

THREE ESSAYS ON THE ECONOMICS OF LOCAL FOOD SYSTEMS, AND RETAIL
MARKET DYNAMICS

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To my mother, Mrs. Hasina and my father, Mr. Milan.

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Abstract

In the present collection of essays, we contribute to the growing literature of the economics of local food systems. In the first chapter, we develop a fully calibrated positive mathematical programming (PMP) model for Hawaii's local food systems to facilitate policy debates regarding local food production. We use the model to assess two proposed policies – a general excise tax (GET) exemption on locally-produced foods, and a public investment in agricultural infrastructure (Whitmore Project). Our analysis suggests that Hawaii's local food systems may benefit from either of the policies but the level of impact may vary significantly, subject to some caveats. In the second chapter, we incorporate noncommercial farming into the PMP model & simulate a recently proposed market-value assessment (MVA) based property tax policy by the County of Maui. Since noncommercial producers are significantly different from commercial farmers, in terms of farming objective, productivity, etc., it is important to understand how they may respond differently to any major agricultural policy change. Our simulations suggest that the proposed policy change will have moderate impacts on commercial farming, but large impacts on most crops under noncommercial farming. Finally, in the third chapter, we investigate the market dynamics of local and imported foods in Honolulu's retail chains using Nielsen retail scanner data for four selected foods. The results from panel vector-autoregressive models and impulse response functions indicate the exogenous determination of the prices of imported foods. Moreover the imported foods sales seem to recover more quickly after a price shock than the local foods sales, perhaps because of consumers' relatively higher dependence on the cheaper imported versions. In addition, local prices were found to be responsive to the variations in prices of their imported counterparts – suggesting competitive pressure.

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1 Chapter 1: A Calibrated Model of Local Food System of Hawaii: What are the Economic Implications of the State's Agriculture Goals and Policies?¹

1.1 Introduction

Although policy-makers' interest in increasing local food production has grown enormously in many parts of the world, policy-makers have lacked a framework that can assess the viability of policies promoting local agriculture. Similar to other parts of the world, residents of Hawaii have expressed strong interest in local food. Given this public interest, and agriculture's sentimental value, policymakers are inclined to take policy initiatives to foster agriculture in the state, despite the fact that the gains from international and inter-state trade may outweigh the gains from localized production in purely economic terms. Given Hawaii's high land and labor costs (Parcon et al., 2011), increasing localization can be particularly challenging if not economically unviable. However, quantitative analysis has been missing from the policy discussion. A formalized economic model of the local food system of Hawaii can help policy-makers evaluate policy actions in quantitative terms and make more informed decisions.

In the present paper, we develop a formalized economic model of local food systems that can be employed to assess various local food policies. The study aims to contribute to the local food literature by providing a necessary tool to inform policymakers and offering a useful case study of Hawaii into the broader economic questions related to food localization. Due to the complexity of food systems, the definition of local food suffers from ambiguity and intractability in measurement (Hinrichs, 2000; Hand and Martinez, 2010; Ostrom, 2007). Our study of an

¹ With Shawn Arita, Richard Howitt, and PingSun Leung.

island economy allows us to circumvent this difficulty in measuring the amount of food coming into the region from other U.S. states and accounting for the intra-country trade of non-local food. Therefore, our definition of local foods is conveniently defined by Hawaii state boundaries and offers a clean case study.

Our model is based on the principles of Positive Mathematical Programming (PMP), one of the most widely used tools to replicate regional agricultural activity and determine policy implications. PMP was first developed by Howitt and Mean (1983) and later formalized in Howitt (1995). In recent years, PMP has been restructured to address the method's key criticisms, which has renewed interest in the method as a reliable agricultural policy analysis tool. Howitt and his colleagues' latest work (Garnache et al., 2017) strengthens the PMP method by addressing the last key criticism of its calibration procedure, offering a new method for calibrating shadow values. While statistical analyses typically require large amounts of data and can be quite limiting in assessing policy effects, PMP models are popular for accomplishing such objectives with limited data requirements. In agricultural modeling and policy analysis, PMP-type models are known for their ability to generate solutions with a realistic diversification of production activities and smooth responses to any change in the variables, without any artificially imposed constraints (Heckelei et al. 2012).

Because of its simplicity and suitability in agricultural and resource policy analysis, the PMP approach is widely used in agriculture and environmental applications. Many regional agricultural models are based on PMP and are repeatedly employed to study agricultural and environmental policy implications. In the US, the Regional Environment and Agriculture Programming (REAP) model (Johansson et al. 2007) based on PMP has been used for studying potential economic and environmental effects of proposed animal waste management policies on

a regional basis. In Europe, the Common Agriculture Policy Regional Impact (CAPRI) model (Gocht and Britz, 2011) also based on PMP has been used for ex-ante impact analysis for regional agriculture and international trade policies in Europe.

In our present paper, PMP will be used for the first time to model Hawaii's local food system and the model will be employed for ex-ante policy analysis. In this regard, we seek a fully calibrated model for Hawaii's agriculture that is consistent with economic theory and also quantitatively meaningful. By calibrating production functions at the county-level, we capture the geographic heterogeneity on the supply side. We assume profit-maximization conditions for each crop at the county-level. Although farm-level analysis would enrich the model and enable it to capture farm heterogeneity, it is not possible in the present study due to the U.S. Department of Agriculture's (USDA) restrictions on providing farm-level data. As for a market clearing module, we calibrate downward-sloping demand functions for all crops following Howitt et al. (2012), and employ a basic Armington budgeting procedure (Armington, 1969) to account for the substitution between local and non-local versions for each food crop. This represents the demand-side of the market, where we assume that all demand comes from the City and County of Honolulu for simplicity in modeling and due to the unavailability of detailed county-level consumption data. We believe that this is a reasonable assumption given that this county accounts for 70% of the state population. The consumer side of the market provides a mechanism for the calculation of consumer surplus in our model. Combining both supply and demand sides, the objective function is to maximize total surplus (i.e., producer surplus and consumer surplus combined) subject to crop-wise resource constraints at the county level.

After calibration and checking for the model's ability to reproduce the base year data, we use our calibrated model to back-cast the disaggregated activity levels for the years 2007 through

2011 to assess the model's performance in reproducing actual activity in those years. Finally, we demonstrate two ex-ante policy simulations using our model – a general excise tax (GET) exemption exclusively on local produce, and a public investment in agricultural infrastructure.

The rest of the paper is organized as follows. Section 2 gives an overview of the related literature and how our present paper fills an existing gap. Section 3 provides a background of Hawaii's food market and its implications on the local economy. Section 4 describes the data and the methodology developed for our study. Section 5 discusses the model's prediction power by backcasting crop-wise activity levels. Section 6 presents the policy simulations and results. Finally, section 7 concludes. Some additional materials are also provided in the Appendices.

1.2 Literature Review

Estimating the complete benefits of localized food production may be a complex task, due to the fact that there are numerous avenues through which local production is perceived to benefit an economy. Fuel saving on transporting foods from many miles away and thus contributing to the global environment can be one example of such a benefit. Pirog et al. (2001) conducted a study on 28 fresh produce imported in Iowa and found that 6.7 to 7.9 million pounds of CO₂ emissions could be saved if 10% of those foods could be produced locally in the state. However, there are studies in the literature that have shown that these gains could be overstated and suggested that these conclusions should be put in a proper context. For example, Weber and Matthews (2008) found that the production phase accounts for 83% of the food-related CO₂ footprint in the U.S. households and final delivery from producer to retail contributes only 4% of life-cycle GHG emissions. They suggested that a dietary shift from foods with high GHG-

intensity (e.g. red meat) to less GHG-intensive foods (e.g. chicken, fish, vegetables, etc.) can be a more effective means of lowering food-related climate footprint than "buying local".

Across the United States, non-profits and municipal governments in cities are creating food policy councils to put emphasis on urban agriculture and local production of foods. Various studies have shown that these efforts were somewhat successful in strengthening local agriculture (Cohen et al., 2012; Colasanti et al., 2010). The encouragement of local production to supply the local markets is viewed as a way to enhance the quality of life for farmers, and protect natural resources related to the agricultural economy (Feenstra, 1997; Hinrichs, 2000; Halweil, 2004). However, local food systems have also been viewed by many researchers as being less efficient when compared to the industrial agriculture model. For example, Sexton (2009) critiques the economics behind local food systems, by arguing that the local food movement is based on an ambitious assumption that "relocalized" food systems will be as efficient as industrial farming. Sexton estimates that under the pseudo-locavore system, maintaining the existing production levels for 40 major field crops and vegetables would require an additional 60 million acres of cropland, 2.7 million tons more fertilizer, and 50 million pounds more chemicals. He continued to argue that the land-use changes and additional inputs requirement will lead to environmental damage and habitat losses. In another study, Paul and Nehring (2003) analyzed farm-level surveys from 1996-2000 and concluded that there are "significant" scale economies in modern agriculture and that small farms are "high cost" operations. Absent the efficiencies of large farms, the use of polluting inputs would rise, as would food production costs, which would lead to more expensive food.

In Hawaii, recent and on-going research has focused on assessing the economic structure of Hawaii's local food system and its overall economic activity in an increasingly competitive

globalized environment. Hawaii's food system has been previously mapped by Loke and Leung (2013). Drawing on detailed data, they rigorously tracked the flow of food products in Hawaii. The study found that only around 12% of all food consumed in Hawaii is sourced locally. Hawaii's high dependence on imported food was found to be due to several reasons, including local farms' much higher factor costs compared to their competitors (Parcon et al., 2011), their relatively smaller size (Naomasa et al., 2013), along with on average 15-20% less efficiency than the U.S. mainland farms in terms of input-output ratios (Arita et al., 2012). While many weaknesses embedded in farm structure force Hawaii to be increasingly dependent on outside sources for its foods, this dependence also hinders farm growth significantly (Arita et al., 2014).

The economic argument for food localization often rests on the perceived gains from increased income and employment growth and its positive impact on local economic activity (Swenson, 2009; Conner et al., 2008; Meter, 2011; Cantrell et al., 2006). Meter (2011) studied Ohio's farm economy and found that if 15% of vegetable consumption can be sourced directly from local producers, there would be an additional farm income of \$2.5 billion annually. Swenson (2009), using input-output models for Iowa, predicted that increases in regional output would lead to higher labor income and job creation. However, it must be noted that this increased income does not come without an opportunity cost of the resources used for local production. Economists have long emphasized the welfare gains from specialization and trade. In agriculture, specialization is very important, because the costs of production depend on climatic factors as well as land and other input costs, which vary across locations giving some places comparative advantage in production (Sexton, 2009).

For the case of Hawaii, Leung and Loke (2008) found that the replacement of approximately 10% of imported foods would amount to some additional \$313 million, or \$94

million at the farm-gate, assuming a 30% farm share. Taking into account the multiplier effects, this \$94 million would generate an estimated economy-wide impact of \$188 million in sales and more than 2,300 jobs. This simple I-O study offers one form of quantitative assessment of food localization, however, they rely on strong assumptions of fixed prices, Leontief production structure, and unconstrained resources. The study does not indicate how this benefit can be realized, or at what cost, and whether this gain justifies the costs associated with achieving it. In the present paper, we are taking into account some but not all costs due to the unavailability of sufficient data. For example, lost jobs in the trade services (dock workers, for instance), etc. caused by reduced imports could not be captured by our present study. However, future studies should capture these areas of the economy to provide a more comprehensive picture, which will further enrich the literature.

Currently, there has been no rigorous effort in the literature to explicitly assess the full implications of food localization. Lack of data and appropriate policy instruments has made ex-post econometric evaluation unfeasible. Study of food localization is inhibited by the difficulty of modeling regional agricultural economies that require a holistic approach to supply and demand with suitable calibration framework. Thus despite strong public interest in local foods, quantitative economic analysis has not been carried out. Our present paper fills this gap in the literature of local food economics by making three major contributions. First, the policy simulations using our local food model will generate valuable policy information for Hawaii's endeavor for increased food localization. Second, with the recent interest in food localization and urban farming, Hawaii is a useful case study for the broader national dialogue. Our explicit quantitative evaluation will be of interest to other researchers currently engaging with the economics of local food systems. Finally, we also intend our model to be a working platform for

future application in issues of biofuels, climate change, water usage, and land issues. Thus our work is expected to contribute substantially to the existing literature of local food economics and other relevant areas.

1.3 Background on Hawaii's Local Food Market

Although, Hawaii is estimated to import more than 88% of its foods from outside the state (Loke and Leung, 2013) and at the other extreme, it would be very difficult if not impossible to attain 100% food self-sufficiency (Leung and Loke, 2008), many members of the community including legislators feel that Hawaii should replace more imports with local production (Ulupono Initiative, 2011). Despite some studies disputing the benefits of local foods (for example, Webber and Matthews, 2008; Sexton, 2009; Paul and Nehring, 2003), local food production is given high priority based on the perceived economic benefits (Balmer et al., 2005; Corrigan, 2011; Larsen and Gilliland, 2009; Armstrong, 2000) and environmental sustainability awareness perspectives (Bregendahl and Flora, 2006; Kerton and Sinclair, 2010; Travaline and Hunold, 2010). Due to these perceived socioeconomic and environmental benefits of local production, the Hawaii State Government has taken a remarkably active stance in increasing its food localization by advocating it as part of its development strategy. The state governor has asserted an ambitious goal to “double” Hawaiian food production by 2020 (“Governor David Ige”, n.d.).

In recent years, several policy measures have been considered to achieve Hawaii's local food aims. In 2010, the state passed bill SB829 mandating a 15% preference for locally grown fruits, vegetables, poultry, eggs and meat that are purchased by public organizations. The Hawaii

Department of Agriculture (HDOA) actively promotes farmers' markets with its "Buy Fresh, Buy Local" call-to-action program. Support for local food has been strengthening, for example, a key interest group called the Local Food Coalition brings together farmers, ranchers, investors and other leading organizations that seek legislative support for local food objectives. Recently, they have put together a comprehensive food self-sufficiency legislation that has laid out a series of policy measures to increase food localization. Specific measures include tax credits for agricultural land usage, public investment in agricultural infrastructure, lowering of state lease rents and extension of long-term leasing agreements, financing assistance, mandated local food procurement for state agencies and tax exemptions for local food products (Ulupono Initiative, 2011).

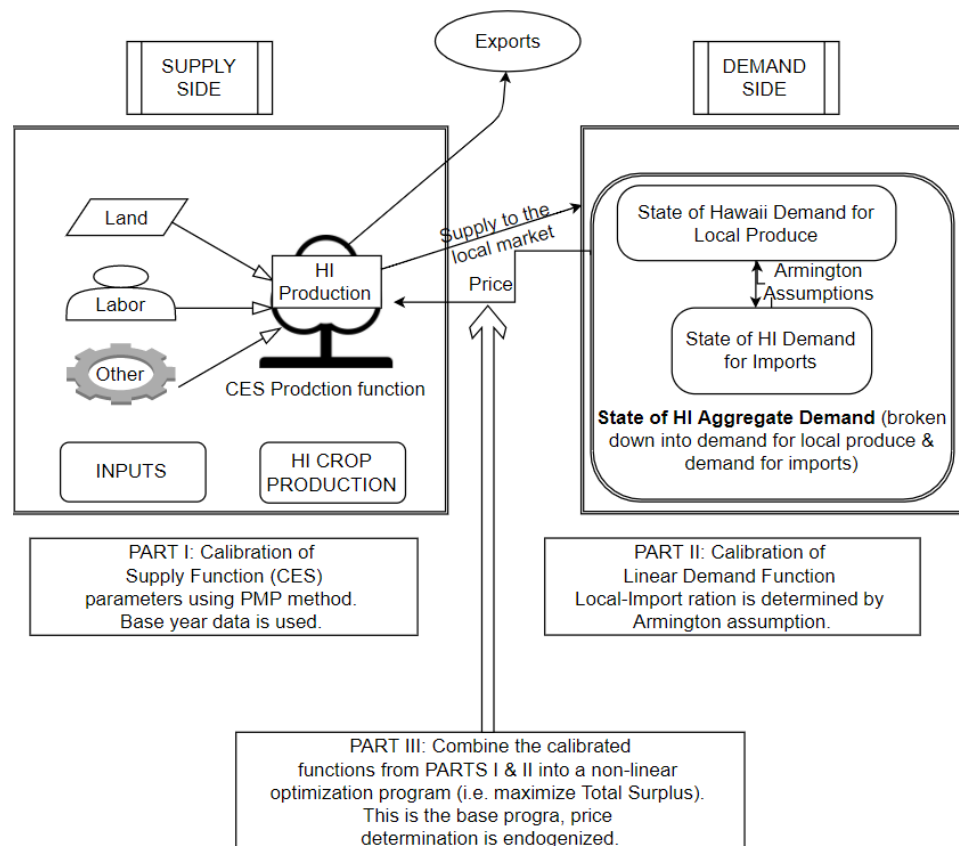
1.4 Methodology and data for calibrating a local food system

The present framework is built upon the previous work by Lee et al. (2016) on Hawaii's local food systems, with several developments and extensions. The production module is disaggregated at the county level, instead of the state-level. This allows us to account for county-level heterogeneity and track the economic effects of agriculture policy more in detail. Furthermore, output prices are endogenously determined. This allows the program to determine new equilibrium prices (simulated), in response to proposed policy shocks.

We illustrate the calibration phase in a schematic presentation in Figure 1.1, where we can see that there are three parts in the procedure. **Part I** or the supply side of the program utilizes the latest one-step calibration procedure adopted from Garnache et al. (2017). This latest PMP framework solves the previously existing limitation of the PMP models in solving for the

shadow values in optimization programs. Our model includes the supply functions of 22 crops across the four counties of Hawaii. Overall, there are 88 unique production functions that we calibrate on the supply side.

Figure 1. 1 Components of the calibration procedure



Part II constructs the consumer side of the market following Howitt et al. (2012). We assume downward-sloping demand functions for all foods, which allows our model to incorporate the consumer side, and provides a mechanism to determine the value of the consumer surplus (Howitt et al., 2012). Furthermore, our model also accounts for substitution between local and non-local foods using an Armington assumption (Armington, 1969). The Armington first-order condition is based on a consumer utility maximization problem involving

the demand for local versus imported goods (in our case, demand for local versus non-local foods).

Finally, **Part III** constructs a nonlinear (base) program, combining Parts I and II. This is the final program of the calibration phase i.e. the base program. The base program is used to first ensure that the calibrated model reproduces observed base year conditions and then it is provided with policy shocks to simulate policy outcomes.

We construct county-level production data for each of the crops from the Hawaii Census of Agriculture for 2012 for 22 food crops. Since the county-level data is not complete due to many disclosure restrictions imposed by the USDA, we resort to interpolation of some of the data are at the county-level². The collated base-year dataset contains crop-level data for 4 counties of Hawaii, covering 22 food crops for the year 2012. Out of the 22 local foods crops covered in our study, 17 crops are considered to be local foods, namely, cabbage, cucumber, eggplant, lettuce, other vegetables, taro, tomato, basil, ginger, other herbs, banana, other fruits, papaya, dry onion, green onion, sweet-potato, and watermelon. The remaining five crops, i.e., coffee, macadamia nut, pineapple, sugarcane, and seed corn are export crops. Although all of 22 crops are considered for calibration purpose, only the local foods are considered for the calculation of various economic values attributed to the local foods in this study, for example, when we calculate the total producer surplus generated or total GET collected from local foods, etc. The four counties of Hawaii are Honolulu, Big Island (Hawaii), Kauai and Maui. Table 1.1 summarizes production data for these food crops.

² Approximately 18-20% of the county-level data needed interpolation.

Table 1. 1 Summary of 22 food crops – state-wide acreage, production, farm-gate price, and sales value from Hawaii Census of Agriculture, 2012.

Crop	Acreage (acres)	Production (pounds)	Farm-gate Price/lb (USD)	Value of farm- gate sales (USD)
Seed	6,800	13,040,000	19.38	252,715,200
Pineapple	12,600	415,800,000	0.32	133,056,000
Coffee	9,673	13,757,180	4.8	66,034,464
Macadamia Nut	17,773	52,360,298	0.78	40,841,032
Other vegetables	1,622	13,332,135	0.8	10,665,708
Sweet-Potato	2,848	18,700,000	0.55	10,285,000
Papaya	1,916.5	27,900,126	0.35	9,765,044
Lettuce	464.7	3,565,795	2.66	9,485,015
Other herbs	371	2,927,462	2.71	7,933,422
Banana	919	12,107,353	0.65	7,869,779
Tomato	828.7	10,557,184	0.69	7,284,457
Basil	210	4,200,000	1.55	6,510,000
Cucumber	434.4	6,995,596	0.57	3,987,490
Watermelon	540	13,122,000	0.3	3,936,600
Cabbage	422.2	10,775,198	0.31	3,340,311
Eggplant	100	3,300,000	0.98	3,234,000
Onion, dry	208	1,737,905	1.21	2,102,865
Onion, green	85	1,420,855	1.39	1,974,988
Sugar	17,500	2,828,000	0.32	904,960
Other fruits	161.05	456,375	1.97	899,059
Taro	114	820,723	0.67	549,884
Ginger	14	221,392	1.4	309,949

In the following subsections, we describe each part of the calibration procedure in detail along with the equations representing the local food model.

1.4.1 Production Module

In order to construct an optimization program, we first define the production functions for I activities (crops) utilizing up to J inputs and resources (land, labor, and water)³ for each of the geographical locations g (four counties of Hawaii) as follows

$$q_{g,i} = \alpha_{g,i} \left(\sum_j \beta_{g,i}^j (x_{g,i}^j)^{\rho_i} \right)^{\frac{\delta_i}{\rho_i}}. \quad (1.1)$$

Here $\mathbf{x}_{g,i} = (x_{g,i}^1, \dots, x_{g,i}^J)$ is the vector of inputs j used in activity i in county g . Each crop is produced q_i amount, where $\alpha_{g,i}$ is the CES technology parameter, $\rho_i = (s-1)/s$ where s is the elasticity of substitution between inputs. Following Howitt et al. (2012), we assume the elasticity of substitution parameter to be 0.22 in order to reflect the fact that in the agricultural sector, the elasticity of substitution between inputs is quite low. δ is the returns to scale parameter. Furthermore, $\boldsymbol{\beta}_{g,i} = (\beta_{g,i}^1, \dots, \beta_{g,i}^J)$ is the vector of share coefficients of each of the inputs and resources used in activity i in county g .

Since our CES production function is strictly concave, we specify our expenditure functions as linear in input quantities. This allows for smooth responses to policy shocks and without needing any ad-hoc parameters to calibrate. Our expenditure functions are as follows:

$$e_{g,i}^1(c_{g,i}^1, x_{g,i}^1) = (c_{g,i}^1 + \mu_{g,i}^1)x_{g,i}^1 \quad (1.2)$$

$$e_{g,i}^j(c_{g,i}^j, x_{g,i}^j) = c_{g,i}^j x_{g,i}^j \quad \text{for } j \geq 2; \quad (1.3)$$

³ Other input costs are incorporated into the land cost component $c_{i,l}$, as in the previous work by Lee et al. (2016)

Here $c_{g,i}^j$ is the cost of input or resource j in activity i . And $e_{g,i}^j$ is the function representing the expenditure on production factors. The term $\boldsymbol{\mu} = \mu_{g,1}^1, \dots, \mu_{g,i}^1$ represents the entire vector of per acre unobserved costs/benefits for each of the I activities.

The profit-maximization program is as follows, subject to available lands in each county, b_g and county-specific shadow value λ_g .

$$\begin{aligned} \max_{x \geq 0} \sum_{g=1}^G \sum_{i=1}^I \left(p_{g,i} \alpha_{g,i} \left(\sum_j \beta_{g,i}^j (x_{g,i}^j)^{\rho_i} \right)^{\frac{\delta_i}{\rho_i}} - \mu_{g,i}^1 x_{g,i}^1 - \sum_j c_{g,i}^j x_{g,i}^j \right) \\ \text{subject to } \mathbf{x}_g^1 \leq \mathbf{b}_g \end{aligned} \quad (1.4)$$

Without the need for a calibration by the program, we can determine the returns to scale coefficient, δ_i parameter from an exogenous value of the supply elasticity, η for simplicity – termed as myopic δ_i^{myopic} (Garnache et al., 2017). Garnache et al. (2017) show that the returns to scale coefficient δ_i is related to the supply elasticity, η as:

$$\delta_i^{myopic} = \frac{\bar{\eta}_i}{1 + \bar{\eta}_i} \quad (1.5)$$

Here $\bar{\eta}_i$ represents supply elasticities, which are exogenous to the system and thus obtained from outside estimates.

Now that we have set up our model specifications, we move on to specify the programs to calibrate the production parameters. The PMP calibration procedure offered by Garnache et al. (2017) addresses the last remaining criticism regarding the calibration of shadow values. We conduct our calibration based on this new technique, where all unknown parameters and the shadow values will be calibrated based on the original model specifications in one single step without needing any additional constraints or ad hoc measures. In our calibration, $\bar{\lambda}_g$ represents

county-specific shadow values of constrained resources i.e. land. Following Garnache et al. (2017), we setup our calibration to minimize the sum of squared errors between observed expenditures and model expenditures as follows.

$$\min_{\bar{\lambda} \geq 0} \sum_g \sum_{i=1}^I (\mu_{g,i}^1(\bar{\lambda}_g) \bar{x}_{g,i}^1)^2 \Leftrightarrow \min_{\bar{\lambda} \geq 0} \sum_g \sum_{i=1}^I (p_{g,i} q_{g,i} \delta_i(\bar{\lambda}_g) - \sum_j c_{g,i}^j x_{g,i}^j - \bar{\lambda}_g A_{g,i} \bar{x}_{g,i})^2 \quad (1.6)$$

This optimization program is used to calibrate all necessary parameters, subject to several constraints to capture the base year characteristics. First, all production levels $q_{g,i}$ are constrained to the base year level as specified in equation (6), and the input share parameters β_j^i sum to one. First-order conditions for crop-level profit-maximization from equation (9) form the next set of constraints. The error minimization program (11), coupled with these base-year optimization constraints, leads to the calibration of all production side parameters.

Our production dataset, used for calibrating these production functions, contains acreage, resource inputs, input costs, production levels and a set of parameters, such as own-price elasticity of demand, Armington elasticities, and input substitution parameters for the CES production functions, are collected from the literature. Farm-gate price is collected from the Statistics of Hawaii Agriculture. Retail prices have been set at 100% retail markup on respective farm-gate prices.

Relative import prices: The relative price of non-local foods here is assumed to be one in the baseline condition. A change in price, such as due to sales tax differential, would lead to a change in the relative price, thus will lead to a new non-local consumption share as per the Armington assumption. We checked our simulation results with different relative price of non-local foods (0.80 versus 1.00), as the baseline condition. As we will explain later in the results section, the two relative prices lead to very similar simulation results.

1.4.2 Demand Functions

Consumption data is constructed for each crop using U.S. per capita consumption coupled with Hawaii's population. The share of non-local foods in local consumption is identified using inshipment data from Hawaii Statistics of Agriculture for each of the crop similar to the previous study of Hawaii's local food system by Lee et al. (2016).

Since consumers of Hawaii depend on non-local sources for 88% of their foods (Loke and Leung, 2013), it is important to include this feature in our model. The quantitative analysis depends upon the elasticity of substitution between local and imported foods following Armington (1969) in order to capture the role of non-local foods in Hawaii's local food system. In our model, we assume that the consumers make a rational decision in a two-stage procedure. First, they choose the amount of their total consumption by maximizing utility, which is represented by the demand functions for each crop, for which we determine two parameters θ_{0i} and θ_{1i} in the previous section (4.1). In the second phase, consumers decide on the shares of local and non-local goods. For a particular food i , consumers prefer Q_m amount of non-local food and Q_l amount of local foods such that their composite demand for food i is

$$Q_i = Q_{i,l} + Q_{i,m} \quad (1.7)$$

For this purpose, we use Armington elasticity of substitution between quantities of local foods and imported foods (in our case, non-local foods). The substitution is based on the assumption that the share of non-local consumption will depend on the relative prices of local and non-local foods that are substituted for each other. The rate of substitution will depend on a constant rate, the Armington elasticity of substitution when the relative prices change. For

example, an Armington substitution elasticity of 1.48 for lettuce means that a 1% increase in price for local lettuce relative to non-local will lead to a 1.48% increase in the non-local-to-local ratio of lettuce consumption. Therefore, under current market conditions (such as relative prices), consumers' problem is to maximize their utility by choosing the shares of local and non-local foods. The first order condition of this utility maximization problem is described by the following equation which relates the ratio of non-local and local food quantities to the relative prices as follows (see, for example, Xu et al. 2015a uses this equation to determine the Armington elasticity of substitution for lettuce in Hawaii food market).

The utility function is as follows

$$U_{consumption} = \left[\gamma Q_{i,m}^{\frac{\sigma-1}{\sigma}} + (1 - \gamma) Q_{i,l}^{\frac{\sigma-1}{\sigma}} \right]^{\sigma/(\sigma-1)} \quad (1.8a)$$

$$\frac{Q_{i,m}}{Q_{i,l}} = \left[\left(\frac{\gamma_i}{(1-\gamma_i)} \right) \left(\frac{P_{i,l}}{P_{i,m}} \right) \right]^{\varepsilon_A} \quad (1.8b)$$

where γ_i is the share coefficient⁴.

The relationship between retail prices and farm-gate prices: Following the SWAP model, we relate the crop price at retail P_i to its farm-gate price p_i by using a retail markup conversion. This conversion involves the retail markup rate rmu_i for each crop i .

$$P_i = p_i(1 + rmu_i) \quad (1.9)$$

We construct the demand functions following the procedures developed in Howitt et al. (2012) for the California Statewide Agricultural Production Model (SWAP) based on PMP

⁴ For the original work on Armington Elasticity of Substitution, please refer to Armington (1969). This parameter is widely used in models involving consumer theory and international trade. In our framework, any food sourced from outside of the State of Hawaii, such as from the U.S. mainland and foreign countries are considered non-local and represents the import part of the Armington formulation.

principles. The interaction between the supply functions and the demand module will lead to equilibrium prices and quantities. The demand functions are constructed as linear and downward sloping represented by the following equation:

$$P_i = \theta_{0i} + \theta_{1i}(\sum_g Q_{gi}) \quad (1.10)$$

Here P_i is retail price for each crop i ; θ_{0i} and θ_{1i} are constant and slope terms respectively of the demand function for each crop i . Q_i is consumer demand for crop i .

Now, assuming the own-price elasticity of demand ε^d is known, we can solve for the two constant terms, θ_0 and θ_1 . The slope parameter and the intercept are determined as follows

$$\theta_{1i} = \frac{\varepsilon_i^d P_i}{\sum_g Q_{gi}} \quad (1.11)$$

$$\theta_{0i} = P_i - \theta_{1i}(\sum_g Q_{gi}) \quad (1.12)$$

For equation (14), the values of own-price elasticities ε^d are collated from the literature (Lin et. al. 2009; Naanwaab and Yeboah 2012).

1.4.3 Non-linear Optimization Program and Endogenous Prices

The final outcome of our calibration procedure is a nonlinear base program, which can be used to first ensure that the calibrated model reproduces observed base year conditions. Later, we introduce shocks to this very system to determine the economic effects. This program also allows us to combine the consumer side (the demand functions, and the Armington budgeting procedure) and the production module to determine equilibrium market conditions. Thus we are able to endogenize prices. We specify an objective function so as to maximize total surplus (i.e.,

producer and consumer surplus combined) (Howitt et al., 2012). The producer surplus is for local portion only, whereas the consumers surplus accounts for the consumption of both local and non-local foods.

$$\begin{aligned} \max Total\ Surplus &= \max(Producer\ Surplus + Consumer\ Surplus) \\ &= \sum_g \sum_i (q_{g,i} P_{g,i} - \mu_{g,i}^1 x_{g,i}^1 - \sum_j c_{g,i}^j x_{g,i}^j) + \frac{1}{2} Q_i (\theta_{0i} - P_i^r) \end{aligned} \quad (1.13)$$

Our convex resource constraints include county-wise land constraints:

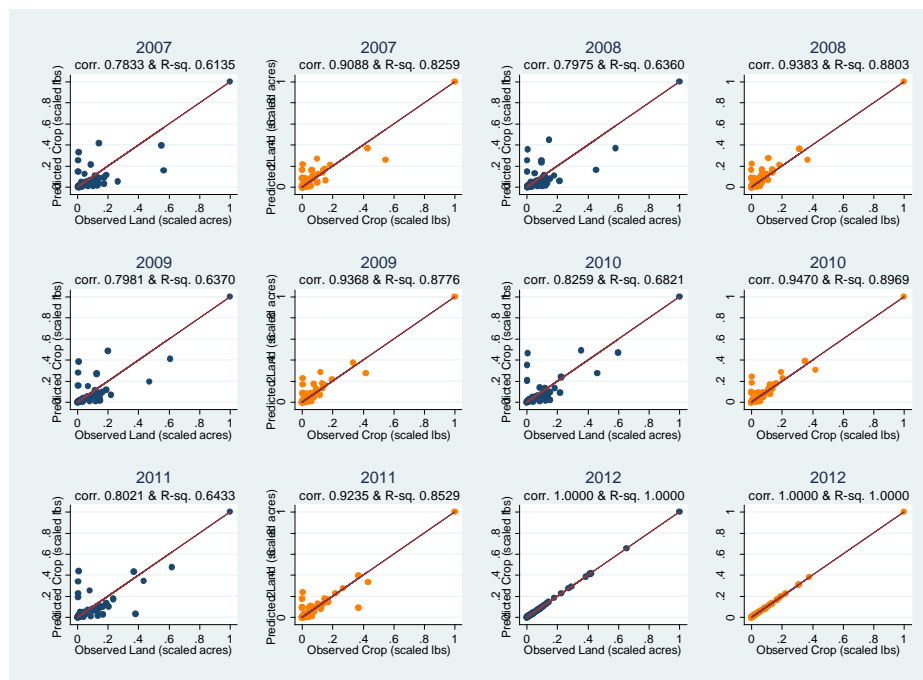
$$\sum_i x_{gi}^1 \leq b_g \quad (1.14)$$

1.5 Model Validation

In general, PMP models are known for their ability to reproduce agricultural activity reasonably well from a calibrated model. We employ our calibrated food system model from the base year 2012 to reproduce the base year activity level and also to backcast the crop production pattern of the past years (2007-2011) to assess model performance. We adjust the costs of labor for the previous years using annual farming labor cost data from Bureau of Labor Statistics for Hawaii (Bureau of Labor Statistics). We also adjust the cost of land using the data of U.S. cropland value from National Agricultural Statistics Service (NASS). Since our local food model is disaggregated at the county-level, we define our model with fixed resource constraint (land) for each county in the respective year to simulate crop-wise land allocations and crop distribution patterns for each of the four counties. We then regress predicted (simulated) levels over observed levels of resource use (land) to evaluate our model's explanatory power. We also conduct the same analysis for the levels of crop-level output (in pounds). Figure 1.3 presents the model evaluation from our analysis with correlation coefficients and R-squared values from regressing predicted over actual values. The left-hand side plots for each year are for predicted over

observed land allocation (navy) and the right-hand side plots are for crop production pattern (orange). Correlation coefficient and *R-squared* values are provided under the heading of each plot; the solid line indicates the 45-degree line representing perfect prediction. By examining the model's predictability for land allocation, we see that the minimum correlation coefficient is 0.78 in 2007 and the minimum *R-squared* is 0.6135 recorded also for 2007. All other years show better performance of the base model and as expected the further away it is from the base year (2012) predictive power diminishes. The model's performance is reasonable in simulating crop production patterns for all years. Both land allocation and crop production levels reveal the model's prediction power in a similar way. This is expected given that the production level is dependent upon land allocation, as per the model specification.

Figure 1. 2 Backcasting of resource allocation (land) using the calibrated model of the base year 2012.



Note: Axes are scaled so that the maximum value is 1 to prevent disclosure of confidential individual data.

1.6 Policy application

In this section, we employ our local food model to simulate two proposed policies. First, we discuss a background of general excise tax (GET) in local food context and summarize results from simulating the exemption of GET on local produces. Then, we provide a brief overview of the Whitmore Project and summarize the (simulated) impact of an investment (estimated) in 1,200 acres of agricultural land. Finally, we compare the two proposed policies and demonstrate how our PMP model can be used to inform policy analysis.

1.6.1 Background on general excise tax

According to microeconomic theory, an excise tax is expected to raise the prices of commodities to the consumers and reduce the net prices received by producers. It is also expected to reduce the equilibrium quantity to be marketed and consumed. This tax imposed on either consumer or seller has the exact same economic consequences (Krugman and Wells, 2006). We illustrate this scenario in Figure 1.2 in a simplified way, where imposing a tax shifts the supply curve to the left, increasing the market price and reducing quantity. In other words, a GET is expected to result in higher purchase price for the consumers, which creates a smaller market for a commodity than would otherwise exist. It should be pointed out that the present illustration (Figure 1.2) is an oversimplified version of the market forces, where the feedbacks from import demand to local and vice versa, are not explicitly shown.

Concerning this contractionary effect of GET and in expectation of recovering some of the market inefficiency, exemption of GET on Hawaii's local produce is being considered as a policy tool to energize the local food market. The hope is that this may induce residents to buy

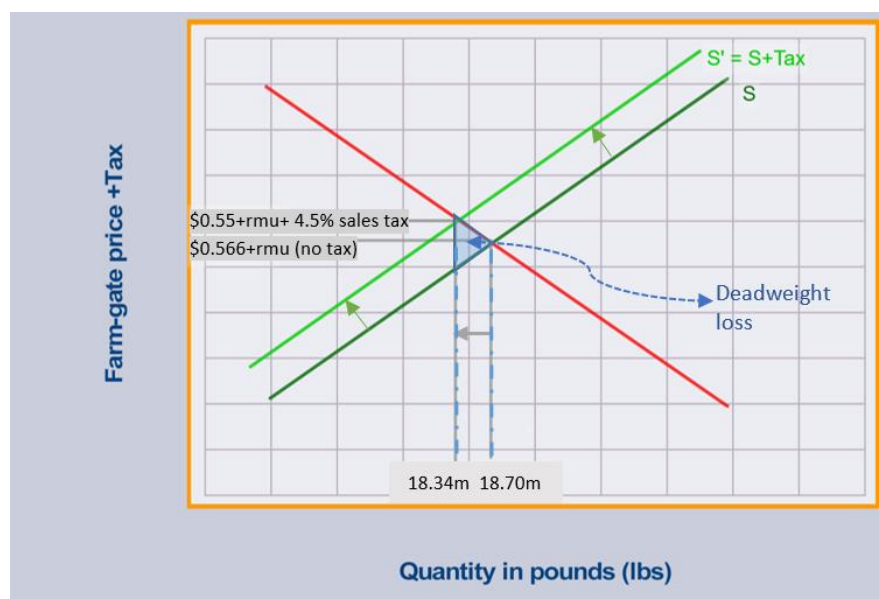
more local foods. Sales tax burden in Hawaii remains the highest in the nation with \$50.07 per \$1,000 of personal income (Laffer et al., 2015). Laffer et al. (2015) also pointed out that higher tax burden on residents may have a counterproductive effect on tax revenue via lack of economic activity and slower regional growth.

Currently, Hawaii retailers collect from buyers a GET⁵ of 4.5% on both local and imported food items at retail stores. In Figure 1.2, we illustrate a comparison of equilibrium prices and quantities of sweet-potato between actual market condition with tax and a simulated condition assuming no GET. If there were no tax on sales of sweet-potato, our model estimates that the farm-gate (producers') price would increase from \$0.55 to \$0.566 per pound. Although the farm-gate price is higher in this simulated case, the final out-of-pocket price for consumers will still be lower than previous final price including tax. For example, the current final price with 100% retail markup is \$ 1.1495 (\$ 0.55 farm-gate rice + \$0.55 retail markup + \$0.0495 GET at 4.5%). On the other hand, the final price is lower at \$1.132 (\$0.566 farm-gate price + \$0.566 retail markup at 100% + \$0.00 tax) under the no-tax scenario. According to our model simulation, the aggregate quantity in equilibrium would be higher in the no-tax scenario at 18.70 million pounds, as opposed to the existing actual equilibrium volume of 18.34 million pounds. These differences in price and quantity allow us to estimate the deadweight loss created by imposing the tax, which is depicted by the blue triangle in Figure 1.2. We estimate the value of the deadweight loss for all crops combined to be \$ 14.83 million annually.

⁵ GET stands for General Excise Tax, which is levied on gross income of business activities in Hawaii and is imposed on businesses instead of the consumers as in GET. The current GET imposed on sales of food items at the retail level in the City and County of Honolulu is 4.5%, but businesses can charge their customers up to 4.712%. While the GET rate of the other counties in Hawaii is at 4.0%, for the purpose of this analysis, we use 4.5% uniformly throughout. Since most of Hawaii's demand for food comes from Honolulu (with about 70% of the state population), we believe that the assumption of 4.5% GET across the board is relatively reasonable. More details can be found here: <http://tax.hawaii.gov/geninfo/get/>

This simulation exercise indicates the model's capability to realistically capture the efficiency loss in the market due to the GET. Next, we use our model to estimate the economic benefit that can be generated if the GET can be exempted exclusively on the sales of local produce.

Figure 1. 3 (Simplified) illustration of the effect of GET. Adapted from: “Microeconomics”, Krugman and Wells (2015).



1.6.2 Simulation results of GET exemption on local foods

Our model, equipped with a market clearing module and an Armington budgeting procedure, allows us to study the effect of policy shocks on demand side of the market. By simulating this shock of GET exemption exclusively on local produce, we expect each crop to be consumed in higher quantity, thus generating higher consumer surplus. Since relative prices (including the GET) for non-local foods are now relatively higher under the proposed GET policy, some of the imports will be replaced by cheaper local foods. This substitution is

determined by the Armington budget condition illustrated in equation (16). According to the Armington model (Armington, 1969), the non-local to local ratio of consumption quantity is inversely related to the relative price of non-local goods. Lower final prices of local produce (i.e. higher relative price of non-local foods) will encourage consumers to substitute local foods for non-local versions. In Table 1.2, we present the simulated changes in farm-gate prices in response to the GET exemption. After GET exemption, farm-gate prices are higher than original prices. Although farm-gate prices have increased due to the exemption of GET, final prices will be still lower for the consumers at the retail level due to the absence of any GET. For example, the farm-gate price of sweet-potato is increased from \$0.55 to \$0.569 per pound - a 3.45% increase due to GET exemption. This is in line with the economic rationale discussed above in subsection 5.1, which purports that the change in price is expected to be positive but less than the tax rate exempted. For all other crops, we see similar positive changes. In summary, consumers and producers share the tax burden, therefore both benefit from dropping the tax.

Relative import prices: As discussed earlier, we assume the relative price of imports to be one. However, for robustness check, we checked for (base-year) relative import price of 0.80 also. In Appendix Table A3, we illustrate the case of local GET exemption (change in demand and farm-gate prices due to the exemption) using both the relative prices as the baseline condition, and we can see that the differences in simulated results are negligible. Since our present model captures the market only in a partial equilibrium context, which ignores other sectors of the economy - a GET exemption from either base-year relative price leads to very close results. In future models, however, this check should be conducted again to ensure that the present price assumption holds valid in new modeling criteria.

Table 1. 2 Impact of GET exemption (local foods) on farm-gate prices of 17 local food crops

Crop	Farm-gate price		
	After GET		
	With GET	exemption	Change
Banana	0.65	0.66	1.54%
Basil	1.55	1.61	3.87%
Cabbage	0.31	0.32	3.23%
Cucumber	0.57	0.58	1.75%
Eggplant	0.98	1.01	3.06%
Ginger	1.4	1.44	2.86%
Lettuce	2.66	2.75	3.38%
Other fruits	1.97	2.03	3.05%
Other herbs	2.71	2.80	3.32%
Onion, dry	1.21	1.25	3.31%
Onion, green	1.39	1.43	2.88%
Other vegetables	0.8	0.82	2.50%
Papaya	0.35	0.36	2.86%
Sweet-Potato	0.55	0.57	3.45%
Taro	0.67	0.69	2.99%
Tomato	0.69	0.71	2.90%
Watermelon	0.3	0.31	3.33%

In Table 1.3, we present the effects of the GET exemption (local foods) on the consumption levels and consumer surplus for local food crops. In column (1), changes in equilibrium quantity for each of the 17 local crops are all positive but small, and they range between 0.01% (other fruits) to 0.96% (other herbs). Increases in consumer surplus are relatively higher, which is in line with the fact that consumers now also pay less per pound of consumption

due to the GET exemption. The increases in consumer surplus range from 0.17% (cabbage) to 1.92% (other herbs).

Table 1. 3 Impact of GET exemption on quantity and consumer surplus.

Crop	Change	
	Equilibrium quantity	Consumer Surplus
Banana	0.22%	0.86%
Basil	0.38%	0.77%
Cabbage	0.08%	0.17%
Cucumber	0.89%	1.84%
Eggplant	0.74%	1.73%
Ginger	0.08%	1.03%
Lettuce	0.10%	0.45%
Other fruits	0.01%	0.97%
Other herbs	0.96%	1.92%
Onion, dry	0.02%	0.21%
Onion, green	0.13%	0.32%
Other vegetables	0.15%	0.54%
Papaya	0.73%	1.55%
Sweet-Potato	0.80%	1.81%
Taro	0.05%	0.26%
Tomato	0.33%	0.76%
Watermelon	0.58%	1.48%

Further, we also present expected change in economic welfare from this proposed policy in Table 1.4. Here, we see that total consumer surplus increases by \$2.72 million, and total producer surplus would increase by \$4.66 million. Combining both increases, we find a welfare

gain of \$7.39 million against the loss of Hawaii's GET tax revenue by \$ 6.27 million. While there is an estimated net gain of \$1.12 million ($=\$7.39-\6.27 million), it should be noted that there would still be some public and private technical and administrative costs involved in implementing this particular proposed policy. For example, retail stores would have to establish two additional codes for every food crop, local and import, in order to implement the GET exemption – which would require some more administrative costs. Also it may be pointed out that of the \$14.83 million in dead-weight loss caused by GET on these food crops, only \$1.12 million would be recouped by dropping GET on the local crops. However, producer surplus gain is much larger – which is a major objective.

From this analysis, the proposed policy can potentially generate welfare worth of \$118 per \$100 of policy cost. Although the policy may create more benefits than its costs, there lie some important distributive questions stemming from the policy implications, such as whether a tax exemption on local produce can benefit all residents homogeneously. For example, if people with higher income disproportionately consume more local produce, the tax exemption may not directly benefit people with lower income. Although it is beyond the scope of the present paper, it may be important to consider and evaluate the tax-exemption policy as a transfer of wealth from taxpayers to farmers and wealthier purchasers of local foods. Another key question is whether an exemption on GET for local foods only would be a legitimate policy in the United States (i.e. discriminating against products from other U.S. states) or in a World Trade Organization (WTO) sense. Policy-makers should consider evaluating these issues among others to ensure viable policy decisions.

Table 1. 4 Calculation of economic benefit (welfare) per dollar of policy cost (tax revenue loss).

Estimated Surplus and Forgone Tax Revenue	Million \$
Increase in consumer surplus	2.72
Increase in producer surplus	4.66
Increase in total surplus (welfare gain)	7.39
Tax revenue loss due to GET exemption	6.27
Benefit per \$100 cost (tax revenue loss)	118 (in \$)

Similar to the simulation above, next we employ our local food model to examine the effects of an agricultural infrastructure project in following sub-sections.

1.6.3 Background on the Whitmore Project

The Whitmore project is a reflection of the sentiment contained in the State’s constitution, which states its commitment to “conserve and protect agricultural lands, promote diversified agriculture, increase agricultural self-sufficiency, and assure the availability of agriculturally suitable lands” (Article XI, Section 3). Under the project in 2012, the State of Hawaii purchased 1,200 acres of land for approximately \$13 million from the Galbraith Estate and invested another \$13.75 million in the installation of irrigation systems (Star-Advertiser, October 2, 2016). The goal of the project is to dedicate these lands in perpetuity for farming so that farmers can scale up local production levels in line with the state’s local food goals.

The Whitmore project is a detailed plan by the state government to boost the local agriculture of Hawaii by creating partnerships between farmers and the government. According to the

project document “The Whitmore Project is an active, comprehensive plan to revitalize Central Oahu's agricultural landscape and economic footprint.” The goal is to increase local food production, create jobs and housing for the residents. Some of the components of the project are outlined below (Hawaii.gov).

- a. Farmland: Agribusiness Development Corporation will lease 1200 acres of land to farmers. Office of Hawaiian Affairs will own 500 acres of farmland.
- b. Agricultural Hub: There will be an agricultural-industrial park to facilitate food safety, packaging and processing facilities, and office space.
- c. Warehouse: A structure called the “Tamura’s Warehouse” will be included for additional food safety, packaging and processing facilities, storage and office space.
- d. Workforce housing: an initiative will be taken by the government to provide affordable housing for the farmers.

Overall, the Whitmore project intends to aid local farmers in a number of ways, including long-term lease options, reduction of cost and time of transportation by providing centralized facility for farming, building structures to facilitate food safety, storage, and other logistics needs, providing co-operative options to leverage the high costs of equipment, and supplies. In terms of production, the project’s aim is to divert arable land into active production and diversify agricultural products to meet consumption needs of the local residents.

1.6.4 Simulation results of an infrastructure initiative

Although it is beyond our model’s scope to capture the detailed impacts of the Whitmore project, we now employ our model to examine the economic impact of a similar change in

acreage in the Central Oahu. In this simulation exercise, we use our model to analyze the benefit and cost of a Whitmore-type project to encourage local food production by making available affordable land with necessary irrigation infrastructure in Central Oahu. However, this is by no means an evaluation of that particular project, since the present model does not contain the fine details for such an evaluation. This exercise rather attempts to capture the impact of a simplified version of the actual infrastructure. Further rigorous modeling is required for complete evaluation of an actual Whitmore-like project. Not modeling labor, for instance, is a major limitation of the current version. Therefore the simulated results should be considered as a preliminary analysis, rather than a complete evaluation of the actual project.

On the supply side of our model, the land is the only constrained input in our local food model. When this resource constraint is relaxed by increasing land availability, producers will choose a new mix of crops based on profitability and market demand. In Table 1.5, we present the simulation results of injecting 1,200 acres of land. Only crops with substantial increases in acreage are presented individually in the table and the rest of the crops are shown combined. Based on the model specification, we expect that crop-level profitability will be the driving force in determining the distribution of newly introduced agricultural lands. In Table 1.5, we can see that sweet-potato, other vegetables, tomato, banana, watermelon, cucumber, and lettuce would account for most of the new parcels (column 2). Similarly, we can see in column 3 that sweet-potato also has the highest increase in production (179,884 pounds). All other crops exhibit increases in acreage and production as well. Due to this project, all local crops exhibit decreases in farm-gate prices, which we report in Appendix Table A4. The lower relative prices of local foods lead to downsizing of the inshipment amount (nonlocal foods), which is evident in Table 1.5 (column 4). Interestingly, the decreases in inshipments are substantially lower than to the

increases in local production. This indicates that injecting 1,200 acres may lead to mostly distribution of (new) revenue among local producers, instead of substantial substitution for nonlocal foods.

Table 1. 5 Impact of 1,200 acres of land on changes in local production and nonlocal inshipment

Crop	Change in land (acre)	Change in production (lb)	Change in inshipment (lb)
Banana	132	140,634	(55,004)
Cucumber	67	72,568	(2,902)
Lettuce	34	40,970	(26,777)
O-Vegetable	198	156,783	(102,968)
Sweet-Potato	269	179,884	(12,473)
Tomato	182	72,188	(28,417)
Watermelon	91	114,764	(9,415)
Rest of the crops	226	N/A	N/A
Total change in acreage	1,200	N/A	N/A

Similar to the GET exemption scenario, here we evaluate the project in terms of economic welfare in Table 1.6. It should be pointed out that here we again assume the actual case of the market with GET still imposed on all foods to make this case (Whitmore) comparable to the previous case of the local GET exemption. The inclusion of the 1200 acres could lead to an estimated increase in consumer surplus of \$2.81 million and increase in producer surplus by \$1.12 million. Therefore, the net welfare gain from this additional land is estimated at \$3.93 million per year.

Table 1. 6 Calculation of economic benefit (welfare) per dollar of investment cost (Whitmore).

Estimated Annual Surplus and Project Cost	Million \$
Increase in consumer surplus	2.81
Increase in producer surplus	1.12
Increase in total surplus (welfare gain)	3.93
Annual project cost	1.10
Benefit / \$100 cost (project cost)	357 (in \$)

Total investment amount for this Whitmore project is \$26.75 million, comprising \$13 million for land acquisition, and \$13.75 million for irrigation systems. Our annual cost calculation assumes a 20-year life of the irrigation systems procured, and a 2% real discount rate. At 2% real discount rate, the annualized cost for the 1200 acre project is estimated to be \$1.10 million, whereas the net welfare gain is estimated by our model to be \$3.93 million per year. As a robustness check, we also check for different real discount rates of 2% & 5% (see Appendix Table A5), which still costs the state government less than the estimated welfare gain. Therefore, on annual basis, \$100 investment in Whitmore-like infrastructure development may lead to a potential economic benefit of about \$357 per year. However, it should be pointed out that the total investment of \$26.75 million could be spent on other state programs which could also generate economic welfare and we should put the comparison in this proper context. While the present model accounts for the heterogeneity at the county level, it does not take into account the specificity of the Whitmore land and thus the simulated results should be viewed as such. The model also is only a partial equilibrium model that ignores other sectors of the economy, for

example, the land employed in the Whitmore project could have a more productive use – which is not considered in the current model.

The actual Whitmore project has been on-going for a few years now but has not achieved the level as predicted by the model. This could be due to other factors (e.g. labor availability) unaccounted for by the model as well as other technical difficulties in implementing the initiative. As mentioned earlier, one important limitation is that we have not accounted for the availability of labor. Merely making affordable agricultural land available may not be sufficient and it is well reflected by the differences in the predicted model results and what is actually happening. While the present model's results from the simulation of a Whitmore-like project constitute just a possibility, further work is necessary to capture more detailed aspects of such projects.

1.7 Conclusion

Using our local food model of Hawaii to simulate economic responses, we have been able to assess proposed policies in quantitative terms. Our study sheds light on some of the crucial information on long-term improvement and sustainability of Hawaii's agricultural food systems. It is important to point out that our policy simulations do not account for the heterogeneity of the farms, due to USDA's policy on non-disclosure of farm-level data. Our model uses average profitability of crops as a proxy for the profitability of a representative farm to circumvent the modeling limitation.

It is important to address some major caveats of the present model. First, the present model treats the two policies (local GET exemption and Whitmore project) quite distinctly – for

instance, while the Whitmore project adds new land to Hawaii's agriculture, thus directly enhances local production, the former mainly creates consumer and producer surplus through changes in prices. Second, the Whitmore project is still in a developing phase and may need some time to fully reap its benefits (Dela Cruz, 2016). The unavailability of agricultural labor and irrigation water sources could be major drawbacks for successful project implementation - a rigorous project assessment can identify the improvement areas for this project. This implies that our analysis simply indicates the potential of the project, not the actual outcomes in reality, which depends on many other factors. Also, our present model does not take into account the opportunity costs of the lands in full, which may bias our estimates upward in favor of the project. Third, in our optimization problem we assume a social planner who attempts to maximize welfare – which is in reality difficult to attain and solving such optimization problem requires access to a significant amount of data. These are some of the caveats of the present model of Hawaii's food systems, which can be enriched through more rigorous modeling in the future. Therefore, the detailed results should be viewed with caution, but the general directions and magnitudes of the simulations are good indications as to what could be the economic consequences of the proposed policies. Nevertheless, we believe that this paper contributes to the fundamental research concerning an increasingly discussed agricultural and food phenomenon. At the local level, the quantitative evaluation of proposed policies will inform policymakers of rigorous economic intelligence to guide their policy debates.

The study is intended to be a working platform for many future applications as well. Our model can be tailored to model noncommercial farming, which differs from larger profit-maximization producers in terms of the agricultural goal. Incorporating infrastructure modules such as inter-island transportation, irrigation systems or water resource management, etc. can

enrich the model for future uses. These future extensions based on our work will open up the door to address many more future research possibilities.

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2 Chapter 2: Potential consequences of market-value assessment (MVA) based property tax on noncommercial farmers & some policy implications

2.1 Introduction

Agricultural land is generally taxed based on preferential terms, mainly to encourage conservation of farmland and support local agricultural production. These privileges are provided often through use-value assessment (UVA) of agricultural land instead of market-value assessment (MVA) for property tax purposes because UVA is substantially lower than MVA for farmlands and thus leads to significantly lower tax bills for eligible farmers. A move from UVA to MVA may have significant economic consequences on the agricultural activity of the relatively smaller farmers of the region in question. Therefore, it is important to evaluate the proposed policy for its impact on different groups of farmers. In the literature of agricultural land valuation, there have been several studies that have explored the significance of preferential property tax policy including use-value assessment, circuit breakers, etc. (see for example: Conklin and Leshner, 1977; Dunford, 1979; Chicoine et al., 1982; Tavernier and Li, 1995; Williams et al., 2004)⁶. However, there is not much information on how moving away from such incentive policies may affect regional agriculture. Our present study attempts to fill this gap by analyzing such a move using our extended local food production model.

⁶ Some states allow farmers to claim state income tax credits to offset their local property tax bills (known as circuit breakers programs), such as in Michigan, New York and Wisconsin. Sometimes it is in the form of a federal tax refund given to low income individuals and families whose state property tax liability is a large percentage of their yearly income (Lyons et al., 2007). More details can be found here: farmlandinfo.org.

In Hawaii, the County of Maui's agriculture land is currently assessed based on its agriculture-use value, which is based on a 1965 University of Hawaii study on the agricultural productivity of land (Land Study Bureau, hawaii.gov). However, a new bill to assess agricultural land at the market value is currently proposed by the County, mainly to increase government revenue and eliminate the disparity of tax burden among different types of properties. It is argued that some individuals abuse the current agricultural valuation system by carrying out agriculture only at the minimum level to avail substantial tax relief on their (primarily) residential property. On the contrary, farmers and ranchers believe that the new bill will dramatically increase their property taxes, making it costlier to farm, and eventually, may force them off their land (The Maui News, 2016)⁷.

In our present paper, we explore the heterogeneity of policy responses based on farm-type and emphasize its policy implications. We incorporate noncommercial farming, also known as gentleman or hobby farmers, into our positive mathematical programming (PMP) model of Hawaii's food production for this analysis. This study is expected to make three important contributions to the local food literature. First, the study incorporates noncommercial farming into Hawaii's local food model by taking into consideration the non-profit-seeking behavior of the hobby farmers. To the best of our knowledge, this is the first attempt to model Hawaii's hobby farmers for policy analysis. Second, by demonstrating the case of Maui's proposed policy to move away from UVA and capturing heterogeneous responses, our study demonstrates the importance of considering responses of different farm-types to policy changes. Third, the study lays the

⁷ New rates & MVA-based assessments can be found here: <http://mauiexclusiverealestate.com/maui-property-tax-rates-for-2014-2015/>

foundation for future modeling of heterogeneous farm-behavior for various policy analyses, such as for designing federal or state level farm programs (see Woods, 1987).

The rest of the paper is organized as follows. The next section provides a brief overview of noncommercial farmers. Section 3 presents a relevant literature review and section 4 describes the empirical methodology and data. Section 5 presents the simulation results and discusses some key policy implications, and finally, section 6 concludes.

2.2 Brief background on noncommercial farmers

2.2.1 Definition of noncommercial farms and their farming goal

According to the U.S. Department of Agriculture (USDA), farms with gross cash farm income (GCFI) of \$ 10,000 or less are classified as noncommercial farms⁸. GCFI is chosen because it is a complete measure of the revenues received by the farm business. It includes farm business income from all sources—sales of commodities, government payments, and other farm-related income—while excluding income received by landlords and production contractors. (Hoppe et al. 2010)

Noncommercial farms are particularly distinct from other size groups in a number of ways. While commercial farms are motivated by profit and operate as businesses, their noncommercial counterparts are losing money on average and would not continue to farm if they were seeking profits (Blank, 2002). Noncommercial farms, in fact, make up 54% of all farms by number in the United States. Most operators of noncommercial farms have a nonfarm job as their

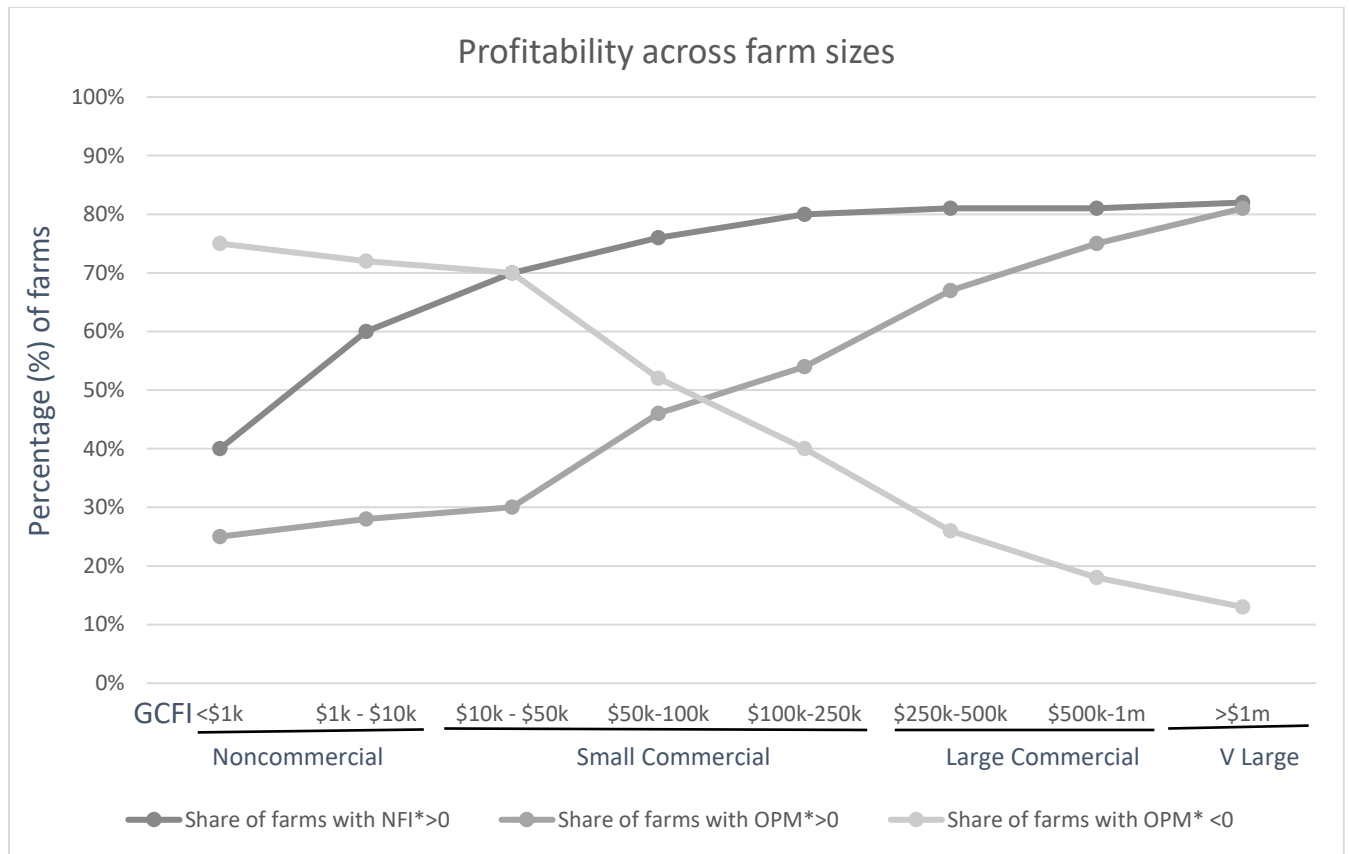
⁸ In the USDA report, Hoppe et. al (2010) divided the US farms into four size classes based on GCFI - noncommercial farms (sales less than \$10,000), small commercial farms (GCFI of \$10,000-\$249,999), large farms (GCFI of \$250,000-\$999,999), and very large farms (GCFI of \$1 million or more).

major occupation, while some are no longer in the paid workforce (Hoppe et al., 2010). They accept losses for reasons beyond being a profitable farm, such as receiving long-term capital gains, sheltering off-farm income from taxation, living a rural lifestyle, and holding onto the homestead over multiple generations. These farms are likely to exist, as long as their losses justify the benefit that they get from farming and the losses can be covered by off-farm income after meeting living expenses (Hoppe et al., 2010).

2.2.2 Profitability and productivity of noncommercial farms in the United States

The USDA report (Hoppe et al., 2010) also gives a picture of the relative profitability of different size groups of farmers. Figure 2.1 summarizes some of the report's findings. In figure 2.1, the red line indicates the percentage of farms generating negative operating profit margin (OPM) in each size group. We can see that approximately 75% of noncommercial farms have negative operating profit. On the other hand, less than 20% of very large farms fall into this category. The blue line represents the percentage of farms with positive net farm income. Finally, the green line represents the percentage of farms with positive operating profit, where we see that the percentage of profitable farms increases with the size of the farms. This confirms the fact that smaller farms are systematically less profitable and the majority of the noncommercial farms are operating at loss.

Figure 2. 1 Profitability across different farm sizes in the United States



* GCFI stands for Gross cash farm income, used for farm-type classification by USDA

**NFI & OPM stands for net farm income and operating profit margin, respectively.

Source: Constructed by authors from data presented in Hoppe et al. (2010).

2.3 Literature Review

The original argument on the efficient policies to tax agricultural properties started in the nineteenth century. George (1884) initiated the arguments on site value taxation in the context of rapidly growing cities, such as San Francisco, where worthless land was becoming expensive due to the influx of new residents (Bird and Slack, 2002). In modern days of urbanization, agricultural

lands close to urban areas rapidly become susceptible to development, making it difficult to maintain agricultural lands. This concern encourages many policymakers across the globe to differentiate between agricultural land and urban land for property tax purposes, although economic theory consistently suggests that such discrimination does not allow for the most efficient use of natural resources (Hady and Sibold, 1974; Dunford and O'Neill, 1981).

There are both theoretical and empirical studies in the literature addressing areas related to agricultural property tax, farmland conservation, and policy impacts. The theoretical studies have a wide range of methodologies and research questions. Tavernier and Li (1995) developed an agricultural model based on search theory and theoretically showed that farmland preservation under UVA is dependent on farm income and volatility in the real estate market. Other theoretical works have studied the relative merits of different assessment methods, or the effects on the timing of development using an optimal timing model (for example, Anderson and Bunch, 1989; Anderson 1993). Using comparative statics analysis, Anderson (1993) showed that development is delayed when agricultural land is assessed in its actual use rather than its highest or best use, such as conversion. Nelson (1992) argued that UVA has limited success in preserving farmland and mainly leads to speculation. There have been debates on the expected relationship between preferential farmland tax and farmland values (Deaton and Mundy, 1975; Bevins, 1975), the required time for the effectiveness of such tax policy on creating substantial benefits for farmers (Schwartz et al., 1975; 1976), etc. There have been empirical studies that examined the impact of preferential assessment on property tax shifts and related consequences. Conklin and Leshner (1977) studied two counties in New York and found that the effectiveness of use-value assessment of farmland in delaying land conversion was not substantial. Although some studies attempted to address heterogeneous farm behavior, for example, Mills (1981) found that two similar parcels

(equidistant from city center) may differ in their choice and timing of development, the literature lacks rigorous studies to capture responses from farms of different nature and size.

Across the United States, all 50 states give some form of tax relief to agricultural land mainly to preserve it from development for urban use. One of the most widely used methods is to value agricultural land based on its current use, known as use-value assessment (Anderson and Griffing, 2000). Although it may seem to be an effective policy, some studies have argued that this kind of preferential tax rate may not be the key to preserving agricultural land, because the tax differential must be big enough to compensate owners for the forgone capital gain from developing the land (Maurer and Paugam, 2000).

However, this preferential tax for agricultural land along with other factors gave birth to many hobby farmers across the United States. A study by Gaffney (1993) did not agree that property tax relief for agriculture land would be good for farmers and showed that it would attract those looking for tax shelters and speculative investments. His study also pointed out that such nonproductive incentives would ultimately inflate land values overall, making it increasingly difficult for working farmers to access and maintain acreage for the viable agricultural enterprise. Ikerd (2001) pointed out that farmers in the US, historically, have been advised to get bigger or go out of business, but many of these small farmers somehow cope with the market forces and do not expand or become commercial. These noncommercial farms continue to survive on their incomes from outside farming and owners of these farms seem to gain non-monetary benefits from the rural lifestyle (Hoppe et al., 2010).

Hawaii attracts many hobby farms on its islands because of its friendly living environment and beautiful climate. As a result, there are many farmers carrying out agriculture in the islands as a hobby along with larger commercial farms. Arita et al. (2012) studied Hawaii's agricultural farms

across size groups and compared them with those of the U.S. mainland. The study found that the output-input ratio of Hawaii's noncommercial farms is only 0.23, while those of large commercial farms and very large commercial farms are 1.21 and 1.03 respectively. The study also found a negative return on asset (ROA) for noncommercial farms (-1.1%), whereas the ROA's for large and very large commercial farms are positive (1.9% and 0.8% respectively). According to the same study, net operating profit per acre is -\$332 and gross operating profit per acre is -\$190 for noncommercial producers in Hawaii. This is in line with the overall findings for U.S. noncommercial farmers, who operate under loss and generate much less output than their commercial counterparts. While this study reflects the profitability and general characteristics of noncommercial farms of Hawaii, there is no study as yet that systematically examines how this segment of producers would respond to major policy change or how prone they are to urban sprawl.

Recently, after the County of Maui authority communicated its plan to base its property tax on market-value assessment, farmers and ranchers expressed their concerns about the increasing tax burden (The Maui News, 2016). On behalf of the Agriculture Working Group (AWG), Maui-based economist Margaret Stumpp expressed concerns about the urbanization of agricultural land on Maui. In her study, she made use of the publicly available property tax database, which includes assessed land value, classification of land, and property tax data for each Maui Tax Map Key (TMK) ⁹. From this database as of August 2015, she identified 4,620 agricultural properties and compared five alternative assessment approaches, namely “CPI inflation adjustment of all land”, “NASS¹⁰ valuation application to all Maui properties”, “Hawaii county assessment approach”, “Oahu modified market valuation approach”, and “MVA-based

⁹ This is available from the Maui State government site, URL: <https://www.mauicounty.gov/1032/Download-Public-Information>

¹⁰ National Agricultural Statistics Service (NASS) regularly publishes the estimates for agricultural land values. These census figures can be used to benchmark farm real-estate values (usda.mannlib.cornell.edu).

approach for all Maui agricultural properties”. The purpose of the comparisons is to explore how MVA-based assessment substantially increases the tax burden for mostly real farmers, whereas the other four methods are widely practiced policy for agricultural land valuation but without the burdensome impact on farmers. According to her rigorous analysis of the potential increase in tax burden, Maui’s farmers will face an average 750% increase in their tax billings (Stumpp, 2015). Also, her analysis projects that smaller, noncommercial farms located near more expensive areas will naturally face more tax burdens. Although the intent of the proposed MVA-based property tax policy is to discourage the waste of land by non-farmers, who farm minimally only to avail the tax benefits, this can also mean that Maui’s noncommercial farmers will bear a substantial amount of tax burden as a consequence.

In the present paper, we calibrate farm-type specific PMP models for commercial and noncommercial farming to evaluate the consequences of the proposed MVA-based policy on the local agriculture. By doing so, we expect to shed light on heterogeneous policy responses across different farm-types in Hawaii. Previously, mathematical programming (MP) models were not deemed useful for policy analysis because of their inability to reproduce the observed farm activity and their tendency to produce jumpy responses in simulations (Buysse et al., 2007). However, Howitt (1995) has renewed the interest in using MP in agricultural policy analyses, by enabling it to provide a more realistic representation of agricultural supply responses by providing calibration procedures whereby the base year of observed behavior can be replicated exactly, yielding smoother responses in simulation exercises (Heckelei and Britz, 2005). Overall, the appropriateness of the PMP approach to model noncommercial farming can be justified by at least two important benefits. First, PMP models can be constructed from a minimal dataset, which is particularly advantageous given the fact that data for noncommercial farmers of Hawaii is scarce

and time-series data are unavailable or inaccessible. Second, by modeling various resource and policy constraints explicitly as an inherent part of the model, it is possible to capture responses of agricultural activity to a change in policy in a more realistic way. Therefore, we believe that the PMP model of Hawaii's agriculture is well suited for the policy analyses of our interest at hand.

Because of the above-mentioned advantages, PMP models are increasingly being used to study agricultural and environmental policy implications. For example, the Regional Environment and Agriculture Programming (REAP) models in the US are developed to investigate potential economic and environmental effects of proposed animal waste management policies on a regional basis (Johansson et al. 2007). The Common Agriculture Policy Regional Impact (CAPRI) models in Europe are regularly used for ex-ante impact analysis for regional agriculture and international trade policies in Europe (Gocht & Britz, 2011).

2.4 Model modification and data

In this section, we extend our Hawai'i's local food model developed in our previous paper Khan et al. (2017) to incorporate noncommercial farming. First, we describe our data and distinguish between commercial and noncommercial farming in the context of Hawai'i's food production. Then we specify our model for commercial farming, which is based on a typical profit-maximizing assumption. Then we extend our model to capture noncommercial farming by accounting for the unobserved utility of noncommercial farming.

We obtained data for Hawaii's commercial and noncommercial farming from Hawaii Census of Agriculture for the year 2012, which is the base year for our calibration purpose. The collated final dataset contains crop-level data for 22 food crops. Out of the 22 major food crops,

13 crops are produced in Maui, namely banana, macadamia nut, papaya, coffee, other fruits, cabbage, lettuce, tomato, cucumber, sweet-potato, taro, other herbs, and other vegetables.

Table 2. 1 Comparison between Commercial & Noncommercial farming - production efficiency – for the State of Hawaii in 2012.

Crop	Production per acre (lbs)			Production efficiency of Noncommercial
	Commercial	Noncommercial	Difference	
Banana	15,305.67	4,455.70	-70.89%	29.11%
Cabbage	25,485.35	25,465.71	-0.08%	99.92%
Coffee	1,060.18	584.74	-44.84%	55.16%
Cucumber	16,104.56	16,062.56	-0.26%	99.74%
Herbs	7,686.27	2,222.12	-71.09%	28.91%
Lettuce	7,841.01	2,894.00	-63.09%	36.91%
Macadamia Nut	3,041.02	1,349.93	-55.61%	44.39%
Fruits, others	2,070.33	920.54	-55.54%	44.46%
Vegetables, other	9,400.43	5,217.14	-44.50%	55.50%
Papaya	14,620.23	11,624.02	-20.49%	79.51%
Sweet-potato	6,729.64	6,558.84	-2.54%	97.46%
Taro	44,792.48	7,524.18	-83.20%	16.80%
Tomato	12,849.26	8,156.47	-36.52%	63.48%

Figure 2. 2 Comparison between commercial & noncommercial farming – productivity per acre.

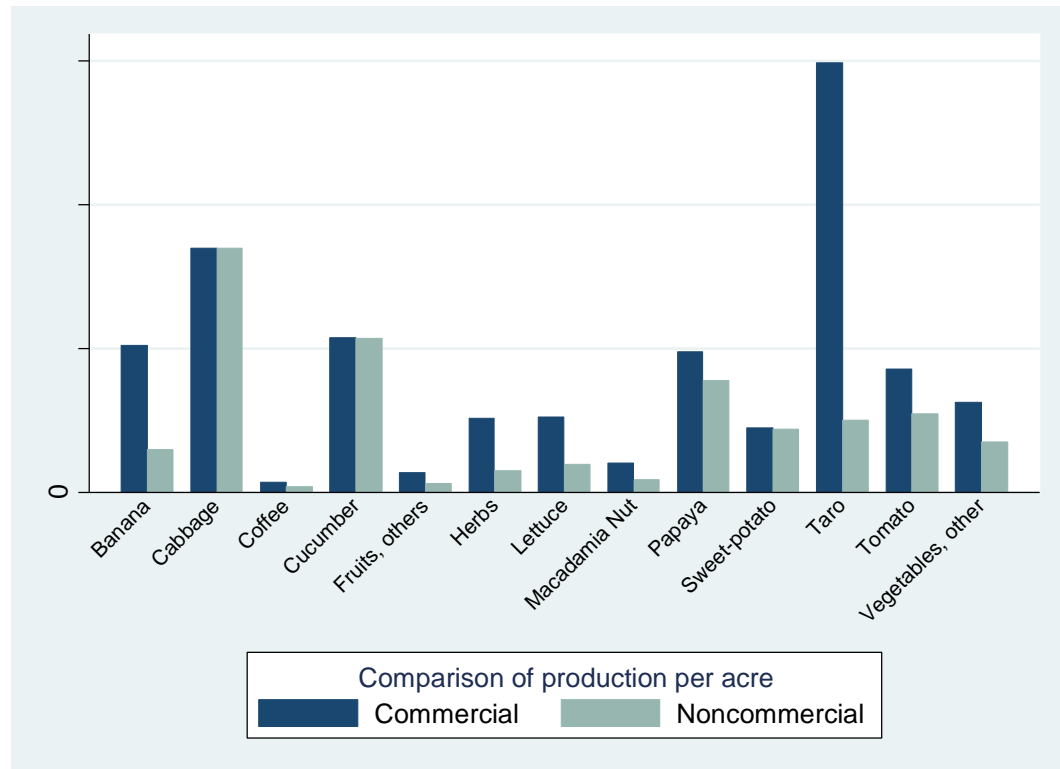


Table 2.1 presents a comparison of production per acre between commercial and noncommercial producers for these crops for Hawaii. Column 3 presents how much lower noncommercial production rate is compared to their commercial counterparts. We see that all commercial productions have much higher production per acre rate, compared to their noncommercial counterparts (columns 1 and 2). Noncommercial producers are competitive comparably to their commercial counterparts only in cabbage, cucumber, and sweet-potato production. Noncommercial cabbage, cucumber, and sweet-potato production rates are only -0.08%, -0.26%, and -2.54% respectively lower than their commercial counterparts. On the other hand, the relative production rate is the lowest for other herbs (-71.04%). Column 4 reports the production efficiency of noncommercial producers (in terms of the ratio between noncommercial

and commercial production rates). These ratios reflect that noncommercial producers of most crops are substantially less efficient in using their acreage than the commercial farmers. The findings are in line with the general notion that noncommercial farms do not operate with business intent, which we attempt to capture in our model. We assume that the noncommercial farms utilize only a part of their land to maximize profit, and they maintain the rest of the land for reasons other than agriculture. We will elaborate more on this in the following subsections.

2.4.1 Commercial Farming

Following Garnache et al. (2017), our PMP model assumes a profit-maximization objective function for each crop for commercial purpose subject to fixed resources (land). Similar to our previous work Khan et al. (2017), we assume a generalized constant elasticity of substitution (CES) production function for each crop to capture the nonlinearity in production and low substitution between inputs, and we choose a linear expenditure function for simplicity. This model specification comprised of a CES production function and a linear expenditure function allows the PMP model to calibrate the base year without adding any ad hoc constraints or parameters and produces smooth responses to policy shocks. We define the production functions as follows

$$q_{g,i} = \alpha_{g,i} \left(\sum_j \beta_{g,i}^j (x_{g,i}^j)^{\rho_i} \right)^{\frac{\delta_i}{\rho_i}}, \text{ for all commercial farming.} \quad (2.1)$$

where we define indices g , i , and j for counties, crops, production inputs, respectively.

Similar to Khan et al. (2017), $\mathbf{x}_{g,i} = (x_{g,i}^1, \dots, x_{g,i}^j)$ is the vector of inputs j used in activity i in county g . Each crop is produced q_i amount, where $\alpha_{g,i}$ is the CES technology parameter, $\rho_i =$

$(s - 1)/s$ where s is the elasticity of substitution between inputs. Following Howitt et al. (2012), we assume the elasticity of substitution parameter to be 0.22 in order to reflect the fact that in the agricultural sector, the elasticity of substitution between inputs is quite low. δ is the returns to scale parameter. Furthermore, $\beta_{g,i} = (\beta_{g,i}^1, \dots, \beta_{g,i}^j)$ is the vector of share coefficients of each of the inputs and resources used in activity i in county g . The CES scale parameter is defined for each crop technology across the four counties as α_{gi} , input shares as β_{gi}^j . Then we also define (transformed) inputs elasticity of substitution as ρ_i , and the return to scale parameter as δ_i . As per the recommendation by Garnache et al. (2017) for simplicity, we define the returns scale coefficient δ_i to the assumed supply elasticity as follows

$$\delta_i^{myopic} = \frac{\bar{\eta}_i}{1 + \bar{\eta}_i} \quad (2.2)$$

We assume an elasticity of substitution parameter, σ to be 0.22 to account for low substitution between inputs in agricultural production, as evident in the literature (Howitt et al., 2012). Therefore, our transformed elasticity of substitution can be expressed as $\rho = \frac{\sigma-1}{\sigma}$.

Assuming a linear expenditure function with input costs $c_{g,i}^j$, we define the objective function as below, subject to availability of land x_{gij} bounded at the county level.

$$\max_{e, x \geq 0} \sum_g \sum_{i=1}^I \left(p_{g,i} \alpha_{g,i} \left(\sum_j \beta_j^i (x_{g,i}^j)^{\rho_i} \right)^{\frac{\delta_i}{\rho_i}} - \sum_j c_{g,i}^j x_{g,i}^j \right), \text{ for all commercial activities} \quad (2.3)$$

$$\text{subject to } \sum_i x_{gij} \leq b_{g,j}, \text{ for } j = 1$$

2.4.2 Noncommercial Farming & Unobserved Utility

There are twofold reasons for modeling noncommercial farms differently from larger and profitable commercial farms. First, modification need arises from the fact that our parent PMP framework is dependent on the “non-negativity” assumption of profit, violation of which leads to spurious calibration of the production functions. However, most noncommercial crops in our data violate this assumption by generating negative profits. Therefore, the model should be specified in such a way that allows us not to violate this assumption. We circumvent the issue of negative profit by scaling inputs so as to let noncommercial producers partially behave like commercial producers. Therefore, noncommercial producers in effect make a positive profit on a portion of their inputs, and the rest of the input costs are incurred for the additional benefit (e.g. hobby), which is unobserved. We model this unobserved portion benefit through a “utility maximization” model.

In the book “The Economics of American Agriculture: Evolution and Global Development”, economist Steve Blank argued that hobby farmers’ pursuit of farming as a hobby should not be “valued at \$0”. He presented a simple mathematical framework to emphasize that when farmers forgo gains (or incur a loss) due to their involvement with agriculture, then “hobby” must be included in their utility maximization objective (Blank, 2014). Previously PMP procedure has been applied to calibrate expected utility model to capture farmer’s profit expectations and attitude towards risk. Louhichi et al. (2013) assumed a utility maximization objective function to develop a farm household model in a developing country context to assess farm livelihood strategies and responses to policy and technological changes. In this paper, the authors took risk into account with the mean-standard deviation (E-V) approach in which expected utility is calculated based on expected returns, farm-specific risk aversion parameters,

and income variances. A similar approach has been taken by Liu and Huang (2013) to assess pesticide use behavior by risk-averse farmers, and also by Arribas et al. (2017) to study an EU-wide individual farm model to assess risk management related policies, such as insurance schemes. To the best of our knowledge, however, the unobserved benefit of noncommercial farming as a hobby has not been modeled previously. In this section, we attempt to model the behavior of Hawaii's noncommercial farmers under a PMP framework to fill this gap.

First, we calculate m_i for each crop i , the ratio between noncommercial and commercial production rates to represent the relative productivity of resources of the noncommercial farmers. Then we assume that noncommercial producers take on a profit-maximization objective similar to commercial producers, but only on an m_i portion of the land available to them. In other words, we assume that non-commercial farmers do not utilize all available resources to their full potential to produce. This solves the problem of negative profit since the fraction of land employed to make a profit now incurs significantly less cost. This is a reasonable assumption because noncommercial producers do not seem to employ the whole acreage into production. Here, m_i is determined in the following manner:

$$m_i = \frac{N_i}{C_i} \quad (2.4)$$

where C_i and N_i are (average) production per acre for commercial and noncommercial producers respectively for each crop i . Therefore, similar to commercial farming, the CES production function of these farmers is

$$q_{g,i} = \alpha_{g,i} \left(\sum_g \sum_j \beta_{g,i}^j (m_i x_{g,i}^j)^{\rho_i} \right)^{\frac{\delta_i}{\rho_i}}; \text{ where } 0 < m_{i,j} < 1 \quad (2.5)$$

Here $m_{i,j}$ values range from 0 to 1 to account for their relative efficiency. The profit function is as follows.

$$\pi_i = p_{g,i} \alpha_{g,i} (\sum_j \beta_j^i (m_i x_{i,j}^g)^{\rho_i})^{\frac{\delta_i}{\rho_i}} - \sum_j c_{g,i}^j m_i x_{g,i}^j \quad (2.6)$$

Now we specify our noncommercial production model to capture the unobserved benefits of farming. The second modification is conducted to capture the realistic nature of the noncommercial producers. It is well documented in the literature that noncommercial producers operate with objectives beyond earning farm revenues, such as having a rural lifestyle, preferential tax benefit, etc. (Hoppe et al., 2010). Although these benefits are evidently availed by the loss-incurring noncommercial farmers, there is currently no data available to represent these benefits of farming. We circumvent this limitation of data by specifying our model in terms of “utility maximization” from the portion of acreage not generating any profit, i.e. $(1-m_i)$ portion of the inputs which is in addition to the profit generated from m_i portion of the resources. We also assume that the maximization of unobserved utility is constrained by the available budget from the farmers’ off-farm income used to cover the cost of nonproductive lands. In doing so, we assume that the production efficiency rates, m_i remain constant at the crop level. As we will see later in section 5, this model specification performs well in calibrating the activities of noncommercial farmers and also reproduces the base year activity levels quite satisfactorily. This can be deemed sufficient to enable our model to conduct policy simulations, producing realistic outcomes.

To capture the non-farming motivation of the noncommercial farmers, we define a Cobb-Douglas type utility function that depends on two components – productive use of land and non-productive use of land. Now we assume that noncommercial farmers maximize their utility from

hobby farming (i.e. nonproductive use of land), $(1 - m_{i,j})x_1^{g,i}$, and also from productive use of land, $m_i x_1^{g,i}$. The utility specification is provided in the following equation:

$$\max_x \sum_g \sum_{i=1}^I ((1 - m_{i,j})x_1^{g,i})^{\gamma_{gi}} (m_i x_1^{g,i})^{1-\gamma_{gi}} \quad (2.7)$$

subject to $\sum_i x_{gi}^1 \leq X_g^1$, and

$$\sum_j c_j^{g,i} x_j^{g,i} \leq Y_{gi}$$

Here γ_{gi} is the utility elasticity of the agricultural and non-agricultural benefits. Land availability is constrained by X_g^1 , the total amount of land available under noncommercial farming in each county. We assume that noncommercial farmlands cannot be used for commercial purpose. We believe that this may a reasonable assumption, given the fact that most noncommercial farmlands are very small parcels located in relatively expensive locations and may not be suitable for commercial use. Total cost of farming is constrained by the available funds Y_{gi} , which represents the current level of on-farm expenditures by noncommercial producers. We also set lower bounds for each variable at greater than zero (e.g. $x_1^{g,i} > 0$), to account for non-negativity and also for programming requirement, since GAMS (General Algebraic Modeling System) solver that we use often has trouble solving problems, when variables involve zero as a possible value (Kalvelagen, 2003).

The idea behind this optimization program (7) is that, during the calibration procedure, we are using our model to determine the unknown parameters γ_{gi} and specify all functions (i.e. crop production, utility function) under the assumption that such specifications maximize utility from using $(1-m)x$ amount of land for non-profit purpose and mx for profit-maximization

purpose. In the simulation phase, when we provide shocks to this program (7), the program determines new activity levels to ensure the baseline conditions (i.e. profit-maximization and utility-maximization) still hold under the new circumstances.

2.4.3 Calibration of commercial and noncommercial production functions

Now we calibrate the above-mentioned food model comprised of commercial and noncommercial farms based on our calibration procedure adapted from Garnache et al. (2017). This latest calibration procedure has successfully addressed the last major criticism of the framework regarding the calibration of the shadow values in the literature, primarily by Heckeleei and Wolff (2003). The new method calibrates all unknown parameters including the shadow values simultaneously using the actual structural forms, such as the CES production functions and linear expenditure functions.

We specify county-wise shadow values λ_g , which need to be calibrated including other unknown parameters specified in the above-mentioned production and utility functions of Hawaii farmers. As per Garnache et al. (2017), we calibrate the model by minimizing the sum of squared errors between observed expenditures and model expenditures, resulting from the estimation process of these shadow values, as follows:

$$\min_{\bar{\lambda} \geq 0} \sum_g^G \sum_{i=1}^I (\mu_{g,i}^1(\bar{\lambda}_g) \bar{x}_{g,i}^1)^2 \Leftrightarrow \min_{\bar{\lambda} \geq 0} \sum_g^G \sum_{i=1}^I (p_{g,i} q_{g,i} \delta_i - \sum_j c_{g,i}^j x_{g,i}^j - \bar{\lambda}_g A_{g,i} \bar{x}_{g,i})^2 \quad (2.8)$$

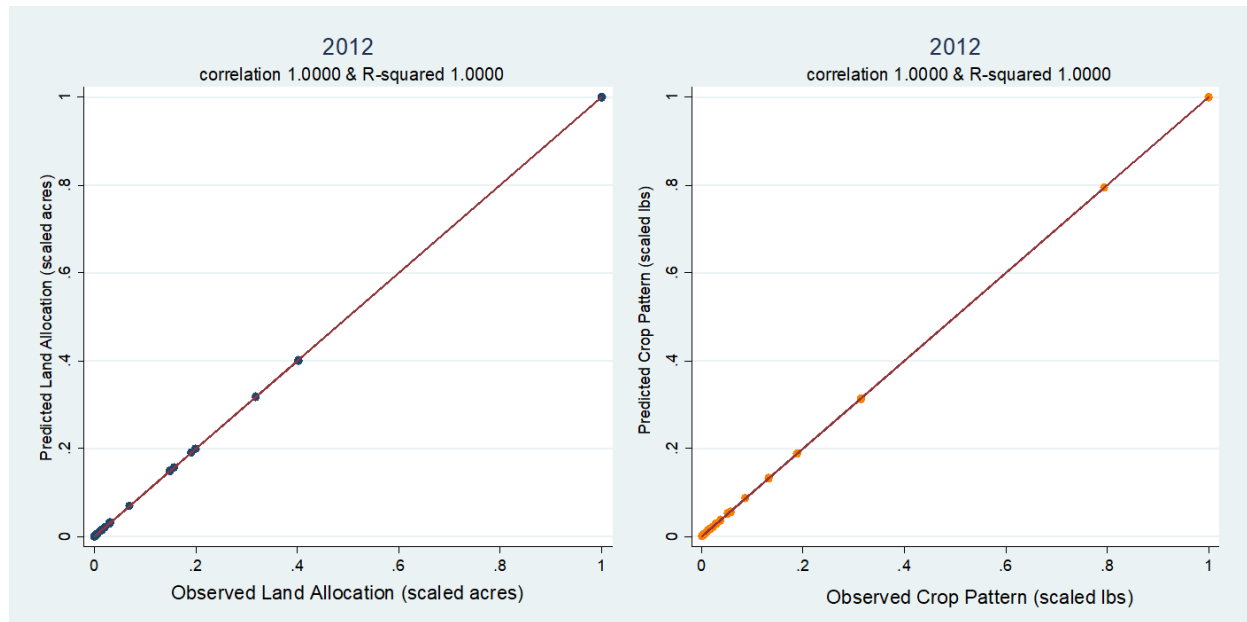
This final program ensures successful calibration of all necessary parameters. In addition to the specifications described in equations (1) to (7), the model also assumes that the input share parameters β_j^i in each production function sum to one.

We collect data and model agricultural activity for all four counties of Hawaii. Our production dataset contains acreage, resource inputs (land, labor, and water), input costs (other various costs, such as are included in the land cost), production levels and a set of parameters, such as own-price elasticity of demand, Armington elasticities, and input substitution parameters for the CES production functions, which are collected from the literature. Farm-gate prices are collected from the Statistics of Hawaii Agriculture. Retail prices have been set at 100% retail markup on respective farm-gate prices. Substitution elasticity of production inputs is set to be 0.22 across all crops in order to acknowledge low substitutability between agricultural inputs, as suggested in the literature (Howitt et al., 2012). Please see Khan et al. (2017) for more details.

2.4.4 Model validation

As the standard practice, in this part, we conduct validation of our calibrated model. First, we simulate the base year activity level and crop production pattern using our model. In Figure 1.3, we can see that the activity levels (land allocation) are perfectly reproduced by our model (left-hand plot). Similar results can be seen with the crop production pattern also (right-hand panel). While the observed values are the acreage and production levels from data, the predicted values were simulated using the calibrated functions and actual land availability. We can see that all acreage and production levels are accurately simulated, as represented by the predicted values. All acreage and production values are scaled (0 to 1). The correlation coefficients and R-squared values are also reported at the top of each plot. This exercise shows that our model was able to perfectly reproduce the base year.

Figure 2. 3Simulation of the base year to check calibration of the model



In addition, we increase and decrease inputs by 1% to check for any jumpy responses. All of such inputs change lead to smooth reasonable responses (not shown here). Since PMP models are expected to provide smooth responses to policy changes, this test ensures the stability of the underlying model specification.

2.5 Policy simulations

2.5.1 5.1 Maui property tax background

Currently, Maui County offers farmers substantial tax relief by imposing a tax based on use-value assessment (UVA) instead of market value assessment (MVA). However, the County

government has recently proposed to use market-value assessment (MVA) to eliminate the existing disparity of tax burdens across different classes of properties, while another important goal is to raise revenue collection. However, many farmers, ranchers and other agencies such as the Agriculture Working Group (AGW)¹¹ have expressed their concerns before the Maui County Council Budget and Finance Committee (The Maui News, 2016), fearing that the new policy may actually harm Maui's agriculture and gradually lead to urban sprawl.

The objective of this simulation exercise is to demonstrate how our modified food model can examine the impact of a proposed property tax policy on regional agriculture. For the estimates of the potential tax burden, we resort to the estimation provided by Margaret Stumpp, an economist based on Maui, in her testimony on behalf of the Agriculture Working Group (AWG)¹². According to the testimony, the proposed policy to base property tax on market-value assessment would increase the tax burden on Maui farmers by 750% on average, which will add to the production cost significantly given the already high factor costs of production across the state. However, the estimated increases in tax billing are expected to vary significantly across different farm sizes as presented in the following Table 2.2.

¹¹ The Agriculture Working Group (AWG) acts as a committee of different groups working on the issues related to Hawaii's agriculture and its agricultural land issues. It serves as a hub for policy discussions related to local agricultural economy. More details can be found in their homepage at University of Hawaii's CTAHR department's webpage: <https://www.ctahr.hawaii.edu/awg/index.asp>

¹² It should be pointed out that we resort to these property tax estimates, because of the unavailability of any other alternative sources. Although the present source apparently conducted a rigorous analyses of the potential tax burdens of Maui's farmers, the estimates are not expected to be perfect. More detailed tax estimates could enrich our present study.

Table 2. 2 The estimated increase in tax burden due to MVA, across different farm sizes in Maui.

Farm/ranch size (acres)	Change in assessment value (USD)	Total land (acres)	Increase in property tax (USD)	Avg. increase in tax/acre (USD)
0 to 1	101,968,122	507	349,990	690.32
1 to 2	317,176,800	1,572	1,197,080	761.50
2 to 5	508,030,210	3,117	2,166,440	695.04
5 to 15	713,384,738	7,293	3,297,820	452.19
15 to 100	840,248,327	22,199	4,370,270	196.87
Above 100	1,341,110,896	247,888	7,631,650	30.79

Source: Margaret Stumpp testimony on behalf of Agriculture Working Group (AWG)

From Table 2.2, we see that the farms with smaller acreage (under 5 acres) have annual tax burden increases between \$690.32 and \$761.50 per acre on average under MVA assessment. This is the range that we use for noncommercial farms for our simulation exercise. We assume that the rest of the tax burden falls upon commercial farms. This is a reasonable assumption, because, according to our data, the acreage of noncommercial farms is between 0 to 5 acres on average and commercial farms have larger acreage on average. Due to the USDA's non-disclosure policy, it was not possible to employ farm-level data, which could capture farm heterogeneity and would lead to more precise estimates of the tax burden.

2.5.2 Simulation of MVA-based property tax & its policy implication

Now we employ our PMP model to capture the effect of the proposed property tax policy on Maui's agricultural activity and food production. It needs to be pointed out that our tax estimates are based on (estimated) average property tax bills of noncommercial producers, which do not take into account actual farm heterogeneity. Moreover, since our model does not capture non-agricultural sectors of the economy, the present results should be considered based on a partial equilibrium context. Therefore, the simulation results should be considered as a general indication of the potential outcome, not as a precise analysis of the actual policy. More rigorous modeling is required for actual replication of the proposed policy, which is presently not possible mainly due to the lack of farm-level data among other modeling limitations.

The simulation results are presented in Figure 2.4 and 2.5 to demonstrate the impacts on acreage and production respectively. In both plots, noncommercial, commercial and total (Maui) figures are presented together for comparison. In Figure 2.4, we present the percentage changes in acreage for commercial farms (light grey), noncommercial farms (grey), and the total for Maui (black). We see that all commercial crops have moderate changes in response to MVA-based property tax. A detailed result is provided in Appendix Table A6. Acreage in commercial banana, coffee, other fruits, lettuce, cucumber, other herbs and other vegetables have slight reductions. On the other hand, macadamia nut, papaya, cabbage, tomato, sweet-potato, taro have slight increases in acreage. The highest loss of acreage has occurred for seed (1.14%), while acreage of cabbage has the highest increase (0.6%). However, noncommercial farms (green bars) were more vulnerable to the increases in property tax. We see that all crops have substantial reductions in acreage, other fruits acreage decreasing the highest (36.40%), and cabbage acreage

decreasing the lowest (8.17%). Overall for Maui, the highest decrease in acreage was for other fruits (11.20%), whereas cabbage acreage increased slightly (0.59%).

In Figure 2.5, we see that the production level for all commercial crops has changed at a moderate rate, with the highest decrease in production for seed (0.38%) and the highest increase in macadamia nut production (1.93%). Similar to changes in acreage, noncommercial crops' production levels, however, have moderate to substantial decreases. Highest production loss occurred for other fruits (13.86%) and cabbage had the lowest decrease in production (2.77%).

Upon looking at various quantitative differences between commercial and noncommercial farms in terms of productivity, it seems that non-commercial farms with relatively larger deficiency in productivity are more responsive to the increased property tax. Therefore, it can be implied that the magnitude of productivity difference from their commercial counterparts is a major factor behind the heterogeneous responses of noncommercial crops.

The simulation results are in line with the fact that noncommercial farms are already operating at loss and a sizeable increase in property tax is expected to impact them substantially. According to Hoppe et al. (2010), most of the noncommercial farm-owners cover up for the loss of farming by their off-farm (primary) occupation, which poses as a stringent budget constraint. In addition to these impacts on Maui's agriculture, some spillover effect could be expected in other counties. However, in our simulation, the spillover effects were negligible as reflected by insignificant changes in acreage in other counties. Therefore, we do not report any spillover effects in our results. One main channel of the spillover effect could be from the labor market. Due to the reduction in acreage from noncommercial farming in Maui, more labor could be available for other counties. Since, noncommercial farms occupy substantially lower amount of formal labor, change in their production level could have little impact on the labor market.

Nevertheless, modeling labor market of local food systems can enrich future studies involving regional agriculture.

Figure 2. 4 Effect of MVA-based property tax on acreage.

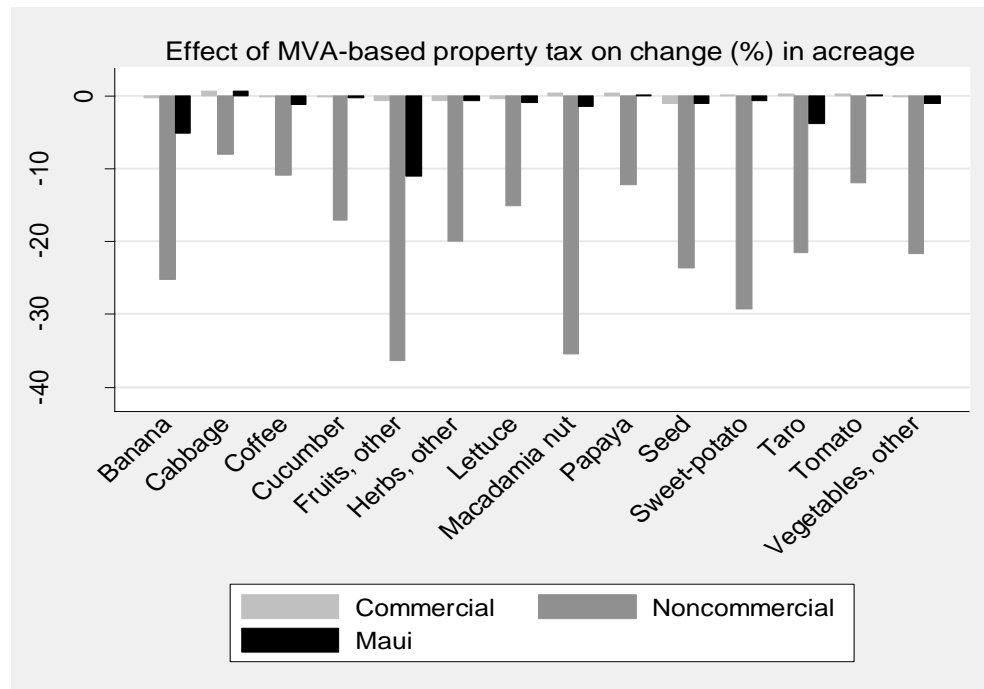
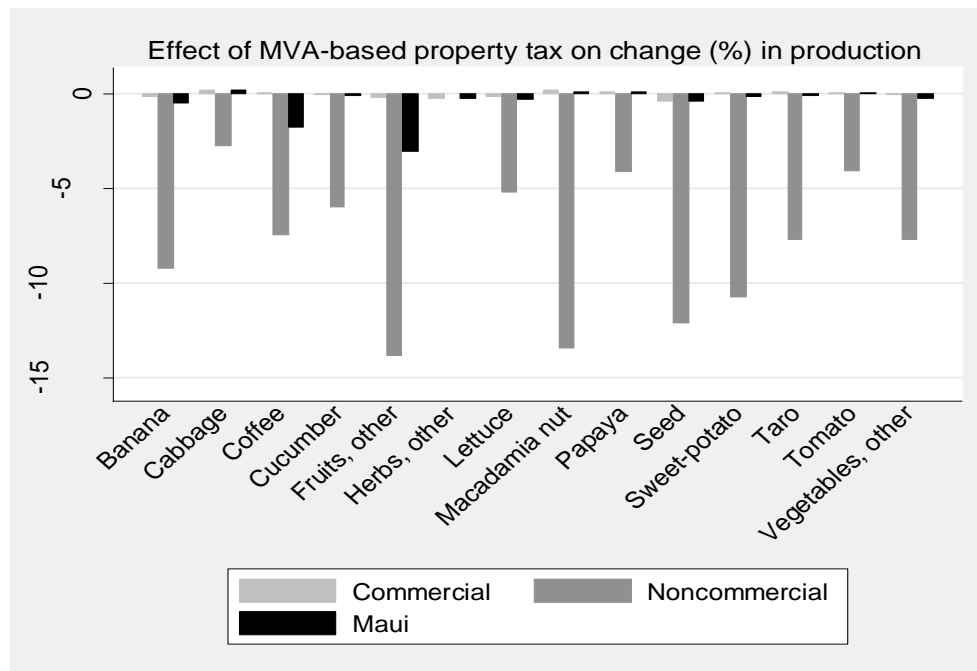


Figure 2. 5 Effect of MVA-based property tax on production.



It is noteworthy that there are also varied responses across crops within noncommercial farmers. Crops such as coffee, other fruits, macadamia nut, see, and sweet-potato, for example, exhibit more responses to increase in property tax. On the other hand, crops such as cabbage, cucumber, lettuce, papaya, and tomato exhibit small responses. Although the intention of the proposed property tax policy is to weed out land-owners who abuse the existing policy to evade taxes, substantial decreases in acreage and production of some profitable crops, such as coffee and macadamia nut indicate that it will also impact some hobby farmers, who are contributing to the local agriculture to a certain extent. For example, coffee production is particularly popular among hobby farmers in Hawaii, and it is one of the most profitable crops too. Therefore, it is unlikely that much of the acreage under coffee production is currently not truly intended for agricultural use, rather just a tax shelter. Our simulation result thus emphasizes that the proposed

policy may have major undesired side-effects on at least some of the valuable crops produced by noncommercial farmers.

The results from our simulation exercise offer a better understanding of how proposed policies can affect different segments of producers differently. For example, it is generally believed that noncommercial producers are less likely to convert into commercial enterprises to get rid of their increasing losses. Instead, adverse policies may force noncommercial farmlands into urban development more rapidly than otherwise would have occurred. We can see that an MVA-based property tax policy may potentially hurt the smaller noncommercial farmers who have very little cash revenue from farming and often operate incurring a loss. When faced with a substantial increase in property tax, such as in the case of the proposed policy of concern, their already costly agricultural lifestyle may face sufficient amount of pressure to exit farming. While even the commercial producers claim that the recent drops in farm revenues do not justify even the current level of taxes (based on UVA), the new policy may well push many noncommercial producers out of production. It is noteworthy, however, to mention that our present model does not allow noncommercial farmers to become commercial or vice versa. Future model developments should allow this kind of flexibilities to incorporate more response possibilities in policy simulations. Nevertheless, our present model has attempted to capture at least one perspective of the proposed policy's possible consequences – which, will hopefully better inform the policy-makers.

2.5.3 Policy Implications

These findings have some important policy implications for Maui's plan for the future of its rural landscape. The policy-makers face a clear trade-off between conserving (or even

expanding) local agriculture and increasing property tax revenue. According to the published “Revenue and Expenditure Summary” by the Maui County government (mauicounty.gov), robust real estate sector growth has been a driving force behind the recent recovery of the county’s revenue performance in FY 2016. During recent years, the tourism sector’s performance has been slower than the expected 2-3% growth. However, this under performance was compensated to some extent by the revenue growth from other sectors, especially the growth in revenue from the real property taxes. For the financial year 2016, the real property taxes generated an estimated \$255.6 million or about 43% of total county revenues. Real property tax is an important source of funds for Maui County, not only because it generates a significant amount of tax revenue, but also because Hawaii state law permits the county to retain 100% of real property tax levied within its jurisdiction (Mauicounty.gov).

In Maui, agriculture and real estate sectors seem to have a contrasting picture in the recent years and the trend is likely to continue in the future. Maui agriculture has recently shrunk to some extent, a major instance of which is the shutdown of the last sugar plantation of Hawaii spanning 36,000 acres of land in Maui. Although the efforts from seed companies, such as Monsanto and Dow Agro may help the county to diversify its agriculture, the community members have opposed their products and GMO-based farming techniques (“Maui vs. Monsanto”, 2017). On the other hand, a booming real estate sector is expected to provide persistent growth in the county revenue in coming years, as forecasted by the above-mentioned county revenue report based on historical data available until 2014 (mauicounty.gov).

It is evident from the literature that agricultural land and natural landscape play a key role in local tourism, and also real-sector value. In the face of struggling commercial agriculture, when more support is needed to keep local agriculture alive, additional pressure on smaller farms

pose a serious threat to the conservation of many open-spaces that add value to the adjacent neighborhood and help to attract tourists. Therefore, current ambition to boost county revenue may cost local economy in the future, particularly given the state's strong commitment to nature conservation.

In the short-run, a more stringent property tax policy may not have direct consequences on local agricultural production, as our simulation results suggest. However, it may pose a great risk for some agricultural land currently operated by non-commercial farms. Once these farmlands are developed, they cannot be recovered for agricultural use in the future. Since smaller commercial farms generally also have lower profitability, it can be implied that MVA-based assessment may hurt them as well. More rigorous study on Maui's different farm-size groups can inform policy-makers better on the actual costs of similar proposed policies.

2.6 Conclusion

In the present paper, we demonstrate how Hawaii's local food model can be modified and employed to capture different responses of different types of producers to a regional policy change. By calibrating at the farm-size level (commercial and noncommercial), we identified the range of activity responses to policy changes. This allows us to capture the fact that policies may have heterogeneous responses from Hawaii's farmers, which in turn may have adverse consequences for the state's agricultural goals. However, there are some limitations in our present study. Since, in general, both production decisions and property tax vary widely at the farm-level, it is important to account for the farm heterogeneity as well. However, due to USDA's non-disclosure policy for farm-level data, we could not do so. The present study is

based on average productivity and tax burden of noncommercial farmers as a proxy for those of a representative hobby farmer to circumvent this data limitation. Moreover, as mentioned before, the present model does not allow for any shift between farm-types, nor exit from farming to use land for other purposes – which are important possibilities for future model development. Therefore, the present results should be considered accordingly, although the general policy implications still hold valid.

Although the proposed tax policy’s objective is to discourage some of the property-owners from abusing the existing UVA-based tax-incentives intended for real farmers, we see from our simulation results that a substantial amount of noncommercial farming could also be discouraged by the proposed policy. For example, noncommercial coffee producers contribute significantly to the local agriculture in terms of production, and coffee growers themselves benefit from living a desired lifestyle. What this implies is that a more rigorous impact analysis is required, and an overall increase in property tax may have undesired effects on many of the hobby farmers who may be vital for local agriculture in their own rights. We believe that our study makes important contributions to the literature related to local agricultural policies and their economic impacts by incorporating generally ignored “noncommercial farmers” in policy discussions. Noncommercial farming was modeled in a novel way using utility-maximization as the objective function instead of the widely used profit-maximization assumption, which is not a realistic assumption in this case. By incorporating heterogeneity in responses across farm-types to a proposed policy, our study provides a working tool to better inform policy-makers in areas such as farmland conservation, local food policy, etc. Since noncommercial farmers play an important role in the agricultural landscape, more research addressing issues concerning them is required. Our hope is that the present study will encourage more such future works.

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3 Chapter 3: Who leads the price in Honolulu food market? - An evaluation of the competitiveness of local foods.

3.1 Introduction

Hawaii is largely dependent for its food on imports from both foreign suppliers and relatively low-cost mainland producers. Local farmers in Hawaii face competitive pressure from relatively cheaper imports, which have captured much of the market share over the recent years as evidenced in the retail chains and superstores, such as Foodland, Walmart, and Costco, etc. According to the Hawaii Department of Agriculture (HDOA), while price competition from imports has benefited consumers in general, competitive pressure on local producers has heightened as well (Southichack, 2007). Such market competition coupled with increasing local production cost is a growing concern for the pro-local movement in Hawaii's food market. However, the nature of influence local producers and their imported counterparts exert on one another in terms of price and sales - is an important question yet to be answered empirically.

In the present paper, we investigate the relationship between local and imported versions of four important food items, namely lettuce, tomato, eggs, and milk in the Honolulu food market. During recent years, imports have constantly increased for these foods. In Hawaii, local food continues to struggle to avail a substantial market share – as per the latest estimate, only 11.6% of food demand is met by locally produced foods (Loke and Leung, 2013). Faced with increasing production cost, local producers must also compete with cheaper imports in Hawaii and therefore may follow the prices set by their imported counterparts to stay competitive in the market. To the best of our knowledge, however, there is currently not much work in the literature

on the price dynamics of local and imported foods. The present study will shed some light on the nature of the competition between local and imported foods in the Honolulu food market.

New trade policies, advancements in technology, and overall globalization have a profound impact on retail food markets, especially on local producers. There are several sources of pressure on pricing by local producers in the food market, such as change in food preservation and packaging technology, bargaining power of large retail chains, big-box retailing, pre-packaged and often pre-cooked imported foods, etc. Technological changes, such as improvements in food preservation and increasing shelf-life help remote suppliers gain access more easily to local markets and often offer much lower prices. For example, European milk producers have been struggling in recent years to compete with imported milk, because new pasteurization techniques and other preservation techniques have allowed producers in other countries to ship milk to Europe, whereas local producers cannot keep pace with the falling market prices (Brett, 2015). In the Australian pork market, the increasing volume of imported pork from overseas in pre-cooked and pre-packaged form has been found to be a key reason behind the building up of price competition on local pork producers (Thompson, 2017). These pork products are cooked and packaged in a way that their shelf-life can be up to two years without refrigeration. Thompson (2017) also pointed out that prices of pork had declined as a result of the influx of pre-packaged imported pork, which could potentially displace the fresh local product in Australia.

Another source of increased price competition for local producers is that the vertical price leadership is changing – i.e. the price leadership is shifting from producers to retailers (Kuiper and Meulenbergh, 2002). Retailers often enjoy monopsony power (in terms of bargaining) over prices. On top of that, some retailers have their own private labels, such as Walmart's Great

Value or Safeway's Safeway Kitchen, etc.; retailers also frequently source low-priced imports from nonlocal sources to offer competitive prices for consumers. In other words, retailers often compete based on price. Price leadership of retailers have been studied extensively in the marketing literature (see, for example, Kuiper and Meulenbergh, 2002; Kadiyali et al., 2000; and Lee and Staelin, 1997). Empirical studies have also pointed out that more than half of the retail food market is controlled by only a handful of large retailers in the United States (Heijbroek et al., 1994; Seth and Randall, 1999). Major retail chains are often larger than suppliers and possess substantial control over marketing decisions pertaining to distribution and pricing, and also make a wide range of substitutes available in the market (Choi, 1996) – which make market competition even fiercer for the local suppliers. This phenomenon is particularly an important concern in the context of Hawaii's producers, who are usually much smaller than their mainland counterparts, and their growth is hindered by competition from imports (Arita et al., 2012; Arita et al., 2014).

Because of such various facets of competition, it is important to study the retail market dynamics in a systematic manner to help the formulation of effective policies that can support local producers. Evaluating how responsive the price and sales of a product are to those of its rivals can shed light on the product's competitiveness in the market. In the present paper, we explore such market dynamics covering a diverse group of foods in the Honolulu food market using vector autoregressive methods. The VAR models are often used as a theory-free approach and to avoid the endogeneity problem between prices and quantities (see, De Crombrughe et al., 1997; Wang and Bessler, 2006). Fang et al. (2017) previously studied Honolulu's market dynamics of grape and cherry tomatoes, using vector autoregressive models. However, the related literature can be enriched by including more products from the Honolulu food market and

by employing a panel-data approach. Panel data covering multiple food categories provide our present study with a large number of data points resulting from more cross-sections and longer time— which contain more degrees of freedom and more sample variability, hence leads to relatively more accurate estimate of model parameters (Hsiao, 1995). We believe that our vector autoregressive model applied in panel data context will extend the study of Honolulu’s food market dynamics and will contribute to the local food literature in a number of ways. First, our present study is able to explore the price-quantity interactions using the VAR method , which is considered to be “a theory-free method to estimate economic relationships, thus being an alternative to the "incredible identification restrictions" in structural models” (Sims, 1980), Secondly, our study covers a relatively wide range of products – from vegetables with high local market share to vegetables with very small local market share, from perishable items to not-so perishable items, etc. - which makes our analysis more representative of the food market in concern.

After estimation of the VAR regressions, we complement our analyses with impulse response functions (IRF) to explore how each endogenous variable responds to a shock in one of the other variables and identify their dynamic interactions. We also conduct variance decomposition to further identify how much of each variable’s variability can be explained by the movements of the other variables.

The rest of the paper is organized as follows. The next section provides a literature review, and section three presents a brief background of the Honolulu food market. Section four describes the data used in the present study, section five describes the methods, and section six discusses the results. Finally, section seven concludes.

3.2 Literature Review

Liberalization of global markets has intensified the competition for local businesses, which not only requires them to compete with their peers from home but also virtually from the whole world. In line with this development of global competition, there has been a growing interest in the literature in addressing interactions and market dynamics in the local food markets. In Hawaii, there has been a growing interest in local food in recent years among policy-makers as well as the general public. Therefore, understanding the viability of local food producers to remain competitive with relatively much cheaper and abundant imported substitutes is important for effective policy formulation. Although local foods are often preferred by consumers for their taste and freshness among other factors, Hawaii's local food producers have been largely unable to gain sizeable market share so far. Various factors were found responsible in the literature for Hawaii's high dependence on imported foods, such as, much higher production costs compared to foreign suppliers (Parcon et al., 2011), relatively smaller size of producers, and lack of efficiency - on average around 15-20% less efficiency than the U.S. mainland farms in terms of input-output ratios (Arita et al., 2012), etc. However, to our knowledge, the dynamic relationships between local and non-local foods in Hawaii's retail food market have not been studied so far.

The market interaction between domestic and imported foods have been studied for various food and other consumer products in different economies. Rodgers et al., (2006, unpublished) examined prices of eight (four local and four imported) individual brands of preserved mushrooms in Australia using double-log demand models and explored own-price and cross-price elasticities. They found that local brands were equally price-responsive as imported brands, despite the perception that local brands had superior brand loyalty and could be less price

sensitive. Gallus et al. (2006) studied cigarette consumption in 52 countries from Europe using consumption, smoking prevalence, retail prices of local and foreign brands, etc. among other data and found higher price elasticity for foreign brands, however, the study did not explore cross price-elasticities or price interactions between local and imported brands.

There have been studies on the existence of price transmission process in the context of anti-dumping duties to increase import prices and to evaluate if that leads to an increase in prices of locally produced substitutes. Asche (2001) showed that an anti-dumping measure by the US on imports of farmed salmon from Norway did not bring about the outcome intended by the new policy to enhance the local share in the salmon market and to increase the price of local salmon at the same time. Using cointegration analysis, the study found that even though Norway was the largest supplier in the global market for fresh salmon, increasing the price of Norwegian salmon through anti-dumping duties did not increase the price of local salmon – indicating lack of price integration between Norwegian and the U.S. salmon. Pincinato and Asche (2016) studied Brazil's shrimp market – where the United States' anti-dumping measure effective from 2003 forced Brazilian suppliers of farmed shrimps to sell at the domestic market in Brazil, which had been traditionally served by local suppliers of wild-caught shrimp. The study's objective was to examine how competitive the newly introduced farmed shrimp was in the local market. By testing market cointegration, the study found that the wild shrimp and the newly introduced farmed shrimp markets were cointegrated, indicating substitutability between the two species – which can benefit the domestic consumers by not letting shrimp prices go up due to the recent shortage of the wild variety.

For cereal markets in a developing country context, market integration between global and domestic prices of rice and their adjustment speeds have been studied (for example, Hassanzoy

et al., 2015; Conforti, 2004, etc.). For Afghanistan, Hassanzoy et al. (2015) found heterogeneity in adjustment speeds of price across rice qualities, such as the long-lasting effect of a shock in the global market price of low-quality rice on the local market price of the same. For crustaceans market in Germany, Bronnmann et al. (2016) used cointegration methods to evaluate how price changes affect competing substitutes and found partial market integration at the import-level for all crustacean species but found only weak evidence for market integration at the retail-level. Markets of fresh vegetables, such as potatoes, tomatoes, and cucumbers in Greece have been examined for price transmission mechanisms between producer and consumer prices using VAR methods, with allowance for asymmetric adjustments to positive and negative changes in the price variables (Rezitis and Pachis, 2016).

Apart from local-versus-import type comparisons, some studies have examined market integration and price dynamics between close substitutes within the same market, such as wild versus farmed shrimp species in Brazil (Pincinato and Asche, 2016), different species of crustaceans in Germany (Bronnmann et al., 2016), and tilapia species in the United States (Norman-Lopez, 2009). Ankamah-Yeboah et al. (2017) found mixed results for market integrations across different items – for instance, the shrimp market was found to be partially cointegrated, while the lobster market was found to be fully integrated. They concluded that since wild and farmed crustaceans interact through substitution effects, the market is shielded from volatile and rising prices due to supply shocks.

While some studies have studied price transmission and market integration across product space, other studies have investigated the same across geographical space. For fresh tomatoes in the United States, market integration has been tested between Florida and Mexico by Jordan and VanSickle (1995). Using weekly shipping-point price data of fresh tomatoes and

applying reduced form VAR models, the authors showed that tomatoes of Florida and Mexico were integrated into the same market, but price changes of one location were not instantaneously reflected in the other. Furthermore, it was found that Florida leads the price formation process, and Mexico responded to price shocks in Florida. Ravallion (1986) studied spatial market integration in the context of a famine condition in post-independence Bangladesh, proposing and applying a dynamic approach, where the price series of multiple regional markets were permitted to have their own autoregressive structures and dynamic relationships with prices of other regions.

In addition to food markets, other retail sectors have interesting findings in exploring competition in the retail sector. Sun (2011) studied the retail market of wooden beds in the United States, which is dominated by two outside suppliers – China and Vietnam. China was found to be the price leader, and its price was found to evolve more independently. Myers et al. (1990) studied the Australian wool market using VAR methods to explore the effect of supply, demand, and policy shocks to unexpected fluctuations in prices. They found that while demand shocks could be the lead cause for the fluctuations in the market in absence of a policy intervention by the Australian Wool Corporation, the intervention was successful in dampening the effects of the shocks, reducing fluctuations and even increasing the average price and revenue.

In the developing country context, some studies have assessed how increasing global prices may affect food prices and food security in local markets. Uganda, as a land-locked and net food exporting country, was found to be partially shielded from rising global food prices due to their relatively higher dependence on locally grown staples. Consequently, the sharp rise in food prices in 2008 was attributed to regional issues and not directly caused by global prices

(Benson et al., 2008). Moreover, it was suggested that rising global prices will hurt some part of the population, including the urban poor who rely on imported cheaper maize instead of locally grown other staples.

For Hawaii, Nakamoto et al. (1989) analyzed the variability and uncertainty of prices of local head cabbage in the retail market. A then-ongoing pilot project under the Hawaii Agricultural Statistics Service (HASS) collected and disseminated actual planting and harvesting information intended to help stabilize the market prices by the means of added market information. Using autoregressive integrated moving average (ARIMA) model of price variances, the study evaluated the effectiveness of the pilot program in reducing price variability and uncertainty. In recent years, partly as a response to Hawaii's commitment to promoting local foods, there has been a growing interest in understanding the market dynamics of Honolulu food market. Honolulu's tomato market has been recently studied to understand the market competition between local and imported varieties (Fang et al., 2017). The study used a VAR model of the tomato market using retail price and volume data and found asymmetry of substitutability between local and imported varieties. However, an extended study covering a range of food items can be helpful to have a more concrete evaluation of the nature of market dynamics in Honolulu food market. To fill this gap, we adopt a panel data approach and hope that the study will generate useful insights about the nature of competition between local and imported foods, which in turn has important policy implications in promoting local food production.

3.3 Hawaii's food market

Hawaii is located approximately 2,506 miles away from the continental United States and imports most of its foods from the mainland and foreign countries. Loke and Leung (2013)

estimated that only about 11.6% of Hawaii's consumption of food is sourced locally. According to a report in 2008, Hawaii is close to self-sufficiency in some crops such as tomatoes, sweet-potato, cucumber, and sweet corn. On the other hand, imports provide the majority of most other vegetables, including lettuce (Lee and Bittenbender, 2008). According to a recent estimate, Hawaii's production of local tomatoes accounted for about 77% of total market supply between 2007 and 2011 (Xu et al., 2015a). On the other hand, local production of lettuce accounts for only 10.7% of total consumption in Hawaii (Xu et al., 2015b).

In the United States, wholesale channels control 99% of total consumption of agricultural products (Martinez, 2010). Also, several large wholesale companies in Hawaii are responsible for storing, and distributing most of the commercially grown produce from the local farmers to the retailers. For example, Armstrong Produce is one of the largest wholesalers of foods in Hawaii and manages about 125 to 130 local producers across the state (Hawaii Retail Grocer, 2011).

There have been some consumer preference studies of the Honolulu food market to explore various marketing aspects. A study by Ulupono Initiative in 2011 of 1200 Oahu¹³ shoppers found that they spend only 8% of their food budget on local foods, while they spend 92% on imported foods. Out of those surveyed, a smaller sample of 600 shoppers were asked about prices that they were willing to pay for local tomatoes, and eggs, to which they expressed willingness to pay up to \$1.69 more per pound for local tomatoes, and \$1.25 more per dozen for local eggs (Ulupono Initiative, 2011). Interestingly, while empirical studies using Nielsen scanner data of Honolulu retail stores did find a price premium for local eggs, no

¹³ The City and County of Honolulu is situated on the island of Oahu, and is in effect the demand center of Hawaii with about 70% of the state population.

premium for local tomatoes could be found (Loke et al., 2016; Xu et al., 2015a). Similar empirical studies also found that there was a local premium for milk, but no local premium for lettuce (Loke et al., 2015; Xu et al., 2015b).

3.4 Data

We employed Universal Product Code (UPC) level Nielsen scanner data for four foods – lettuce, tomato, milk, and eggs from Honolulu’s major retail chains for the years 2014 through 2016. The data includes several key features of each UPC, such as brand details, product type, packaging type, unit weight, food-specific features (such as origin, color, organic attribute, size variety, type of processing, etc. as applicable), weekly unit price, and weekly sales. Some UPCs had missing weight data, for which we visited the supermarkets in person and searched online to verify and include those details. We then segregate the UPCs into local and nonlocal (imported) categories, based on the information available in the data and after verifying the origin of the product on the internet or by visiting the supermarkets in person to collect details about the product.

From this data, we construct four weekly time-series - two price series (local and import) and two sales volume series (local and import) for each of the foods. Based on the availability of Nielsen Scanner data, we are able to include fourteen different sub-types in total under the four food categories. For lettuce – there are green leaf lettuce and Manoa (butterhead as the imported counterpart) lettuce; for tomato – there are grape & cherry tomato, and regular tomato. Also, there are six sub-types of milk based on fat-content and package size, and four sub-types of eggs

based on their color and size. We construct local and imported price (in dollar per unit¹⁴) and volume (weekly sales quantity in pounds) series for these sub-types.

The four time-series for lettuce and tomato run from the first week of 2014 to the end of 2016 and the series for milk and eggs run from the middle of 2014 to the end of 2016¹⁵. We adjust all raw price data with Honolulu's all urban-consumers CPI¹⁶ in terms of 2016 dollars. As mentioned above, in order for a balanced comparison of each food, we conduct our analyses at the UPC-level by matching a local food product with its appropriate imported counterpart. However, if multiple food items (UPCs) offer the same features, such as color, packaging, etc., except for the brand name, we combine the UPCs and consider them as one food item. For example, for our green-leaf lettuce, there are more than one local UPC, which are identical in terms of product attributes, such as color and packaging and only differ in brand name. Therefore, we consider the weighted average price and total sales volume of the similar UPCs to construct the two time-series for local green-leaf lettuce. Also, it should be pointed out that we are unable to consider organic food items (UPCs) under any food categories, because of the unavailability of any matching pair of UPCs in Nielsen Inc. data, where both (local and imported) UPCs have the "organic" attribute.

A table of summary statistics has been provided in Appendix Table A7. We see that the prices of local varieties are much higher than their imported counterparts in all foods, except for tomatoes. The prices of local tomatoes are only about 61 cents (or 9%) higher than their imported counterparts (local weekly average price per pound \$6.87 versus \$6.26 per pound). On

¹⁴ The price series is price per count for eggs and price per pound for the rest of the foods. Similarly, the sales volume series is in count for eggs and in pounds for the rest of the foods.

¹⁵ Because of the data availability from Nielsen Inc., data for milk and eggs start from the middle of 2014.

¹⁶ The relevant Consumer Price Index (CPI) can be found here: <https://data.bls.gov/pdq/SurveyOutputServlet>

other hand, the local lettuce prices are more than twice the prices of imported versions (\$9.37 versus \$3.88 per pound). Similarly, the prices of local milk and eggs are about 22% and 40% higher than their imported versions, respectively. We also see that local tomatoes also have the highest market share (about 41%, in terms of sales volume) among all these foods. All other local foods' (weekly average) market shares range between only about 12-19%.

3.5 Methods

Dynamics of Hawaii's retail food market have been previously explored by Fang et al. (2017) for grape and cherry tomatoes. The authors utilized a vector autoregressive (VAR) model as their empirical method. In the present paper, we include multiple fresh food products (fourteen sub-types of foods under four food categories), and we also include a longer time period of 104 to 156 weeks, which provide our analysis with a rich set of panel data.

Our panel VAR model is specified as a system of equations consisting of four endogenous variables in their log forms, namely the price of local food (lp) and price of imported food (mp), sales volume of local food (lv) and sales volume of imported food (mv). The general model is as follows:

$$z_{i,t} = \Gamma_0 + \Gamma_1 z_{i,t-1} + f_i + d_{i,t} + e_t \quad (3.1)$$

where $z_{i,t}$ is the vector consisting of the four variables {lp, mp, lv, mv} as described above and all these endogenous variables enter the model with a lag¹⁷. The indices t , and i denote respectively time (week), and food sub-type (or UPC). The fixed effect component is denoted by

¹⁷ We have followed standard lag selection procedure using different information criterion, such as Bayesian and Akaike Information Criterion (BIC, AIC).

f_i to account for product-level heterogeneity, and a food-specific time (monthly) dummy $d_{i,t}$ is introduced to account for food-specific, market-wide shocks that may affect all sub-types of a food in the same way in a given period. Γ_0 , Γ_1 are the vector of constants and the matrix of autoregressive coefficients, respectively. Finally, e_t is the white-noise error term. We check stationarity of all our time-series using Augmented Dickey-Fuller panel unit root tests (Fisher-type); the tests results are summarized in Appendix Table A8. As we can see from the p-values, none of our panel series have unit root at the 1% significance level. Therefore, we use all of our series in their log forms at levels.

The model can identify the effect of a change in one of the regressors on the dependent variable. For example, we can determine the dynamic change in the price of a local food item as a consequence of shocks to its own sales or shock to the sales (or price) of its imported counterpart. We conduct these analyses by utilizing the orthogonalized impulse response functions. When shocks are orthogonal, we can identify the effect of one particular variable holding other factors constant.

Since we are applying our VAR models in a panel data context, we are imposing the restriction that the underlying structure is the same for each cross-sectional unit i.e. for each sub-type of food. In reality, this assumption is likely to be violated (Love and Zicchino, 2006). Therefore, to take care of this restriction on parameters, we allow for “individual heterogeneity” by incorporating fixed effects, f_s in our panel VAR model. To eliminate the fixed effects component from the equations (see, for example, Grossmann et al., 2014), the mean-differencing procedure is commonly used – which is equivalent to including (controlling for) the fixed effect component in the equations. However, since our model includes the lagged dependent variable on the right-hand side, the mean-differencing procedure would lead to biased coefficients (Love

and Zicchino, 2006). We avoid this problem by using “Helmert procedure” (Arellano and Bover, 1995), which removes only the forward-mean. This transformation preserves the orthogonality between the variables and their lagged regressors – therefore, the lagged regressors can be used as instruments and coefficients can be estimated by system GMM (Love & Zicchino, 2006). It may be helpful to note that we use the current STATA package for panel VAR models, known as “pVAR” (Abrigo and Love, 2016)¹⁸. We include food-specific (monthly) time dummies, d_{it} , which are for each month of the year for each of the (four) foods to control for the time-of-the-year effects that may affect all brands (UPCs) under a food category in the same way – for example food-specific seasonality, supply shocks, etc. In other words, these time dummies capture the (time-variant) shocks that may affect all cross-section units in the same way (Love & Zicchino, 2006). We take care of the dummy component by subtracting the means of each variable calculated for each month, which is equivalent to including (controlling for) the time dummy component (see, for example, Grossmann et al., 2014, and Love and Zicchino, 2006).

Once the VAR models are run, we construct the IRFs for each variable to study their responses to the shocks in the other variables. In addition to the IRFs, we also conduct the variance decomposition analysis to determine how much of the variability (in percentage terms) of one variable can be explained by each of the other variables.

¹⁸ The STATA package makes it straight-forward to take care of this kind of econometric techniques using easy-to-use regression options, such as “fod” for the “Helmert Procedure” in a panel VAR regression context as mentioned in this section. For more information and to install the pVAR package, the following link can be used: <https://sites.google.com/a/hawaii.edu/inessalove/home/pvar>

3.6 Results and discussion

3.6.1 Panel VAR

After running VAR model, we construct the IRFs and variance decomposition of each of the endogenous variables. Figure 3.1 presents the impulse responses (IRFs) of each of the variable to one standard deviation shock in the other variables. The shaded area around the response functions denotes 95%-confidence bands, whereby a lower bound above the zero line indicates a positive significant response and an upper bound below the zero line indicates a significant negative response. In practice, IRFs are more useful in interpreting the dynamic interactions between variables than the VAR coefficients themselves, because orthogonalized IRFs can provide useful information about the effects of the shock in one variable, holding other variables constant. Hence many studies report the VAR regression tables as a supplement and focus their discussion on the IRFs instead. We report the VAR regression table in the appendix Table A9. However, our discussion is mainly based on the IRF plots in Figure 3.1. The x-axis of each IRF plot denotes the time steps (in weeks), and the y-axis denotes the responses in the response variables (in original units, i.e. log of each series or in other words, percentage changes) in response to one standard deviation shock in the respective impulse variable. The case of the same impulse and response variable in the plots (for example, mp to mp) represents how the responses of that variable to its own (one S.D.) shock subside over time, i.e., how the effect of its own shock disappears. While each shaded area differs in width because of different scaling on the y-axis to display the magnitude of the changes more precisely, it is primarily important to note if the zero line lies outside the shaded area – which would denote the statistical significance of the response.

Before we explore the interactions between local and imported foods, we would like to look at the interactions between own price and sales. First, we investigate the own-price and sales relationship to determine whether the expected downward sloping demand curve is represented by our results. In Figure 3.1, column 1 presents the IRFs for local sales (lv), where we see that the contemporaneous response of the local sales volume to its own-price (lp) is negative both in estimated coefficients and in impulse response functions. The contemporaneous response of import sales to its own price is also negative and significant. However, responses gradually subside as part of the adjustment process, which is reflected by diminishing impulse responses in the subsequent periods. This means that the import sales adjust quickly to a shock in the price, whereas the local sales seem to take 2-3 weeks before the significant negative impulse responses subside. Since, local versions are generally priced higher than their imported counterparts, a further increase in price may lead to an impact on sales over a longer period than in the case of the imported versions. On the other hand, consumers of imported foods may tend to come back quickly even after a price increase, perhaps because imported foods often do not have cheaper local alternatives. The results are not surprising – both local and imported food sales exhibit negative price-sales relationship, which implies a downward sloping demand curve. It should be pointed out that although VAR point estimates only indicate a relationship of the left-hand side variable with lagged values of the variables on the right-hand side. Therefore, most studies rely on the IRFs to examine the contemporaneous relationship among the two variables (using orthogonalized IRFs) as well as the dynamic behavior of such responses to impulses over time. For example, although the VAR regression estimates exhibit insignificant negative response for local sales to (lagged) local price, and positive significant response for imported

sales to (lagged) imported price; from IRFs, however, we see that both the relationships are significant negative contemporaneously (i.e., at step zero).

Similar to the responsiveness of sales to the price shocks, the prices are also influenced by sales shocks. Both local and import prices respond positively to increase in their respective sales. This is expected because higher sales imply higher demand in the market – thus leads to increase in price in the subsequent periods (see, for example, Gilbert, 2010¹⁹). The positive relationship also implies that weak sales will lead to price reductions (or promotions) in the subsequent periods, which is in line with existing literature on marketing and promotions in supermarkets (see, for example, Aguirregabiria, 1999; Pesendorfer, 2002).

If we look at the responses of prices to their own shocks (the IRFs for lp to lp , and mp to mp), we find that in both the cases, the responses take about the same period (6-8 weeks) to subside. This can be partially explained by the fact that when retailers need to increase the price of a food, they do so gradually over a period to avoid abrupt price shocks, and eventually the price settles at a desired level and no more changes are visible. Huda (2014) cited energy price surges as an important factor in elevating food prices – a price-surging shock that takes a relatively longer period to disappear. Since, both imported and local foods are dependent on inshipment (imported foods depend directly and local foods depend through raw materials that need to be imported), any major price surge taking several weeks to be alleviated could be a reasonable phenomenon for both food sources, given both of their dependency on transport cost shocks. This also explains in part why local prices follow increases in imported food prices – as we will see below. We discuss here only the price movement in general, whereas the asymmetry

¹⁹ Gilbert (2010) studied the factors affecting agricultural price booms and using a capital-asset pricing type model they established “demand growth” as a major factor that Granger causes the prices positively.

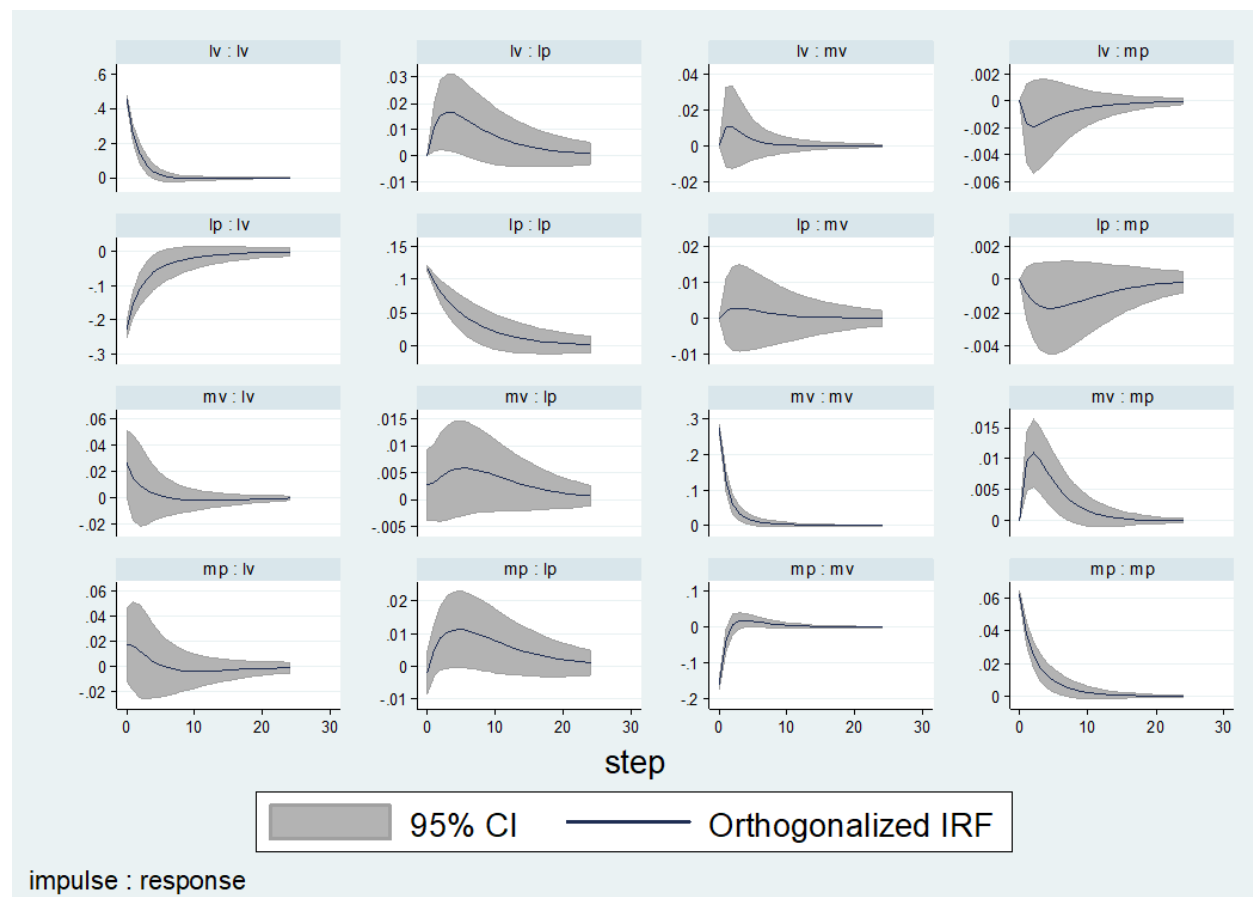
between price decreases and increases is an important part of the marketing literature (see for example, Ward, 1982). However, the asymmetry of these relationships is beyond the scope of the present study, which we believe to have important research prospect and should be explored in the context of local food systems.

Now we explore the cross-interactions between local and imported foods. Unsurprisingly, import prices are not influenced by either local sales or price – as indicated by the 95%-confidence bands of the IRFs covering the response values of zero in both cases. Overall, we can say that import prices do not depend on the sales and prices of their local competitors in Honolulu. This is expected, given the fact that import prices are determined in the global market based on global demand and supply (Headey, 2011; Trostle, 2010). In addition, the IRFs of import sales also do not respond to the shocks in local sales or price – as indicated again by the IRFs. The responses of import sales and price indicate that the demand for imported foods is relatively isolated from the market for local foods, and rather depends mainly on its own price.

On the contrary, we observe that the impact of import price shock on local price is somewhat significant (at the 10% significance level). The result is in line with the existing literature of influence of global food prices on the local market, which showed significant influence of global food prices on the prices of local foods (see, for example, Cudjoe et al., 2010). The impulse response function is marginally significant as we can observe that the lower bound of the IRF is barely above the zero line after one week. This means that a decrease in import price may cause local producers to reduce the price to maintain the market share. On the other hand, an increase in the prices of the imported foods may encourage increases in the prices of the (counterpart) local foods as well. However, these responses are relatively weak and hence we need more evidence before a strong conclusion can be made. Therefore, if we consider this

impact of import price on local price, we can say that the price dynamic is unidirectional at best in nature – where import price shocks influence local prices but not vice versa. This result indicates the fact that local foods may face relatively more market pressure than their imported counterparts and import prices are relatively independently determined. In addition, we could not find significant response of local sales to the shocks in either import price or sales.

Figure 3. 1 Impulse response functions for the panel VAR model



Note:

1. The variables lv, lp, mv, and mp denote local sales, local price, import sales, and import price, respectively.
2. The x-axis represents time (week), and the y-axis represents changes in the response variable.
3. The shaded area around the IRFs denotes 95% confidence interval.

Table 3. 1 Variance decomposition from the VAR model

	mp	mv	lp	lv
lp	0.018	0.005	0.943	0.034
lv	0.002	0.003	0.256	0.739
mp	0.930	0.065	0.003	0.002
mv	0.226	0.772	0.000	0.003

Note:

1. Variance decompositions are calculated for 10 periods ahead.
2. Percent variations in each row variable are explained by the column variables.

Next, we present the variance decomposition for our panel VAR model in Table 3.1. The results are similar to those discussed so far based on coefficient estimates and impulse responses. In row 2 (i.e., for local sales, lv), we see that local price explains 25.6% of the variance in sales of the local foods; and similarly, import price explains 22.6% of the variation in sales of the imported foods – both support the fact that both local and imported food sales are influenced by their respective prices – as was seen in the IRFs as well. Variation in local price and import price are also explained by their own sales respectively, however, both magnitudes are rather small – 3.4% and 6.5% respectively. In addition, variation in local price can be explained slightly by import price; only about 2%. On the other hand, variation in import price cannot be explained by local price, as indicated by the variance decomposition percentage of only 0.3%.

3.6.2 Product-wise VAR

In order to check for the above analysis at the crop level, we run VAR models separately for each of the four food categories. The IRF plots are provided in the Appendix Figure A2. For all four products, import prices were found not to respond to the shock in local prices, while local prices were found to follow the shocks in import prices of lettuce, milk and eggs. Only for tomato, the impact of import price on local price is found to be insignificant. Perhaps, the relatively larger market share of local tomatoes than the other local food types could lead to such finding. Since local tomatoes enjoy a substantial market share, their prices seem to be less volatile in response to shocks in imported tomato prices.

3.7 Concluding remarks

Hawaii's distinctive geographical location offers a unique opportunity to define and study its "local" foods in a more precise and discernible manner. In addition to the issue of clearly defining local food, the lack of appropriate and sufficient data makes it difficult to conduct cost study or demand system estimation (Martinez, 2010; Fang et al., 2017). We circumvent this limitation by employing a panel VAR approach, which allows us to study the dynamic relationships among the variables of interest with limited data requirement and also overcomes the typical endogeneity problem between price and quantity that often poses estimation issues (De Crombrughe et al., 1997; Wang and Bessler, 2006). The present study also covers a relatively wide range of foods, which makes the sample more representative of the local food system. However, it should be pointed out that the present study does not take into account the retail sales of local foods in the farmers' markets – which may have significant market influence in reality. Therefore, future studies can improve the present analyses by incorporating farmers'

markets. Moreover, although we attempted to include as many foods as possible in our study, we were constrained by the data availability and budget to procure Nielsen scanner data of more food categories. Covering more food categories, such as meat, fruits, etc. in future research can enrich the present study.

The present paper explores the dynamic relationships between prices and sales in the food market and also examines the interactions between local and imported foods. The results confirm that the import prices are determined in the global market based on global demand and supply, rather than by the market dynamics in the Honolulu food market. The sales of both local and imported foods were found to be dependent on the movements in prices – as expected. In addition, our study identified some interesting dynamic interactions between local and imported brands. Although price movements of imported foods were not found to be influenced by the shocks in the local food prices, some evidence could be found in favor of the other direction, i.e. the prices of local foods were found to be responsive to the shocks in import prices. This can be partially explained by the fact that in order to remain competitive in the market, the prices of local foods may respond to the changes in those of their imported counterparts. Hawaii's local foods are sold mainly in the local market, and therefore face relatively more competitive pressure than their imported counterparts to generate sales. The previous work by Fang et al. (2017) on Hawaii's grape and cherry tomatoes could not find this relationship (mp to lp) significant using regular VAR model. We believe that a panel VAR approach might be more appropriate to capture the market dynamics, primarily because of a more representative set of data – which makes the estimates more reliable. Also, our present study found negative price-sales relationship (in contemporaneous period) – which is expected according to the general microeconomic theory. In addition, we found that this negative impact on sales due to a price

increase exists longer in case of the local foods compared to the imported foods. One possible explanation could be, as explained earlier, that most consumers are dependent on relatively cheaper imported foods, which often do not have cheaper local substitutes. More empirical research is necessary to shed light on the differences of price responsiveness between local and imported foods.

Our study extends the current literature of local food market dynamics by including more representative food items from Honolulu's retail food market using a panel VAR approach, and thus complements the previous work by Fang et al. (2017). However, we still emphasize the need for more research to construct an elaborate demand system incorporating consumer-side data. Future research should also explore the cost structures of local farms and compare them to those of outside farms to better understand the nature of the competition and the viability of Hawaii's local food systems in the competitive marketplace.

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Appendix

Table A1. Simulation of exempting GET on retail sales of both local and non-local foods.

	Aggregate Demand (Million pounds)		Farm-gate price (USD per pound)	
	Base (1)	Simulated (2)	Base (3)	Simulated (4)
Banana	37.60	38.50	0.65	0.67
Basil	0.75	0.76	1.55	1.60
Cabbage	13.81	13.87	0.31	0.31
Cucumber	7.50	7.75	0.57	0.58
Eggplant	2.15	2.20	0.98	1.01
Ginger	2.78	2.90	1.40	1.40
Lettuce	12.27	12.46	2.66	2.66
Other fruits	24.82	25.88	1.97	2.03
Other herbs	0.75	0.76	2.71	2.79
Onion, dry	21.80	21.98	1.21	1.22
Onion, green	2.18	2.20	1.39	1.39
Other vegetables	33.84	34.28	0.80	0.82
Papaya	17.30	17.52	0.35	0.36
Sweet-potato	20.05	20.44	0.55	0.57
Taro	0.38	0.38	0.67	0.69
Tomato	12.78	13.03	0.69	0.69
Watermelon	17.30	17.59	0.30	0.31

Table A2. Simulation of exempting GET on exclusively local foods.

	Aggregate Demand (Million pounds)		Farm-gate price (USD per pound)	
	Base (1)	Simulated (2)	Base (3)	Simulated (4)
Banana	37.60	37.68	0.65	0.66
Basil	0.75	0.75	1.55	1.61
Cabbage	13.81	13.82	0.31	0.32
Cucumber	7.50	7.57	0.57	0.58
Eggplant	2.15	2.17	0.98	1.01
Ginger	2.78	2.78	1.4	1.44
Lettuce	12.27	12.28	2.66	2.75
Other fruits	24.82	24.82	1.97	2.03
Other herbs	0.75	0.76	2.71	2.80
Onion, dry	21.80	21.80	1.21	1.25
Onion, green	2.18	2.18	1.39	1.43
Other vegetables	33.84	33.89	0.8	0.82
Papaya	17.30	17.42	0.35	0.36
Sweet-potato	20.05	20.21	0.55	0.57
Taro	0.38	0.38	0.67	0.69
Tomato	12.78	12.83	0.69	0.71
Watermelon	17.30	17.40	0.3	0.31

Table A3. Comparison between simulations using different relative import prices (1.0 vs 0.8) – the case of local GET exemption.

	Simulated New Aggregate Demand (Million pounds)		Simulated new Farm-gate price (\$/pound)	
	using relative	using relative	using relative	using relative
	$P_m = 1$	$P_m = 0.8$	$P_m = 1$	$P_m = 0.8$
Banana	37.68	37.67	0.66	0.66
Basil	0.75	0.75	1.61	1.60
Cabbage	13.82	13.82	0.32	0.32
Cucumber	7.57	7.56	0.58	0.58
Eggplant	2.17	2.17	1.01	1.01
Ginger	2.78	2.78	1.44	1.44
Lettuce	12.28	12.28	2.75	2.76
Other fruits	24.82	24.82	2.03	2.03
Other herbs	0.76	0.76	2.80	2.80
Onion, dry	21.80	21.79	1.25	1.25
Onion, green	2.18	2.18	1.43	1.44
Other vegetables	33.89	33.90	0.82	0.82
Papaya	17.42	17.42	0.36	0.36
Sweet-potato	20.21	20.21	0.57	0.57
Taro	0.38	0.38	0.69	0.69
Tomato	12.83	12.83	0.71	0.72
Watermelon	17.40	17.41	0.31	0.31

Table A4. Simulation of injecting 1,200 acres of agricultural land under Whitmore Project.

	Equilibrium Quantity (Million pounds)		Farm-gate price (USD per pound)	
	Base (1)	Simulated (2)	Base (3)	Simulated (4)
Banana	37.60	37.69	0.65	0.643
Basil	0.75	0.75	1.55	1.55
Cabbage	13.81	13.82	0.31	0.307
Cucumber	7.50	7.57	0.57	0.564
Eggplant	2.15	2.17	0.98	0.97
Ginger	2.78	2.78	1.4	1.386
Lettuce	12.27	12.28	2.66	2.633
Other fruits	24.82	24.82	1.97	1.95
Other herbs	0.75	0.75	2.71	2.71
Onion, dry	21.80	21.80	1.21	1.198
Onion, green	2.18	2.18	1.39	1.376
Other vegetables	33.84	33.90	0.8	0.792
Papaya	17.30	17.43	0.35	0.346
Sweet-potato	20.05	20.22	0.55	0.544
Taro	0.38	0.38	0.67	0.67
Tomato	12.78	12.83	0.69	0.683
Watermelon	17.30	17.40	0.3	0.297

Table A5. Calculation of acquiring cost of 1200 acres of land Whitmore Agriculture Project – under different real discount rates.

	Amount of Land (acres)	Purchase Cost (in Million \$)	Cost per Acre (\$)	Annual Cost (\$) at 2% Real i^*	Annual Cost (\$) at 5% Real i^*
Land	1,200	13	10,833	260,000	650,000
Irrigation Systems		13.75	11,458	840,905	1,103,336
Total Cost per year				1,100,905	1,753,336
Cost per acre per year				917	1,461

* Real i stands for the real discount rate.

Table A6. Effect of MVA-based property tax on Maui's Agriculture - acreage, and value of production.

Crop	Change in acreage			Change in production value at farm-gate		
	Commercial	Noncommercial	Maui	Commercial	Noncommercial	Maui
Banana	-0.35%	-25.40%	-5.30%	-0.12%	-9.21%	-0.52%
Macadamia nut	0.41%	-35.45%	-1.63%	0.193%	-13.46%	0.122%
Papaya	0.34%	-12.18%	0.08%	0.11%	-4.18%	0.09%
Coffee	-0.22%	-11.00%	-1.39%	0.01%	-7.52%	-1.82%
Fruits, other	-0.63%	-36.40%	-11.20%	-0.21%	-13.86%	-3.10%
Cabbage	0.60%	-8.17%	0.59%	0.20%	-2.77%	0.20%
Lettuce	-0.44%	-15.11%	-0.91%	-0.14%	-5.25%	-0.30%
Tomato	0.20%	-11.99%	-0.07%	0.07%	-4.13%	0.02%
Cucumber	-0.14%	-17.24%	-0.35%	-0.05%	-6.04%	-0.09%
Sweet-potato	0.15%	-29.24%	-0.70%	0.05%	-10.77%	-0.12%
Taro	0.27%	-21.53%	-3.90%	0.09%	-7.69%	-0.11%
Herbs, other	-0.75%	-20.11%	-0.75%	-0.25%	0.00%	-0.25%
Vegetables, other	-0.12%	-21.62%	-1.08%	-0.04%	-7.72%	-0.22%

Table A7. Descriptive Statistics of endogenous variables of the panel VAR model - lp, mp, lv, mv (weekly).

Food	Variable	weeks	Mean	Std.	Min	Max	
lettuce	lprice	156	9.37	0.98	6.98	12.28	
lettuce	mprice	156	3.88	1.14	2.11	7.00	
tomato	lprice	156	6.87	0.96	4.21	8.22	
tomato	mprice	156	6.26	1.07	3.87	8.77	
milk	lprice	104	1.17	0.24	0.25	1.40	
milk	mprice	104	0.96	0.10	0.75	1.16	
eggs	lprice	104	0.49	0.08	0.33	0.70	
eggs	mprice	104	0.35	0.10	0.13	0.52	

Food	Variable	weeks	Mean	Std.	Min	Max	Market share (weekly avg.)
lettuce	lvol	156	202.34	90.08	1.43	389.07	15%
lettuce	mvol	156	1,123.72	694.26	1.42	3,295.19	85%
tomato	lvol	156	825.89	429.93	4.17	3,263.30	41%
tomato	mvol	156	1,209.20	788.15	31.16	4,943.08	59%
milk	lvol	104	1,110.65	1,116.76	23.12	11,153.36	12%
milk	mvol	104	8,526.51	4,357.81	952.96	24,409.80	88%
eggs	lvol	104	28,482.23	27,016.33	69.60	100,241.90	19%
eggs	mvol	104	121,800.20	113,705.50	485.52	527,021.80	81%

Note:

1. mp, mv, lp, lv stand for import price, import sales volume, local price, and local sales volume respectively.
2. The price series is price per count for eggs and price per pound for the rest of the foods. Similarly, the sales volume series is in count for eggs and in pounds for the rest of the foods.

Table A8. Panel Unit Root tests, Fisher-type ADF Tests

	Z-statistic	p-value
lp	-4.4367	0.00
lv	-6.1335	0.00
mp	-6.2985	0.00
mv	-7.9781	0.00

Table A9. Results from panel VAR model

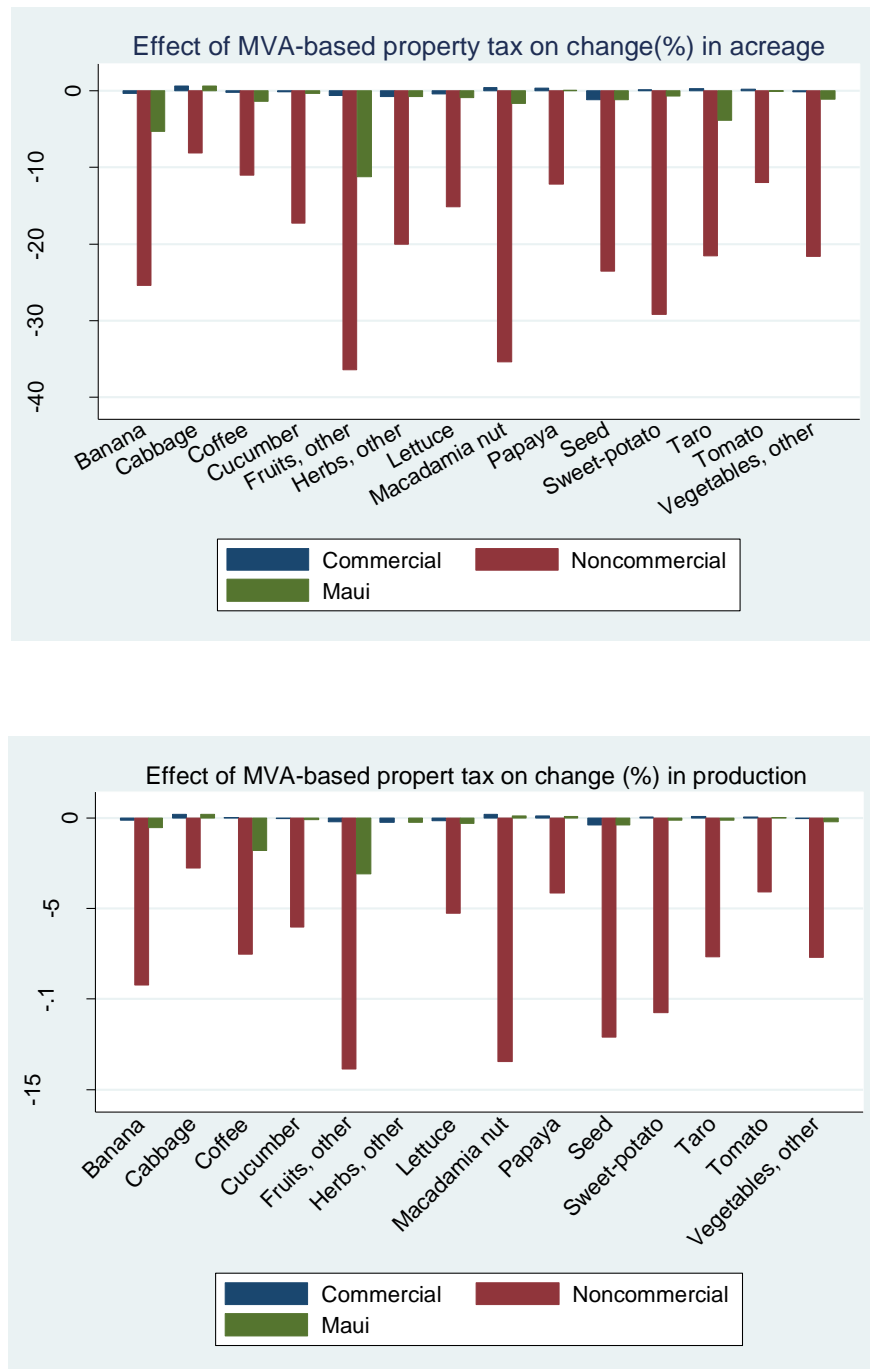
Variables	(1) mp	(2) mv	(3) lp	(4) lv
mp _{t-1}	0.70323*** (0.05185)	0.56883** (0.25219)	0.10434* (0.05371)	0.11917 (0.25020)
mv _{t-1}	0.03507*** (0.00988)	0.44836*** (0.05885)	0.00053 (0.01002)	0.00504 (0.05344)
lp _{t-1}	-0.01438 (0.00999)	0.06062 (0.06353)	0.87541*** (0.04592)	-0.24155 (0.16438)
lv _{t-1}	-0.00368 (0.00368)	0.02286 (0.02437)	0.02370** (0.00980)	0.55676*** (0.05337)
Weeks	156	156	156	156

Note: mp, mv, lp, lv stand for import price, import sales volume, local price, and local sales volume respectively.

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.10

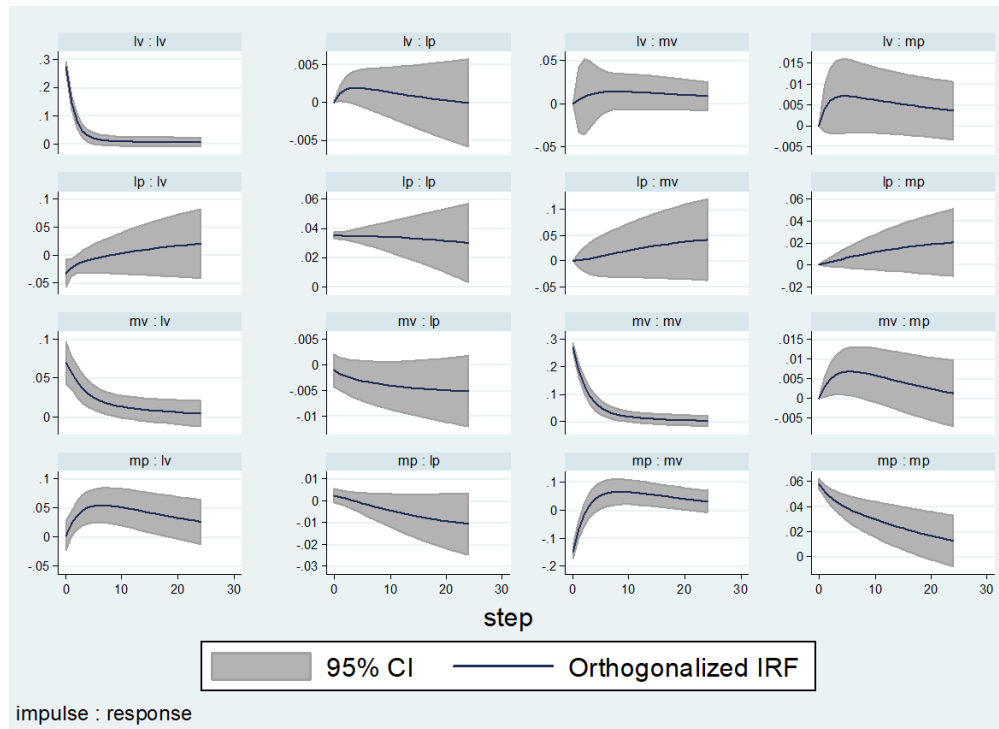
Figure A1. Color plots of figures 4 and 5



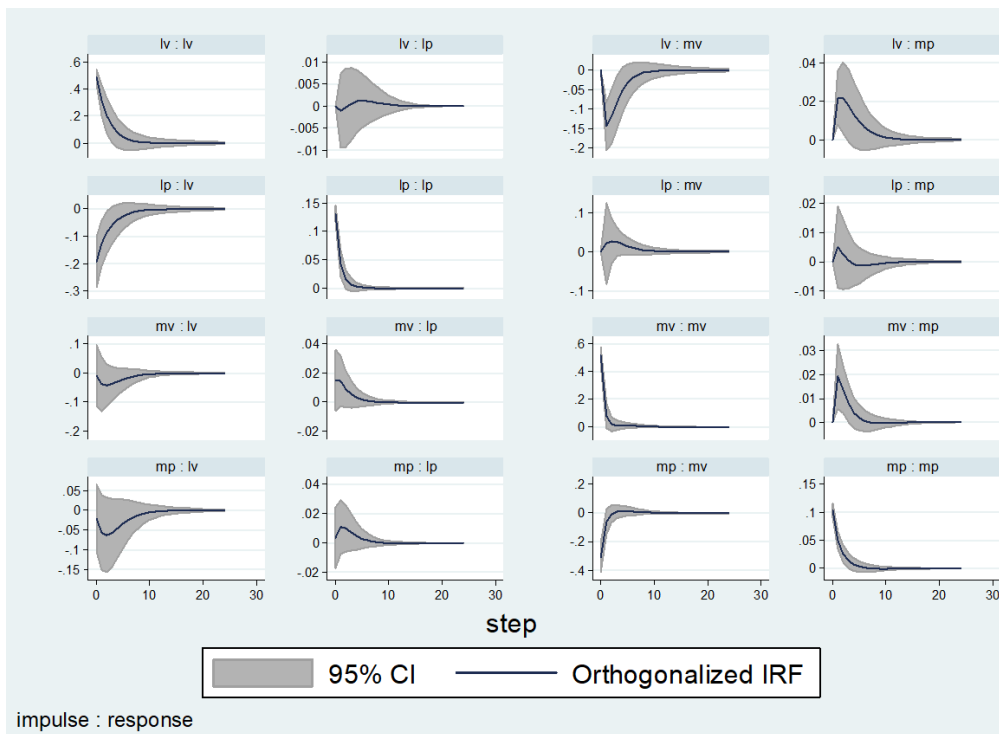
Note: Commercial: Light grey to navy, non-commercial: grey to red, Maui: black to green.

Figure A2. Product-wise VAR models

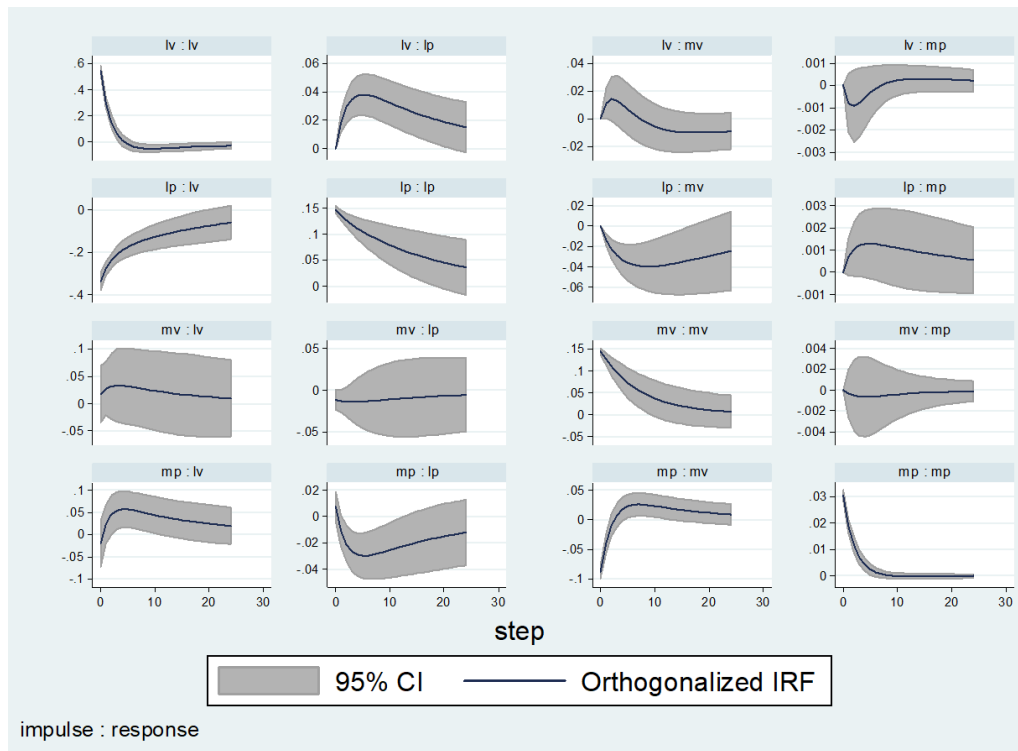
a. Lettuce:



b. Tomatoes:



c. 3. Milk:



d. 4. Eggs:

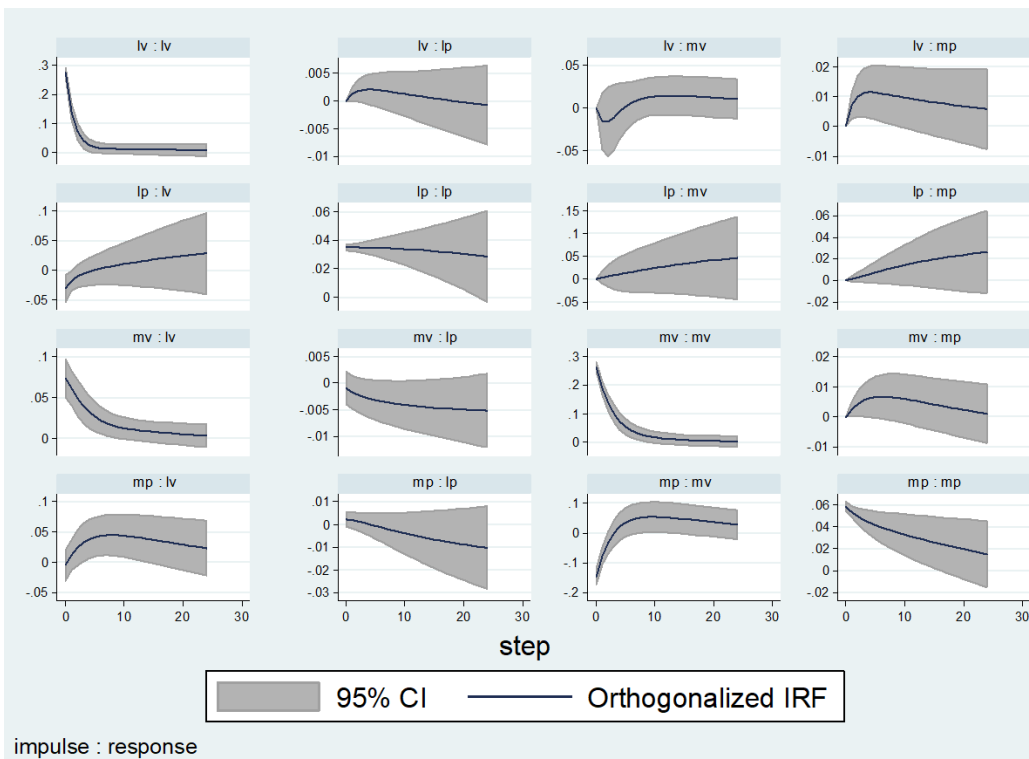
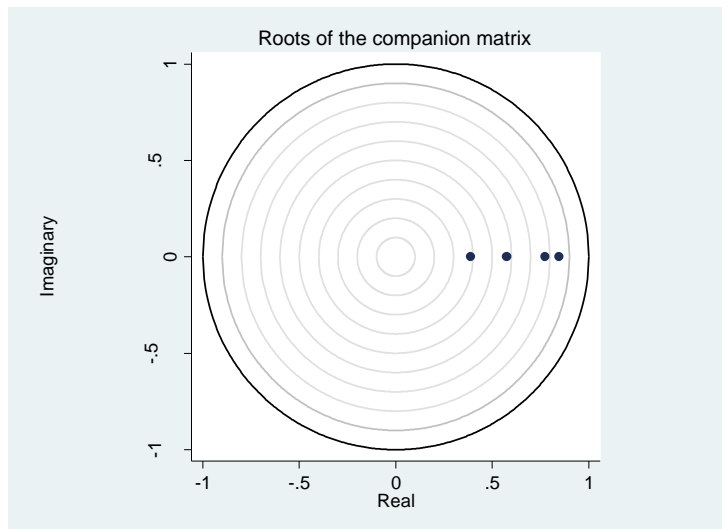


Figure A3. Roots of the companion matrix to test for stability of the panel VAR model



Note: All the eigenvalues are within the unit circle, which denote the stability of our estimated VAR model (Abrigo et al., 2016).

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