapse the instrument set in order to limit instrument proliferation. When instruments are many, they tend to overfit the instrumented variables and bias the results toward those of OLS. It creates one instrument for each variable and lag distance, rather than one for each time period, variable, and lag distance. In small samples, it helps to avoid the bias that arises as the number of instruments climbs toward the number of observations.

Table 5 and 6 report the results of certified acreage and production and yield response functions, respectively. In the model (1) and (2), Table 5, the acreage has been estimated as a function of the lagged certified and transition acres and the lagged three-year moving average of price variables: organic price premiums or the prices of organic (PO) and conventional (PC). In the model (3) and (4), Table 5, the lagged yield is also included as an explanatory variable. In table 6, the production and yield are estimated as a function of the lagged dependent variable, transition acres, and price variables, respectively. All variables except for price premium are log-transformed.

We conducted several statistical tests to check the consistency of estimation results. The results in Table 5 and 6 show that the Hansen test cannot reject the null hyphothesis of the over-identifying restrictions. We also conducted the Arellano-Bond test for first and second order autocorrelated disturbance, which represents there exist first-order autocorrelation but no evidence for significant second-order autocorrelation in residuals. According to Arellano and Bond (1991), when the model presents a good specification, it is preferable to use the one-step estimation since two-step standard errors tend to be biased downward in the case of small sample.

In table 5, the results from columns (1) and (2) show that all variables except for conventional price are significant and have positive signs as expected. A percent increase in price premium and own-price increase the certified acres by 0.42% and 0.57%, respectively, in the short run. This indicates that higher organic prices are able to cover the costs of organic system and thus attract growers to organic production. As the organic prices increase, new farms may begin their operations with organic system rather than conventional system, and for existing farms, they are likely to make the transition from conventional to organic farming system. The prices of conventional apples are not significant, meaning that organic farmers may account for own-prices rather than the prices of competitive products. The results from columns (3) and (4) where the lagged yield per acre is included as an independent variable show that only price premium variable is significant and the effect is smaller than in column (1).

In table 6, for the yield function, responses to price premium and own-price are also positive and statistically significant as expected with economic theory. A percent rise in organic premium and own-price induces yields increase of about 0.34% and 0.63%, respectively, in the short run. On the other hand, production only responds to own prices. One percent increase in own-price increases production by 0.46%.

From the estimated coefficients in Table 5 and 6, we calculate supply elasticities of price in short and long run. Table 7 represents supply elasticities of price variables. The short-term supply elasticity is the estimated coefficient, and the long term elasticity is calculated by a_2 in equation (1). In the long run, acreage supply is price elastic (1.524[6] and 2.368), which is consistent with those found by Willet (1993). Willett (1993) showed that the response of the change in apple acreage to a lagged three year moving average of apple prices is elastic as 1.84 to 3.68. The long-run production and yield elasticities are found to be 1.015 and 0.579 and 1.104, respectively, which is relatively inelastic than acreage responses. Whereas, in the short run, the elasticities are not much different across acreage, production, and yield responses. The results

[6] The price premium elasticity of acreage is 2.445 with the result from column (3) in Table 5.

suggest that in general, higher organic premium and/or own-price induce producers to expand acreage and improve their crop yields. On the other hand, one of the possible explanations for the higher elasticities of acreage in the long run is the feature of organic industry where organic producers can always sell their organic products as conventional depending on market conditions. This may encourage organic apple producers to overinvest in organic apple acres because it allows them for more supply flexibility when the organic premium is high. Therefore, the acreage supply is more price elastic than production and yield responses since they can sell their organic production as conventional if the price drops, but they can't quickly expand organic production if the organic premium increases.

3.3.2 Farm-level distribution of prices, yield, and revenue

In Table 3, the average of production, acre, and price of all farms are 772,935 pounds, 23.088 acres, and 0.297 dollars per pound, respectively, but the variations are found to be very large. Figure 2, 3, and 4 represent distributions of supply quantities, acres, and prices of all apple varieties, and all distributions are skewed right. About 73% of observations have supplied quantity less than the average, 772,935 pounds, 72% of them operate farmland less than 23.088 acres, and about 63% of them received prices less than the average, 0.297 dollars. On the other hand, Figure 5 shows that the distribution of yields per acre is less right-skewed, which is very different from the distributions of acres and production. Even if farms have the same farm acres, some may have higher yield rate, which might be due to the prices they received, different price premiums by apple variety, and their locations.

Figure 6, 7, 8 and 9 show the distributions of production, acres, prices, and yields per acre by variety, in which the distributions of all varieties are similar, but the degrees of skewness are different across varieties.

3.3.3 Farm-level supply elasticity

For perennial crops, in the short run, farms can adjust their supply only within their existing capacity, either increasing or decreasing their yield rate. Therefore, supply response is estimated by fitting a yield function in the short run. The key determinant of change in yield rate is the prices farms actually received and organic premium for the variety in the previous production year, which can shift yield rates in the short run. Farms also change their yield rate depending on the previous yield rate and the adjusted acreage. The equation of yield rate is expressed as:

$$q_t = \alpha_1 + \alpha_2 q_{t-1} + \alpha_3 p_{t-1} + \alpha_4 PP_{t-1} + \alpha_5 ac_t + \varepsilon_q \tag{10}$$

and

$$q_t = \alpha_1 + \alpha_2 q_{t-1} + \alpha_3 p_{t-1} + \alpha_4 PO_{t-1} + \alpha_5 PC_{t-1} + \alpha_6 ac_t + \varepsilon_q \tag{11}$$

where q is the yield per acre, p is the price received, PP is organic premium for the variety, PO and PC represent the prices of organic and conventional for the variety, respectively, ac is the acres of farm-variety pair, and ε is the disturbance term.

On the other hand, changes in area of perennial crops can occur in the long run. Apple producers can either expand or shrink their area to desired amount of acres to be allocated to the specific varieties. The possible determinant of change in desired area could be profitability of each variety, which can be represented by lagged variables of organic premiums, since organic production needs years to acquire organic certification. The determined acreage affects farms to adjust their yield rates. The acreage response equation is specified as:

$$ac_t = \beta_1 + \beta_2 ac_{t-1} + \beta_3 PP_{t-i} + \varepsilon_A \tag{12}$$

and

$$ac_t = \beta_1 + \beta_2 ac_{t-1} + \beta_3 PO_{t-i} + \beta_4 PC_{t-i} + \varepsilon_A \tag{13}$$

We have a system of structural equations, where some equations contain endogenous variables among the explanatory variables. Under our hypothesis, we expect that the determined acreage affects farms to adjust their yield rates. To account for the endogeneity, the model is simultaneously estimated using three-stage least squares (3SLS) following Zellner and Theil (1962).

In our structural system, the variables, yield and acreage, are explicitly endogenous by appearing as dependent variables in Equations (10)-(13). Lagged yield rates, lagged prices, lagged acreage, lagged price variables for the variety, and 10 county and 9 apple variety dummies are used as the exogenous variables. All variables except for price premium and dummy variables are log-transformed.

Results with farm-level data are represented in Table 8. For comparative analysis, all parameters are also estimated using ordinary least squares (OLS). The results from Breusch-Pagan test show that we can reject the hypothesis that the correlations of the residuals in two equations are zero, implying that the 3SLS model may be more reliable. Therefore, the discussion centers on the results of 3SLS estimation unless specifically stated otherwise.

In the short-run supply response model with yields rate per acre, the signs of the coefficients for the lagged yields and lagged prices are found to be positive as expected. One percent increase in previous year prices increases production per acre by 0.5%. Farms may expect larger profit from product and conduct more intensive cultivation as they received higher prices. On the other hand, the market price that is represented by lagged organic price premium (*PP*) is found to be positive but insignificant, while the individual farm's yield responds to own-variety market prices in the model (2). One percent rise in own-variety prices induces yield increase of about 3.5%, which is larger than the effect of prices that farms actually received. This result suggests that farms respond to the average market prices more than the prices they received, and thus they are more likely to depend on organic market conditions when they determine the crop yields. This is because the prices that farms received may include the price of apples sold as conventional, but most growers may consider the organic market to sell their products when they invest in apple production. On the other hand, one of the reasons for the large coefficient on organic market price would be that farms sometimes sell one year of production over more than one calendar year, and they may decide the time to sell their products largely depending on the organic market prices. The sign of the coefficient for the current certified acreage is also positive, which may represent the economies of scale of apple farms, but the effects is relatively small.

The long-run supply is given by acreage response model in Table 8. We test one- to three-year lagged price premium variables. Results show that when one-year and two-year lagged premiums are used as the organic premium variable, the effects are found to be insignificant at the 10% level. On the other hand, one percent increase in three-year lagged organic premium significantly increases organic certified acres by about 0.2%. As three-year lagged organic premiums increase, farms may invest in expanding the acres of specific variety to draw long-run profitability. Since farms are required three years to transition from conventional to certified organic production, it may be reasonable that farms consider three-year lagged organic premiums to expect their future profitability and adjust their farm size. On the other hand, the coefficients on market prices of organic and conventional apples are as expected but not significant. This suggests that organic apple producers may depend on the organic premiums rather than organic prices when they invest in organic apple acres. Higher premiums would be more helpful for organic producers to offset future uncertainties in organic markets than organic price increases by itself.

3.4 Conclusion

This study aims at determining the impacts of price premium on the supply of organic crops. We estimate an econometric model of land adjustment, production, and yields to determine how the elasticity of supply depends on the market-level organic premium versus farm-level prices. For this purpose, we analyze Washington organic apple supply at aggregate- and farm-levels.

The aggregate-level results show that acreage, production, and yield responses to price premiums and/or own prices are significantly positive. The estimated elasticities underline that in the short run, the elasticities are not much different across acreage, production, and yield responses. On the other hand, the long-run production and yield elasticities are found to be price inelastic relative to acreage responses. This may be due to that organic producers can have more supply flexibility when the organic premium is high because they can always sell their organic products as conventional depending on market conditions, and thus this allows them to overinvest in organic apple acres. However, they cannot quickly expand organic production if the organic premium increases, and they need more time to make necessary production adjustment. Therefore, the acreage supply is more price elastic than production and yield responses.

On the other hand, the farm-level results suggest that farm's yield responds to the average market prices more than the prices they received, and thus they are more likely to depend on organic market conditions when they determine the crop yields. Also, individual farm's land adjustment responds to organic premiums, but not to own-variety prices. This suggests that organic apple producers may depend on the organic premiums rather than organic prices when they invest in organic apple acres. Higher organic premium allows for more supply flexibility since they can sell their products as either organic or conventional, and thus it would be more helpful to offset future uncertainties in organic markets than organic price increases by itself.

TABLES AND FIGURES

Table 3.1. Summary statistics of aggregate-level data

	Obs	Mean	s.d	Min	Max
Transition acres	147	321.10	335.85	0.5	1,541.26
Certified acres	151	1,713.40	1,508.00	8.00	8,032.70
Organic premium	167	0.46	0.27	-0.04	1.26
Organic price	170	36.21	12.14	18.84	81.00
Conventional price	167	25.20	9.98	13.05	64.27
Production	116	982,362	1,019,222	29,000	5,662,000
Yield per acre	116	471.09	173.30	70.21	894.45

Table 3.2. Summary statistics of aggregate-level data by variety

Variety	Variable	Obs	Mean	s.d.	Min	Max
Fuji	Transition acres	22	458.32	372.13	76	1,222
	Certified acres	22	2,648.25	1,677.94	165	5,579
	Organic premium	26	0.44	0.21	-0.04	0.97
	Organic price	26	34.67	6.70	24.69	50.42
	Conventional price	26	23.33	4.89	17.04	42.99
	Production	17	1,631,529	958,505	254,000	3,108,000
	Yield per acre	17	517.33	116.94	236.94	685.63
Gala	Transition acres	22	484.67	362.42	76	1,266
	Certified acres	22	3,157.16	2,249.13	223	8,033
	Organic premium	26	0.47	0.25	0.18	1.02
	Organic price	26	34.46	7.12	25.77	48.95
	Conventional price	26	23.64	4.35	18.12	36.82
	Production	17	2,320,588	1,584,185	465,000	5,662,000
	Yield per acre	17	628.73	156.08	325.40	894.45
Granny Smith	Transition acres	21	243.24	218.04	4	655
	Certified acres	22	1,346.35	724.92	158	2,976
	Organic premium	26	0.53	0.26	0.23	1.26
	Organic price	26	33.88	6.88	22.59	50.94
	Conventional price	26	22.23	2.74	16.51	27.02
	Production	17	707,000	380,176	212,000	1,485,000
	Yield per acre	17	482.82	142.34	256.35	708.91
Golden Del.	Transition acres	19	146.32	139.51	3	515
	Certified acres	21	1,035.81	290.46	603	1,638
	Organic premium	26	0.53	0.30	0.16	1.20
	Organic price	26	31.14	5.98	21.49	45.82
	Conventional price	26	20.63	3.13	14.68	25.80
	Production	17	296,941	92,940	115,000	464,000
	Yield per acre	17	301.42	116.30	70.21	460.30
Red Del.	Transition acres	23	297.83	338.82	4	984
	Certified acres	23	1,263.90	316.75	681	1,872
	Organic premium	26	0.56	0.27	0.16	1.11
	Organic price	26	26.42	4.35	18.84	36.70
	Conventional price	26	17.13	2.58	13.05	21.75
	Production	17	627,118	185,174	288,000	916,000
	Yield per acre	17	485.71	130.45	235.68	693.65
Honeycrisp	Transition acres	19	445.59	469.20	11	1541
	Certified acres	19	1,693.43	1,777.34	151	6170
	Organic premium	14	0.22	0.12	0.11	0.47
	Organic price	17	65.10	7.45	53.72	81.00
	Conventional price	14	53.56	6.74	41.42	64.27
	Production	14	738,500	716,403	29,000	2,309,000

	Yield per acre	14	341.92	124.92	97.32	534.52
Pink Lady	Transition acres	21	154.82	143.82	0.5	532
	Certified acres	22	835.83	471.86	8	1,820
	Organic premium	23	0.35	0.27	-0.02	0.91
	Organic price	23	38.04	7.85	22.79	54.05
	Conventional price	23	28.32	3.30	22.13	33.28
	Production	17	511,824	286,380	67,000	989,000
	Yield per acre	17	516.88	194.59	143.47	805.86

Table 3.3. Descriptive statistics of farm-level data

Variable	Mean	s.d.	Min	Max
Production	734,843	1,215,087	48.78	9,762,450
Yield	31,057	177,34	93.75	175,000
Price	0.307	0.321	0.001	4.186
Acres	22.74	35.47	0.01	305.22
Organic premium	0.256	0.083	0.054	0.403
Obs		1,319		

Table 3.4. Descriptive statistics of farm-level data by variety

Variety	Variable	Obs	Mean	s.d.	Min	Max
Fuji	Production		859,721	1,411,176	200	8,187,175
	Yield		287,14	15,103	400	75,704
	Price	256	0.307	0.251	0.011	2.081
	Acres		28.42	41.93	0.25	272.17
	Organic premium		0.259	0.025	0.226	0.286
Gala	Production		1,027,625	1,510,357	925	9,762,450
	Yield		33,455	14,988	313	85,100
	Price	251	0.297	0.180	0.006	1.353
	Acres		28.34	39.28	0.1	305.22
	Organic premium		0.252	0.014	0.236	0.270
Granny Smith	Production		618,225	896,242	90	5,153,750
	Yield					
	Price	149	0.276	0.410	0.003	4.186
	Acres		20.19	30.22	0.02	170.5
	Organic premium		0.357	0.032	0.333	0.403
Golden Del.	Production		548,236	1,054,078	500	6,622,000
	Yield		31,291	16,298	700	80,564
	Price	145	0.215	0.235	0.001	1.537
	Acres		15.32	30.68	0.05	196.77
	Organic premium		0.349	0.023	0.324	0.381
Red Del.	Production		824,447	1,255,429	75	9,208,375
	Yield		32,901	17,087	94	94,042
	Price	135	0.245	0.370	0.004	3.842
	Acres		23.87	36.79	0.01	303.28
	Organic premium		0.311	0.066	0.229	0.392
Honeycrisp	Production		520,381	989,214	131	5,300,750
	Yield		24,861	20,508	204	173,171
	Price	124	0.622	0.448	0.012	3.058
	Acres		19.13	29.09	0.05	203.7
	Organic premium		0.133	0.022	0.110	0.161
Braeburn	Production		394,021	569,881	48.78	4,398,375
	Yield		32,234	20,272	925	150,732
	Price	113	0.208	0.222	0.008	1.246
	Acres		12.97	18.39	0.02	137.3
	Organic premium		0.218	0.058	0.140	0.283
Pink Lady	Production		891,361	1,235,461	200	6,060,600
	Yield		34,424	21,980	200	175,000
	Price	82	0.352	0.278	0.010	1.676
	Acres		27.71	42.32	0.01	239.64
	Organic premium		0.180	0.050	0.114	0.236
Cameo	Production	64	409,092	756,953	489	3,389,200

Yield	26,134	15,424	2,336	60,372
Price	0.275	0.366	0.009	2.151
Acres	16.20	25.89	0.01	107
Organic premium	0.099	0.047	0.054	0.164

Table 3.5. GMM estimation results of aggregate-level acreage response

	Acreage			
	(1)	(2)	(3)	(4)
Certified acres (t-1)	0.727***	0.761***	0.890***	0.911***
	(0.105)	(0.130)	(0.141)	(0.120)
Yield (t-1)			0.157**	0.158**
			(0.071)	(0.063)
Transition acres (t-1)	0.084***	0.105***	0.090***	0.116***
	(0.032)	(0.027)	(0.020)	(0.014)
PP	0.416**		0.269*	
	(0.177)		(0.150)	
PO		0.566**		0.188
		(0.256)		(0.311)
PC		0.146		0.711
		(0.425)		(0.744)
Year	0.009	0.004	-0.005	-0.004
	(0.012)	(0.015)	(0.016)	(0.016)
N	120	120	100	100
Hansen Chi2	4.30	0.36	4.79	4.45
AB test for AR (1)	-1.88*	-1.96**	-2.28**	-2.26**
AB test for AR (2)	0.57	1.18	1.16	0.95

Standard errors are in parentheses.
***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Table 3.6. GMM estimation results of aggregate-level production and yield response

	Production		Yield	
	(1)	(2)	(3)	(4)
Production (t-1)	0.438***	0.544***		
	(0.104)	(0.009)		
Yield (t-1)			0.406***	0.434***
			(0.101)	
Transition acres (t-1)	0.0006	0.009	-0.078***	-0.071***
	(0.014)	(0.012)	(0.007)	(0.008)
PP	0.181		0.344***	
	(0.148)		(0.109)	
PO		0.463*		0.625***
		(0.241)		(0.179)
PC		0.166		-0.096
		(0.276)		(0.212)
Year	0.049	0.033	-0.0007	-0.002
	(0.030)	(0.027)	(0.013)	(0.012)
N	95	95	95	95
Hansen Chi2	5.52	4.63	1.79	0.52
AB test for AR (1)	-2.09**	-2.05**	-2.30**	-2.09**
AB test for AR (2)	1.52	1.33	1.29	1.32

Standard errors are in parentheses.
***, **, and * denote significance at 1%, 5%, and 10% levels, respectively.

Table 3.7. Price supply elasticities

	Acreage		Production		Yield	
	LT	ST	LT	ST	LT	ST
PP	1.524	0.416	-	-	0.579	0.344
PO	2.368	0.566	1.015	0.463	1.104	0.625

Table 3.8. Farm-level regression results

	(1)		(2)	
	3SLS	OLS	3SLS	OLS
(Eq.1)				
q_{t-1}	0.396***	0.395***	0.406***	0.407***
	(0.036)	(0.038)	(0.036)	(0.038)
$price_{t-1}$	0.493***	0.463**	0.483***	0.449**
	(0.177)	(0.184)	(0.175)	(0.182)
PP_{t-1}	0.455	0.583		
	(0.847)	(0.881)		
PO_{t-1}			3.530**	4.044***
			(1.383)	(1.421)
PC_{t-1}			-0.789	-0.992
			(1.029)	(1.067)
ac_t	0.057**	0.016	0.054**	0.013
	(0.025)	(0.024)	(0.024)	(0.024)
Cons	5.760***	5.816***	-2.782	-3.703
	(0.421)	(0.437)	(2.661)	(2.729)
R^2	0.324	0.328	0.337	0.340
(Eq.2)				
ac_{t-1}	0.967***	0.968***	0.967***	0.968***
	(0.012)	(0.012)	(0.012)	(0.012)
PP_{t-3}	0.205**	0.136		
	(0.102)	(0.107)		
PO_{t-3}			0.146	0.167
			(0.173)	(0.180)
PC_{t-3}			-0.090	-0.155
			(0.261)	(0.271)
Cons	-0.067	-0.044	-0.206	-0.082
	(0.067)	(0.068)	(0.320)	(0.331)
R^2	0.926	0.926	0.926	0.926
B-P test (χ^2)	26.57***		25.06***	
Obs		662		

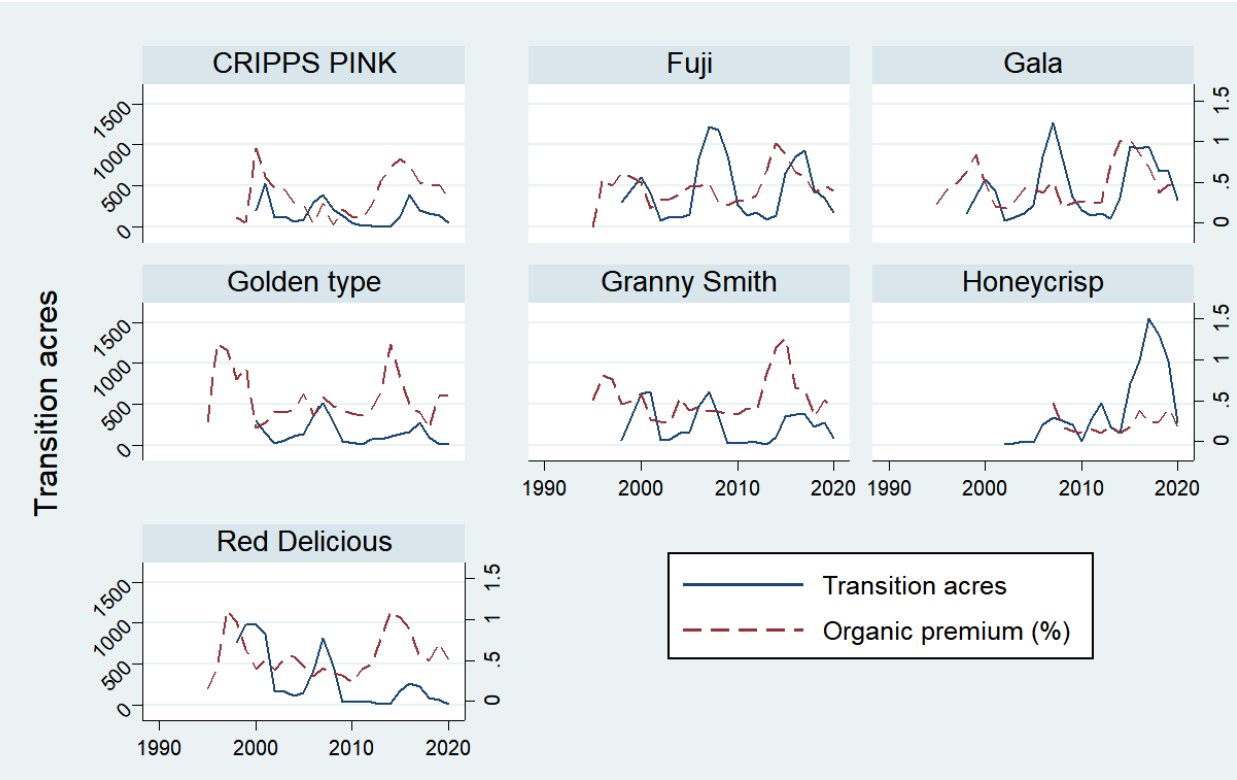

Figure 3.1. Trends of transition acres and organic premium by variety

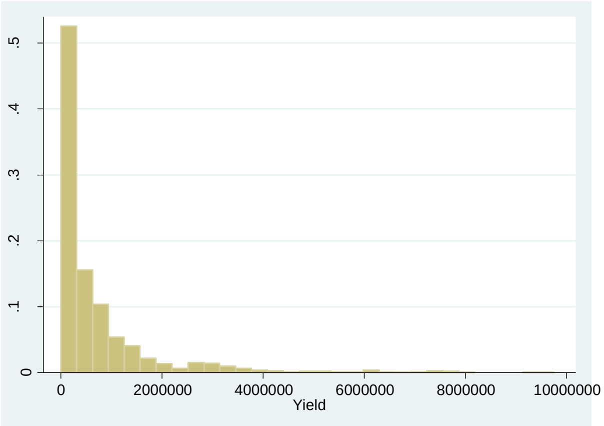

Figure 3.2. Distribution of yields (All apples)

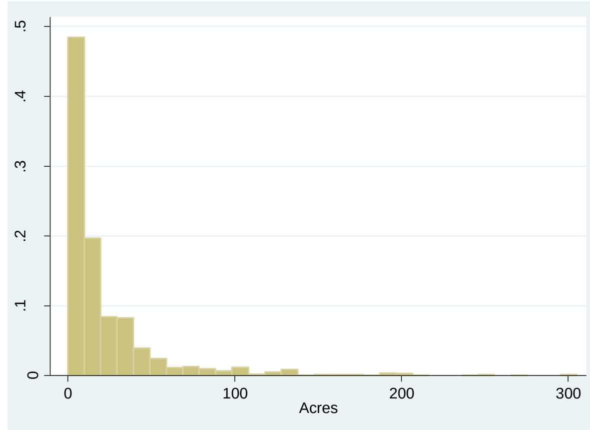

Figure 3.3. Distribution of acres (All apples)

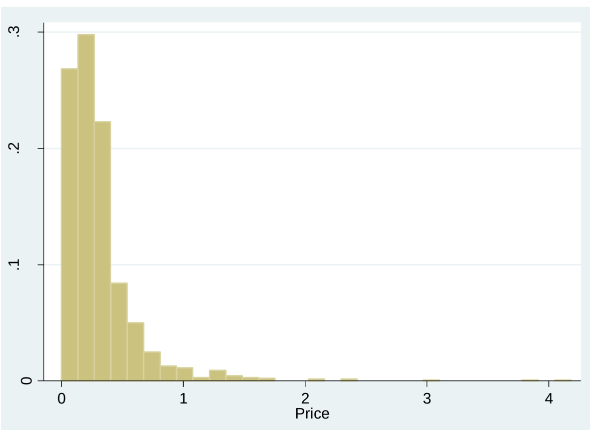

Figure 3.4. Distribution of prices (All apples)

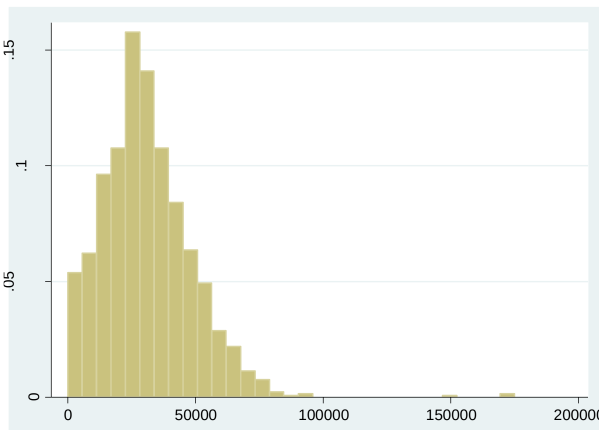

Figure 3.5. Distribution of yields per acre (All apples)

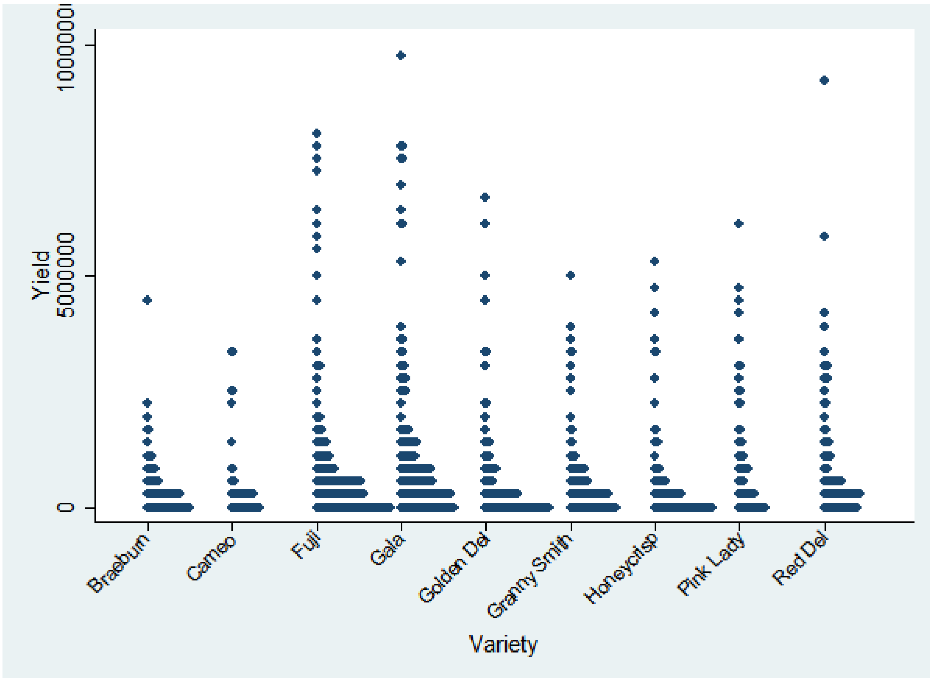

Figure 3.6. Distributions of yields by apple variety

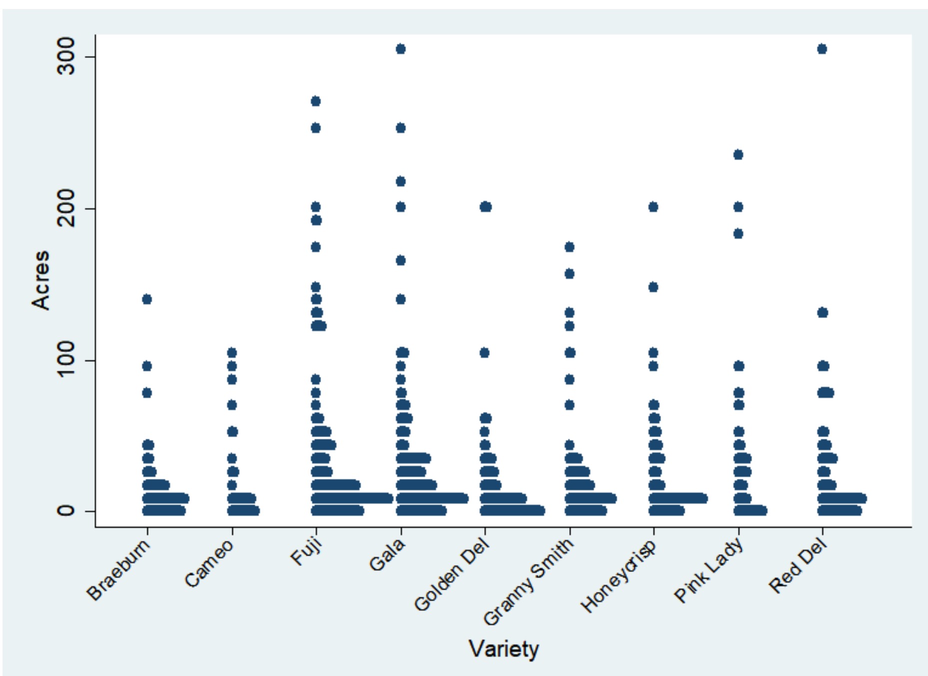

Figure 3.7. Distributions of acres by apple variety

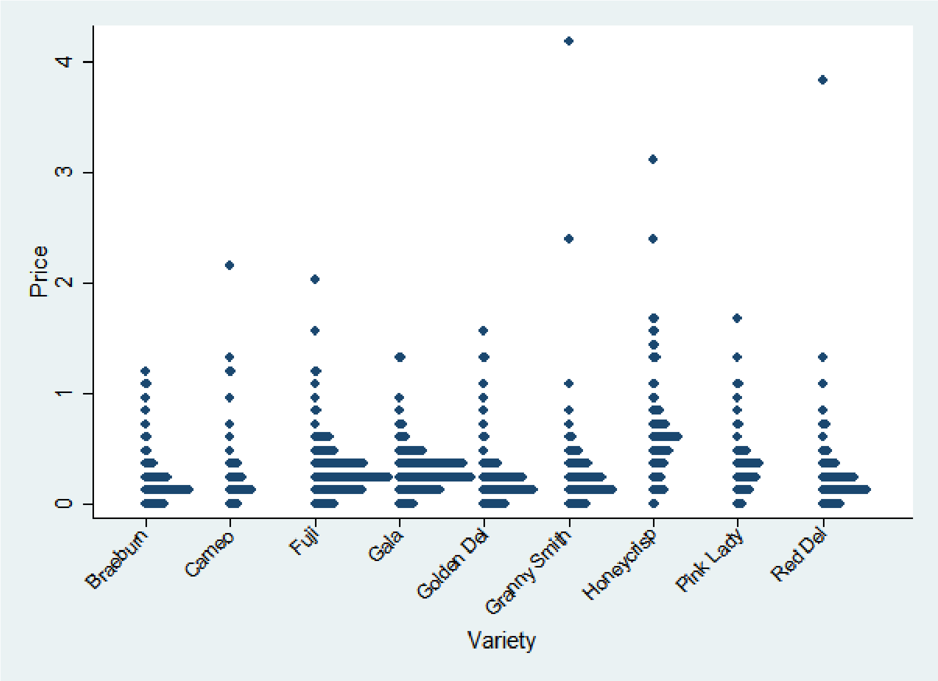

Figure 3.8. Distributions of prices by apple variety

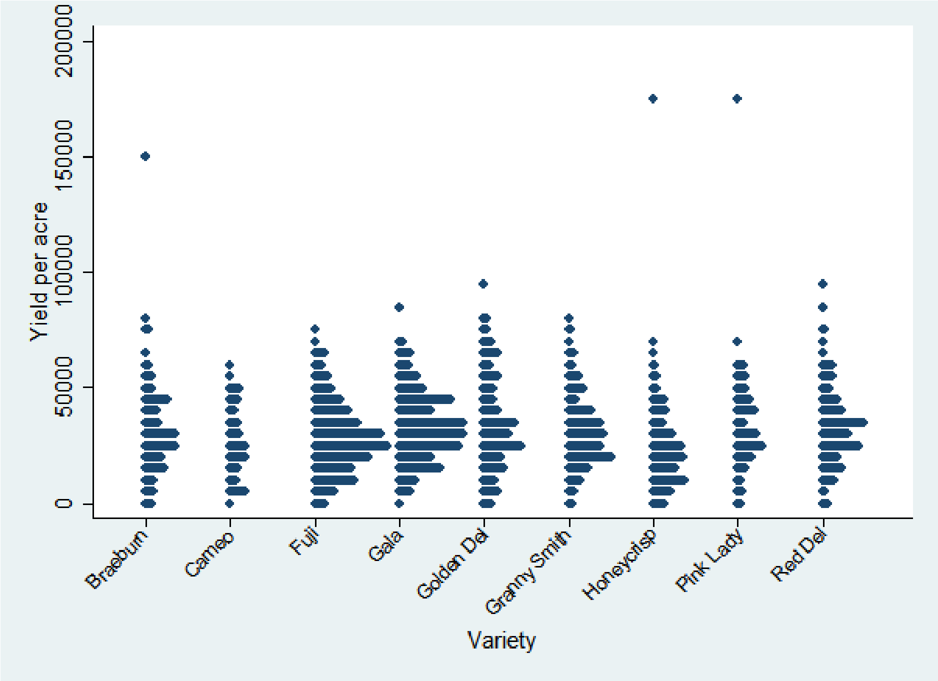

Figure 3.9. Distributions of yields per acre by apple variety

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