EMPIRICAL ESSAYS ON EFFICIENCY, PRODUCTIVITY, STRUCTURAL CHANGES AND RESOURCE USE IN HAWAI'I AGRICULTURE

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By

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By
Dilini Hemachandra
To my parents and sister
for their love and encouragement.
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ABSTRACT

This dissertation is a collection of empirical essays that investigate Hawai‘i agriculture. Chapter 1 presents a general introduction and an overview of the dissertation. Chapter 2 gives an account of the present status of Hawai‘i agriculture and discusses the availability of agriculture data.

Chapter 3 examines efficiency and productivity of vegetable farms in Hawai‘i using data from five census years (1982, 1987, 1992, 1997 and 2007) and employing Data Envelopment Analysis (DEA). The DEA efficiency scores suggest considerable inefficiencies in Hawai‘i’s vegetable farms. The technical efficiency of an average vegetable farm has deteriorated over the years. While the technical efficiency of small farms has decreased, the technical efficiency of large farms has increased. However, farms are found to be relatively scale-efficient. The deterioration of technical efficiency is mainly due to a decrease in pure efficiency. Malmquist Index (MI) productivity analysis reveals that aggregate productivity of Hawai‘i’s vegetable farming sector has decreased on average. The MI decomposition shows that technical efficiency on average has declined significantly.

Chapter 4 examines productivity changes in Hawai‘i’s vegetable sector arising from the entry, exit and survival dynamics. Melitz and Polanec (2014) extension of the dynamic Olley-Pakes (1996) productivity decomposition is employed in this analysis. The study finds that exiting and new farms show low productivities compared to continuing farms. Therefore, while farm exits contribute positively to the aggregate productivity growth, new farm entry contributes negatively to the aggregate productivity growth. The study also finds that the aggregate productivity of continuing firms has increased between census years. Productivity gains in continuing farms are found to be mainly a result of market share reallocation between farms.

Chapter 5 presents a mathematical model that aids in simulating policy or environment changes under limited data conditions. Hawai‘i crop sectors were modeled and calibrated to the base year 2007 data using the Positive Mathematical Programming (PMP) method. The study simulates the scenario of a loss of farmland to assess its effect on acreage allocation among crops. The study identifies the possibility of modeling Hawai‘i’s agriculture for policy simulations and suggests ways to improve a state-wide agricultural model to closely represent real situations.
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CHAPTER 1
GENERAL INTRODUCTION AND DISSERTATION OVERVIEW

The agriculture sector plays a vital role in any economy. It provides a livelihood, contributes to national income, generates employment opportunities and supplies food and fodder, raw materials, and green-space. As policy makers identify the importance of the agriculture sector in their economies, they have taken a high interest in the sustenance and advancement of agriculture, sometimes at the expense of efficiency and comparative advantage.

Hawai‘i’s agriculture has the advantage of the tropical weather when compared to most other States in the USA. It can grow a large variety of tropical crops year-round. However, Hawai‘i’s high cost of production has hurt its agriculture producers in competition with imports. Hawai‘i’s farmers’ largest competitors are located on the US mainland. Even the cost of shipping imports to Hawai‘i has been unable provide a buffer against the competitive pressure from cheaper imports from the US mainland. Therefore for Hawai‘i, achieving high efficiency and productivity in agriculture is very important not only as a way to increase production without adding to the cost.

Though the importance and need to sustain and advance Hawai‘i’s agriculture have been widely acknowledged, quantitative economic analysis is missing in policy discussions. Economic studies on Hawai‘i’s agriculture are lacking for several reasons. Hawai‘i is excluded in national level studies due to its small significance in national agriculture, and also due to administrative difficulties as Hawai‘i is not a part of the continental USA. The lack of studies is exacerbated by the unavailability of data needed for rigorous econometric analysis, a fact that further discourages researchers. The importance of Hawai‘i’s agriculture for the welfare of its residents cannot be underestimated, however, and the interests of the residents cannot be ignored.

To fill the void in economic studies, this dissertation is dedicated to applied economics research on Hawai‘i agriculture. Each chapter attempts to make use of available data with
appropriate analytical methods to gain insight into Hawai‘i’s agriculture. Specifically, the chapters aim to examine the efficiency and productivity changes of the vegetable farming sector and to develop a State-wide mathematical model that can aid in policy analysis. Based on the results of the economic analyses of these chapters, I explore policy implications and directions for further research.

Chapter 2 presents an overview on Hawai‘i’s agriculture and sources of agriculture data. The current status of Hawai‘i’s agriculture and its challenges are discussed and a comparison with the US mainland is provided. The chapter concludes by discussing the available data for economic analysis.

Chapters 3 and 4 focus on Hawai‘i’s vegetable farming sector, a sector identified as one with potential for further growth. Chapter 3 examines the efficiency and productivity of vegetable farms using data for five recent census years. The objectives of the first chapter are to estimate efficiency scores and productivity indices for Hawai‘i’s vegetable sector across the Census years 1982, 1987, 1992, 1997 and 2007. In achieving the objectives, the most efficient production frontier for vegetable farms in each year is estimated employing a non-parametric method to frontier estimation: the Data Envelopment Analysis (DEA). Biases in DEA efficiency scores are corrected using the bootstrapping technique. DEA decomposes efficiency and productivity of the vegetable farming sector to technical efficiency, technical change, pure and scale efficiency components. This decomposition facilitates identifying areas that need improvement and hence helps in designing effective policies. Further, the link between efficiency and productivity and farm size is examined. The efficiency scores suggest considerable inefficiencies in Hawai‘i vegetable farms. Farm efficiency has deteriorated over the years. The efficiency of small farms has decreased while that of large farms has increased. However, farms are found to be relatively scale-efficient. Malmquist Index productivity analysis reveals that productivity has decreased on average over the period. However, it is not statistically significant. The productivity decomposition shows that average technical efficiency has reduced significantly.
Chapter 4 examines productivity changes arising from the entry, exit and survival dynamics. Dynamic Olley-Pakes (1996) productivity decomposition, as modified in Melitz and Polanec (2014), is applied to Hawai‘i’s vegetable sector to decompose productivity changes. Specifically, it aims to understand productivity gains/losses due to industry changes or structural changes. This chapter is among the first studies to empirically apply the Melitz and Polanec (2014) extension of the dynamic Olley-Pakes (1996) productivity decomposition. This study uses micro-level farm data from Hawai‘i’s Census of Agriculture to track farms over time to identify their presence in the vegetable sector. The study finds that farm entry and exit dynamics have contributed substantially to the aggregate productivity growth in the vegetable sector. While farm exits contribute positively to the aggregate productivity growth, new farm entry contributes negatively to the aggregate productivity growth. The aggregate productivity of continuing firms has increased between census years. Productivity gains in continuing farms are mainly a result of market share reallocation between farms.

Chapter 5 is an exploratory study and one of the first attempts at building a mathematical model of Hawai‘i’s agriculture for policy analysis. The programming method used here is a calibrated optimization modeling technique: Positive Mathematical Programming (PMP). Simulations involving resource shocks are analyzed to assess the impact of these scenarios on possible land allocation. The aggregate State model is calibrated to the base year 2007. Simulation exercises find that the loss of vegetable farmland decreases the harvested acreage of low-value vegetable crops. It increases the harvested acreage of high-value crops employing labor released from the lost farmland. When labor moves freely across fruit and vegetable sectors, the loss of vegetable farmland tends to increase the harvested acreage of fruit crops. The chapter identifies the possibility of modeling Hawai‘i’s agriculture for policy simulations and suggests ways to improve a state-wide agricultural model to closely represent real situations.
2.1. Introduction

Composed of tropical islands, Hawai‘i is home to an agriculture sector specializing in tropical crops. With the fall of sugarcane and pineapple plantation agriculture, Hawai‘i shifted its focus towards diversifying and is now predominantly a diversified agriculture. While its tropical climate is an advantage, its isolated location imposes cost disadvantages. However, Hawai‘i residents have taken an unprecedented interest in Hawai‘i agriculture. As a result, there is constant discussion about ways and means to improve and advance Hawai‘i’s agriculture.

There were an estimated 5,800 farms in Hawai‘i in 2012. Of these, 3,000 were commercial farms (i.e. farming making annual sales greater than or equal to $10,000). Total cropland was around 174 thousand acres. Major crop sectors, by sales volume, were seed crops, sugarcane, macadamia nuts, coffee, floriculture, banana, and papaya. Hawai‘i is the only coffee and pineapple growing State in the US and the largest papaya growing State. The total farm sales value of Hawai‘i in 2011 was estimated as $719.5 million. In 2014, agriculture contributed to only 0.7 percent of GDP Hawai‘i’s food exports totaled 175.5 thousand tonnes. Seed crops are the highest value generator in Hawai‘i’s agriculture. Seed corn contributed 96% of the total sales value of seed crops. It is a highly concentrated sector with only 11 farms operating as of 2011. The second and third highest value agriculture sectors are sugarcane and cattle, respectively. A list of major agriculture sectors by the value of sales is shown in Annex 1. The total farm workforce of 10,200 workers in 2010 was comprised of 6400 hired workers, 1,000 unpaid workers and 3,800 self-employed farm operators (National Agricultural Statistics Services, 2011).

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1 Farms that have annual sales of $1,000 or more are considered here.
2 This value is calculated using data from Bureau of Economic Analysis, U.S. Department of Commerce. Accessible at http://www.bea.gov/iTable/iTTable.cfm?reqid=70&step=1&isuri=1&acrdn=1#reqid=70&step=10&isuri=1&7003=200&7035=1&7004=naics&7005=-1&7006=15000&7036=-1&7001=1200&7002=1&7090=70&7097=2014&7093=levels.
Ulupono Initiative (2011) estimated that Hawai‘i consumers spend only 8% of their food budget on locally produced food, while spending the rest on imports. The locally produced and imported consumable food in Hawai‘i was estimated as 1.14 million tonnes in 2010. According to Loke and Leung (2013), only 11.6% of available food for consumption in Hawai‘i was sourced from local production in 2010. Therefore, there is a growing concern about Hawai‘i's high dependency on imported food items, which has also created an increasing interest in local agriculture.

A large majority of the food consumed in the islands is supplied by the US mainland, which is also the chief source of competition for Hawai‘i agriculture. Arita et al. (2012) found that Hawai‘i farmers underperform their counterparts in US mainland. They further identify higher labor costs faced by Hawai‘i farms compared to the US mainland farms and the difficulty in exploiting economies of scale as the primary causes of this underperformance. Geographically isolated from cheaper sources of labor, Hawai‘i farms incur a significantly higher cost of labor. On average, the cost of labor in Hawai‘i is 43% higher than the US mainland (Arita et al., 2012). Furthermore, Hawai‘i’s farms operate at a smaller scale (on average, less than half the size of the average US mainland farm). The superior economic performance found in larger farms in both Hawai‘i and US mainland suggests that Hawai‘i’s smaller farm size has further aggravated the cost disadvantages making it difficult to compete with US mainland farms. High residential and commercial land values and the more vibrant tourism sector also compete with agriculture for the limited resources. Though shipping costs between Hawai‘i and the US mainland may provide a slight buffer of protection between Hawai‘i and US farm gate prices (Yu and Leung et al., 2012; Parcon et al., 2010), intense import competition has greatly reduced the profit margins for Hawai‘i farms leading to potential contraction of local production. The cost disadvantages suggest that Hawai‘i farmers may be challenged in sectors as they face high import competition. One strategy to sustain Hawai‘i’s agriculture may be to focus on the sub-sectors with high import costs. Parcon et al. (2010) suggest that highly perishable products and those with low value per shipping weight may be more promising sectors to compete with imports. The vegetable and
melon sector has been identified as one such sector. Arita et al. (2012) found that Hawai‘i’s vegetable and melon farms performed relatively strongly, operating at a similar output-input efficiency as the US mainland when compared to other sectors. According to Arita et al. (2012), while all other sectors seem to be trailing further behind the US mainland, the vegetable and melon sector has improved its relative performance over the last decade. However, high labor costs in Hawai‘i can still be a competitive disadvantage in the vegetable and melon sector.

Another strategy to improve the competitiveness of local agriculture is to increase the demand and preference of local consumers for locally grown food. Hence, there is a renewed interest in food localization from consumers, farmers and policy makers. Fruits and vegetable crop cultivation and livestock production have gained significance. There are plans, strategies and movements set forth to cultivate the preferences for local food through increased education and marketing campaigns. Though economic theories of efficiency and trade do not agree with the need to increase food self-sufficiency, it has been a major interest for every country in the world. Hawai‘i is a geographically isolated place in the Pacific Ocean. It is approximately 2,506 miles away from the US mainland. Recent economic phenomena (the great recession during 2007-2009 and the global food crisis in 2008) have made residents and policy makers contemplate its vulnerability to natural disasters and global events that might affect shipping and hence the food supply.

2.2. Agriculture Data

The main sources of published agriculture data for Hawai‘i are the Agriculture Census and the annual Statistics of Hawai‘i Agriculture. The Hawai‘i Census of Agriculture provides a baseline level for the annual estimates contained in the Statistics of Hawai‘i Agriculture publication. The Agriculture Census is carried out at 5-year intervals, with reference years ending in 2 and 7.

The Hawai‘i Census of Agriculture collects farm data on all the farms in Hawai‘i except seed farms. It includes crop, livestock, and aquaculture farms. Over the years, the data collection process has improved to increase the coverage of the Census and the farmer
response rate. The small number of farms in Hawai‘i compared to the US mainland enables it to cover the entire farm population in Hawai‘i. The summarized farm Census data comes out as a Census publication every 5 years. Summarized data provides little scope for economic analysis. In contrast, the Census micro-data is a rich source of farm information. It includes ownership status of farmland, acreage allocation for different agricultural activities by each farm, number of animals/birds in livestock/poultry operations, sales value of the farm, participation in agricultural programs (credit, conservation, payments etc.), production expenses by input, labor use, farm demographics and location etc. However, this data is not publicly available. We were able to get permission from the US Department of Agriculture (USDA) to access the Census micro-data for six census years from 1982 to 2007 for a limited period. As independent researchers outside the USDA, we are the first to use Hawai‘i’s census micro-data for economic analyses.
### APPENDIX

**Table A2.1: List of Agriculture Sectors by Sales Value in 2011**

<table>
<thead>
<tr>
<th>Commodity</th>
<th>Value of Production (S'000)</th>
<th>Commodity</th>
<th>Value of Production (S'000)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Seed crops</td>
<td>242,970</td>
<td>Milk</td>
<td>9,547</td>
</tr>
<tr>
<td>Sugar cane (unprocessed)</td>
<td>78,100</td>
<td>Sweet potatoes</td>
<td>7,348</td>
</tr>
<tr>
<td>Cattle</td>
<td>46,369</td>
<td>Basil</td>
<td>6,225</td>
</tr>
<tr>
<td>Macadamia Nuts</td>
<td>38,220</td>
<td>Lettuce</td>
<td>5,453</td>
</tr>
<tr>
<td>Coffee</td>
<td>31,540</td>
<td>Onions, Dry</td>
<td>3,267</td>
</tr>
<tr>
<td>Algae</td>
<td>25,230</td>
<td>Honey</td>
<td>3,137</td>
</tr>
<tr>
<td>Floriculture</td>
<td>13,465</td>
<td>Cabbage, Head</td>
<td>2,790</td>
</tr>
<tr>
<td>Bananas</td>
<td>11,310</td>
<td>Taro</td>
<td>2,747</td>
</tr>
<tr>
<td>Papayas</td>
<td>9,722</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>


Note: Value of potted palms, dendrobiums, dracaena and cut anthuriums are summed here as floriculture.
REFERENCES


CHAPTER 3
EFFICIENCY AND PRODUCTIVITY CHANGES IN HAWAI’I’S VEGETABLE FARMING SECTOR: FROM 1982 TO 2007

3.1. Introduction

The U.S. agricultural sector has been undergoing significant structural and economic changes in recent decades. There is a general trend of declining number of farms, increasing average farm size, decreasing labor use and increasing agricultural value across the country. These changes have received serious concerns over the likely impact they have on different segments of the farming communities. For instance, the increasing drive towards larger farms is perceived as a threat to the long-term economic viability of the small farms and traditional farming communities. Thus, there has been growing interest to support small farmers while at the same time increasing production efficiency of the sector.

Productivity gains have been a driving force for the growth in U.S. agriculture. Effects of these changes over the second half of the 20th century were dramatic. In 2000, an average farmer produced 12 times as much output per hour worked as an average farmer did in 1950 (Fuglie et al., 2007). Productivity growth in agriculture allows farm produce to be grown and harvested more cheaply. Cheaper cost of production in agriculture produce benefits not only farmers but also food and textile manufacturers and consumers. A key reason for the small and declining share of family income on the food of an average American consumer is the productivity growth in agriculture. Growth in total factor productivity in the 20th century has made the United States the largest agricultural exporter in the world (Ball et al., 2014). Decrease in price due to increased productivity gives U.S. agriculture a competitive advantage in the export market where U.S. is a net exporter of agricultural commodities. Further, productivity growth has reduced pressure on natural resources.

According to these studies, while some farming sectors have the potential to increase overall efficiency by improving managerial practices (pure technical efficiency) some others by improving scale efficiency or both (Mugera and Langemier, 2011). There is a growing consensus that technical efficiency and productivity growth and economic performance are influenced by farm size. Larger farms are more productive or efficient than small farms (Olson and Vu, 2009; Paul et al., 2004; Mosheim and Lovell, 2009; Sharma et al., 1999; Mugera and Langemeir, 2011; Tauer and Mishra, 2006; Yee et al., 2004).

Adding to the existing literature on farm productivity and efficiency, in this article we assess the efficiency and productivity of vegetable farms in Hawai‘i. Hawai‘i is a high-cost agricultural producer. In Hawai‘i agriculture, vegetable farming has been identified as a sector with a potential. The vegetable farms are diverse in size and may differ in efficiency. (Importance of the vegetable farm industry in Hawai‘i agriculture is discussed in detail in the next section). We employ a non-parametric Data Envelopment Analysis (DEA) to study a small farming sector with limited data availability on farm production, cost, and prices. An advantage of DEA method over parametric method is that it does not make assumptions about the functional form and distribution of error. Further, DEA decomposes efficiency and productivity of a sector/industry to technical efficiency, technical change, pure and scale efficiency components. This decomposition facilitates identifying areas that need improvement and hence target policy interventions. Further, we are interested in understanding the link between efficiency and productivity and farm size.
A major criticism about DEA is its inability to measure noise in the estimation. We use bootstrapping proposed by Simar and Wilson (1998, 2000) to obtain biases and confidence intervals for efficiency and productivity scores. Bootstrapping has not been applied in many recent studies that have examined the farm level technical efficiency of U.S. agriculture. To our knowledge, Olson and Vu (2009) estimated technical, allocative, and scale efficiencies of farms in southern Minnesota using the bootstrap output-based DEA approach for the period 1993-2006 and Mugera and Langemeier (2011) used bootstrap DEA technique to examine efficiency of 564 farms in Kansas for the period 1993–2007. While this study applies bootstrap DEA in our farm efficiency analysis, to our knowledge it is the first study to use bootstrapped Malmquist Productivity Index to examine total factor productivity changes in an agricultural sector in U.S.

We find that Hawai‘i vegetable farms show considerable inefficiencies. Farm efficiency has deteriorated over the years. Efficiency varies significantly by farm size. The efficiency of small farms has decreased while that of large farms has increased. Farms are relatively scale-efficient. We find an average productivity regress over the period that is not statistically significant. The productivity decomposition shows that average technical efficiency has reduced significantly.

The rest of the paper is organized as follows. The section two gives a brief summary of the agriculture sector and particularly vegetable farming sector in Hawai‘i. Section three introduces the DEA used in efficiency estimation, and Malmquist Productivity Index (MPI) approach used for measuring productivity changes followed by a section on data. Section 5 presents and discusses the empirical results. The final section contains concluding remarks.

3.2. Vegetable Farming Industry in Hawai‘i

The demand for vegetables has been growing in the last couple of decades in the United States. Vegetables are considered high-value crops, leading vegetable farmers to be
among the most profitable operators in the agriculture sector. It is anticipated that the demand for vegetables will grow at a higher rate than the growth of population (Economic Research Service, USDA). Heightened interest in health and nutrition and, increased income have been major reasons for the increased demand (Economic Research Service, USDA). Driven by the increase in demand, the production of vegetables has increased significantly in the United States. An increase in agriculture production can be achieved by increased use of inputs as well as by improved efficiency and productivity. With respect to US agricultural production that doubled during 1948-2011, the output growth was mainly driven by productivity growth and there has been only a little contribution from input growth (Ball et al., 2014). As an industry gaining significance, knowing efficiency and productivity growth of the vegetable farming industry sector will be of interest to many parties. Most importantly, this knowledge will enable policy makers to formulate and set policies in the right direction.

We observe a considerable variation in agricultural productivity values among different States and within a state across different agricultural sectors. Though agricultural productivity is extensively studied at the national level, very little attention has been paid to Hawai‘i. An exception is Sharma et al., (1999), which investigated production efficiency in the Hawai‘i swine industry. Hawai‘i is a high-cost agricultural producer. Therefore, the importance of achieving efficiency and productivity growth cannot be overemphasized. With the decline in plantation agriculture in Hawai‘i, diversified agriculture has gained significance (including seed crops, fruits and tree nuts, vegetables, floriculture and nursery products) (Yu et al., 2008). Tropical and subtropical climate prevalent in Hawai‘i facilitates the production of a wide variety of vegetables economically. The vegetable farming industry is important as it caters to the fresh food requirements of the State, and also as a source of employment and export income. The value of vegetables produced in 2011 amounts to $82.4 million. Fruit, tree-nuts, and vegetable farming industries together contribute 29% of the value of all crops produced in Hawai‘i in 2011 (Statistics of Hawai‘i Agriculture, 2011). These farming industries altogether have hired 5633 workers in 2007 (Census of Agriculture, 2007). Recently the vegetable farming industry has been receiving more attention of the researchers and the
general public due to the state’s goals of increasing local food production and consumption.

Isolated from cheaper sources of farm labor, Hawaiʻi faces severe production disadvantages. Farm labor costs are 40% higher than that of the U.S. mainland. Hawaiʻi’s farms on average, are less than half the size of U.S. mainland farms in terms of sales, and 2-3 times smaller in terms of acreage (Arita et al., 2012). Compared to its competitors from Asia and South America, Hawaiʻi is facing significant cost disadvantages in labor, energy, transportation, and other input costs (Parcon et al., 2010). Today, the vast majority of the food consumed in the Islands is supplied by outside sources of production. Arita et al. (2012) find that Hawaiʻi farms are on average 15-20% less efficient in production than U.S. farms. Comparing Hawaiʻi and U.S. mainland farms in terms of simple efficiency and profitability measures, they find that Hawaiʻi farms perform less than U.S. mainland farms. According to the authors, large commercial farms in the Mainland significantly outperform that in Hawaiʻi in terms of output-input ratio, return on assets (ROA) and net profit per acre. In increasing food production under a high input cost environment, it is important that the production units/farms produce efficiently and productively. Knowing how efficiency and productivity of farms have changed over the years would be helpful in determining ways to increase food production in Hawaiʻi and in identifying areas to allocate its limited resources.

3.3 Methodology

Technical efficiency scores and productivity indices are widely used for the purpose of determining the production performance of Decision Making Units (DMU) such as farms and enterprises. Productivity change and efficiency scores of DMUs are typically measured relative to an efficient frontier estimated using either a parametric or non-parametric method. A well-known non-parametric mathematical linear programming approach to frontier estimation is the Data Envelopment Analysis (DEA). The pioneering work on this method are Charnes et al. (1978) and Fare et al. (1985). They provided measures of efficiency in production following Debreu (1952) and Farrell
(1957). DEA has been widely used due to its numerous advantages over parametric methods. A major difference between DEA and parametric methods is that DEA does not assume a particular functional form for the frontier model. DEA is not subjected to assumptions on the distribution errors, which might arise with parametric methods. This approach is especially useful in situations of multiple outputs and inputs with no reliable price data that would allow estimation of stochastic frontier cost functions are available. As with any other estimation technique, DEA is not perfect. A major criticism of the DEA approach to estimate productivity and efficiency is its inability to give a measure of error of the estimates. As a solution, Simar and Wilson (1998 and 2000) proposed consistent bootstrap estimation procedures to estimate the production frontier. This procedure relies on mimicking the data generating process and repeating the DEA computation a large number of times. A standard normal distribution is assumed, and random samples are obtained by sampling, with replacement from the original dataset. The resultant bootstrap distribution is expected to mimic the original unknown sampling distribution of the estimators by using a nonparametric estimate of their densities and thereby provide an estimator of the parameter of interest. Bootstrapping enables the assessment of whether the distribution has been influenced by stochastic effects and aid in building confidence intervals for point estimates that cannot be derived analytically. The DEA estimates are biased by construction, and the empirical bootstrap distribution can be used to estimate the bias. The difference between the original DEA efficiency point estimate and the empirical mean of the bootstrap distribution gives an estimate of the bias. The process of bootstrapping DEA is discussed in detail by Simar and Wilson (1998, 2000).

The Farrell input-based efficiency index for farm $i$ at time $t$ is defined as,

$$ e(x_i^t, y_i^t) = \min \{ \theta \left| (x_i^t, y_i^t) \epsilon T^t \right\} $$

where $y$ is outputs, $x$ is inputs and $T$ is technology set.

Assume there are $K$ inputs and $M$ outputs and each of $N$ firms. For the $i$-th firm inputs and outputs are represented by the column vectors $x$ and $y$ respectively. The $KxN$ input matrix, $MxN$ output matrix and $Y$ represent the data for all $N$ firms.
The mathematical programming problem is,

$$\text{Max}_{\mu, v} (\mu^{'y_i}),$$

Subject to,

$$v^{'x_i} = 1$$
$$\mu^{'y_j} - v^{'x_j} \leq 0 \quad j = 1, 2, \ldots, N$$
$$\mu, v \geq \theta$$

where $\mu$ is an Mx1 vector of output weights and $v$ is a Kx1 vector of input weights. The optimal weights are derived by solving the above mathematical programming problem.

The dual linear programming formulation of an input-oriented DEA is,

$$\text{Min}_{\theta, \lambda} \theta,$$

Subject to,

$$-y_i + Y\lambda \geq 0,$$
$$-\theta x_i - X\lambda \geq 0,$$
$$\lambda \geq 0.$$

where $\theta$ is a scalar and $\lambda$ is N x 1 vector of constants. Value for $\theta$ obtained is the efficiency score for the $i$-th firm. According to Farrell (1957), $\theta \leq 1$ so that the most efficient firms takes the value of one and form the efficient frontier. The above linear programming problem is solved N times, i.e. once for each DMU in the sample. The problem takes the $i$-th firm and seeks the minimum input level feasible for producing the same output level. The input distance function determines the location of a farm in the input space relative to the isoquant. Its objective is to reduce the input amounts by as much as possible while keeping at least the present output levels. A farm is identified as technically efficient when $\theta = 1$ and technically inefficient when $0 < \theta < 1$.

The CRS assumption is appropriate when DMUs operate at the optimal scale. The use of CRS when all farms are not operating at the optimal scale results in TEs that are
confounded by scale efficiencies. Specification of Variable Returns to Scale (VRS) makes it possible to calculate TE devoid of scale efficiencies (SE). The previous CRS problem can be modified to VRS by adding the convexity constraint $N_1'\lambda=1$ where $N_1$ is a vector of ones. This approach builds a convex hull of intersecting planes that envelop the data points more tightly than the CRS conical hull. Therefore, it provides technical efficiency score higher than or equal to those produced by CRS.

3.3.1. Calculation of Scale Efficiencies

Scale efficiency can be measured for each firm by conducting both CRS DEA and VRS DEA and decomposing CRS DEA into two constituents: scale inefficiency (SE) and the other pure efficiency. If CRS DEA and VRS DEA are different for a particular farm that means there is scale inefficiency.

$$TE_{\text{CRS}} = TE_{\text{VRS}} * SE$$

Scale efficiency shows the degree of inefficiency of a DMU arising from its scale of operation. The ratio of a farm’s technical efficiency under CRS to its technical efficiency under VRS yields the scale efficiency score: $SE=TE_{\text{CRS}}/TE_{\text{VRS}}$. Since $TE_{\text{CRS}} \leq TE_{\text{VRS}}$, $SE \leq 1$. A farm with $SE = 1$ is scale efficient in the sense that the chosen input-output mix is optimal and maximizes the average efficiency. If $SE < 1$, the input-output mix is not scale-efficient. That is the DMU in question is operating either in a region of increasing returns to scale (inefficient small-scale) or decreasing returns to scale (inefficient large-scale).

3.3.2. The Nature of Returns to Scale

To understand if a firm is operating at increasing returns to scale or decreasing returns to scale, Non-Increasing Returns to Scale (NIRS) condition is imposed on the VRS DEA problem. This is done by substituting $N_1'\lambda=1$ with $N_1'\lambda \leq 1$. The nature of scale efficiency can be determined by checking if $TE_{\text{NIRS}}$ is equal to $TE_{\text{VRS}}$. If they are not equal increasing returns to scale (IRS) exist. If they are equal decreasing returns to scale (DRS) exist.
3.3.3. Malmquist Productivity Index (MPI)

Total Factor Productivity (TFP) is a measure of the productivity performance of a DMU. TFP is defined as the output per inputs used. The change in TFP is comprised of two components, namely technical efficiency change (TE) and technical change (TC). Improvements in the technical efficiency and technical change enable a DMU to reach higher economic performance level and thus to have a higher competitive power.

The MPI is a measure of productivity change over time. The concept of MPI was first introduced by Malmquist (1953). It has been further studied and developed by several authors (Caves et al., 1982; Fare and Grosskopf, 1992). MPI solves a non-parametric DEA model under time dependent situations to yield productivity change. It is an index evaluating TFP growth of a DMU (a farm in this case) while decomposing TFP growth into

i) progress or regress in efficiency and

ii) the change in the production frontier technology between two periods of time under the multiple inputs and outputs framework.

Therefore, MPI is defined as the product of catch-up (or recovery) and frontier shift (or innovation). Following Cooper et al., (2007), the Malmquist Index (MI) can be computed as follows:

\[ MI = C \times F = \left( \frac{\delta^2 ((x_0, y_0)^2)}{\delta^1 ((x_0, y_0)^1)} \right) \times \left( \frac{\delta^1 ((x_0, y_0)^1)}{\delta^2 ((x_0, y_0)^2)} \right) \times \left( \frac{\delta^1 ((x_0, y_0)^2)}{\delta^2 ((x_0, y_0)^2)} \right)^{1/2} \]

where \( x_0 \) and \( y_0 \) indicate a vector of inputs and outputs, respectively; \( \delta^i ((x_0, y_0)^i) \) denotes the efficiency of \((x_0, y_0)^i\) with respect to period i frontier; and \( \delta^j ((x_0, y_0)^j) \) denotes the efficiency of \((x_0, y_0)^j\) with respect to period j frontier, for \( i=1,2 \) and \( j=1,2 \). Moreover, C is the catch-up effect which denotes efficiency change while \( F \) is the
frontier-shift effect which denotes technology change. If MPI>1, progress in the productivity of the relevant DMU has occurred from period 1 to 2, while MPI=1 and MPI<1 indicate the status quo and deterioration in TFP respectively.

The above-mentioned scores of DMUs are calculated relative to an estimated efficient production frontier, defined as the geometrical locus of optimal production plans. In that case, the MPI is based on the finite sample of observed DMUs. As proposed by Simar and Wilson (1998), the bootstrap method is therefore used to analyze the sensitivity of the MPI relative to the sampling variations of the estimated production frontier. The bivariate kernel estimator of the density of the original distance function estimates is used to preserve any temporal correlation found in the data. In this framework, an input-oriented MPI is calculated with DEA based on a multi-input and single-output model.

Standard software packages do not include procedures for non-parametric efficiency estimators. The general purpose software R includes procedures for statistical inference. Therefore, R and the package FEAR (Frontier Efficiency Analysis with R) were used for the empirical analysis of the study. The FEAR version 1.11 by Wilson (2008) and R 2.8.1 were used to compute the MI and its decompositions. The choice of bootstraps is constrained by available computer resources that enable handling of a large dataset. As indicated in the literature, 2000 replications were performed in this analysis to ensure an adequate coverage of the confidence intervals.

3.4. Data

This study employs farm production data from Hawai‘i Agriculture Census, which is conducted at five-year intervals (i.e. 1982, 1987, 1992, 1997, 2002 and 2007). Annual farm level production data is not available for Hawai‘i. This poses a disadvantage in productivity analysis as productivity change between the five-year interval may not accurately represent the trend within a five-year period. The results are susceptible to extreme agro-climatic and economic conditions prevailing in a particular census year. For instance if the starting census year which experienced an extreme drought is followed by a census year with normal or favorable weather conditions, it will show a high
productivity growth between the five years which may not have been observed during years in between. Similarly, if the starting census year that experienced a favorable weather is followed by a census year with a severe drought, it will show a negative productivity growth. However, one advantage of working with Census data is that it enables us to look at average productivity changes in a longer time span (i.e. 25 years) which important in capturing the technical changes. Another advantage of using Hawai‘i Agriculture Census data is that the Census covered the entire farming population in Hawai‘i with the long version of the report form except in Census 2002. The long report form includes all sales and cost of production data of farms. We excluded Census cohort 2002 in our analysis since only 46% of farms were reached with the long report form that Census year3. Nevertheless, the long time span of data comes with the cost of having a smaller sample size for productivity analysis. Hawai‘i vegetable farming industry has been structurally dynamic with farm exit and entry. Therefore, a complete panel of farms from 1982 to 2007 consists only of a smaller number of farms that survived throughout compared to the farm population in those years. Since it is a small percentage of farms of the industry, generalizing the results for the industry should be carefully done. Further, the results could suffer from selection bias as those farms represent only the group of farms that survived through the 25 years considered. To minimize this problem, productivity changes were analyzed considering panels of farms for two consecutive censuses separately (i.e. from 1982 to 1987, 1987 to 1992, 1992 to 1997 and 1997 to 2007).

The majority of vegetable farms in Hawai‘i are small scale operations. In this analysis, Hawai‘i’s commercial vegetable farms are studied. A farm is identified as a commercial farm if it makes total gross income at or above $10,000 (in 1982 value). This breakdown of farm categories by gross income is the general practice adopted by the Economic Research Service of USDA (Hoppe et al., 2010). The number of farms in the DEA and Malmquist productivity analyzes is shown in Table 3.1. A very high percentage of commercial vegetable farms in each census year is represented in the DEA analysis.

3The census years are selected based on the availability of data. We could only get access to census as far back as 1982. By the time this paper is written census of agriculture 2012 data were not yet available. Therefore the latest data is for the census year 2007.
Except for the census year 1982, more than 89% of the commercial vegetable farm population is in the DEA analysis. The number of farms in the productivity analysis is lower compared to the DEA analysis as we are working with a panel of farms in productivity analysis. The panel of farms from 1982 to 1987 (i.e. 115 farms) represented 31.2% of 1982 farms and 31.3% of 1987 farms. The panel of farms from 1987 to 1992 (i.e. 132 farms) represented 36% of 1987 farms and 39.2% of 1992 farms and the panel from 1992 to 1997 (i.e. 97 farms) represented 28.8% of 1992 farms and 45.5% of 1997 farms. Productivity analysis from 1997 to 2007 (i.e. 56 farms), represented 26.3% of 1997 farms and 40.9% of 2007 farms.

Table 3.1: Number of Vegetable Farms in Efficiency and Productivity Analyses

<table>
<thead>
<tr>
<th>Census Year</th>
<th>Total Farms</th>
<th>Total Commercial Farms</th>
<th>% of Commercial Farms in DEA Analysis</th>
<th>Time Interval</th>
<th>No. of Commercial Farms in Productivity Analysis</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td>732</td>
<td>369</td>
<td>73%</td>
<td>82/87</td>
<td>115</td>
</tr>
<tr>
<td>1987</td>
<td>639</td>
<td>367</td>
<td>89%</td>
<td>87/92</td>
<td>132</td>
</tr>
<tr>
<td>1992</td>
<td>667</td>
<td>337</td>
<td>89%</td>
<td>92/97</td>
<td>97</td>
</tr>
<tr>
<td>1997</td>
<td>491</td>
<td>213</td>
<td>92%</td>
<td>97/07</td>
<td>56</td>
</tr>
<tr>
<td>2007</td>
<td>327</td>
<td>137</td>
<td>94%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

For this analysis, we identify farms in vegetable, potato and melon category in North American Industry Classification System (NAICS). One output and six inputs are used in the DEA model. The output variables used in the analysis is the gross farm income. The input variables are the cost of fertilizer and chemicals, the cost of fuel and utilities, cost of depreciation, harvested cropland acres, and the annual labor hours. Since values and costs are subjected to inflation, they were corrected for inflation by converting all values and costs to 1982 equivalent values using the Honolulu Consumer Price Index. A

4Before 1997, U.S. agriculture census used System of Industry Classification (SIC) to classify farms.
5Total harvested cropland in farms classified as NAICS code 1112 (vegetables, potatoes and melons).
6Depreciation cost is reported only in 2007 census. Therefore, depreciation calculated as 10% of the reported value of machinery for every census year.
7Annual labor hours are not reported in Census. They are calculated based on the annual cost of labor and number of working days. Operator’s labor is not included.
summary of the variables used in the DEA and productivity analysis is shown in Table 3.2. Vegetable farms usually grow a mix of crops and with time the crop mix could change. When evaluating productivity changes of the vegetable farm industry, it is important to know that such changes in crop mix are possible. From 1982 census year to 2007 census year, some changes in the popularly grown crops are observed. 

Table 3.2: Summary of Output and Input Variables (in 1982 values)

<table>
<thead>
<tr>
<th>Census Year</th>
<th>Statistic</th>
<th>Total Sales</th>
<th>Cost of Fertilizer and Chemicals</th>
<th>Cost of Fuel and Utilities</th>
<th>Cost of Machinery Expenses</th>
<th>Cost of All Other Expenses</th>
<th>Harvested Crop Acreage</th>
<th>Number of Labor Hours</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td>Mean</td>
<td>67,549</td>
<td>8,174</td>
<td>3,285</td>
<td>3,653</td>
<td>5,738</td>
<td>11</td>
<td>6,175</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>38,224</td>
<td>3,738</td>
<td>2,150</td>
<td>2,500</td>
<td>2,000</td>
<td>6</td>
<td>2,185</td>
</tr>
<tr>
<td></td>
<td>Std.</td>
<td>79,724</td>
<td>12,802</td>
<td>3,425</td>
<td>3,418</td>
<td>11,721</td>
<td>16</td>
<td>9,575</td>
</tr>
<tr>
<td>1987</td>
<td>Mean</td>
<td>67,126</td>
<td>7,047</td>
<td>2,666</td>
<td>3,504</td>
<td>10,042</td>
<td>12</td>
<td>5,766</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>27,850</td>
<td>2,437</td>
<td>1,540</td>
<td>1,741</td>
<td>3,697</td>
<td>5</td>
<td>2,080</td>
</tr>
<tr>
<td></td>
<td>Std.</td>
<td>122,912</td>
<td>13,041</td>
<td>3,458</td>
<td>5,207</td>
<td>21,525</td>
<td>35</td>
<td>15,059</td>
</tr>
<tr>
<td>1992</td>
<td>Mean</td>
<td>78,731</td>
<td>8,201</td>
<td>3,631</td>
<td>3,573</td>
<td>11,275</td>
<td>17</td>
<td>6,621</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>32,216</td>
<td>3,505</td>
<td>1,493</td>
<td>1,740</td>
<td>4,294</td>
<td>6</td>
<td>2,155</td>
</tr>
<tr>
<td></td>
<td>Std.</td>
<td>149,140</td>
<td>17,972</td>
<td>8,372</td>
<td>5,611</td>
<td>27,392</td>
<td>46</td>
<td>14,969</td>
</tr>
<tr>
<td>1997</td>
<td>Mean</td>
<td>85,640</td>
<td>7,989</td>
<td>3,436</td>
<td>3,245</td>
<td>12,283</td>
<td>19</td>
<td>8,127</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>30,174</td>
<td>2,907</td>
<td>1,840</td>
<td>1,744</td>
<td>4,470</td>
<td>8</td>
<td>2,332</td>
</tr>
<tr>
<td></td>
<td>Std.</td>
<td>219,904</td>
<td>19,051</td>
<td>5,479</td>
<td>5,025</td>
<td>22,761</td>
<td>48</td>
<td>23,456</td>
</tr>
<tr>
<td>2007</td>
<td>Mean</td>
<td>196,373</td>
<td>21,093</td>
<td>13,719</td>
<td>7,589</td>
<td>29,781</td>
<td>40</td>
<td>12,706</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td>45,730</td>
<td>5,283</td>
<td>5,404</td>
<td>2,873</td>
<td>7,368</td>
<td>9</td>
<td>2,526</td>
</tr>
<tr>
<td></td>
<td>Std.</td>
<td>655,544</td>
<td>75,632</td>
<td>34,155</td>
<td>27,511</td>
<td>96,339</td>
<td>176</td>
<td>53,597</td>
</tr>
</tbody>
</table>

8 In 1982, most farms grew snap beans, cucumber, lettuce, tomato, ginger and eggplant. In 1987, farms mostly grew ginger, taro, snap bean, cucumber and green onion. In 1992, they were ginger, taro, snap bean, eggplant, and lettuce. In 1997, most farms grew eggplant, snap bean, cucumber, lettuce, and green onion and in 2007, they are eggplant, lettuce, squash, fresh herbs, and tomatoes.

In terms of harvested crop acreage, lettuce, head cabbage, dry onion, tomato and sweet corn are the largest crops in 1982. In 1987, lettuce, head cabbage, tomato, dry onion and snap bean are the largest. In 1992, lettuce, head cabbage, taro, dry onion and sweet corn are the largest acreage crops. In 1997, head cabbage, lettuce, cucumber, tomato and sweet corn. In 2007, tomato, sweet corn, head cabbage, lettuce and cucumber are the largest acreage crops.
3.5. Results and Discussion

3.5.1. Bootstrapped DEA Efficiency Analysis

Technical efficiencies are estimated using the input-oriented framework. The efficiency estimates under input-orientation yields the possible percentage reduction in inputs in producing the same amount of output. The models were estimated using FEAR package linked to the statistical package R (Wilson, 2008). For all the estimates, 2000 bootstrap iterations were employed. Tables 3.3, 3.4 and 3.5 present the mean technical efficiency scores of the farms in each census year under three different assumptions about the model’s technological set: CRS, NIRS, and VRS respectively. For each table, the second through fifth columns represent the mean of the DEA-estimates, the estimated bias and the 95% confidence lower and upper bounds respectively. The confidence intervals are for the bias-corrected efficiency scores. For our study, the bias-corrected efficiency estimates seem more valid as estimated bias is greater than the standard deviation (Daraio and Simar, 2007).

Table 3.3 presents the mean technical efficiency across years, under CRSs. The lowest original efficiency score is 0.3864 estimated for 2007 (i.e. highest inefficiency is 61%) and the lowest bias-corrected efficiency score is 0.2839 (i.e. highest inefficiency is 72%) for the same year. The highest original efficiency score is 0.5703 estimated for 1987 (i.e. lowest inefficiency is 43%) and the highest bias-corrected efficiency score is 0.4506 for the same year (i.e. lowest inefficiency is 55%). The lower bound ranged from 0.2472 to 0.4024 while upper bound ranged from 0.3596 to 0.5514. The mean difference between the lower and upper bounds over the entire study period is 0.1302 with the highest value being 0.1490 (1987) and the lower value being 0.1124 (2007).
Table 3.3: Input-Oriented Technical Efficiency Scores with CRS Model

<table>
<thead>
<tr>
<th>Census Year</th>
<th>Efficiency Score</th>
<th>Bias Corrected Efficiency</th>
<th>Bias</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td>0.4252</td>
<td>0.3187</td>
<td>0.1064</td>
<td>0.2830</td>
<td>0.3980</td>
</tr>
<tr>
<td>1987</td>
<td>0.5703</td>
<td>0.4506</td>
<td>0.1197</td>
<td>0.4024</td>
<td>0.5514</td>
</tr>
<tr>
<td>1992</td>
<td>0.5200</td>
<td>0.4072</td>
<td>0.1127</td>
<td>0.3633</td>
<td>0.4988</td>
</tr>
<tr>
<td>1997</td>
<td>0.4404</td>
<td>0.3091</td>
<td>0.1313</td>
<td>0.2658</td>
<td>0.4049</td>
</tr>
<tr>
<td>2007</td>
<td>0.3864</td>
<td>0.2839</td>
<td>0.1025</td>
<td>0.2472</td>
<td>0.3596</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>0.4684</strong></td>
<td><strong>0.3539</strong></td>
<td><strong>0.1145</strong></td>
<td><strong>0.3123</strong></td>
<td><strong>0.4426</strong></td>
</tr>
</tbody>
</table>

Note: The table above reports mean technical efficiency score bootstrapped with 2000 iterations. The equality of means test for standard and bias corrected efficiency scores is rejected at 1% level of significance.

Table 3.4 presents the mean technical efficiency across years, under NIRSs. The lowest original efficiency score is 0.3946 estimated for 2007 (i.e. highest inefficiency is 61%) and the lowest bias corrected efficiency score is 0.2897 (i.e. highest inefficiency is 71%) for the same year. The highest original efficiency score is 0.6081 estimated for 1987 (i.e. lowest inefficiency is 39%) and the highest bias corrected efficiency score is 0.4880 for the same year (i.e. lowest inefficiency is 51%). The lower bound ranged from 0.2514 to 0.4320 while upper bound ranged from -0.0162 to 0.5922. The mean difference between the lower and upper bounds over the entire study period is 0.1738 with the highest value being 0.3088 (1997), and the lowers value being 0.1168 (2007).

Table 3.4: Input-Oriented Technical Efficiency Scores with NIRS Model

<table>
<thead>
<tr>
<th>Census Year</th>
<th>Efficiency Score</th>
<th>Bias Corrected Efficiency</th>
<th>Bias</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td>0.4547</td>
<td>0.3416</td>
<td>0.1131</td>
<td>0.3008</td>
<td>0.4295</td>
</tr>
<tr>
<td>1987</td>
<td>0.6081</td>
<td>0.4880</td>
<td>0.1201</td>
<td>0.4320</td>
<td>0.5922</td>
</tr>
<tr>
<td>1992</td>
<td>0.5676</td>
<td>0.4461</td>
<td>0.1215</td>
<td>0.3937</td>
<td>0.5484</td>
</tr>
<tr>
<td>1997</td>
<td>0.4554</td>
<td>0.3414</td>
<td>0.1140</td>
<td>0.2926</td>
<td>-0.0162</td>
</tr>
<tr>
<td>2007</td>
<td>0.3946</td>
<td>0.2897</td>
<td>0.1049</td>
<td>0.2514</td>
<td>0.3682</td>
</tr>
<tr>
<td><strong>Average</strong></td>
<td><strong>0.4961</strong></td>
<td><strong>0.3814</strong></td>
<td><strong>0.1147</strong></td>
<td><strong>0.3341</strong></td>
<td><strong>0.3844</strong></td>
</tr>
</tbody>
</table>

Note: The above table reports mean technical efficiency score bootstrapped with 2000 iterations. The equality of means test for standard and bias corrected efficiency scores is rejected at 1% level of significance.
Table 3.5 presents the mean technical efficiency across years, under VRSs. The lowest original efficiency score is 0.5694 estimated for 2007 (i.e. highest inefficiency is 43%) and the lowest bias corrected efficiency score is 0.4527 (i.e. highest inefficiency is 55%) for the same year. The highest original efficiency score is 0.7057 estimated for 1987 (i.e. lowest inefficiency is 29%) and the highest bias corrected efficiency score is 0.6052 for the same year (i.e. lowest inefficiency is 39%). The lower bound ranged from 0.3982 to 0.5362 while upper bound ranged from 0.5516 to 0.6959. The mean difference between the lower and upper bounds over the entire study period is 0.1657 with the highest value being 0.1753 (1997), and the lowers value being 0.1534 (1982).

### Table 3.5: Input-Oriented Technical Efficiency Scores with VRS Model

<table>
<thead>
<tr>
<th>Census Year</th>
<th>Efficiency Score</th>
<th>Bias Corrected Efficiency</th>
<th>Bias</th>
<th>Lower Bound</th>
<th>Upper Bound</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td>0.5694</td>
<td>0.4527</td>
<td>0.1167</td>
<td>0.3982</td>
<td>0.5516</td>
</tr>
<tr>
<td>1987</td>
<td>0.7057</td>
<td>0.6052</td>
<td>0.1005</td>
<td>0.5362</td>
<td>0.6959</td>
</tr>
<tr>
<td>1992</td>
<td>0.6674</td>
<td>0.5500</td>
<td>0.1173</td>
<td>0.4839</td>
<td>0.6540</td>
</tr>
<tr>
<td>1997</td>
<td>0.5900</td>
<td>0.4639</td>
<td>0.1261</td>
<td>0.4008</td>
<td>0.5761</td>
</tr>
<tr>
<td>2007</td>
<td>0.5940</td>
<td>0.4701</td>
<td>0.1239</td>
<td>0.4058</td>
<td>0.5760</td>
</tr>
<tr>
<td>Average</td>
<td>0.6253</td>
<td>0.5084</td>
<td>0.1169</td>
<td>0.4450</td>
<td>0.6107</td>
</tr>
</tbody>
</table>

Note: The above table reports mean technical efficiency score bootstrapped with 2000 iterations. The equality of means test for standard and bias corrected efficiency scores is rejected at 1% level of significance.

In general, the mean technical efficiency scores of all farms for all census years considered were 47%, 50%, and 62.5%, for the CRS, NIRS and VRS technology sets, respectively. That is CRS technology yielding the lowest efficiency estimates and VRS yielding the highest efficiency estimates. These results conform to the production economics theory as VRS technology set is the least restrictive, and the CRS technology set is the most restrictive, whereas the NIRS technology set lies in between. Overall, the mean technical efficiency of the vegetable sector has deteriorated across the Census years since 1987. The estimated mean confidence intervals for VRS are wider (16.6%) than for
CRS (13%) because VRS production frontier has a greater curvature. Likewise, the CRS technology set displays smaller bias (11.4%) compared with NIRS (11.5%) and VRS (11.7%), where larger bias indicates a larger degree of noise.

The following tables are presented only with VRS technology as it is the least restrictive. Table 3.6 depicts a comparison of summary statistics between original estimates and bias-corrected estimates. The bias-corrected scores, standard deviations and coefficients of variation are lower than that of the original efficiency scores. The percentage of farms that is ranked as perfectly efficient under original efficiency scores but does not have a dominant position in the bias-corrected efficiency ranking is small (highest is 6.8% in 2007). All farms that have perfect original efficiency scores have bias-corrected efficiency scores of less than unity. These are an outcome of the theory behind the construction of the homogenous, smooth bootstrap procedure as outlined by Simar and Wilson (1998, 2000). The coefficient of variation ($\sigma/\mu$) depicts the dispersion of the efficiency scores in a particular year. The spread of efficiency scores is higher in 1982, and it narrows down in 1987 and 1992. It again widened in 1997, and 2007 shows the widest dispersion.

Table 3.6: Summary Statistics of Original and Bootstrapped Technical Efficiency Scores under VRS Model

<table>
<thead>
<tr>
<th>Census Year</th>
<th>Original Efficiency</th>
<th>Bootstrapped Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>1982</td>
<td>0.5694</td>
<td>0.2918</td>
</tr>
<tr>
<td>1987</td>
<td>0.7057</td>
<td>0.2662</td>
</tr>
<tr>
<td>1992</td>
<td>0.6674</td>
<td>0.2563</td>
</tr>
<tr>
<td>1997</td>
<td>0.5900</td>
<td>0.2775</td>
</tr>
<tr>
<td>2007</td>
<td>0.5940</td>
<td>0.3257</td>
</tr>
</tbody>
</table>

Table 3.7 presents the frequency distribution of farms technical efficiencies in different census years under VRS technology. The estimated results reveal that the percentage of farms that operate at less than 50% efficiency level is 62.9% in 1982, 36.6% in 1987, 46% in 1992, 61.8% in 1997, and 56.8% in 2007. The percentage of farms operating at
less than 50% efficiency level has dropped from 1982 to 1987, and it has been increasing since 1987. An interesting observation is the bimodal nature of the distributions in all census years. That is a concentration of farms at the lower end of the distribution and at the higher end of the distribution can be observed in all the census years. This bimodal distribution is clearly evident in the frequency distribution of the year 2007.

Table 3.7: Frequency Distribution of Input Efficiency Scores with VRS Model

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;20</td>
<td>33</td>
<td>12.0%</td>
<td>8</td>
<td>2.4%</td>
<td>4</td>
<td>1.32%</td>
</tr>
<tr>
<td>20-30</td>
<td>62</td>
<td>22.5%</td>
<td>27</td>
<td>8.2%</td>
<td>32</td>
<td>10.53%</td>
</tr>
<tr>
<td>30-40</td>
<td>38</td>
<td>13.8%</td>
<td>39</td>
<td>11.8%</td>
<td>46</td>
<td>15.13%</td>
</tr>
<tr>
<td>40-50</td>
<td>40</td>
<td>14.5%</td>
<td>47</td>
<td>14.2%</td>
<td>58</td>
<td>19.08%</td>
</tr>
<tr>
<td>50-60</td>
<td>20</td>
<td>7.3%</td>
<td>41</td>
<td>12.4%</td>
<td>36</td>
<td>11.84%</td>
</tr>
<tr>
<td>60-70</td>
<td>26</td>
<td>9.5%</td>
<td>23</td>
<td>6.9%</td>
<td>24</td>
<td>7.89%</td>
</tr>
<tr>
<td>70-80</td>
<td>30</td>
<td>10.9%</td>
<td>71</td>
<td>21.5%</td>
<td>77</td>
<td>25.33%</td>
</tr>
<tr>
<td>80-90</td>
<td>19</td>
<td>6.9%</td>
<td>41</td>
<td>12.4%</td>
<td>22</td>
<td>7.24%</td>
</tr>
<tr>
<td>90-99</td>
<td>7</td>
<td>2.5%</td>
<td>34</td>
<td>10.3%</td>
<td>5</td>
<td>1.64%</td>
</tr>
</tbody>
</table>

3.5.1.1 Technical Efficiency Estimates by Farm Size

Table 3.8 presents the estimates of technical efficiency under VRS technology set by farm size. Small, medium and large farms are farms that make sales between $10,000-$100,000, $100,000-$250,000 and ≥ $250,000 respectively. Large farms are more efficient (85%) than small (62%) and medium-sized farms (58%). The ranking of efficiency scores by farm size remains the same under bias-corrected efficiency scores (i.e., 63%, 51% and 46%, respectively) as well. Mean technical efficiency decreased over time in each farm size as well as over the entire sample. Nonparametric Kruskal-Wallis (KW) tests were conducted for all the VRS efficiency measures to test technical efficiency differences by farm size statistically. KW tests reject the null hypothesis that efficiency averages are not different across farm sizes at the 1% significance level. Weersink et al. (1990) and Paul et al. (2004) find a positive relationship between
efficiency and farm size. Though we are not establishing a causal relationship, it is evident that efficiency scores differ by farm size in Hawai‘i’s vegetable sector.

Table 3.8: Technical Efficiency Scores by Farm Size

<table>
<thead>
<tr>
<th>Year</th>
<th>Small</th>
<th>Medium</th>
<th>Large</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Bias</td>
<td>Lower Bound</td>
</tr>
<tr>
<td>1982</td>
<td>0.5661</td>
<td>0.1083</td>
<td>0.4068</td>
</tr>
<tr>
<td>1987</td>
<td>0.6929</td>
<td>0.0925</td>
<td>0.5367</td>
</tr>
<tr>
<td>1992</td>
<td>0.6478</td>
<td>0.1090</td>
<td>0.4777</td>
</tr>
<tr>
<td>1997</td>
<td>0.5595</td>
<td>0.1137</td>
<td>0.3892</td>
</tr>
<tr>
<td>2007</td>
<td>0.6445</td>
<td>0.1281</td>
<td>0.4496</td>
</tr>
<tr>
<td>Average</td>
<td>0.6222</td>
<td>0.1103</td>
<td>0.4520</td>
</tr>
</tbody>
</table>

3.5.1.2. Scale Efficiency

Table 3.9 shows results for scale efficiency. The mean scale efficiency over the sample period was 71%, with the highest scale efficiency attained in 1987 (76%) and the lowest in 2007 (65%). Scale efficiency was consistently high in comparison with technical efficiency over the census years. Table 3.10 shows results for scale efficiency by farm size. On average, medium-size farms are more scale efficient (81%) compared with small farms (69%), and large farms (67%). This suggests that medium farm size is the optimal farm size for most farm operations (i.e. sales volume between $100,000 to $250,000. Paul et al. (2004) find small family farms to be less efficient in terms of both the scale of operation and technical aspects of production than large farms. In our analysis, the percentage of small farms that are scale efficient is only marginally higher than the percentage of large farms that are scale efficient. However, analysis over time indicates that large and medium-sized farms are becoming more scale efficient while small farms are becoming scale inefficient.
### Table 3.9: Scale Efficiency Scores

<table>
<thead>
<tr>
<th>Year</th>
<th>Full Sample</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
</tr>
<tr>
<td>1982</td>
<td>0.7290</td>
<td>0.2290</td>
<td>0.3142</td>
</tr>
<tr>
<td>1987</td>
<td>0.7634</td>
<td>0.1972</td>
<td>0.2583</td>
</tr>
<tr>
<td>1992</td>
<td>0.7530</td>
<td>0.2129</td>
<td>0.2828</td>
</tr>
<tr>
<td>1997</td>
<td>0.6694</td>
<td>0.3346</td>
<td>0.4998</td>
</tr>
<tr>
<td>2007</td>
<td>0.6521</td>
<td>0.2828</td>
<td>0.4337</td>
</tr>
<tr>
<td>Average</td>
<td>0.7134</td>
<td>0.2513</td>
<td>0.3578</td>
</tr>
</tbody>
</table>

### Table 3.10: Scale Efficiency Scores by Farm Size

<table>
<thead>
<tr>
<th>Scale Efficiency</th>
<th>Small</th>
<th>Medium</th>
<th>Large</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Standard Deviation</td>
<td>Coefficient of Variation</td>
<td>Mean</td>
<td>Standard Deviation</td>
<td>Coefficient of Variation</td>
</tr>
<tr>
<td>Year</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1982</td>
<td>0.7177</td>
<td>0.2288</td>
<td>0.3189</td>
<td>0.8613</td>
<td>0.147</td>
<td>0.1707</td>
</tr>
<tr>
<td>1987</td>
<td>0.7661</td>
<td>0.2061</td>
<td>0.2691</td>
<td>0.7782</td>
<td>0.1335</td>
<td>0.1715</td>
</tr>
<tr>
<td>1992</td>
<td>0.7662</td>
<td>0.2139</td>
<td>0.2792</td>
<td>0.7332</td>
<td>0.1898</td>
<td>0.2588</td>
</tr>
<tr>
<td>1997</td>
<td>0.6298</td>
<td>0.3577</td>
<td>0.5679</td>
<td>0.8333</td>
<td>0.1366</td>
<td>0.1639</td>
</tr>
<tr>
<td>2007</td>
<td>0.5682</td>
<td>0.2947</td>
<td>0.5186</td>
<td>0.8458</td>
<td>0.0703</td>
<td>0.0832</td>
</tr>
<tr>
<td>Average</td>
<td>0.6896</td>
<td>0.2603</td>
<td>0.3907</td>
<td>0.8104</td>
<td>0.1354</td>
<td>0.1696</td>
</tr>
</tbody>
</table>

### 3.5.1.3. Analysis of Returns to Scale

The nature of the returns to scale of a farm is determined by comparing technical efficiency scores regarding CRS, VRS, and NIRS frontiers. Returns to scale express the relationship between a proportional change in inputs and the resulting proportional change in output. Constant returns to scale imply that an $n$ percent rise in all inputs produces an $n$ percent increase in output. Increasing returns to scale hold when output rises by a larger percentage than inputs whereas DRS hold when output rises by a smaller percentage than inputs. A VRS frontier exhibits CRS, DRS, and IRS. When $TE_{NIRS} = TE_{CRS} < TE_{VRS}$, IRS holds. When $TE_{VRS} = TE_{NIRS}$ & Scale efficiency is less than unity DRS holds. When $TE_{NIRS} = TE_{CRS} = TE_{VRS} = SE = 1$, CRS holds. Table 3.11 presents the results of the overall number of farms operating under optimal scale (CRS), sub-optimal scale (IRS) and supra-optimal scale (DRS) over the sample period. The data show that the number of farms that operated under supra-optimal scale decreased since...
1987 while those that operated at sub-optimal scale increased. Farms have grown smaller in size than the optimal level resulting in scale inefficiency at large. Returns to scale results indicate that only 9.3% of the farms in the total sample operated at the optimal scale. Further, 64.2% of the farms operated under sub-optimal scale, and 26.5% operated under supra-optimal scale on average. The percentage of farms that operate under DRS is as follows: large farms (19.3%), medium farms (42.7%), small farms (38%) on average. In contrast, the percentage of farms operating at IRS is as follows: large farms 1.2%, medium farms 3.8%, and small farms 95% on average. A very high percentage of small farms operate below the optimal level.

Table 3.11: Overall Percentage of Farms Operating under Optimal Scale (CRS), Sub-optimal Scale (IRS), and Supra-optimal Scale (DRS)

<table>
<thead>
<tr>
<th>Year</th>
<th>IRS Farms %</th>
<th>DRS Farms %</th>
<th>CRS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All</td>
<td>Small</td>
<td>Medium</td>
</tr>
<tr>
<td>1982</td>
<td>72.73</td>
<td>97.00</td>
<td>3.00</td>
</tr>
<tr>
<td>1987</td>
<td>48.34</td>
<td>100.00</td>
<td>0.00</td>
</tr>
<tr>
<td>1992</td>
<td>55.12</td>
<td>99.40</td>
<td>0.60</td>
</tr>
<tr>
<td>1997</td>
<td>68.53</td>
<td>98.52</td>
<td>1.48</td>
</tr>
<tr>
<td>2007</td>
<td>76.34</td>
<td>80.00</td>
<td>14.00</td>
</tr>
<tr>
<td>Average</td>
<td>64.21</td>
<td>94.98</td>
<td>3.82</td>
</tr>
</tbody>
</table>

3.5.1.4. Analysis of Efficiency Distributions

Nonparametric kernel density estimation techniques have become common in graphically illustrating various results of the non-parametric efficiency analysis (Simar and Zelenyuk, 2006; Henderson and Zelenyuk, 2007). Kernel densities have the advantage of providing smoother density estimates compared with histograms, and not being dependent on the width and number of bins (Wand and Jones, 1995). The kernel density estimation is useful in this study as no distributional assumptions were imposed on farm efficiency scores. According to Simar and Zelenyuk (2006) following conditions must be addressed when using kernel density estimation. The random variable considered must have a bounded support. Only the consistent estimate of the efficiency scores should be used, and continuity assumption needed to ensure consistency of the density estimation should
not be violated. It is well-known that kernel density estimates are biased and inconsistent near boundaries of support; to avoid this problem, reflection method described by Silverman (1986) and Scott (1992) is used. Bootstrap DEA is used to compute the consistent efficiency scores. A Gaussian kernel density is estimated using the bias-corrected efficiency scores. The bandwidth is selected according to the Silverman (1986) rule of thumb.

Figure 3.1 depicts the distribution of kernel destiny estimates of the technical efficiency scores under different technologies (CRS, VRS, and NIRS respectively along a row) for each census year (1982 to 2007 along a column). In comparing kernel densities of different census years under VRS, it could be seen that the distributions have narrowed from 1992 to 1987 indicating that inefficient farms in 1982 has become more efficient in 1987. In the subsequent census years, the distribution again has widened as there are more inefficient farms. However, the distribution again had narrowed in 2007. The distribution had clearly taken a bimodal shape in 2007. Note that the x-axis values are Shephard efficiency values. Farrell efficiency scores can be obtained by taking the inverse of the Shephard efficiency scores.
**Figure 3.1: Distribution of Kernel Density Estimates**

<table>
<thead>
<tr>
<th></th>
<th>CRS Technology</th>
<th>CRS Technology</th>
<th>CRS Technology</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td><img src="image" alt="Graph" /></td>
<td><img src="image" alt="Graph" /></td>
<td><img src="image" alt="Graph" /></td>
</tr>
<tr>
<td>1991</td>
<td><img src="image" alt="Graph" /></td>
<td><img src="image" alt="Graph" /></td>
<td><img src="image" alt="Graph" /></td>
</tr>
<tr>
<td>1992</td>
<td><img src="image" alt="Graph" /></td>
<td><img src="image" alt="Graph" /></td>
<td><img src="image" alt="Graph" /></td>
</tr>
<tr>
<td>1997</td>
<td><img src="image" alt="Graph" /></td>
<td><img src="image" alt="Graph" /></td>
<td><img src="image" alt="Graph" /></td>
</tr>
<tr>
<td>2002</td>
<td><img src="image" alt="Graph" /></td>
<td><img src="image" alt="Graph" /></td>
<td><img src="image" alt="Graph" /></td>
</tr>
</tbody>
</table>
3.5.1.5. Malmquist Index Productivity Analysis

The changes in distance function values of a farm over time could be caused by either movement of farms within the input-output space (i.e. efficiency changes), or progress/regress of the boundary of the production set over time (i.e. technological changes). The decomposition used in this analysis makes it possible to distinguish changes in productivity, efficiency, and technological change. Table 3.12 reports various estimates of productivity changes for vegetable farms over across the cohorts between 1982 and 2007.

Table 3.12: Malmquist Index Productivity Analysis

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>CI Lower &amp; Upper Bound</td>
<td>Mean</td>
<td>CI Lower &amp; Upper Bound</td>
<td>Mean</td>
</tr>
<tr>
<td>MI</td>
<td>0.8430**</td>
<td>0.6536</td>
<td>0.9225</td>
<td>0.6912</td>
<td>1.0347</td>
</tr>
<tr>
<td></td>
<td>0.9881</td>
<td>1.0680</td>
<td>1.2383</td>
<td>1.0022</td>
<td>1.0698</td>
</tr>
<tr>
<td>EC</td>
<td>1.0229</td>
<td>0.5537</td>
<td>1.0375</td>
<td>0.5961</td>
<td>0.6328**</td>
</tr>
<tr>
<td></td>
<td>1.2816</td>
<td>1.3369</td>
<td>0.7592</td>
<td>0.7672</td>
<td>0.5294</td>
</tr>
<tr>
<td>PEC</td>
<td>1.0176</td>
<td>0.1200</td>
<td>1.0076</td>
<td>0.1764</td>
<td>0.6777**</td>
</tr>
<tr>
<td></td>
<td>1.3309</td>
<td>1.3626</td>
<td>0.8326</td>
<td>0.9831</td>
<td>0.8309</td>
</tr>
<tr>
<td>SEC</td>
<td>1.0052</td>
<td>0.5624</td>
<td>1.0297</td>
<td>0.2332</td>
<td>0.9339</td>
</tr>
<tr>
<td>TC</td>
<td>0.8241</td>
<td>0.5828</td>
<td>0.8891</td>
<td>0.5837</td>
<td>1.6428**</td>
</tr>
<tr>
<td></td>
<td>1.0054</td>
<td>1.0517</td>
<td>2.2442</td>
<td>2.0636</td>
<td>1.0054</td>
</tr>
</tbody>
</table>

Note: It is geometric means.

Except in the period 1992/97, Malmquist Index has regressed in other periods considered. Between 1992 and 1997, there was a 3.47% increase (i.e.0.69% per year) in productivity. However, it is not a significant increase (Value unity is included in the bootstrap confidence intervals). Between 1982 and 1987, productivity has decreased by 15.7% (i.e. 3.14% per year) and from 1987 to 1992 productivity has decreased by 7.75% (i.e.1.55%
There is 19.5% productivity reduction between 1997 to 2007 productivity (i.e. 1.95% per year). An efficiency increase can only be seen from 1982 to 1987 and 1987 to 1992. The latter pairs of years show an efficiency decrease (i.e. from 1992 to 1997 and 1997 to 2007). Though periods from 1982 to 1987 and 1987 to 1992 show declines in productivity, efficiency has increased by 2.29% and 3.75% respectively. However, these increases are not significant changes. There are large and significant declines in efficiency from 1992 to 1997 (7.34% per year) and 1997 to 2007 (i.e. 4.2% per year). Both pure and scale efficiencies have increased from 1982 to 1987 and from 1987 to 1992, and they reflect an overall efficiency increase in the said years. Likewise both pure and scale efficiencies have decreased from 1992 to 1997 and from 1997 to 2007 as reflected in the decrease of overall technical efficiency in those years. There is technical regress from 1982 to 1987 (i.e. 17.59% or 3.52% per year) and 1987 to 1992 (i.e. 11.09% or 2.22% per year). There is a technical progress from 1992 to 1997 (by 64.28% or 12.85% per year) and 1997 to 2007 (i.e. 39.83% or 3.98% per year). However, only the technical progress from 1992 to 1997 is significant. Interestingly, we observe that efficiency change and technical change go in opposite directions. That is time periods that show a technical progress also show an efficiency regress and vice versa. Latruff et al. (2012) find this opposite pattern as intuitive since technological progress often results in a delay before some farmers adopt the new technique or use it efficiently, while technological regress makes it easier for farmers to catch up with the best performing farms (Latruff et al., 2012 and Bru¨mmer et al., 2002).

Table 3.13 shows the percentage of farms that improved efficiency and/or productivity between the respective census years. A majority of farms show a productivity growth only between 1992 and 1997 census years during which productivity growth is observed in the sector. During the same period, 94% of the farms show a technical progress. This suggests that Hawai‘i vegetable sector improved its technology during 1992 to 1997 period. During the said period, only 22% of the farms show both efficiency and technical progress. Between census years 1982 and 1987, 26% of the farms show both efficiency and technical progress and only 22% of the farms show an efficiency increase. Between 1987 to 1992, 79% of farms show a technical progress with only 25% of farms showing
an efficiency increase, 20% of the farms show both efficiency and technical progress. Between census years, 1997 and 2007, 25% of the farms show both efficiency and technical progress. One very notable change is the high percentage of farms showing a technical progress from 1992 to 1997 and 1997 to 2007.

Table 3.13: Percentage of Farms Showing Efficiency and Technical Progress

<table>
<thead>
<tr>
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<tbody>
<tr>
<td>MI Productivity Increase</td>
<td>45%</td>
<td>42%</td>
<td>51%</td>
<td>39%</td>
</tr>
<tr>
<td>Efficiency Increase</td>
<td>57%</td>
<td>52%</td>
<td>22%</td>
<td>25%</td>
</tr>
<tr>
<td>Technical Progress</td>
<td>26%</td>
<td>20%</td>
<td>94%</td>
<td>79%</td>
</tr>
</tbody>
</table>

It would be interesting to see how Hawai‘i vegetable sector fare in comparison to the vegetable sector in the national agriculture. There is no study on US vegetable sector to carry out a direct comparison between the national situation and Hawai‘i. However, productivity and efficiency studies on US agriculture show that total factor productivity of US agriculture has grown over time. (Fuglie et al., 2007 show the change in aggregate productivity from 1948 to 2004). Farms are using a fewer amount of inputs to produce a unit of output that before. US farms have become efficient over the time. It should be noted that though there is a growth trend in agriculture productivity, year to year fluctuations are large (Fuglie et al., 2007). This could be due to changes in weather, policy interventions, general economic conditions, and other factors. Though our efficiency and productivity analysis on Hawai‘i vegetable sector spans over a period of 25 years, it should be noted that we are looking at the year to year productivity changes. This may explain the large fluctuations observed in the vegetable sector.
3.6. Conclusions

This study evaluates the efficiency and productivity of commercial vegetable farms in Hawai‘i over five years. The five years used in the analysis are 1982, 1987, 1992, 1997 and 2007. Farm data are obtained from the agriculture census data for the above years. Nonparametric frontier estimation method for efficiency analysis: Data Envelopment Analysis is carried out to estimate efficiency scores. Bootstrapping method for efficiency estimates introduced by Simar (2008) is applied to obtain bias corrected efficiency scores and their statistical properties. We present original efficiency scores, bias-corrected efficiency scores as well as confidence intervals for the bias corrected efficiency scores. Further, we estimate the scale efficiency and returns to scale farms. Malmquist Index productivity analysis was carried out to evaluate productivity changes between census years. Finally, we present productivity decompositions for technical changes and efficiency changes.

The following conclusions may be drawn from the analysis. Hawai‘i vegetable farms show considerable inefficiencies and therefore they have immense potential for enhancing profitability by reducing input use through improved efficiency. According to the technical efficiency results under VRS technology, Hawai‘i vegetable farms on average would be able to reduce their input use by 49% (65% under CRS) by operating at full efficiency level with a minimum of 39% and maximum of 55%. There is a 95% confidence that efficiency level ranges between 44.5% and 61%. Large, medium-sized and small farms could reduce their inputs on average by 15%, 42%, and 38% respectively by operating at full efficient level. A majority of farms is more than 50% inefficient (57% in 2007). Therefore, cutting down on input use by efficiency improvement is very important to enhance the profitability of the farms, especially small producers who earn negative net returns from vegetable production. Small farms are more inefficient than large farms. Statistical evidence suggests technical efficiency differs by farm size.

The scale efficiency analysis reveals that farms are more scale efficient than technically efficient. It indicates that inefficiency primarily emanates from poor managerial practices
rather than the scale of operation. The analyzed farms are, on average 29% scale-inefficient. Large and medium-sized farms have become more scale-efficient since 1992 while small farms have become more scale-inefficient. More farms operated under VRTS rather than CRTS. From the overall sample 64% farms are operating at sub-optimal scale, 26% at supra-optimal scale and only 9% at optimal scale. Among farms operating at sub-optimal scale, 95% are small farms, and only 5% are medium-sized and large farms. Among farms operating at supra-optimal scale, 38% are small farms whereas medium-sized and large farms are 43% and 19% respectively. These results show that there is large scope for overall efficiency gains through improved scale efficiency.

The study finds no evidence of improvement in total factor productivity (TFP) on average during the sample period. A TFP growth is observed only between the census year 1992 and 1997. However, it is not a statistically significant growth. On average there is a significant reduction in technical efficiency of 21 percent that is statistically significant. The deterioration of technical efficiency has largely come from a reduction in pure efficiency than from scale efficiency. The reduction in average technical efficiency may be driven by the larger proportion of small farms in the sample. Pure efficiency reduction between 1992 and 1997 and between 1997 and 2007 is significant. Reduction in scale efficiency is not significant. There is a higher percentage of technical growth between 1992 and 1997 and between 1997 and 2007. The technical growth between 1992 and 1997 is significant. In all the panel of farms, higher technical progress is coupled with efficiency reduction. It may be explained by the macroeconomic condition in Hawai‘i during these periods. Hawai‘i’s economy experienced a boom in the 80s which was followed by a recession in the 90s. The improvement in the technical efficiency in the 80s may be explained by the economic boom as farms may be able to do changes to the managerial practices and input use and, adopt practices of technology leaders of the sector. The technical progress of farms at a time of economic recession may be explained by the increased attention on technology, education and extension during an economic downturn. It should also be noted that inputs and outputs used in this study are expressed in value terms. Though the prices are deflated using the CPI, it may not fully account for the relative changes in input and output prices. It is assumed in this paper that both output
and input prices are moving in the same direction and magnitude over the time. However, it may not be the case as the price of agricultural commodities have become cheaper relative to input prices (Fuglie et al., 2007).

In general, the results indicate deterioration of farm technical efficiency emanating predominantly from poor farm management. Therefore, the improvement in efficient farm management can be identified as a way to progress the vegetable farming sector in Hawai‘i. Technological progress during recent periods is coupled with an efficiency reduction. Therefore, this deterioration of the efficiency may not be largely due to farms falling behind but rather due to outward shifts in the efficient frontier. During technological progress, it is difficult for farmers to catch up with the best performing farms. It would also explain why smaller farms have become both technically and scale inefficient compared with larger farms that have become less inefficient over time. In general, larger farms are technology leaders. It takes time for smaller farms to adopt new technologies. The results indicate that any policy aimed at addressing inefficiency in the farm sector should consider the relationship between farm size and efficiency. Further, it is important to design policies that facilitate easy and faster adoption of new technologies.
REFERENCES


4.1. Introduction

The US agricultural sector has been undergoing structural changes during last three decades. By structural changes, we mean changes in the size distribution of farms, market shares and, in the composition of different agricultural sectors. The main structural changes that have been observed in national agriculture are the increase in the number of farms at the very lowest and highest ends of the size distribution and, farm production getting concentrated on the higher end of the size distribution (Aubert and Cornet, 2009; Hoppe et al., 2010; Hazell, 2005 and Census of Agriculture, 2007). Interestingly, the number of US farms has remained remarkably stable during last three decades suggesting that farm exits and entries balance out. This relative stability in the number of farms masks a great deal of dynamism in the agricultural sector.

Understanding farm exits and entries are important for several reasons. Exits help reallocating resources between farming and other economic activities and, within the farm sector itself. For example, farm count declined by 4.5 million between 1935 and 1974 and farm exits were substantially larger than entries (Gale, 1994). This large decline in the number of farms resulted in a massive reallocation of resources from farming to other industries contributing to increased productivity throughout the economy (Hoppe, 1994).

Farm exits and farm entries may play an important role in introducing new technologies and achieving productivity growth, as in other industries. Older, exiting farmers are likely to downsize their operations and disinvest as they age. Farms those absorb the resources of the exited farms, i.e. recent entrants, continuing farms or both, are more likely to use newer technology and a more efficient mix of capital and labor. These changes have enabled the farm sector to produce nearly 50 percent more output over the past three
decades, employing a lesser amount of resources. It has benefited consumers of farm products as well. The price increase of agricultural commodities over most of the last 30 years is much less than both the economy-wide price increases and increases in prices of agricultural inputs. The process of entry and exit may be an important driver of productivity growth of an industry as entering and exiting firms account for significant shares of industry production. The adoption of new technologies and new ways of doing business bring about productivity growth. It is more likely for new firms to adopt new technologies than older farms and hence replace older farms. Even the firms adopting similar technologies may differ in their performance as some firms may be more efficient and better organized than others. Inefficient firms will shrink and exit with time due to competition while efficient firms will survive and grow. Thus, an effective entry and exit process would speed up the adoption of new technologies and methods and facilitate the expansion of more efficient firms at the expense of less efficient firms.

In recent years, economists have devoted greater attention to the study of entry and exit of firms, and their research have led to an altered focus (Bartelsman et al., 2004; OECD 2001). At present, studies seek to understand the processes of entry and exit better and to determine how entries and exits are associated with productivity growth and the spread of technologies. Seminal work of Melitz (2003) on globalization and aggregate productivity growth shows how firm heterogeneity in productivity together with the self-selection decision of firms and falling trade costs lead to a contraction of less productive firms in favor of expansion by more productive firms. The resulting reallocation of production generates important aggregate productivity gains (Melitz, 2003). Following Melitz (2003), there were many empirical trade papers studying entry and exit dynamics and aggregate productivity in the manufacturing sector (Bernard et al., 2006; Greenaway et al., 2008 and Kim et al., 2010). Among the empirical studies looking at entry and exit dynamics and productivity related to the agricultural sector, Jang and Du (2014) studied the linkage between productivity and exit probability in dairy farm industry in the US dairy states. Some other work involves empirically investigating factors that contribute to farm exits and estimate exit probabilities for farms with different characteristics. Stokes (2006) studied factors affecting entry and exit to Pennsylvania’s dairy sector. While
application to crops sectors is less (Adamson and Waugh, 2012; Kirwan et al., 2012), we do not find any application to the vegetable sector.

We contribute to the existing literature on aggregate productivity and structural changes being the first to look at aggregate productivity change due to entry and exit dynamics with respect to an agricultural sector. We apply dynamic Olley-Pakes (1996) productivity decomposition as modified in Melitz and Polanec (2015) to Hawai‘i’s vegetable sector to decompose productivity changes. More specifically, this research will decompose aggregate productivity changes into continuing, new and exiting farms to understand productivity gains/losses due to industry changes or structural changes. We are among the first to empirically apply the Melitz and Polanec (2015) extension of dynamic Olley-Pakes (1996) productivity decomposition. Agricultural sector’s relative homogeneity will minimize price dispersion driven by differentiation in costs, thus sharpening the focus on how productivity differences, rather than product differentiation, affect farm success. This study uses micro-level farm data from Hawai‘i Census of Agriculture to track farms over time to identify their presence in the vegetable sector.

The study finds that farm entry and exit dynamics have contributed substantially to the aggregate productivity growth in the vegetable sector. We find that both exiting and new farms have low productivities compared to continuing farms. Therefore, while farm exits contribute positively to the aggregate productivity growth, new farm entry contributes negatively to the aggregate productivity growth. The Aggregate productivity of continuing firms has increased between census years. Productivity gains in continuing farms is mainly a result of market share reallocation between farms.

The rest of the paper is organized as follows. Section 2 provides background information to the case of the agriculture sector in Hawai‘i. Section 3 reviews the heterogeneous firm literature, production function estimation and productivity decomposition that provide the analytical framework for the study. The subsequent sections present types and sources of data followed by results and discussion. Section 6 presents conclusions.
4.2. Hawai‘i Agriculture

The agriculture sector in Hawai‘i is in the midst of change and revitalization. Once a highly concentrated plantation economy dominated by sugarcane and pineapple, over the past couple of decades it has been shifting towards diversified agriculture at an increasing rate. Today there is a wide diversity of agricultural crops grown that are marketed both locally and internationally. We observe that more crops are being produced for local island consumption over the last 10 to 15 years. However, one major factor that often puts Hawai‘i’s agricultural produce in a competitively disadvantageous position is its high labor and resource costs. Hawai‘i labor costs are 35-55% greater than that of the U.S. mainland, and Hawai‘i’s farms are on average 2-3 times smaller than that of U.S. mainland farms (Arita et al. 2012). Farmers in Hawai‘i face a difficult competitive environment because most agricultural produce that are sold locally comes from areas where costs of production are lower than in Hawai‘i. Under diversified agriculture, Hawai‘i farms tend to be smaller which seem to aggravate further the cost disadvantage. In 2007, 64.0% of farms in Hawai‘i were less than 10 acres in size compared to only 10.5% for the rest of the USA (National Agricultural Statistics Service, 2007). Due to the lack of economies of scale, small farms tend to be in a disadvantageous position in the areas of input, marketing, transportation, and other relevant costs. On the other hand, small farms have the advantage of using family labor. Thus, Hawai‘i presents an ideal case to examine the aggregate productivity gains arising from structural changes in an open economy.

4.2.1. Vegetable Sector

Due to high labor and land costs, Hawai‘i is largely dependent on outside sources for its food supply. According to Loke and Leung (2013), only 11.6% of food available for consumption in Hawai‘i are sourced from local production in 2010. For the US as a whole, the overall import share of the national food consumption is estimated at 7% based on value and 15% based on volume in 2005 (Jerado, 2008). Over the past couple of decades, technological changes in the shipping industry and the trade liberalization have
contributed towards greatly reducing trade costs. These have led to a massive concentration of food production in regions where the advantages of economies of scale could be better captured and hence resulted in more efficient and profitable production. Today much of the fresh produce consumed in Hawai‘i are produced in California with trade providing Hawai‘i’s consumers access to a greater variety of fresh produce (fruits and vegetables) at a lower cost.

Local food production has been receiving greater attention from private entrepreneurs and government officials lately. One argument that has been put forward for local food production is to reduce the “food miles” and thereby gain the benefits of eating fresher food. In response to the growing interest in consuming locally grown food, the state government of Hawai‘i has taken a remarkably active stance in increasing its food localization by advocating it as a part of its development strategy. The doctrine has manifested itself in several policy channels. In 2012, the State passed State House Bill 2703 relating to food self-sufficiency. The Hawai‘i Department of Agriculture (HDOA) actively promotes farmers’ markets with its “Buy fresh, by local” call-to-action program, which is designed to raise an awareness of the benefits of locally grown food. All in all, these policy developments further justify the importance in understanding micro-level impacts to the vegetable sector of Hawai‘i in the context of increasing globalization.

4.3. Producer Heterogeneity and Productivity Decomposition

Recent theoretical and empirical contributions to the international trade literature focus on the role of producer heterogeneity. Guided by the seminal work of Melitz (2003), the role of producer heterogeneity in trade literature stresses specific microeconomic channels of productivity gains via reallocation of economic activity across firms within industries. The key insight from this line of literature is that firms make different choices even when faced with identical opportunities, based on differences in their underlying characteristics, typically productivity. In other words, there is self-selection in the decisions of firms. The existence of trade costs will make only the most productive firms to self-select into the export markets. The implication is an additional source of welfare
gains from trade. That is when trade costs fall, industry productivity rises both because less productive non-exporting firms exit and because high productivity firms can expand through exporting. The mechanism driving productivity growth in this recent literature is Darwinian selection; i.e., more competition weeding out the less efficient firms. The reallocation of resources from low productive to high productive firms raises the average productivity of an industry.

Heterogeneous firm literature offers the following testable hypotheses where increased trade openness:
1. Leads to a more competitive market, forcing the least efficient domestic producers out, expanding the production share of more efficient producers; and
2. Increases the average productivity of local industries.

Empirical literature examining the impact of trade liberalization on micro level firm data has found evidence in support of these claims. Bernard et al. (2006) find industries experiencing larger declines in trade costs exhibit higher levels of productivity growth with less productive plants more likely to die. Though the Melitz model (2003) is general in structure, it has been mostly tested in the manufacturing sector. Only a few research have applied it to the agricultural sector. Echeverria et al. (2009) are an example of applying heterogeneous firm trade theory to the agricultural sector. Their work explores the role of firm heterogeneity in export market participation. Testing Chilean farm data, they find that higher productivity farms are more likely to export. Arita et al. (2012) studied the fresh fruit and vegetable sectors of the State of Hawai‘i applying the heterogeneous firm model and find evidence that import competition negatively affects the growth of small farms.

Empirical evidence suggests that producers are vastly different in terms of their productivity levels, even in narrowly defined sectors. Therefore, aggregate productivity changes over time need not only reflect shifts in the distribution of producer-level productivity (e.g. due to technological change). Assuming that the distribution of productivity fixed, aggregate productivity can also change due to changes in farm
composition; i.e. due to changes in market shares among continuing firms and due to the entry and exit of firms. Empirical studies have consistently shown that these composition changes are an important driver of aggregate productivity changes. This finding has induced the development of productivity decomposition methods that separate aggregate productivity changes into the said four different components (Griliches and Regeve, 1995; Foster et al, 2001; Melitz and Polanec, 2015).

The productivity of farms is commonly estimated as the residual of the production function estimation. Production function estimation using OLS suffers from selection bias and simultaneity and, therefore, many studies have been undertaken to find ways to arrive at a consistent estimation of the production function. O-P in their seminal paper introduce an estimation algorithm that addresses these issues using semi-parametric estimators (series estimators and kernel estimators) which yield consistent and asymptotically normal estimators. They calculate aggregate industry productivity as a weighted average of plant level productivities and decompose it to show the contribution of reallocation of output among plants to the aggregate output. Meltiz and Polanec (2015) provide an extension to the productivity decomposition used in O-P adding productivity changes owing to exit and entry to the decomposition. They argue that this extension eliminates biases in the measurement of contribution of firm entry & exits that are found in the decomposition methods that follow individual producers over time (e.g. Griliches and Regeve, 1995 and Foster et al, 2001 decompositions). Empirically they show that the market share reallocation among continuing firms has a much more substantial contribution to productivity growth, once the biases in entry and exit measurement are eliminated.

4.3.1. Production Function Estimation

Productivity is often derived by approximating the weighted sum of inputs from the estimation of the Cobb-Douglas production function. Such estimates, however, suffer from simultaneity and selection biases. Simultaneity arises because productivity is known to the profit-maximizing firms when they choose their input levels (but not to the
When there is a positive productivity shock firms increase their use of inputs. Parameter estimates of production functions from OLS estimation are biased as OLS method does not take unobserved productivity shocks to account. A fixed-effect estimator will solve the simultaneity problem only if we assume that the unobserved, firm-specific productivity is time-invariant. Other methods including instrumental-variables approach have also been proposed to control for this bias when estimating the parameters of production functions.

Another issue that one needs to be addressed in the estimation of production function parameters is the selection bias. It results from the relationship between the productivity shocks and the probability of firm exit. That is, if a firm’s profitability is positively related to its capital stock, a firm with a larger capital stock has a higher probability of remaining in the market in the face of a negative productivity shock than a one with a smaller capital stock. If not controlled, the negative correlation between capital stock and the probability of exit for a given productivity shock cause the coefficient on the capital variable to be biased downward.

O-P introduced a semi-parametric method that enabled us to estimate the production function parameters consistently by controlling for biases and thus obtain reliable productivity measures. O-P approach addresses the simultaneity and selection problems while estimating the production function parameters and firm-level productivity. Investment variable is used as a proxy for an unobserved time-varying productivity shock in addressing the simultaneity problem, and survival probabilities are used to address selection problems. However, there is a requirement that there should be positive values for investment for all observations. Since this requirement is not met in the dataset used, the focus was shifted to the next most popular method of production function estimation, the Levinsohn and Petrin (2003) method (from now on L-P). A disadvantage of L-P method over the O-P method is that it does not address the selection bias.
4.3.1.1. Levinsohn and Petrin Method

To estimate changes in the aggregate productivity of a sector, first production functions will be estimated for the Hawai‘i vegetable sector.

Assuming Cobb-Douglas technology, the production function of a sector is given by,

\[ y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + e_{it} \]  \hspace{1cm} (1)

where \( y_{it} \) is the log of firm’s output measured as the gross revenue or the value added, \( k_{it} \) is log of the state variable the capital stock, \( l_{it} \) is log of labor input, \( m_{it} \) is log of intermediate inputs \( \omega_{it} \) is the observed productivity shock, and \( e_{it} \) is any unforeseen shock.

Demand for the intermediate input \( m_t \) is assumed to depend on the firm’s state variables \( k_t \) and \( \omega_t \).

\[ m_t = m_t(k_t, \omega_t) \]  \hspace{1cm} (2)

L-P (2003) show that the demand function is monotonically increasing in \( \omega_t \). Therefore, \( \omega_t \) can be written as a function of \( k_t \) and \( m_t \) \( (\omega_t = \phi(k_t, m_t) \) \). Similar to O-P, L-P assumes that productivity is governed by a first-order Markov process.

The value added (gross output net of intermediate inputs) output can be written as,

\[ y_t = \beta_0 + \beta_k k_t + \beta_l l_t + \omega_t + e_t \]  \hspace{1cm} (3)

\[ = \beta_l l_t + \phi(k_t, m_t) + e_t \]

where,

\[ \phi(k_t, m_t) = \beta_0 + \beta_k k_t + \omega_t(k_t, m_t) \]  \hspace{1cm} (4)
By substituting a third-order polynomial approximation in $k_t$ and $m_t$ in place of $\Phi(k_t, m_t)$, L-P show that it is possible to estimate parameters of the value-added equation consistently using OLS. The coefficients $\beta_l$ and $\beta_k$ are identified in two stages.

4.3.1.2. Calculation of Total Factor Productivity (TFP)

Using the estimated input coefficients individual farm productivity (TFP) will be calculated as residuals.

$$ln\varphi_{it} = lnY_{it} - (\bar{\alpha}lnK_{it} + \bar{\beta}lnL_{it} + \bar{\gamma}lnN)$$

(5)

where $\varphi_{it}$ is the productivity of farm $i$ at time $t$ and $\bar{\alpha}, \bar{\beta}, \bar{\gamma}$ are estimated coefficients for capital and labor and land respectively from the L-P production function estimations.

Statistical software package STATA has function levpet for L-P production function estimation and the productivity is predicted.

4.3.1.3. Productivity Decomposition

Aggregate productivity of the vegetable farming sector will be decomposed to within-farm productivity changes, between farm productivity changes, as well as productivity changes due to entry and exit of farms using O-P extension of Melitz and Polanec (2015). This decomposition will aid in identifying components that drive the productivity changes in Hawai‘i vegetable sector.

There are decomposition methods (Griliches and Regev, 1995 and Foster et al., 2001) that follow individual producers from one period to the other and track changes in their market shares and their productivity (market share of an exiting farm is interpreted as it decreases to zero). In contrast, the Olley and Pakes (1996) method does not follow firms over time and instead their decomposition is based on the aggregate productivity level in each period and it is based on moments of the joint distribution of market shares and
productivity. That is for a given group of firms, the weighted average of productivity is decomposed into a moment of the firm productivity distribution (i.e., un-weighted mean), and a moment of the joint distribution with market shares (i.e., the covariance between productivity and market shares). It does not decompose aggregate productivity changes into components that are driven by entry and exit.

This decomposition is

$$\phi_t = \phi_t + \sum_t (s_{it} - \bar{s}_t)(\phi_{it} - \bar{\phi}_t)$$

$$= \phi_t + \text{cov}(s_{it}, \phi_{it})$$

where $$\bar{\phi}_t = \frac{1}{n_t} \sum_{i=1}^{n_t} \phi_{it}$$ is the unweighted firm productivity mean and $$\bar{s}_t = 1/n_t$$ is the mean market share. Change in the unweighted mean $$\Delta \bar{\phi}$$ and the change in covariance $$\Delta \text{cov}$$ yield the changes in productivity $$\Delta \phi$$ over time. While the change in the unweighted mean $$\Delta \bar{\phi}$$ captures shifts in the productivity distribution, the change in covariance $$\Delta \text{cov}$$ captures market share reallocations. The joint cross-sectional distribution of market shares and productivity gives the O-P covariance. That is the O-P covariance increases with the correlation between market shares and productivity.

Melitz and Polanec (2015) argue that O-P decomposition eliminate biases in the measurement of those entry and exit contributions that are a feature of the other decomposition methods that follow individual producers over time. Empirically they show that these biases are substantial for the case of Slovenia’s transition period from 1995-2000, especially when considering longer time spans. In past, the analysis of aggregate productivity changes across countries and over time mainly focused on the distribution of firm productivity (i.e. centered at the unweighted mean of the distribution). However, much of the recent literature note that differences in the market-share covariance account for a considerable portion of those aggregate productivity changes (both over time and across countries). Empirical results of Melitz and Polanec (2015) show that the contribution of market share reallocations among continuing firms
to productivity growth is much more substantial (than found by other decomposition
methods), once the biases in entry and exit measurement are eliminated.

Apart from measuring the contribution of firm entry and exit, the O-P decomposition has
another attractive feature compared to the decompositions that track individual firms over
time. Since the O-P decomposition is based on moments of the distributions of
productivity and market shares, it can be more directly connected to the theoretical
models with firm productivity heterogeneity that are designed to analyze the pattern of
market share reallocations among firms and its consequences for aggregate productivity
(Melitz and Polanec 2015). These heterogeneous firm models feature a market
mechanism that allocates market shares to firms according to their productivity and, other
firm and market characteristics given a distribution of firm productivity. This implies a
given covariance between those market shares and firm productivity – which is one of the
key moments tracked by the O-P decomposition. The other moment, the unweighted
productivity mean, tracks shifts in the distribution of productivity.

In Melitz and Polanec (2015), the aggregate productivity in each period is broken down
to aggregate productivity of the three groups of firms in the industry (continuers, entrants,
and exiters) weighted by their market share.

\[
\Phi_1 = s_{S1}\phi_{S1} + s_{X1}\phi_{X1} = \phi_{S1} + s_{X1}(\phi_{X1} - \phi_{S1}) \quad \text{period one}
\]

\[
\Phi_2 = s_{S2}\phi_{S2} + s_{E2}\phi_{E2} = \phi_{S2} + s_{E1}(\phi_{E2} - \phi_{S2}) \quad \text{period two}
\]

where \(\Phi\) is aggregate productivity, \(s\) is market share and the subscript \(S\) denotes
continuers, \(X\) denotes exits and \(E\) denotes entrants.

Aggregate productivity change is given by,

\[
\Delta\Phi = (\phi_{s2} - \phi_{s1}) + s_{E2}(\phi_{E2} - \phi_{s2}) + s_{X1}(\phi_{s1} - \phi_{X1})
\]
By O-P decomposition (i.e. by equation 5), aggregate productivity change could be written as,

$$\Delta \Phi = \Delta \Phi_S + \Delta cov_S + s_{E2}(\Phi_{E2} - \Phi_{S2}) + s_{X1}(\Phi_{S1} - \Phi_{X1})$$

The contribution of continuing firms is the aggregate productivity that would have been observed if there were no farm entries and exits. However, the productivity of entrants in period 1 and the productivity of exiters in period 2 are not observed. Therefore, we cannot use an identical counterfactual for those groups. Instead, Melitz and Polanec (2015) use the set of continuing firms as a benchmark and investigate how the addition of the group of entrants (or exiters) would affect the aggregate productivity change. Thus, MP contribution of entry \( s_{E2}(\Phi_{E2} - \Phi_{S2}) \), is the change in aggregate productivity \( \Delta \Phi \) generated by adding/removing the group of entrants. Similarly, our contribution of exit, \( s_{X1}(\Phi_{S1} - \Phi_{X1}) \), is the change in aggregate productivity \( \Delta \Phi \) generated by removing the group of exiting firms. Melitz and Polanec (2015) note that to apply this ‘counterfactual’ definition, it is very important to use a different reference productivity level for entrants and exiters. Entrants will generate positive productivity growth only if they have higher productivity \( \Phi_{E2} \) than the continuing) firms \( \Phi_{S2} \) in the same period when entry occurs \((t=2)\); Exiters will generate positive productivity growth only if they have lower productivity \( \Phi_{X1} \) than the continuing) firms \( \Phi_{S1} \) in the same period when exit occurs \((t=1)\). Thus Melitz and Polanec (2015) decomposition feature a contribution of entry to the aggregate productivity hat increases with the productivity of entrants \( \Phi_{E2} \), a contribution of exits that decreases with productivity of exiters \( \Phi_{X1} \) and a contribution of continuing firms that increases with the aggregate productivity difference \( \Phi_{S2} - \Phi_{S1} \).

4.4. Data

This paper employs farm level data for the census years 1982, 1987, 1992 1997, and 2007 for the State of Hawai‘i obtained from the U.S. Census of Agriculture. The Agriculture Census reaches virtually all the farms in the state with the long form version of the USDA Census (Except for the year 2002 in which only 46% of the farming population were sent the long form. The short report form does not collect the cost of production information. Therefore, we excluded census 2002 from the analysis). This analysis is
carried out only on the farms that responded to the Agriculture Census, and they are
carried out only on the farms that responded to the Agriculture Census, and they are
considered collectively as the vegetable-farming sector of Hawai‘i in this paper. The
Census data includes a personal identification number for individual farms (POID), the
year started operations, total sales of the farm, land and labor usage and other input costs.
The variable value-added sales of a vegetable farm are taken as the dependent variable in
the L-P production function estimation. The independent variables are the cost of labor,
acres of harvested cropland and annualized capital stock.

Table 4.1 shows the number of farms in a particular census year. It shows the number of
new farms in a census year, the number of farms present in this census year but absent in
the following census year (identified as farms that are exiting) and, the number of farms
present in both this census year and the following census year. It should be noted that
whenever ownership changed hands (sold or passed down to next generation) a farm is
identified with a new identification number in census data (but not known to the
researcher). In such a case, the farm with the new identification number is recognized as
a new farm, and the farm with the old identification number is recognized as a farm that
exited. Also, if a particular farm identification number is missing in the following census,
it is considered as a farm that exited. If that farm identification number reappears in a
later census year, it is considered as a new farm. Of the 388 new farms that appeared in
1987 census, 247 (64%) farms did not appear in 1992. That is 64% of new farms in 1987
have exited by 1992. Of the total number of farms that exited between 1987 to 1992, 66%
were new farms in 1987. Of the 360 new farms that appeared in the 1992 census, 273
(76%) farms did not appear in 1997. Of the total number of farms that exited between
1992 to 1997, 59% were new farms in 1992. Two hundred and eighty-three new farms
that appeared in the 1997 census and 231 (82%) of those farms do not appear in 2007. Of
the total number of farms that exited between 1997 to 2007, 62% were new farms in
1997. This shows that the majority of new farms did not make it to the next census year.
This further shows that the majority of farms exiting are relatively younger farms. Older
farms seem to survive better. Table 4.2 shows the mean, mode and the median age of
vegetable farms and further provides evidence in support of this claim. From Table 4.1, it
is obvious that the Hawai‘i vegetable farming sector has been very dynamic with farms

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entering and exiting the sector continuously (It should also be noted that non-respondent farms may accrue to this dynamism in part). This suggests the importance of studying aggregate productivity changes arising from this dynamism of the vegetable sector.

Table 4.1: Number of New, Exited and Continuing farms

<table>
<thead>
<tr>
<th>Census year</th>
<th>New Farms</th>
<th>Exited</th>
<th>Continuing</th>
<th>New Farms Exited&lt;sup&gt;9&lt;/sup&gt;</th>
<th>New Farms Continuing&lt;sup&gt;10&lt;/sup&gt;</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td>483</td>
<td>305</td>
<td>307</td>
<td>247</td>
<td>141</td>
</tr>
<tr>
<td>1987</td>
<td>388</td>
<td>386</td>
<td>307</td>
<td>247</td>
<td>141</td>
</tr>
<tr>
<td>1992</td>
<td>360</td>
<td>461</td>
<td>206</td>
<td>273</td>
<td>87</td>
</tr>
<tr>
<td>1997</td>
<td>283</td>
<td>372</td>
<td>117</td>
<td>231</td>
<td>52</td>
</tr>
<tr>
<td>2007</td>
<td>210</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.2 depicts the mean, mode and the median age of the continuing and exiting farms. Continuing farms have higher averages than exiting farms.

Table 4.2: Age of Continuing and Exiting Farms

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Mode</td>
<td>Median</td>
<td>Mean</td>
</tr>
<tr>
<td>Exiting Farms</td>
<td>12</td>
<td>1</td>
<td>6</td>
<td>11</td>
</tr>
<tr>
<td>Continuing Farms</td>
<td>13</td>
<td>4</td>
<td>8.5</td>
<td>12</td>
</tr>
</tbody>
</table>

Table 4.3 summarizes the mean and median (in parentheses) total sales of a vegetable farm. Average farm sales of farms that will exit are much less than the farms that will continue. This indicates that smaller farms are more likely to exit than larger farms. Average farm sales of new farms are also very much less than that of continuing farms. Most farms begin on a small scale.

<sup>9</sup> Farms newly appeared in a census year and not observed in the following census year.
<sup>10</sup> Farms newly appeared in a census year and also observed in the following census year.
Table 4.3: Average Sales Size\textsuperscript{11} of Farms by Exit, Entry and Continuing Categories

<table>
<thead>
<tr>
<th>Census Year</th>
<th>Exit</th>
<th>Continuing</th>
<th>New</th>
</tr>
</thead>
<tbody>
<tr>
<td>1982</td>
<td>54,629</td>
<td>96,947</td>
<td>(15,820) (38,420)</td>
</tr>
<tr>
<td>1987</td>
<td>46,357</td>
<td>143,533</td>
<td>63,376</td>
</tr>
<tr>
<td></td>
<td>(19,005) (42,020) (22,920)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1992</td>
<td>55,346</td>
<td>152,482</td>
<td>45,558</td>
</tr>
<tr>
<td></td>
<td>(15,987) (42,300) (14,100)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>68,857</td>
<td>153,791</td>
<td>53,260</td>
</tr>
<tr>
<td></td>
<td>(12,800) (41,600) (11,494)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2007</td>
<td></td>
<td>1,52,298</td>
<td>(10,000)</td>
</tr>
</tbody>
</table>

Table 4.3 shows the percentage of continuing and exiting farms in different sales categories. The first panel shows the percentages out of total farms and the second panel shows percentages out of continuing/exiting farms. The highest exit percentage is found in the non-commercial farming category (<$10,000 sales) followed by small commercial ($10,000-$250,000) and large commercial farm categories. The highest continuing farm percentage is observed with the small commercial farm category. Of the continuing farms (second panel), small commercial farms make up the majority with over 50% in all census years considered followed by non-commercial farms. Of the exiting farms, non-commercial farms make up the majority with over 50% in all census years considered followed by small commercial farms. This further establishes the observation made in Table 4.3 that continuing farms are larger compared to exiting farms.

\textsuperscript{11}Dollar values are adjusted for inflation using the Honolulu CPI. Yeah 2007 is taken as the base year.
Table 4.4: Composition of Continuing and Exiting Farms

<table>
<thead>
<tr>
<th>Census Year</th>
<th>% of Total Farms</th>
<th>% of Continuing/Exiting Farms</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>&lt;$10,000</td>
<td>$10,000-$250,000</td>
</tr>
<tr>
<td></td>
<td>Continue</td>
<td>Exit</td>
</tr>
<tr>
<td>1982</td>
<td>14.6</td>
<td>36.4</td>
</tr>
<tr>
<td>1987</td>
<td>14.0</td>
<td>30.3</td>
</tr>
<tr>
<td>1992</td>
<td>10.0</td>
<td>39.4</td>
</tr>
<tr>
<td>1997</td>
<td>8.2</td>
<td>48.3</td>
</tr>
</tbody>
</table>

Table 4.5 depicts mean and median profitability of new, continuing and exiting farms. The average profitability of continuing firms is very much higher than that of exiting firms. The profitability of new farms is lower than that of continuing farms. Together with the observations made in Table 4.4, this indicates that smaller and less profitable farms are more likely to exit.

Table 4.5: Average Profitability of New, Exiting and Continuing Farms

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gross Profit</td>
<td>Net Profit</td>
<td>Gross Profit</td>
<td>Net Profit</td>
<td>Gross Profit</td>
</tr>
<tr>
<td>New</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>24,458</td>
<td>(12,814)</td>
<td>10,609</td>
<td>(6,460)</td>
<td>24,103</td>
</tr>
<tr>
<td>Exit</td>
<td>36,521</td>
<td>(11,689)</td>
<td>26,971</td>
<td>(7,209)</td>
<td>23,518</td>
</tr>
<tr>
<td>Continue</td>
<td>62,336</td>
<td>(25,154)</td>
<td>45,785</td>
<td>(17,336)</td>
<td>41,032</td>
</tr>
</tbody>
</table>

4.5. Results and Discussion

The coefficient estimates of the production functions of the Hawaiʻi’s vegetable sector are depicted in Appendix Table 4.1. The individual farm productivity is calculated as the residual using these coefficient estimates. The aggregate productivity of the vegetable sector is calculated according to equation (5) for each cohort. They are presented in Table 4.6. The first panel shows aggregate productivity levels of continuing farms in the first period (i.e. farms those are continuing to the second period) and exiting farms (i.e. not present in the next period). The second panel shows aggregate productivity levels of continuing farms in the second period (i.e. farms which continued from the first period to
the second period) and new farms. It could be seen that the aggregate productivity of vegetable sector has increased from 1982 to 1987 and has slightly decreased from 1987 to 1992. From 1992 to 1997 aggregate productivity has again increased and it sees a further increase during the ten year period from 1997 to 2007. The same pattern could be observed with respect to continuing farms. Farms continuing from 1982 ($\Phi_{S1}$ in panel 1) to 1987 ($\Phi_{S2}$ in panel 2) show a large increase in productivity while farms continuing from 1987 to 1992 show a decrease in productivity. Farms continuing from 1992 to 1997 show an increase in productivity. Farms continuing from 1997 to 2007 have increased productivity from 1997 to 2007 considerably (However, note that the year gap is 10 years). Farms that are not present in the following census year (exiting) show a low level of productivity in comparison to continuing farms in all census years. However, the exiting farms also show an increase in productivity except those exited in 1992 (i.e. farms present in 1987 but not present in 1992). New farms (panel 2) show a lower level of productivity compared to the continuing farms in all census years. However, new farms also show an increase in productivity in all census years except in 1992. All in all continuing farms show a higher productivity than exiting farms and those farms continuing from the previous year show a higher productivity than new farms.

We report aggregate productivity decompositions for each of the two consecutive censuses since 1982 to 2007 in Table 4.7. The first two columns report break-down of productivity change of continuing farms to within and between farm components. The 3rd columns report productivity changes of farms continuing for the next immediate census year. The 4th and 5th columns report productivity changes decomposed into new and exiting firms respectively. All productivity changes are reported in log values (multiplying the log values by 100 give percentage point changes). We find a negative contribution of entry to aggregate productivity change because, on any given year, entrants have an aggregate productivity $\Phi_{E2}$ that is below the aggregate productivity of continuing farms $\Phi_{S2}$ for that period. Thus, in all years, the entrants’ productivity is below the overall aggregate productivity level $\Phi_2$ and therefore their presence pulls the aggregate productivity level downward.
We find a positive contribution from exiting farms to aggregate productivity change because exiting farms have an aggregate productivity $\Phi_{X_1}$ that is lower than the aggregate productivity of continuing firms $\Phi_{S_1}$ for that period. Aggregate productivity has increased by 16.9%, 40.8%, 52.1% and 29.8% in 82/87, 87/92, 92/97 and 97/07 periods respectively as a result of farm exits.

It is expected that the aggregate productivity of an industry will increase over time due to technological advancements of the industry over time. Similarly, we see an aggregate productivity growth between consecutive census years. Except between 1987 and 1992, aggregate productivity has increased by a large percentage. Aggregate productivity changes of continuing farms are decomposed into productivity changes resulting from shifts in the productivity distribution (via the change in the first moment or in other words within-firm productivity changes $\Delta \Phi_S$) and another component capturing market share reallocations via the change in covariance (between farm). In the empirical literature, the largest contribution is seen to come from the shift in productivity distribution of continuing farms which is expected to be positive over time. In contrast, we find that the largest contribution of productivity change is coming from market share changes in the vegetable sector (i.e., between firms). Melitz and Polanec (2015) work has been to show that the contribution from between firm productivity changes to aggregate productivity growth is underestimated in previous decomposition methods. Nevertheless, they find that the contribution by within-firm productivity changes is still larger than that of the between firm productivity change. For Hawaiʻi’s vegetable sector, the contribution of between firm productivity changes to the changes in the productivity of continuing firms is prominent. Overall aggregate productivity change of continuing farms is positive except during 1987/92 period.

There could be various reasons for farm exits. Farming as a business should exit if it is not profitable in the long run. Less productive farms make less profit compared to more productive farms. Therefore, less productive farms are more likely to exit in the long run. Rising import competition for Hawaiʻi over time is a fact. Import competition selects more productive firms over less productive firms and less productive farms exit the
market. Among other reasons are failure to find a successor, mergers and acquisitions and unfavorable external environmental factors. However, negative long-run profits is the major factor among them. Hawaiʻi’s vegetable sector has been facing a large number of farm exits between the census years. If only less productive or profitable farms exit the market, there should be a positive impact from farm exits on aggregate productivity change. That is the aggregate productivity of exiting farms should be less than that of continuing farms. We find that in Hawaiʻi’s vegetable sector low productivity farms have exited contributing to a productivity increase of the overall sector.

Further, heterogeneous firm trade models explain the expansion of more productive firms. That is the market share created by exited firms is captured by more productive firms. For Hawaiʻi vegetable sector productivity changes coming from market share reallocations seem to play a very important role. The period 1987 to 1992 yield negative productivity contribution by continuing farms which results in low aggregate productivity growth for the vegetable sector during the said period. Hawaiʻi experienced an economic boom during the late1980’s. During an economic boom, firms invest more in resources and expansion of the firms. As a result, the efficiency and productivity could decrease. Unlike in manufacturing, it takes more time to realize the output from new investments in agriculture. Entering of new firms consistently has decreased the aggregate productivity. That is the aggregate productivity of new farms are less than the aggregate productivity of the continuing farms. One reason could be that at the beginning of a business overhead costs are large and therefore, new farms seems less productive than continuing farms. Lack of experience and managerial skills of new farms compared to continuing farms may be another reason. These suggest that the structural changes taking place are very important for the productivity gains/losses of the sector.
### Table 4.6: Absolute Productivity Levels (in log values)

<table>
<thead>
<tr>
<th>Year</th>
<th>$\phi_1$</th>
<th>Continuing</th>
<th>Exiting</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\phi_{S1}$</td>
<td>Market Share</td>
</tr>
<tr>
<td>$t=1$</td>
<td>$t=2$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1982</td>
<td>1987</td>
<td>4.1755</td>
<td>4.3425</td>
</tr>
<tr>
<td>1987</td>
<td>1992</td>
<td>4.7682</td>
<td>5.1762</td>
</tr>
<tr>
<td>1992</td>
<td>1997</td>
<td>4.7604</td>
<td>5.2813</td>
</tr>
<tr>
<td>1997</td>
<td>2007</td>
<td>5.0628</td>
<td>5.3613</td>
</tr>
<tr>
<td>2007</td>
<td></td>
<td>5.7399</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Year</th>
<th>$\phi_2$</th>
<th>Continuing</th>
<th>New</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$\phi_{S2}$</td>
<td>Market Share</td>
</tr>
<tr>
<td>$t=1$</td>
<td>$t=2$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1982</td>
<td>1987</td>
<td>4.1755</td>
<td>5.1537</td>
</tr>
<tr>
<td>1987</td>
<td>1992</td>
<td>4.7682</td>
<td>5.0576</td>
</tr>
<tr>
<td>1992</td>
<td>1997</td>
<td>4.7604</td>
<td>5.4082</td>
</tr>
<tr>
<td>1997</td>
<td>2007</td>
<td>5.0628</td>
<td>5.7882</td>
</tr>
<tr>
<td>2007</td>
<td></td>
<td>5.7399</td>
<td></td>
</tr>
</tbody>
</table>

### Table 4.7: Aggregate Productivity Changes

<table>
<thead>
<tr>
<th>Period</th>
<th>$\Delta \phi_S$</th>
<th>$\Delta \text{cov}(s_{it}, \phi_{it})$</th>
<th>$\phi_{S2} - \phi_{S1}$</th>
<th>$\Phi_{E2}(\Phi_{E2} - \phi_{S2})$</th>
<th>$\text{S}<em>{X1}(\Phi</em>{S1} - \phi_{X1})$</th>
<th>$\phi_2 - \phi_1$</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>82/87</td>
<td>0.0365</td>
<td>0.7205</td>
<td>0.7570</td>
<td>-0.3850</td>
<td>0.1694</td>
<td>0.5414</td>
<td></td>
</tr>
<tr>
<td>87/92</td>
<td>-0.0128</td>
<td>-0.0715</td>
<td>-0.084</td>
<td>-0.2961</td>
<td>0.4080</td>
<td>0.0276</td>
<td></td>
</tr>
<tr>
<td>92/97</td>
<td>-0.0763</td>
<td>0.1260</td>
<td>0.0497</td>
<td>-0.3378</td>
<td>0.5209</td>
<td>0.2328</td>
<td></td>
</tr>
<tr>
<td>97/07</td>
<td>0.0518</td>
<td>0.2843</td>
<td>0.3361</td>
<td>-0.0363</td>
<td>0.2984</td>
<td>0.5982</td>
<td></td>
</tr>
</tbody>
</table>

There is little doubt the need for more empirical evidence to underpin an informed debate on these issues. However, access to data is often difficult and only longitudinal data farm data available is agriculture census data. Similar to national agriculture, the Hawai‘i vegetable sector shows a relative stable number of farms from 1982 to 2007. Hence Hawai‘i, though a smaller picture in magnitude, provides an interesting case to study productivity changes arising from structural changes. There is a growth in the number of Hawai‘i’s vegetable farms reported as 574 in Census 2007. Majority of it (306 farms) were making sales less than $10,000 (hence non-commercial farms). From 1982 to 2007 census we do not see much change in the total number of vegetable farms. The most recent 2012 census reports 744 farms, an increase of 170 farms from 2007 census. Interestingly, only 267 farms are reported as non-commercial farms.

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12The total number of Hawai‘i’s vegetable farms is reported as 574 in Census 2007. Majority of it (306 farms) were making sales less than $10,000 (hence non-commercial farms). From 1982 to 2007 census we do not see much change in the total number of vegetable farms. The most recent 2012 census reports 744 farms, an increase of 170 farms from 2007 census. Interestingly, only 267 farms are reported as non-commercial farms.
of non-commercial farms as well as the number of large farms. Farm production is getting concentrated in the large farms. Though it seemed to be a very stable sector, the vegetable sector has been subjected to a large number of farm exits and new entries between census years similar to the national situation.

During recent census years, the contribution of changing productivity distribution of continuing farms to the aggregate productivity is remarkable. This coincides with the increasing market share of large farms. Table 4.5 showed that the average profitability of continuing farms is greater than that of new and exiting farms. Hawai‘i vegetable farm production has been concentrated on few farms. Large farms also have the advantage of economies of scale in using modern technology. Therefore, they could be more productive than smaller farms. The aggregate productivity of the industry rises when farms with higher productivities capitalize the market share of exited farms.

**4.6. Conclusions**

In this paper, we estimated a production function for Hawai‘i vegetable farming sector according to Levinsohn and Petrin (2003) algorithm. We calculated aggregate productivities and decomposed aggregate productivity to continuing farms, exiting farms and new farms according to the dynamic Olley-Pakes method introduced in Melitz and Polanec (2012). The study finds that farm entry and exit dynamics have played an important role in aggregate productivity growth in the vegetable sector. We find that both exiting and new farms have low productivities compared to continuing farms. Therefore, while farm exits contribute positively to the aggregate productivity growth, new farm entry contributes negatively to the aggregate productivity growth. The aggregate productivity of continuing firms has increased between census years. Productivity gains in continuing farms is a mainly a result of market share reallocation between farms. Market share of exiting firms is captured by high productive farms and hence market share reallocations contribute substantially to the aggregate productivity growth.
**APPENDIX**

**Table A4.1: Levinsohn-Petrin Productivity Estimation**

<table>
<thead>
<tr>
<th>Independent Variables</th>
<th>Coefficient</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Number of Workers</td>
<td>0.4087</td>
<td>(0.0295)</td>
</tr>
<tr>
<td>Log Acres of Land</td>
<td>0.2576</td>
<td>(0.0370)</td>
</tr>
<tr>
<td>Log Capital Expenditure</td>
<td>0.1222</td>
<td>(0.0578)</td>
</tr>
</tbody>
</table>

| Number of Observations      | 1018        |
| Number of Groups            | 701         |
| Minimum Observations per Group | 1        |
| Average Observations per Group | 1.5      |
| Maximum Observations per Group | 5        |
| Wald Chi-Sq Test Statistics | 10.74       |

Note that the dependent variable is log of value added sales. Standard errors are given in parentheses.
REFERENCES


CHAPTER 5

RESOURCE USE AND OUTPUT SUPPLY RESPONSE IN HAWAI‘I
AGRICULTURE: AN EXPLORATORY STUDY

5.1. Introduction

Survival and growth of a production entity depend on its long-term profitability. In a resource constrained environment firms that are profitable survive and grow relatively to those which are not. In resource-constrained environments, there is a constant competition between residential, industrial and agricultural uses for the limited resources and among different sectors of a particular industry. For instance if a particular sector uses one input intensively, in a situation of rising price of that input, that sector will shrink relatively to the others. As a result, the output prices of those sectors will rise and hence will be unable to compete with imports.

This paper is an exploratory study and one of the first attempts at building a mathematical model for Hawai‘i agriculture for policy analysis. Land, being a limited resource in Hawai‘i, is classified under different zones namely agriculture, conservation, urban and rural. Rising population pressure has increased the demand for urban land in Hawai‘i. Consequently, there have been instances where land classified as agriculture are being allocated to urban development projects, and it is largely experienced in Honolulu County: the State capital. The most recent re-zoning of agricultural land in Hawai‘i took place in Hoopili and Koa Ridge in Honolulu County. Approximately, Hoopili and Koa Ridge projects rezoned 1300 acres and 600 acres of farmland respectively. Against this backdrop, this paper explores the effects of changes in land availability on the land allocation of different farming sectors taking the State of Hawai‘i as the case in point.

The programming method used here is a calibrated optimization modeling technique: Positive Mathematical Programming (PMP). Simulations involving resource shocks are analyzed to assess the impact of these scenarios on possible land allocation. The aggregate State model is calibrated to the base year 2007. Since the farmland rezoning affected land that is suitable and being used for vegetable farming, we simulated how the
decrease in vegetable land availability would change the acreage allocation among farming sectors.

We find that loss of vegetable farmland decreases the harvested acreage of low-value vegetable crops. It increases the harvested acreage of high-value crops employing labor released from the lost farmland. When labor moves freely across fruit and vegetable sectors, the loss of vegetable farmland tends to increase the harvested acreage of fruit crops.

This paper is organized as follows. First, a description of Hawai‘i agriculture is given, which is followed by a description of the modeling approach: PMP. In the subsequent sections, we describe data and results. Finally, we present conclusions, limitations of the study and future directions.

5.2. Hawai‘i Agriculture

Hawai‘i agriculture is important for the State economy as an income generator for around 10,000 workers (National Agricultural Statistics Service, 2011). The sustenance of the agriculture sector is important for the overall welfare of Hawai‘i’s people. Hawai‘i residents attribute a strong value to the local agriculture irrespective of whether they are from farm families or not. However, Hawai‘i is a high-cost agriculture producer. The plantation sector once dominated the Hawai‘i agriculture. As Hawai‘i lost its cost advantage in plantation agriculture, it gradually shifted into a more diversified agriculture i.e. fruits and nut farming, vegetables and floriculture.

Hawai‘i being a group of small islands, land is scarce and, therefore, there is a constant competition among residential, industrial and agricultural uses of land. Hawai‘i’s agriculture land is protected from being converted to other uses through land policy laws and zoning. However, we observe agriculture land being released for residential use on some occasions due to rising demand for the residential use of land (Hoopili and Koa Ridge are recent examples). On the other hand, labor is costly as cost of living is very high. Hawai‘i labor costs are 35-55% greater than that of the U.S. mainland, and Hawai‘i’s farms are on average 2-3 times smaller than that of U.S. mainland farms (Arita et al., 2012). Farmers in Hawai‘i face a difficult competitive environment because most
agricultural produce that are sold locally comes from areas where costs of production are lower than in Hawai‘i. Against this background, farming sectors compete for limited resources and market forces will allocate resources to most profitable sectors. Further, some farming sectors intensively use one resource relative to other sectors. Therefore, the impact of changes in the availability of these resources on different farming sectors also varies. Policy makers are challenged with taking appropriate policy decisions that improve the welfare of the society. However, quantitative analysis has been missing from the policy discussion. Therefore, there is a need for formalized economic models that can quantitatively evaluate alternative policy actions.

5.3. Method: Positive Mathematical Programming (PMP)
Mathematical programming has long been used to model farm behavior. The major criticism of mathematical programming approach to modeling farm behavior is that it yields unrealistic resource allocations. For instance, the model may suggest that a particular crop is grown which is not observed in practice due to many other complex and spatially distributed reasons such as consumer preferences. To address the problem of unrealistic optimization results from a profit-maximizing farmer in the model, Howitt (1995a) introduced a calibrated optimization procedure where it is assumed that observed output reflects optimal choices given the farmer’s current information set. Such a calibrated optimization model should, as a simulation model, generate results close to the observed levels. For instance, the output from a calibrated optimization model should reproduce observed production. It is called positive mathematical programming (PMP). The ‘positive’ model, once calibrated to observed behavior, can be used for policy formulation as a predictive tool to investigate farmer behavior under different conditions (climate, input and output prices, etc.) (Medellin-Aiziara et al, 2010). Being a deductive approach PMP begin with the assumption of optimal behavior of farmers. The farmer decides on crop mix and timing, and input allocation to maximize profits under resource and institutional constraints. The constraints would be crop prices, input costs, resource availability (land, water, labor etc.) agro-climatic conditions, and risk and management practices etc. (Medellin-Aiziara et al, 2010, Howitt, et al 2012).
PMP has several advantages over other mathematical programming techniques and econometric methods. Compared to econometric methods, PMP does not require large datasets to provide endogenous price variability. Therefore, PMP facilitates modeling farm optimization behavior with limited data availability. This is the main reason for selecting PMP technique to model farm behavior for Hawai‘i. As an improvement in mathematical programming technique, the PMP cost function calibrates closely to observed values of output and input use. The inputs of production usually include, but are not limited to land, water, and labor. Further, PMP adds flexibility to the profit function by replacing the assumption that total costs are in a fixed proportion to output following the traditional Leontief formulation.

The processes of mathematical modeling include model specification, calibration, and policy optimization. The models are solved for the policy and macroeconomic scenarios. A new set of cropping patterns, resource allocation and supply are obtained as potential effects of changes in policy variables, technical parameters or macroeconomic effects. The outcomes of base run and policy run are compared, and conclusions are made on the possible effects of alternative agricultural policies and/or macroeconomic effects.

The farm level or simple farm management model could be used to predict the response of individual farmers, which can be aggregated to regional and even national supply response. Essentially, these models involve a comparison of (expected) gross margins among the competing crops and a decision rule to change the cropping pattern by preferring the most profitable crop that is allowed by the agronomic constraints, assuming that the marginal cost is constant until the next resource constraint is binding. This approach is expected to yield a considerably more realistic farm level decision pattern and also provides a plausible prediction (Howitt, 1995a). When aggregated over the region it provides the secondary sector model with base values. Results from the application of programming models often result in suggestions for general or specific policy reform and manipulation to achieve specific economic and policy objectives.

PMP is a method for calibrating models of agricultural production and resource use. The approach involves non-linear yield or cost functions. The idea of PMP is that a sufficient number of non-linear relationships are added to an LP model to calibrate exactly to the
base year data. The addition of non-linear terms improves the diversity of the optimal solution. There are, however, often an insufficient number of independent non-linear terms that can be added to accurately calibrate the model (Howitt, 1995a, b, 2005a). The ability to calibrate the model with complete accuracy depends on the number of non-linear terms that can be independently added. By introducing a sufficient number of non-linearity, PMP procedure calibrates the models exactly to the base year in terms of output, input use, objective values and dual values of model constraints (Howitt, 1995a).

Since non-linear terms in the supply side of the profit function are needed to calibrate a production model, the task of PMP is to define the simplest specification needed in an exact calibration. PMP uses the observed acreage allocations and outputs to infer marginal cost conditions for each observed crop allocation. This inference is based on those parameters that are accurately observed, and the usual profit-maximizing and concavity assumptions of the standard micro-economic theory (Howitt, 1995a).

The PMP approach became very popular in country-specific agricultural sector modeling from the 1990s and has been applied even in relatively large European Union Wide models (Heckelei and Britz, 2000). This is because of the features of PMP approach as discussed earlier. It is useful in overcoming problems of the structural model specification and validation and works well in applied research.

5.3.1. Calibration in PMP

When the model does not calibrate to the observed production activities with the full set of the general constraints that are empirically justified by the model, a necessary condition for profit maximization is that the objective function be non-linear at least in some of the activities (Howitt, 1995a). The ability to calibrate the model with complete accuracy depends on the number of non-linear terms that can be independently calibrated\(^\text{13}\). The PMP method involves three stages: 1. solving constrained linear programming models (LP) to generate dual values 2. parameter calibration and 3. model specification of non-linear programming models (NLP). The first stage is the construction of linear programming (LP) models with resource and calibration constraints using all

\(^{13}\) Howitt (1995a) proposition 1 and 2 in appendix A solve for these conditions.
the available information to derive a vector of shadow prices, $\lambda$, of the limiting allocable resources and the differential marginal cost vector, $\rho$, of vector of realized resource allocation or output levels. The structure of the constrained LP is of the form:

Maximize

$$\pi = \sum_i x_i (P_i yld_i - c_i)$$

Subject to:

$$Ax \leq b \quad [\lambda] \text{ (Structural constraints)}$$

$$x_i + \epsilon \leq x_i^* \quad [\rho] \text{ (Calibration constraints)}$$

$$x_i \geq 0 \quad \text{(Non-negativity assumption)}$$

where $\pi$ is the objective function to be maximized over a vector of decision variables, $x_i$ is the acreage of land allocated to crop $i$, $yld_i$ is yield per acre of crop $i$ and $x$ is an $n \times 1$ vector. In our study, the decision variables are land acreage allocated to each observed crop $i$. $P_i$ and $c_i$ are marginal revenue and variable cost of crop $i$ respectively. ‘A’ is the matrix of technical coefficients involving limiting input levels with $m \times n$ dimension where $m < n$. Parameter $b$ is the vector of availability of limiting allocable inputs, and $x_i^*$ is the vector of observed activity levels. The vector of shadow prices, $\lambda$, is associated with the allocable input of the structural constraints while the vector of differential marginal costs, $\rho$, is associated with the calibration constraints. The parameter $\epsilon$ (epsilon) is a small number used to calibrate the model. The calibration constraints (3) force the program to reproduce base year observed cropping patterns. It is included to decouple the resource and calibration constraints. At the optimum, the calibration constraint will be binding for the activities with higher average gross margin while the resource constraint will restrict the acreage of the crop with lower average gross margins.
The primary intent of the first stage is to generate particular dual values to obtain an accurate and consistent measure of marginal costs (MC) associated with the vector of observed activity levels, $x^*$. 

In stage 2, the dual values ($\rho$) calculated in the first stage are used together with the data based average cost function to derive uniquely the calibrating cost function parameters. The total variable cost (TC) function is assumed to take the quadratic form,

$$TC_i = \alpha_i x_i + 0.5\gamma_i x_i^2$$

(5)

The marginal cost (MC) function becomes,

$$MC_i = \alpha_i + 0.5\gamma_i x_i$$

(6)

If they are $n$ number of crops, there will be $n$ number of $\alpha$s and $n$ number of $\gamma$s. Therefore, $2n$ number of equation are solved for $\alpha$s and $\gamma$s. From total variable cost function (5) the average cost (AC) function for crop $i$ is be derived as,

$$AC_i = \alpha_i - 0.5\gamma_i x_i$$

(7)

Howitt (1995) show that the dual on the LP calibration constraint $\rho$ is the difference between average cost (AC) and the marginal cost (MC).

$$\rho = MC - AC$$

(8)

Therefore, equation (8) can be solved for $\rho$ as,

$$\rho_i = 0.5\gamma_i x_i$$

(9)

Optimization requires that MR=MC at observed land allocation $x^*$. Therefore, parameters $\alpha$ and $\gamma$ is calculated sequentially solving for $\gamma_i$ in (9) and $\alpha_i$ in (7) with base-year crop allocation $x^*$. 

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In the third stage, the cost function parameters ($\alpha$s and $\gamma$s) derived in the second stage are used with the base-year data to construct non-linear (NLP) programming models using a specification that is linear in the parameters that reproduce the base year solutions without calibration constraints. Since we assume a quadratic cost function in this paper, we combine information on parameters into the unconstrained (calibrated) quadratic cost problem:

Maximize

$$\pi = \sum_i x_i (P_i yld_i - \alpha_i + 0.5\gamma_i x_i)$$

(10)

Subject to

$$Ax \leq b \quad [\lambda] \text{ (Structural constraints)}$$

$$x \geq 0 \quad \text{(Non-negativity assumption)}$$

The calibrating model exactly reproduces the base year activity levels i.e. primal and dual solutions of the NLP model are exactly equal to the primal and dual solution of the constrained LP model. This model is then often used to simulate the impact of agricultural policy changes.

5.3.2. Developments in PMP

Though application of PMP models date back to nearly 30 years. Its widespread use and popularity began with Howitt (1995a)’s formalization of the model. Since Howitt (1995a), the interest in the application of PMP in modeling agriculture sectors of different economies grew and the model was improved to overcome technical challenges in parameter estimations and to yield more realistic simulations. The recent developments in the PMP literature have clearly driven towards a better understanding and improvement of related model specifications.
The initial formulation considers calibrating the parameters of a variable cost function that has the typical multi-output quadratic functional form holding constant variable input prices at the observed market level as follows. Later other functional forms were introduced to the PMP method. Among other functional forms are constant elasticity of transformation production function (Graindorge et al., 2001), generalized Leontief and the weighted-entropy variable cost function (Paris and Howitt, 1998) and the constant elasticity of substitution (CES) production function (Howitt, 1995b).

The initial purpose of the PMP was to calibrate model parameters so that the maximization problem of farm profits under resource and policy constraints would replicate the observed base year allocation. A weakness identified was that the supply response of many of the applications of this model was not consistent with the exogenous prior information (i.e. supply elasticities). Therefore later, came the need to selecting a set of calibrating parameters that would lead to unreasonable implied supply elasticities from the model. Two ways have been suggested by Heckelei and Britz (2005) to improve the empirical base of PMP models. One way is to use the exogenous information on supply responses (i.e. elasticities) and shadow prices of resources in calibrating the models to observed activity levels in a base year. Another way is estimating programming model parameters in an econometric sense using multiple observations.

Since then, the use of prior information in calibration such as price data for the dual values or resource constraints and exogenous elasticities has clearly increased. Merel and Bucaram (2010) point out that most studies using the prior information on supply elasticities perform a ‘myopic’ calibration. According to Merel and Bucaram (2010) those studies ignore the change of resource shadow prices when applying the elasticity information to model parameters. Merel and Bucaram (2010) show the conditions under which a programming model can be exactly calibrated to exogenous own-price supply elasticities.
Estimating programming model parameters using multiple observations is termed as Econometric Mathematical Programming (EMP). Application of this method has not taken as much as the use of prior information on supply elasticities.

5.4. Data
There are only a few sources of published agriculture data in Hawai‘i. Main publications include the Agriculture Statistics Bulletin and Census of Agriculture: Hawai‘i State and county data are published annually by National Agriculture Statistics (NASS). Hawai‘i Agriculture Statistics Bulletin gives data on farm gate prices, yield and acreage for the main crop and livestock sectors. Agriculture census is usually carried in five-year intervals, and hence census publication comes out in five-year intervals. Census publishes summary data on farm demographics, acreage, revenue and cost of production and, agriculture support programs. Most of these published data are aggregated by crop sectors (e.g. fruits, berries and nuts and, vegetables, melons and potatoes). Since several of Hawai‘i agriculture sectors are highly concentrated (i.e. few large farms having a large market share, revenue and cost of production data are not summarized for individual crop sectors to avoid disclosure of information about individual operations. We received access to farm level data in census 2007. We obtained the cost of production data for our model from farm level data.

Hawai‘i agriculture census contains individual farm information. Among individual farm information are, acres dedicated to individual crop sectors by each farm, the cost of production and sales of each farm. Variable input costs for individual crop sectors are derived from the agriculture census data for the year 2007. However, the cost of production or sales of a farm is not broken down by crop type which is a major disadvantage. A farm may grow several crops and livestock. However, the cost of production and revenue of a farm is for the entire crop portfolio that a farm cultivates. We need to identify the cost of production related to a particular crop. Farms were first identified separately as fruit farms and vegetable farms according to the North American Industry Classification (NAICS) code. Farms making less than $1000 annual sales were excluded from the analysis. Subsequently, farms whose total harvested acres comprised of a single crop were separated out. Per acre costs and per acre labor use for different
crops are derived for these farms. Yield information is not available in census data. Therefore, yield and farm price information are obtained from the agriculture statistical bulletin published by National Agriculture Statistics Service (NASS) for the year 2007. Fifteen major fruit and vegetable sectors were included in the model. The list of the crop sectors is shown in the following Table 5.1.

<table>
<thead>
<tr>
<th>Crop Sector</th>
<th>Harvested Acreage</th>
<th>Sales Quantity ('000 lb)</th>
<th>Sales Value ('000 $)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coffee</td>
<td>6,400</td>
<td>7,500</td>
<td>31,875</td>
</tr>
<tr>
<td>Macadamia Nuts</td>
<td>15,000</td>
<td>41,000</td>
<td>24,600</td>
</tr>
<tr>
<td>Banana</td>
<td>1,300</td>
<td>25,600</td>
<td>10,496</td>
</tr>
<tr>
<td>Papaya</td>
<td>1,310</td>
<td>33,400</td>
<td>13,094</td>
</tr>
<tr>
<td>Avocado</td>
<td>350</td>
<td>1,160</td>
<td>789</td>
</tr>
<tr>
<td>Guava</td>
<td>170</td>
<td>4,165</td>
<td>675</td>
</tr>
<tr>
<td>Dry Onion</td>
<td>160</td>
<td>1,400</td>
<td>1,680</td>
</tr>
<tr>
<td>Lettuce</td>
<td>100</td>
<td>1,000</td>
<td>710</td>
</tr>
<tr>
<td>Chinese Cabbage</td>
<td>258</td>
<td>6,300</td>
<td>1,890</td>
</tr>
<tr>
<td>Head Cabbage</td>
<td>440</td>
<td>10,400</td>
<td>3,016</td>
</tr>
<tr>
<td>Sweet Potato</td>
<td>350</td>
<td>5,300</td>
<td>2,703</td>
</tr>
<tr>
<td>Taro</td>
<td>380</td>
<td>4,000</td>
<td>2,360</td>
</tr>
<tr>
<td>Tomato</td>
<td>740</td>
<td>14,300</td>
<td>9,667</td>
</tr>
<tr>
<td>Ginger</td>
<td>60</td>
<td>1,800</td>
<td>2,880</td>
</tr>
<tr>
<td>Herbs</td>
<td>250</td>
<td>5,000</td>
<td>8,506</td>
</tr>
</tbody>
</table>


5.5. Features of the Model

We formulated an aggregate sector model for Hawai‘i. The model included 15 crop sectors. The crop sectors represent six major fruit, berry and tree nut sectors and vegetable farming sectors in Hawai‘i. Crop sectors in the fruit, berry and tree nut sectors are coffee, macadamia nuts, guava, banana, papaya and avocado. Crop sectors in the vegetable category are dry onions, lettuce, Chinese cabbage, head cabbage, sweet potato, taro, tomato, ginger and herbs. The fruit, berry and tree nut category considered in this model comprise of 75% of the total harvested acreage in fruit, berry and tree nut sector and vegetable category considered in this model comprise of 46% of the total acreage in the vegetables and melons sector.
The model is defined for the Hawai‘i State and assumes that farmers maximize profits subject to resource constraints. The model selects crops and allocates land acreage to the crops that maximizes the sum of producer surplus subject to constraints on land and labor and also subject to economic conditions regarding prices, yields and costs. The model optimizes production at the extensive margin by adjusting the crop mix and land acreage. It will also fallow land in response to resource conditions.

The study consisted of two phases i.e. model calibration and policy analysis phases. We first solve a linear mathematical model subject to fixed resource and calibration constraints. We obtain quadratic cost function parameters using the opportunity cost of land from the calibration. We calibrated the model to the 2007 base year values. The model calibrates to the base year in terms of land and labor inputs used in each crop sector. Finally, we simulated changes in resource availability on the calibrated model.

The model calibration approach is driven by the first order conditions and fixed resource constraints. Since the underlying objective is to maximize profits, subject to inequality constraints on the fixed inputs, each regional crop production activity (i.e. crops that are actually grown) must have a positive gross margin over variable costs at the base calibration values.

5.5.1. Constrained Linear Programming Model

In this step, we solved a linear program of farm profit maximization with calibration constraints set to observed values of land use. The Lagrangian multipliers on the calibration and resource constraints are used in the next step to parameterize a quadratic PMP cost function. We define sub-index $i$ for crop groups and $j$ for production inputs. We solved a linear program to obtain marginal values on calibration and resource constraints. The linear program objective function is to maximize the sum of farm profits across all crops by optimizing land use $x_{i,land}$. Equation (5) defines the objective function,

$$\max_{x_{i,land}} \pi = \sum_i (v_i y_i d_i - \sum_j \omega_{ij} a_{ij}) x_{i,land} \quad (5)$$
where $\omega_{ij}$ is input costs and $a_{ij}$ is,

$$a_{ij} = \frac{\bar{x}_{ij}}{x_{i,\text{land}}}$$

$\bar{x}_{ij}$ is the observed level of inputs.

Production is constrained by resource availability: land and labor.

The land and labor constraint is defined as,

$$\sum_i x_{i,\text{land}} \leq b_{\text{land}}$$

where $b_{\text{land}}$ is land availability constraint.

The labor availability constraint is

$$\sum_i x_{i,\text{lab}} \leq d_{\text{lab}}$$

The calibration constraint forces the program to reproduce base year observed cropping patterns. We included a perturbation or epsilon (0.01) to decouple the resource and calibration constraints as detailed in Howitt (1995a),

$$x_{i,\text{land}} \leq \bar{x}_{i,\text{land}} + \varepsilon \quad (6)$$

We added the calibration constraint to land only and used the shadow value of land $\lambda^*_i$ as the marginal cost needed to calibrate optimal land allocation in Equation (6). Two tests are applied to the output of the linear model. The first test measures any deviation in regional crop input allocation by the model. The percentage deviation in inputs used by a crop is less than 1%. This is considered permissible given the small perturbations in the calibration constraints, but any input deviation greater than this implies negative gross margins or unduly restrictive fixed input constraints. The second calibration test is that
the number of non-zero dual values on calibration constraints plus the number of non-zero shadow values on binding resource constraints should be equal to the number of non-zero production activities in each region. If this test does not hold, the model will not have sufficient cost information to calibrate the full set of non-zero activities as some crops should have interior solutions, but do not have calibration shadow values to derive them (Howitt et al., 2012).

5.6. Results and Discussion

5.6.1. Simulation Exercise: Loss of Vegetable Farmland

To test the model for simulation analysis we assumed a loss of 10% of vegetable land. Quadratic cost function models are not suitable to simulate large changes (Howitt et al., 2012). Therefore, a 10% reduction in land available for vegetable cultivation is considered in this study. The optimized simulation results are shown in Table 5.2. The extensive margin adjustments are both positive and negative, as would be expected as farmers adjust to a changed comparative crop advantage. The second column shows the percentage change in harvested crop acreage with no constraint on labor movement across fruit and vegetable sectors and the third column shows the percentage change in cultivated crop acreage with constraint to labor movement across fruit and vegetable sectors.

Loss of vegetable land has adversely affected taro acreage harvested the most followed by head cabbage and Chinese cabbage. It could be observed that though there was no direct loss of harvested acreage of fruit, berries and tree nut category there is a reallocation of land in this sector. This is because some of labor released from the loss of vegetable land is being available for use by other sectors as well. Some of released labor is absorbed by higher profit making crops namely herbs, lettuce, tomato and ginger and, as a result, the harvested acreage of these vegetable crops increase. However, there is an excess labor of 7.4%. When a constraint on labor movement between fruit and vegetable sectors is imposed, available vegetable land acreage is reallocated within the same sector while there is no reallocation of land among fruit, berry and tree nut sectors. This results
in more excess labor (10.5%). That is more farm workers will not have jobs when labor
cannot move easily across different farming sectors.

Table 5.2: Extensive Margin Adjustments due to 10% Loss of Harvested Vegetable
Land

<table>
<thead>
<tr>
<th>Crop Sector</th>
<th>% Change in the Cultivated Area from the Base</th>
<th>With no constraint on labor movement across fruit and vegetable sectors</th>
<th>With constraint on labor movement across fruit and vegetable sectors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coffee</td>
<td>4.8%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>Macadamia Nuts</td>
<td>3.7%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>Banana</td>
<td>1.3%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>Papaya</td>
<td>0.3%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>Avocado</td>
<td>8.9%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>Guava</td>
<td>6.8%</td>
<td>0.0%</td>
<td></td>
</tr>
<tr>
<td>Dry Onion</td>
<td>-1.1%</td>
<td>-1.1%</td>
<td></td>
</tr>
<tr>
<td>Lettuce</td>
<td>9.8%</td>
<td>9.8%</td>
<td></td>
</tr>
<tr>
<td>Chinese Cabbage</td>
<td>-9.7%</td>
<td>-9.7%</td>
<td></td>
</tr>
<tr>
<td>Head Cabbage</td>
<td>-18.2%</td>
<td>-18.2%</td>
<td></td>
</tr>
<tr>
<td>Sweet Potato</td>
<td>-5.0%</td>
<td>-5.0%</td>
<td></td>
</tr>
<tr>
<td>Taro</td>
<td>-30.1%</td>
<td>-30.1%</td>
<td></td>
</tr>
<tr>
<td>Tomato</td>
<td>5.5%</td>
<td>5.5%</td>
<td></td>
</tr>
<tr>
<td>Ginger</td>
<td>1.4%</td>
<td>1.4%</td>
<td></td>
</tr>
<tr>
<td>Herbs</td>
<td>10.0%</td>
<td>10.0%</td>
<td></td>
</tr>
</tbody>
</table>

5.7. Conclusions

An aggregate farm model was developed for the State of Hawai‘i employing positive
mathematical programming (PMP) technique introduced by Howitt (1995a). The aggregate farm model consisted of 15 crop sectors in fruit, berry and tree nut category and vegetable category. The year 2007 is taken as the base year and the model was calibrated for the base year. The model was used to simulate 10% loss of vegetable farmlands. The loss of farmland decreases the harvested acreage of low-value vegetable crops. It increases the harvested acreage of high-value crops employing labor previously used in the lost farmland. When labor moves freely across fruit and vegetable sectors, the loss of vegetable farmland tends to increase the harvested acreage of fruit crops. However, some farm workers will be laid off. Therefore, it is important for policy makers to consider not only the loss of farmland and farm production due to development projects but also the loss of employment opportunities for farm labor.
5.8. Limitations and Future Directions

This study used a simple PMP model in calibrating farm behavior in Hawai‘i. Urban sprawling and its impact on agriculture is a more complex issue. In the debate on the costs and benefits of agriculture land rezoning for development projects, one argument put forward by the pro-development side is that agriculture land is not a limiting factor for Hawai‘i. Of total land in Oahu, only 67,048 acres (17.5%) are zoned as agricultural land. In the whole State of Hawai‘i, 46% of the land is classified as agricultural land and only a small percentage of this is in active farmland. Further, since the fall of large plantations in Hawai‘i, a large amount of land became available for diversified agriculture. However, most of these released land is not yet being used. Therefore, there is enough land left for re-zoning for growing urban demands. The counter argument is that not all land classified as agriculture are not suitable for agriculture. When the Land Use Commission was established and land use classification is carried out in Hawai‘i, all land remaining after zoning for conservation and urban purposes were classified as agricultural without an evaluation of these land for agricultural uses. In a nutshell, not all 46% of land classified as agricultural are suitable for agriculture and hence agriculture land is not in abundance as it seems to be. One important fact in Hoopili and Koa Ridge development projects in particular is that the farmland displaced by these projects are prime agriculture land. That is land that is the most suitable for crop cultivation. When prime agriculture land is lost, agriculture may move to a less productive land without necessarily reducing the active farm acreage. In such a situation, the yield may reduce or cost of cultivation may increase. In fact, there have been discussions about swapping land in Kalihi for agriculture land in West Oahu (where Hoopili and Koa Ridge are). In capturing the full impact of rezoning of agriculture land, the model needs to be enhanced with more variables and constraints. For instance, the model assumed that there will not be a replacement for the loss farmland. It employed only two factors of production (land and labor). Other important factors of production (e.g. water availability) are excluded in this model. Disaggregate inputs to the production function allow for a more accurate representation of the response of farmers to external shocks in policy simulations. These data are not readily available and therefore, should consult farmers, extension officers and industry specialists in developing a more elaborate model for Hawai‘i.
Though Hawai‘i is considered as one region in this model, it consists of four main islands: Hawai‘i (big island), Oahu, Maui and Kauai. Labor does not move freely across ocean as it is across the land. Therefore, excess labor from Oahu might not move to fruit, berry and tree nut sector which is predominantly cultivated in the big island. Further, input use and intensities may differ among islands. Breakdown of the model by islands would be able to accommodate these constraints.
REFERENCES


