Demand of U.S. Imports of Fresh Citrus Products:
An Incomplete LINQUAD Demand Approach

by

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STATEMENT BY AUTHOR

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This Thesis has been approved on the dates shown below

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ABSTRACT

Recent developments in the markets of oranges, clementines, and tangerines call for more scrutiny on the import behavior of citrus. Imports of these products are highly variable during the period from 1989 to 2003. Imports are characterized by marked seasonality, variable price, and unobservable quantities and prices. Incomplete LINQUAD demand approach is estimated using semi-annual import data. Symmetry and negative semi-definiteness of the Slutsky matrix are not rejected. Own- and cross price elasticities are small in general. Income elasticity estimates are diminishing.

CHAPTER ONE

1. INTRODUCTION

The advantage of applied demand analysis is the ability to translate market dynamics into proper, plausible, and empirically estimable mathematical statements. The increasing availability of data on highly disaggregated agricultural commodities has made it possible to focus on the nature of their markets, estimate their demands, and measure the welfare impacts of government policies. Almost all empirical demand studies of agricultural products have focused on highly aggregated food products. There are cases, however, where the goods of interest are specific food items. These items usually account for a very small share of consumer's consumption bundle, and they are not always consumed regularly. Relevant examples are fresh fruit products which are increasingly diverse. Fresh citrus products are now comprised of dozens of new varieties like clementines, satsumas, blood oranges, tangelos, and other hybrids. Seasonality and zero consumption are expected to be more pronounced features at higher levels of disaggregation of data requiring more attention to be paid to the relevant econometric technicalities. Econometric remedies, in conjunction with a proper functional representation, determine the quality of the underlying demand analysis and the corresponding model estimates.

1.1 Research Motivation

Recent developments in the markets of oranges, clementines, and tangerines call for more scrutiny on the import behavior of citrus. Increasing exposure to international competition in the citrus market has provoked domestic growers to file petitions against citrus imports (Karst). Opponents of citrus imports argue that prices of domestic navel oranges and tangerines were driven down as a result of increasing imports of clementines, particularly from Spain. In order to validate this claim more information is needed on the nature of competition as well as the degree of substitution between domestic and imported products. Moreover, existing trade agreements and the rapid pace of bilateral trade negotiations with countries that are considered major citrus producers are also expected to have affect domestic markets, mainly through trade concessions. Finally, concerns about phyto-sanitary issues of citrus imports have been preoccupying potential stakeholders in the citrus market. Fears that imported products might introduce foreign pathogen, that would jeopardize domestic production, have lead in some cases to the adoption of very stringent phyto-sanitary measures. A relevant example is the import ban on Spanish clementines that was implemented between December, 2001 and April, 2003 after the interception of live Med-Fly larvae in some shipments. Hence, the need for quantifying the impact of these measures on the movement and volume of imports is of a high importance for policy makers who are interested in knowing the ultimate welfare effect of such domestic policies on consumers and producers.

1.2 Research Methodology

The analysis of import demand is one part of studying the general behavior of foreign trade flows. Import demand and export supply analysis have been traditionally conducted within a general (or partial) equilibrium framework. Econometric methods such as gravity and simultaneous equation models are also common approaches. However, this thesis focuses only on the import demand of a subgroup of closely related fresh citrus products. Consumer theory provides the ground to econometrically estimate import demand models explaining the quantity demanded of a particular imported good in terms of its own-price, related products' prices, income, and other determining factors. The particular model in this study represents an importer demand rather than a consumer demand. Nevertheless, it implicitly links importer demand to consumer demand at retail. The domestic demand of citrus products, though, is beyond the scope of this study because of serious shortcomings in California production data.

Important outcomes of import demand analysis using econometric techniques include the estimation of income and price elasticities, which quantify the responsiveness of import volumes to any change in prices and income, and the estimation of relevant welfare measures. Reliable and consistent income and price elasticities are derived from demand models that are theoretically consistent and statistically plausible. Exact welfare measures are more likely to be obtained from models that are consistent with consumer theory.

There are many approaches that are used to gauge the impact of price and income changes in the context of import demand. Incomplete demand systems (IDS) have recently received more attention as a convenient approach, particularly in studies involving a small number of closely related goods. The IDS approach does not assume weak separability of the imported citrus products. The system of incomplete import demand for citrus products, however, distinguishes between the expenditure on these products from that on a composite commodity encompassing all other good. In addition, the satisfaction of weak integrability assumptions will recover the underlying expenditure function of the targeted product at no theoretical cost.

The LINQUAD version of the IDS is considered as a flexible demand specification because of the addition of quadratic price terms (Agnew). It ensures the satisfaction of theoretical assumptions of weak integrability and also generates consistent elasticity estimates. The two testable hypothesis associated with demand analysis are symmetry and quasi-concavity of the Slutsky substitution matrix which are usually imposed on demand models. The rejection of these restrictions may affect the reliability of the elasticity estimates and the model's explanatory power. However, the rejection of theoretical restrictions is a common occurrence in many empirical studies. Rejection of these restrictions may occur because the model is not properly specified or because the sample data do not exactly reflect a demand relationship.

Descriptive analysis of citrus imports is essential to understand market dynamics and characteristics. Depicting the evolution of citrus imports over a period of fifteen years reveals a seasonal import pattern with varying trends across products and countries of origin. Discontinuous availability and marked seasonality are the most apparent features of citrus imports. The nature of seasonal availability differs across products and over time. The countries from which the United States import citrus also change over time.

The existence of such features requires the introduction of some econometric adjustments to the standard demand model. The absence of imports in some periods reduces the sample size by limiting the observations on selected prices and quantities.

This lack of selected observations is similar to the problem of missing values. However, in the sample of citrus imports the observations are not randomly missing. Instead, there is a non-random sample, where missing values have been selected out of the sample by a selection (truncation) criterion. Remedying the bias resulting from selection (truncation) is usually accomplished by embodying selection outcomes to the demand system and estimating the system parameters by either maximum likelihood techniques or two-stage Heckman procedure. Another plausible , but less desirable, approach is to aggregate observations over a certain period of time to avoid truncation. Temporal aggregation, however, reduces significantly the sample size.

1.3 Research Objectives

In this thesis, a descriptive analysis of imports is conducted for clementines, tangerines, and oranges. Market trends, the evolving composition of imports, and other characteristics of these imports are analyzed .

The potential truncation problem in the monthly time-series import sample is defined and explained. A proposed two-step estimation procedure is also delineated for the case of nonlinear, multivariate regression model and double, static selection rules. However, this approach is not empirically pursued because of difficulties in obtaining reasonable elasticity estimates using monthly data.

As an alternative, semi-annual data are constructed such that truncation no longer occurs. Months with zero imports are aggregated with months when imports occur so that zero import quantities and missing prices disappear. The LINQUAD incomplete import demand system is employed to estimate price and income elasticities of demand. The evaluation of results sheds some light on the particular demand relationships embodied in the sample data and also validates the functional form of citrus import demand.

1.4 Research Organization

The second chapter of this thesis provides a descriptive analysis of imports of fresh tangerines, clementines, and oranges. Chapter three is devoted to theoretical background in addition to a literature review on incomplete demand systems, in particular the LINQUAD version. Also, the nature of sample truncation and the proposed econometric approach to handling truncation are explained. Chapter four presents the empirical approach including the construction of data, the definition of model variables, and the imposition of theoretical restrictions. Chapter five reports the hypothesis tests and estimation results. Elasticity measures are also presented and discussed. Finally, chapter six concludes the thesis by summarizing the major findings and proposing further research ideas.

CHAPTER TWO

2. DESCRIPTIVE ANALYSIS OF IMPORTS

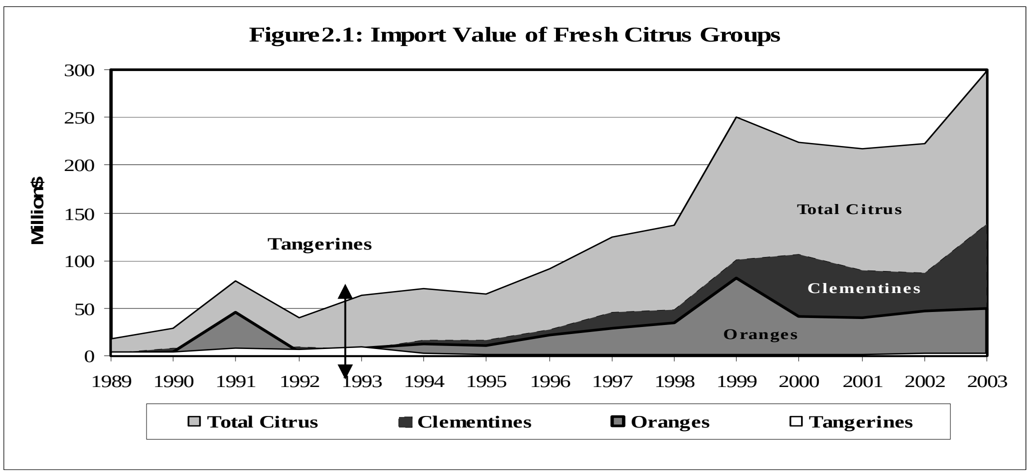
Following the up-to-date Harmonized Tariff Schedule (HTS) of the United States, the group of fresh citrus fruits is comprised of four main subcategories, namely: oranges; mandarins (orange-like citrus), grapefruits, and lemons. Oranges and mandarins, however, can be distinguished from the other subcategories with respect to their different fruit characteristics and utilization purposes. Accordingly, the following analysis of U.S. citrus imports deals only with oranges and mandarins.

Orange and mandarin subcategories include a number of varieties that are differentiated by several aspects i.e. time of maturity, appearance, juice and seed content. However, the 10-digit HTS[1] classifies imported oranges into temple oranges and other oranges. Imported mandarins are classified into tangerines and "other mandarins". The "other oranges" group contains, among others, navel, valencia, and midseason oranges. The group of "other mandarins" consists mainly of clementine, satsuma, and "hybrid" mandarins. For terminology convenience, the "other oranges" and "other mandarins" groups will be referred to as oranges and clementines, respectively. The temple group is excluded from the analysis since its import share in total fresh citrus imports is minimal and diminishing over time. The analysis of citrus imports therefore will focus only on orange, clementine, and tangerine groups

[1] U.S. 10-digits harmonized tariff schedule codes of oranges , mandarins, and tangerines, are 08051000-40, 08052000-40, and 08052000-20 respectively.

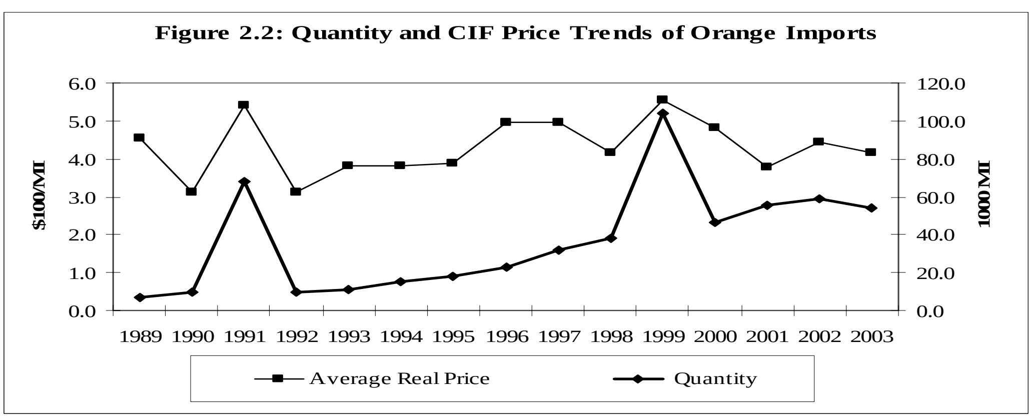
2.1 Import Growth

The U.S. import value of fresh citrus grew in nominal terms from US$ 19 million in 1989 to US$ 298 million in 2003 at an annual average rate of 20%. Orange and clementine import volumes increased at average rates of 20% and 28% per year, respectively. By contrast, tangerine import value declined at a yearly rate of 3% (see figure 2.1).



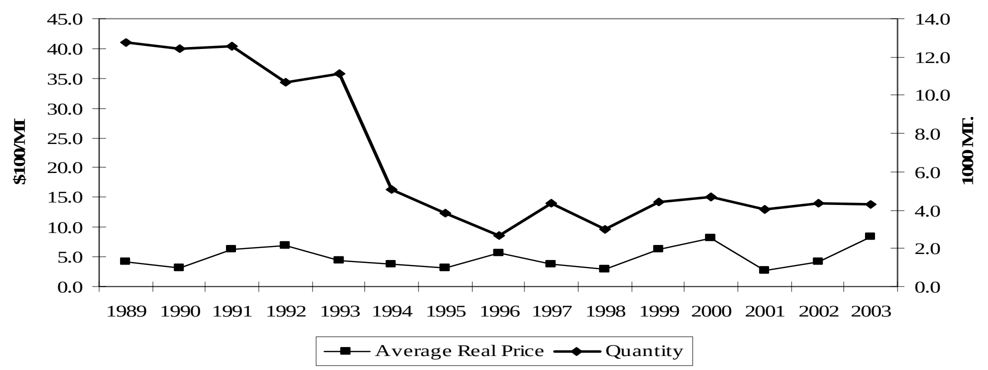
Source: U.S. Foreign Trade Reports (FATUS)

The growth in import value of oranges (see figure 2.2) as well as the contraction in tangerines (see figure 2.3) is mainly a result of the change in import quantities rather than a change in real import price levels.



Source: U.S. Foreign Trade Reports (FATUS)

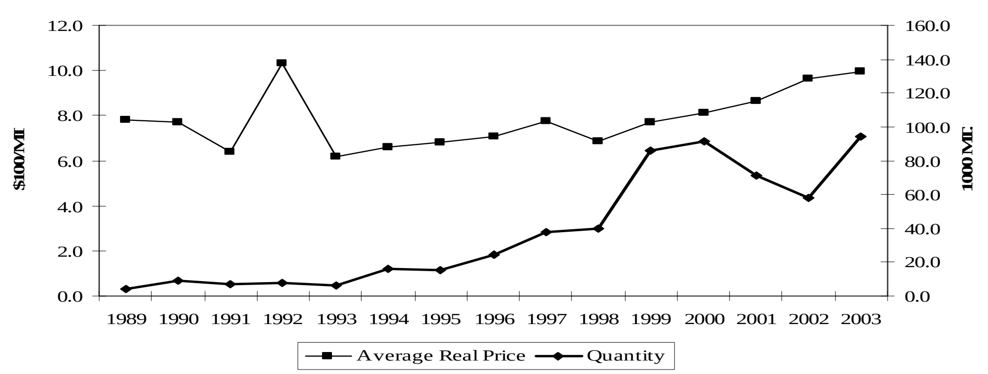
Figure 2.3: Quantity and CIF Price Trends of Tangerine Imports



Source: U.S. Foreign Trade Reports (FATUS)

On the other hand, the expansion in clementine import value (see figure 2.4) results from increases in both quantity and real price.

Figure 2.4: Quantity and CIF Price Trends of Clementines Imports



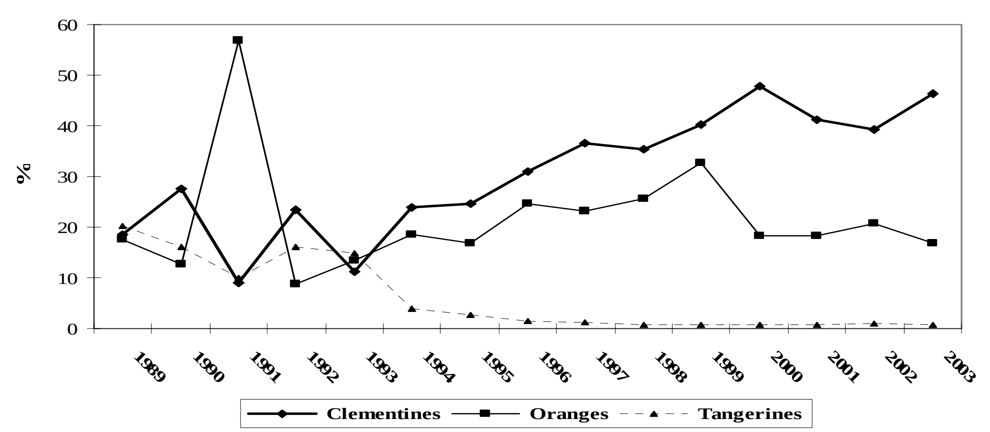
Source: U.S. Foreign Trade Reports (FATUS)

Orange and clementine imports were almost flat until 1994 (with an exception of orange imports in 1991) when they began to grow steadily during the last decade. Orange imports tripled while clementine imports increased ten fold over the last 15 years. Tangerine imports dropped significantly by almost two thirds during the same period.

In the period 1989 to 1993, the import values of the three groups, on average, accounted for 30.5% of the total import value of fresh citrus. The remaining 69.5%

represents the share of other citrus products particularly grapefruits, lemons, and limes. Oranges had the highest share of 22%, followed by clementines with 18% and tangerines with 15%. In the last five years, the share of total citrus import volume for the three subgroups altogether increased slightly to 37%.

Figure 2.5: Evolution of Import Value Shares of Various Citrus Groups



Source: U.S. Foreign Trade Reports (FATUS)

Clementines' import share grew significantly representing 46% of total citrus imports in 2003 (see figure 2.5). On the other hand, tangerines' import share decreased drastically to 1% of total citrus imports. As for oranges, its import share remained almost the same around 22%. In summary, clementine and orange subgroups increased both in absolute and relative terms to total citrus import volume, while tangerines showed a considerable decline in both terms.

2.2 Imports Origin

Only a few countries export the majority of different fresh citrus to the United States. A quick look at U.S. imports' origin reveals a small number of countries as the traditional import partners. Roughly 98% of U.S. imports of oranges, clementines, and tangerines originate from only 7, 5, and 3 countries, respectively. The current major exporters to the U.S. market are Spain, Mexico, Australia, South Africa, and Morocco.

In general, the countries from which citrus is imported have changed little in the past 15 years. The orange import market used to be dominated by Mexico, which still maintains a share of nearly 30%, and by Dominican Republic with a share of 16%. Imports from those countries span the entire year as they have counter-seasonal production seasons. In the last decade, however, imports of oranges from Australia and South Africa increased significantly replacing imports from Dominican Republic. Currently, Australia, Mexico, and South Africa account for 83% of total orange imports.

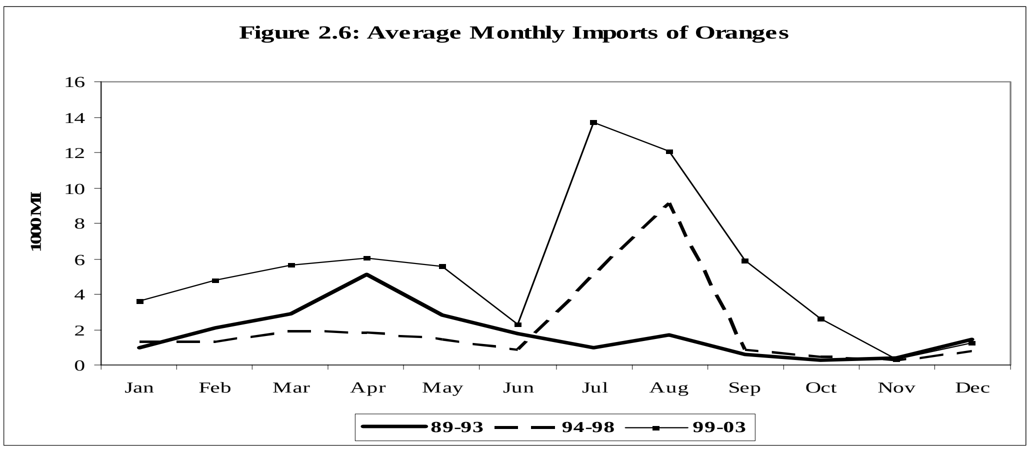
Spain remains the top import source for clementine imports. Its relative share increased from 73% to 83% over the last 15 years. Import quantity also rose remarkably by a factor of 12. Other current important importing sources with relatively smaller shares are South Africa, Morocco, and Australia.

Although tangerine imports shrank drastically, Mexico still leads with a share of 85% of total imports. Nevertheless, Israel has the potential to increase its exports to the United States and in recent years represents 12% of total tangerine imports.

2.3 Seasonality of Imports

U.S. citrus imports are characterized by marked seasonality that is driven by the seasonal nature of product supply in the exporting countries. However, seasonality of imports is not due solely to seasonal production. Other factors may cause shocks to production, and hence to the seasonal distribution of imports. Weather, pest control, quality attributes, introduction of new varieties, new countries of origin, market integration, and phyto-sanitary policy may alter the import flows or, in extreme cases, stop imports. In the early 1990s, drought and its effects on product quality caused the reduction and even absence of orange imports from Spain in some years. Moreover, activities such as grafting and plant breeding in exporting countries also changed the seasonal availability of products. The increased switching from valencia to navel oranges in most countries made it possible to export oranges throughout the calendar year. The adoption of new early maturing clementine hybrids in Spain stretched the seasonal availability of U.S. imports. The source of imports such as northern vs. southern hemisphere countries permits counter-seasonal imports of the same product from different sources, such as navels from Spain and Australia which mature in different, non-overlapping seasons. Quarantine measures can virtually stop imports. A recent example is the U.S. imposed ban on Spanish clementines in 2001-2002 season after the interception of live Med-Fly larvae in some shipments.

Apart from market and policy-driven factors, two types of import seasonality are distinguished with respect to import disappearance. One type is when the product is available year around but peaks in certain months. Imports of orange and clementines display such seasonal peaks. The orange import season usually starts in November through the following October (see figure 2.6). Depending on the country of origin, there are two potential import peaks. Most of the orange imports from Mexico and the Mediterranean region (Spain, Morocco) take place from February through May. Between 1989 and 1993, for instance, when such countries were the major sources of imports, 61% of orange were imported in these months, with nearly one quarter in April alone. In the last ten years, however, nearly 60% of oranges were imported in June through November when more imports come from the Caribbean (Dominican Republic, Jamaica, and the Bahamas) and from the southern hemisphere countries (Australia and South Africa).

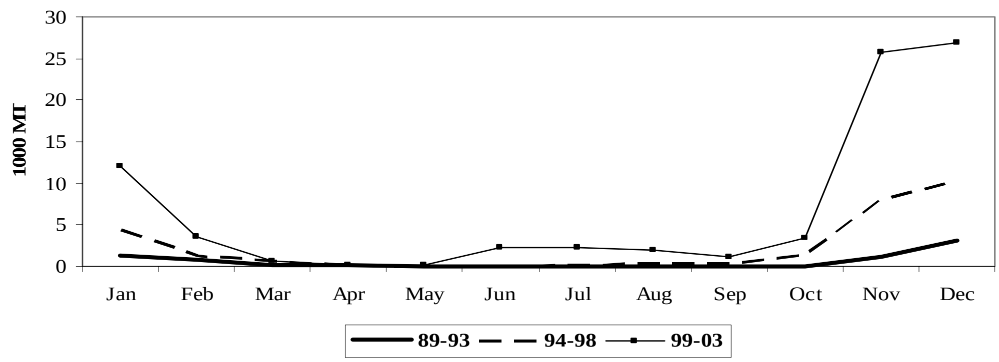


Source: U.S. Foreign Trade Reports (FATUS)

Clementines' traditional production season is October through February (see figure 2.7). Usually 94% of clementines is imported within these months, and around 40% occurs in December. However, imports from Australia and South Africa, which have grown in recent years, have contributed to early availability of clementine imports.

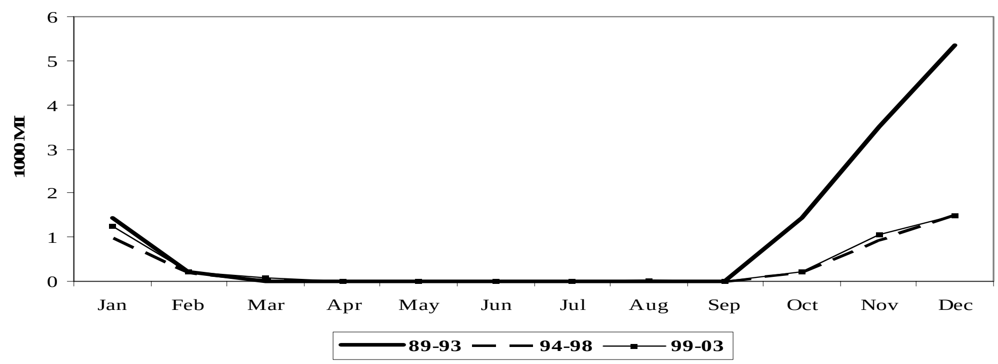
A second type of seasonality is displayed by tangerines. Imports occur only from October through February (see figure 2.8). There are no imports the rest of the year. This is due to the short period of product supply, and to the fact that no new countries have begun to export tangerines to the United States.

Figure 2.7: Average Monthly Imports of Clementines



Source: U.S. Foreign Trade Reports (FATUS)

Figure 2.8: Average Monthly Imports of Tangerines



Source: U.S. Foreign Trade Reports (FATUS)

CHAPTER THREE

3. THEORETICAL FRAMEWORK

Estimation of incomplete import demand system for these products is undertaken using a class of price-independent generalized linear (PIGL) quasi-expenditure function known as LINQUAD. Estimates of citrus price and income elasticities are then derived.

There are a plethora of empirical applications using complete demand systems. Incomplete demand systems are by far less common. A study by Agnew (1998) used data on dairy products to compare various specifications of demand systems with the more generalized PIGL model. Agnew found the PIGL functional form represented a more flexible functional form than other model specifications. In this thesis, the model that was developed by Agnew and the notation used in delineating his model are adopted. In another study, Fang and Beghin (2002) estimated urban final demand for edible oils and fats in China using the LINQUAD incomplete expenditure system.

Econometric studies of import demand for fresh fruits are quite scarce in the literature. Schmitz and Seale 2002 used annual Japanese fresh fruit import data to analyze import patterns of Japan's seven most popular fresh fruit imports. They tested five different demand systems. Among the five models, only the Rotterdam model gave good results.

The following section provides background information on incomplete demand systems. It also summarizes the theoretical underpinnings and common structures of such models. Complete specification of the utilized system is given thereafter.

3.1 Incomplete Demand Systems

3.1.1 Background

Complete demand systems intuitively require the availability of disaggregated micro data on all commodities consumed. However, data on all consumed commodities are seldom available. Accordingly, the search for alternative approaches has become of high practical value. Aggregation across products, separability , and incomplete systems are three alternative approaches that have been used in applied demand analysis.

Complete demand systems of commodity aggregates utilize highly aggregated data on quantities and prices. Hence, the number of parameters of the demand system to be estimated is reduced. This solution, although practically reasonable, comes at a high cost. Theoretical consistency is compromised with such a level of aggregation. Equally important, the usefulness of this approach becomes questionable when information on individual commodities is of interest.

The separability approach rests on the assumption that within the consumers' utility function there is a subset of goods that are weakly separable from all other goods. Given weak separability, a complete system of conditional demands for the targeted goods can be estimated. Functional separability and Hicksian separability are two methods used to obtain conditional demand functions under two different situations. The functional separability approach models consumption for the goods of interest conditional on their total expenditure. Some constraints on the structure of preferences should be imposed. One drawback of this approach is the bias resulted from the joint determination of quantities demanded of goods of interest and their expenditure (LaFrance 1990). Using Hicksian separability or the so called “Hicksian composite good” the demand of targeted goods is modeled as a function of their prices, total income, and the composite good’s price index. In this approach, constraints on the price movements are imposed. However, the conditions necessary for using such a composite good are seldom met in empirical settings.

The complications associated with previous approaches have given rise to the use of incomplete demand systems (IDS). This approach has gained some popularity with applied demand analysts for two major reasons. First, it is a convenient method when the focus is on a particular set of commodities, which form a subset of the household’s budget. Second, it allows a more general class of functional forms since the adding-up condition is an inequality restriction on the total expenditure for the goods in interest (LaFrance and Hanemann).

The IDS approach implies that some demand functions for a group of commodities are directly specified. However, for these demand functions to be consistent with the duality theory, well behaved expenditure and indirect as well as direct utility functions should be recoverable. In other words, if these demand functions can be integrated back to recover the underlying preference ordering, they are therefore analogous to the theoretically consistent demand functions derived from maximizing the original utility function. The drawback of IDS is that all information on other commodities, which appears in the constant of integration cannot be retrieved.

Integrability conditions for IDS require that specified demand functions satisfy four properties. Zero degree homogeneity in prices and income, positive demand value, symmetry, and negative semi-definiteness of the Slutsky matrix are satisfied by IDS demand functions as by their counterparts of complete systems. The adding-up property is what distinguishes the IDS as the expenditure on a subgroup of commodities is strictly less than income. Although symmetry and concavity of the Slutsky matrix are imposed restrictions, they remain as testable hypotheses. Functions that satisfy such properties are said to be integrable. Weak integrability, proposed by LaFrance and Hanemann, is a flexible condition and represents a minimal set of assumptions for recovering the underlying utility function. The advantage of weak integrability is that it relaxes the assumption of uniform functional form between individual demand functions for expenditure on goods of interest and aggregate demand function for expenditure on other goods (Agnew).

3.1.2 Structure

A quick look at the literature on IDS reveals the domination of linear, log-linear, and semi-log incomplete demand structures. LaFrance (1985, 1986, 1990) and von Haefen have extensively studied these structures. LaFrance and von Haefen derived the necessary weak integrability restrictions for an exhaustive set of functional forms. The imposition of symmetry on the price effects matrix (Slutsky) implies relatively strong restrictions on price and income effects as well as on preferences mappings.

Integration of demand functions that are linear in quantities, prices, and income reveals the class of deflated linear quasi-expenditure function. Further, LaFrance (1990) concluded that the addition of a quadratic term in prices to the expenditure function makes it more flexible and therefore gives the demand functions generated from it more desired qualities (Agnew). This modified class of quasi-expenditure function generates a demand model knows as "LINQUAD".

The name LINQUAD emphasizes the inclusion of linear and quadratic price terms in the functional form. The LINQUAD model has many advantages over other models, particularly, the linear and the semi-logarithmic. Unlike the linear model, LINQUAD relaxes the restriction on income coefficients as they may be zero, negative, or positive. It does not require homothetic preferences as semi-logarithmic model requires. More importantly, it significantly reduces the number of model coefficients that need to be estimated.

Another class of quasi-expenditure functions is the logarithmic one (PIGLOG). It is the logarithmic version of the LINQUAD where the natural logarithms of expenditure, prices, and income replace those same variables in the linear form. The models that are derived from this class are expenditure share models. A well-known application of these models is the Almost Ideal Demand System (AIDS) introduced by Deaton and Muellbauer (1980). However, one key difference is that AIDS uses group expenditure whereas LINQUAD uses income.

3.1.3 LINQUAD Model Specification

Assume that consumer demand for a set of n goods can be represented by the following system of Marshallian demand functions:

$$x_i = x_i(\mathbf{p}, \mathbf{q}, y, \boldsymbol{\beta}), \qquad i = 1, \ldots, n. \tag{3.1}$$

where x_i is the consumer's Marshallian demand for good i, $\mathbf{p}$ is a vector of prices for the n goods in (3.1), $\mathbf{q}$ is a vector of prices of m other goods whose demands are not explicitly defined, y is the consumer's income, and $\boldsymbol{\beta}$ is a vector of structural parameters. In order for this set of demand equations to satisfy the first property for integrability, homogeneity-of-degree-zero is imposed. Prices and income ($\mathbf{p}$, $\mathbf{q}$, y) are all normalized by $\pi(\mathbf{q})$ a homogeneous-of-degree-one price index for the m other goods.

Following LaFrance (1990), assume that Marshallian demands are linear in income and are linear and quadratic in prices. Integration of these demand functions reveals the structure of deflated expenditure functions

$$\varepsilon(\mathbf{p},\mathbf{q},\mathbf{z},\theta) = \mathbf{p}'\alpha + \mathbf{p}'\mathbf{A}_{\mathbf{z}}\mathbf{z} + 0.5\mathbf{p}'\mathbf{B}\mathbf{p} + \delta(\mathbf{z}) + \theta(\mathbf{q},u,\mathbf{z})e^{\gamma p} \tag{3.2}$$

where $\mathbf{z}$ is a set of demographic shifters, relevant other prices or lagged quantities (Agnew). $\delta(\mathbf{z})$ is an arbitrary real valued function of all variable in $\mathbf{z}$, $\theta(\mathbf{q},u,\mathbf{z})$ is the constant of integration and $\alpha,\mathbf{A}_{\mathbf{z}}$, γ and $\mathbf{B}$ are the parameters[2] to be estimated. Solving the partial differential equation of (3.2) with respect to the logarithm of p_i generates demand models of the form,

$$\mathbf{x} = \alpha + A\mathbf{z} + B\mathbf{p} + \gamma\left[\theta(\mathbf{q},u,\mathbf{z})e^{\gamma p}\right]. \tag{3.3}$$

Solving (3.2) for the integration constant, and replacing expenditure with y for income, gives the final system of demand equations to be estimated

$$\mathbf{x} = \alpha + A\mathbf{z} + B\mathbf{p} + \gamma\left[y - \alpha'\mathbf{p} - \mathbf{p}'\mathbf{A}\,\mathbf{z} - 0.5\,\mathbf{p}'\mathbf{B}\,\mathbf{p} - \delta(\mathbf{z})\right]. \tag{3.4}$$

Assuming an additive stochastic error term, the variance-covariance matrix of the previous system is heteroskedastic (Agnew). However, multiplying both sides of each

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[2] When a parameter is in italic form it is a vector of parameters; it is a matrix of parameters otherwise.

equation by its corresponding price avoids this problem and reveals a system of expenditure equations. The final econometric model to be estimated is

$$e_i = p_i\{\alpha_i + A_i\mathbf{z} + \mathbf{B}_i\mathbf{p} + \gamma_i[y - \alpha'\mathbf{p} - \mathbf{p}'\mathbf{A}\,\mathbf{z} - \mathbf{0.5}\,\mathbf{p}'\mathbf{B}\,\mathbf{p} - \delta(\mathbf{z})]\} + u_i \tag{3.5}$$

where $i \in \{Oranges, Mandarines, Tangerines\}$, and $e_i \equiv p_i x_i$.

The derivation of price and income elasticities, and the imposition of the remaining theoretical restrictions are explained in the next chapter when the empirical approach is outlined.

3.2 The Partially Truncated Demand System

One common problem in empirical demand studies is *truncation*. When data are not drawn randomly from larger population of interest, the resulting sample is no longer random, and it does not reflect the true characteristics of the population. One form of truncation is when the data generating process systematically excludes information, i.e. observations from the sample. The exclusion or truncation can be from above or below (or both) when observations are greater or less than a truncation value are excluded from the sample . Surveys that target only certain households are typical examples of a process that generates non-random samples. Another form of truncation is the *sample selection problem (incidental truncation)*, where the exclusion of information occurs *before* choosing the sample as a result of a selection mechanism. Truncation is distinguished from *censoring* where some of the sample information is suppressed rather than excluded (Davidson & MacKinnon).

In the following application, a partial truncation case is encountered in estimating the incomplete import demand system for three citrus products. The nature of the truncation problem is first discussed. Then, the proposed estimation approach for correcting the truncation bias is outlined.

3.2.1 The Nature of Partial Truncation

Citrus imports, as mentioned earlier, are characterized with marked seasonality. The import patterns across products reveal a supply-driven seasonality as the imports of certain products increase or decrease as production (supplies) from exporting countries increase or decrease. In some periods, there are no import quantities for a particular product. Consequently, corresponding import prices for that product are unobservable.

Imports may disappear when at least one of the following scenarios takes place. First, imports might be infeasible due to supply-related factors. Unfavorable weather conditions can virtually stop imports because of reduced yields or decreased product quality. Domestic and international competition may also determine whether imports occur as exports are supplied to destinations where prices are higher. Second, possible economic and non-economic factors may preclude trade from occurring even though it is technically feasible. For example, sanitary and phyto-sanitary restrictions could reduce or prohibit imports in a given time period. Trade embargoes implemented for political reasons might also block trade entirely. Third, it could be the case that there is no demand for an imported product in a particular period of time as consumers collectively[3] choose not to buy it. This case is similar to the occurrence of zero expenditures in cross-sectional household surveys where consumers decide not to

[3] Import quantities in our example represent the total importer demand for imports.

purchase certain goods due to their high relative prices. The validity of the last scenario to import demand is questionable because consumers cannot observe import prices in periods when none of the products is imported.

Evaluating seasonal variation of imports usually involves the construction of an exogenous dummy variable taking a value of one when imports occur and a value of zero otherwise. However, if the incidence of positive imports is based on a selection mechanism, treating import disappearance as an exogenous argument is not correct.

When imports for a particular product do not occur in a particular period of time, a kind of sample selection problem may result. Prices and quantities are only observed for the part of sample when imports actually take place. It is plausible that the occurrence of imports is the outcome of a binary decision that imports are either feasible or not. A “feasibility constraint” that includes the entire set of factors that may influence the realization of imports, can be considered as a selection equation. The feasibility variable is latent and only its binary outcome can be observed.

The literature is full of applications dealing with sample selection problems (incidental truncation). They address situations such as single, double (sequential is a special case), and self-selection. Greene constructed a regression model with sample selection for predicting expenditures of credit recipients. The sample displays selection since it is of individuals to whom credit has already been given. The double-selection situation was thoroughly analyzed by Tunali. He discussed the problem of selectivity under various sample selection regimes that result from models with two selectivity criteria and distinguished according to the amount of information available. Lahiri and Song studied the incidence of smoking diseases after accounting for two sequential self-selection decisions, i.e. the decision to start and then to quit smoking. Maddala provides a thorough analysis of self-selection problems in evaluating the benefit of social programs on participants.

In almost all empirical applications, samples displaying incidental truncation (selection) are cross-sectional, where the selection takes place at a single point of time, *t*. In the sample of citrus imports, truncation is viewed from a time-series perspective. The selection happens at different time periods, t_i, where *i* could be any time unit such as a month. Although the two cases look similar, they are quite different. In addition to the statistical assumptions underlining the selection criteria, i.e. asymptotic assumptions, in time-series case, the selection criterion is assumed to be the same over time, i.e. exact set of regressors for all periods, t_i.

In the present application an incomplete demand system with three goods is considered. A special truncation case occurs due to a contemporaneous double-selection situation which results in four different truncation regimes. In the following, a partially truncated import demand model for three citrus products is delineated.

Let quantities of the ith good in the tth time period be denoted by x_{it}. Let $\mathbf{P}_t$ be a vector of own-and cross-prices. Also, denote income in the tth time period as y_t. Depict the parametric form to be estimated of the Marshallian demand function (3.1) from the seemingly unrelated incomplete demand system as

(3.6) $$x_{it} = x(\mathbf{P}_t, y_t | \boldsymbol{\beta}) + u_{it} \qquad \mathbf{u}_t \sim N[\mathbf{0}, \boldsymbol{\Omega} \otimes \mathbf{I}_T] \text{ or } E[u_{it}, u_{jt}] = \omega_{ij} \quad i \neq j.$$

where $i \in \{clementines, tangerines, oranges\}$, $\boldsymbol{\beta}$ is a vector of unknown parameters, and $\boldsymbol{\Omega}$ is the contemporaneous covariance matrix.

The selection or truncation equation in the context of the import demand model is referred to as "feasibility" constraint. The feasibility variable is latent. The observed variable is an indicator variable equal to one if imports are feasible, and equal to zero otherwise.

(3.7) $$I_{it}^{*} = \boldsymbol{Z_{it}\gamma_{i}} - \boldsymbol{\varepsilon_{it}} \qquad i \in \{clementines, tangerines\}$$

$$I_{it} = \begin{cases} 1 \text{ if } I_{it}^{*} > 0 \\ 0 \text{ otherwise} \end{cases}$$

where $\mathbf{Z_{it}}$ is a row vector of explanatory variables that explain feasibility of imports, $\boldsymbol{\gamma}$ is a vector of corresponding parameters, and $\varepsilon_i \sim N(0, \sigma_i^2)$ is the error term. Recall that oranges are imported year around so prices and quantities of imported oranges are always observed.

The variance-covariance matrix of the five equations system, i.e. two selectivity equations and three demand equations, is given by

(3.8) $$E\left\{\begin{bmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \\ \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \begin{bmatrix} u_{1t} & u_{2t} & u_{3t} & \varepsilon_{1t} & \varepsilon_{2t} \end{bmatrix}\right\} = \begin{bmatrix} \omega_{11} & \omega_{12} & \omega_{13} & \rho_{11} & \rho_{12} \\ & \omega_{22} & \omega_{23} & \rho_{21} & \rho_{22} \\ & & \omega_{33} & \rho_{31} & \rho_{32} \\ & & & \sigma_{11} & \sigma_{12} \\ & & & & \sigma_{22} \end{bmatrix}$$

The upper-left-hand 3×3 block is the contemporaneous variance-covariance matrix of the incomplete demand system. The upper-right-hand 2×3 block is the matrix of correlation coefficients between the errors from the demand system and the selectivity equations. The lower-right-hand 2×2 block is the variance covariance matrix of the selectivity equations.

According to the “feasibility” constraint equation, clementines and tangerines are supplied to the United States in time periods $t \in \{s_1, s_2\}$ where there may be at least some time during the year in which the two periods overlap. By contrast, oranges are supplied year-round. Thus, partial truncation is determined by the export supply of both clementines and tangerines (Thompson).

The table below depicts the nature of the truncation (selection) problem as a result of imports’ feasibility.

Table 3.1: The Partial Truncation of Citrus Incomplete Import Demand System

<table>
<tr><td></td><td colspan="4">Months throughout the Year</td></tr>
<tr><td></td><td colspan="4">T</td></tr>
<tr><td></td><td colspan="2">S₁</td><td></td><td></td></tr>
<tr><td>Imports</td><td></td><td colspan="2">S₂</td><td></td></tr>
<tr><td>Clementines (s_1)</td><td colspan="2">$\mathbf{Z}_{it}, p_{clem,t}, q_{clem,t}, y_t$</td><td></td><td></td></tr>
<tr><td>Tangerines (s_2)</td><td></td><td colspan="2">$\mathbf{Z}_{it}, p_{tang,t}, q_{tang,t}, y_t$</td><td></td></tr>
<tr><td>Oranges (t)</td><td colspan="4">$\mathbf{Z}_{it}, p_{orange,t}, q_{orange,t}, y_t$</td></tr>
<tr><td>Truncation</td><td>Partial
$q_{tang,t} = 0$
$p_{tang,t}$
unobserved</td><td>None</td><td>Partial
$q_{clem,t} = 0$
$p_{clem,t}$
unobserved</td><td>Partial
$q_{clem,t} = q_{tang,t} = 0$
$p_{clem,t}, p_{tang,t}$
unobserved</td></tr>
</table>

The two selection equations and the three Marshallian demand equations represent a general model similar to that of Tunali. However, the regression in Tunali’s model is a single equation rather than a demand system. Using the dichotomous variables I_{1t} and I_{2t} to indicate the outcomes of the two selection equations, the observations in the original sample are classified as follows:

$$I_{1t} = \begin{cases} 1 & \text{if } I^*_{clem,t} > 0 \\ 0 & \text{if } I^*_{clem,t} \le 0 \end{cases}$$

and

$$I_{2t} = \begin{cases} 1 & \text{if } I^*_{tang,t} > 0 \\ 0 & \text{if } I^*_{tang,t} \le 0 \end{cases}$$

It should be mentioned that the dichotomous variable I_{it} here encompasses the simultaneity in observing import quantity and price, i.e. only when I_{it} equals one are both quantity and price of product *i* observed.

The results of the selection process are expressed in the following table, where R_j denotes the set of observations (regimes) falling into the j^{th} sub-sample, $j = 1,...,4$.

Table 3.2: Observability of Various Sub-Samples

		I_{1t}	
		0	1
I_{2t}	0	R_1	R_2
	1	R_3	R_4

Each of the sub-samples R_j, is not a random sample. The R_4 regime represents the sub-sample that has a complete price vector; each dependent variable of demand equations along with all the explanatory variables are observed.

In summary, the structure of demand estimation problem is one of sample selection or incidental truncation. Two selection rules determine the import sample with which the incomplete demand system is estimated. It represents a subset, i.e. regime R_4, of the entire population of import, hence it is a non-random sample. Linear regression estimates, i.e. ordinary least squares (OLS) estimates, of this sub-sample's parameters are biased and inconsistent. Seemingly unrelated regression (SUR) techniques would also result in biased parameter estimates if sample selection is ignored. Alternative estimation techniques must account for the selection bias introduced to the sample in order to yield unbiased and consistent estimates.

3.2.2 The Estimation Approach

Maximum likelihood estimation (MLE) and Heckman two-step procedure (Heckit) are common methods used to correct for the sample selection bias. In correcting sample-selection bias using MLE, the objective function to be maximized is the product of conditional probabilities over the whole sample where the condition represent the “observability” criteria. Direct estimation of the likelihood function via MLE will yield consistent estimates of the parameters as well as consistent estimates of the asymptotic covariance matrix. As with many objective functions, however, the parameter estimates obtained from a nonlinear model may not correspond to the global maximum. Some examples of empirical studies that applied this approach include Wales and Woodland (1980), Arias and Cox (2001), and Lahiri and Song (2000).

Assuming bivariate normal distribution between the regression and the selection error terms, Heckman (1979) derived the so called “inverse mill’s ratio” from estimating a simple probit model for a single selectivity equation. He then included it as a generated regressor in the original regression model to correct for selection bias. Olsen (1980) generalized Heckman’s method by relaxing the assumption of bivariate normal distribution. He derived Heckman’s results assuming only the normality of the selection's error terms and the linearity of the conditional expectation of the regression's error term. Many applications have employed the two-step procedure to correct sample selection bias. Tunali (1986), Greene (1998), Shonkwiler and Yen (1999), and Lee (1982) are a few examples.

3.2.2.1 Two-Step Approach for Citrus Import Demand System

Conventional estimation of the incomplete demand system for three citrus products only makes use of observations that have full set of information on both dependent and independent variables. Observations that fall under regime R_4 constitute that estimation sample (Table 3.2).

From (3.6), the conditional mean of the dependent variable is given by:

(3.9) $$E[x_{it}|\mathbf{P}_{it}, y_{it}, \mathbf{Y}] = (\mathbf{P}_{it}, y_{it})\boldsymbol{\beta} + E[u_{it}|\mathbf{P}_{it}, y_{it}, \mathbf{Y}]$$

where **Y** denotes the joint outcome of the two selection rules. From (3.7) the two selection rules can be written as

<u>*Clementines' Import "Feasibility" Constraint*</u>

(3.10) $$\varepsilon_{1t} > -\boldsymbol{Z}_{1t}\gamma_1$$

where $\mathbf{Z}_{1t}$ is a vector variables which are assumed to explain the occurrence of clementine imports for a particular period of time *t*.

<u>*Tangerines'' Import "Feasibility" Constraint*</u>

(3.11) $$\boldsymbol{\varepsilon}_{2t} > -\boldsymbol{Z}_{2t}\gamma_2$$

where $\mathbf{Z}_{2t}$ is a vector of variables which are assumed to explain the occurrence of tangerine imports for a particular period of time *t*.

Substituting (3.10) and (3.11) in (3.9), the expected value of x_{it} taking into account the double selectivity equations is

$$E\left[x_{it} \middle| \varepsilon_{1t} > -\mathbf{Z}_{1t}\gamma_1, \varepsilon_{2t} > -\mathbf{Z}_{2t}\gamma_2\right] = (\mathbf{P}_{it}, y_{it})\boldsymbol{\beta} + E\left[u_{it} \middle| \varepsilon_{1t} > -\mathbf{Z}_{1t}\gamma_1, \varepsilon_{2t} > -\mathbf{Z}_{2t}\gamma_2\right]$$

The conditional expectation of the error is now given using Tunali's notation as

$$\begin{aligned} E\left[u_{it} \middle| \varepsilon_{1t} > -\mathbf{Z}_{1t}\gamma_1, \varepsilon_{2t} > -\mathbf{Z}_{2t}\gamma_2\right] &= \rho_{i1} \frac{\phi(\mathbf{Z}_{1t}\gamma_1)\boldsymbol{\Phi}(c_2)}{p} \\ &\quad + \rho_{i2} \frac{\phi(\mathbf{Z}_{2t}\gamma_2)\boldsymbol{\Phi}(c_1)}{p} \\ &= \rho_{i1}\lambda_1 + \rho_{i2}\lambda_2 \end{aligned}$$

where, $c_1 = \dfrac{\mathbf{Z}_{2t}\gamma_2 - \rho\mathbf{Z}_{1t}\gamma_1}{(1-\rho^2)^{1/2}}$, $c_2 = \dfrac{\mathbf{Z}_{1t}\gamma_1 - \rho\mathbf{Z}_{2t}\gamma_2}{(1-\rho^2)^{1/2}}$ and $p = \boldsymbol{\Phi}_2(\mathbf{Z}_{1t}\gamma_1, \mathbf{Z}_{2t}\gamma_2, \rho)$.

λ_j are called the inverse mills ratios or the hazard ratios. The bivariate normal cumulative distribution function is denoted by $\boldsymbol{\Phi}_2$. The univariate normal density and distribution functions are denoted by ϕ and $\boldsymbol{\Phi}$.

Step One: Bivariate Probit

Following the two-step procedure of Heckman, the estimation of the first step involves a bivariate probit estimation assuming $E[\varepsilon_{1t}\varepsilon_{2t}] = \sigma_{12} \neq 0$. This estimation will yield estimates of $\hat{\gamma}_1, \hat{\gamma}_2$, and $\hat{\rho}$ which will be used to estimate λ_1, and λ_2.

The bivariate probit likelihood function as suggested by Tunali is

$$\mathrm{L} = \prod_{\mathrm{R}_1+\mathrm{R}_2+\mathrm{R}_3} [1 - \boldsymbol{\Phi}_2(c_1, c_2; \rho)] \cdot \prod_{\mathrm{R}_4} \boldsymbol{\Phi}_2(c_1, c_2; \rho).$$

Step Two: Linear Regression

Having estimated $\hat{\lambda}_{1t}, \hat{\lambda}_{2t}$, the feasible generalized least squares (GLS) approach for SUR can be estimated with the new regressors using OLS estimation with each equation and then using the least squares residuals to consistently estimate the elements $\hat{\omega}_i$ of $\mathbf{\Omega}$. The estimates of these elements are then used to transform the independent variables of the system as follows:

$$
\begin{aligned}
x_{it} &= (\mathbf{P}_{it}, y_{it})\boldsymbol{\beta}_{\mathbf{GLS}} + \hat{\omega}_i \sum_{j=1}^{2} \rho_{ij} \hat{\lambda}_{jt} + \hat{\omega}_i v_{it} \\
&= (\mathbf{P}_{it}, y_{it})\boldsymbol{\beta}_{\mathbf{GLS}} + \sum_{j=1}^{2} \beta_{\lambda_j} \hat{\lambda}_{jt} + \tilde{v}_{it} \\
&= \left(\mathbf{P}_{it}, y_{it}, \hat{\lambda}_{jt}\right)\boldsymbol{\beta}_{\mathbf{GLS}} + \tilde{v}_{it}
\end{aligned}
$$

CHAPTER FOUR

4. EMPIRICAL FRAMEWORK

The estimation of the incomplete demand system using monthly data is not pursued in this thesis. Preliminary estimation results of this system before correcting for truncation bias were considerably irregular. Given those poor results, semi-annual data were used instead to estimate this model. The utilization of semi-annual data will reduce the estimation complexity that arises from the joint use of the highly variable monthly data and the highly nonlinear estimation approach for handling partial truncation. Aggregation of data is an alternative remedy to the adjustment for truncation presented in the previous chapter. Aggregating monthly data to semi-annual observations decreases significantly the sample size and conceals partially the seasonality aspect that exists in the monthly data. However, it rids the sample of zero import quantities and unobservable prices.

4.1 Data

The dataset used in estimating the incomplete demand system contains semi-annual time series observations on demand variables. The data were transformed from raw data series in order to fit the purpose of the undertaken analysis. In the following, data sources and definition of terminology are described.

4.1.1 Sources

The data were collected from three different statistical sources in the United States. Citrus import data, which includes import quantities and c.i.f. import values, were taken from the U.S. Foreign Agricultural Service trade reports of the United State Department of Agriculture. The f.o.b. prices of domestic navels were taken from the 2003 annual report of Florida citrus products. The consumer price index for all items less food was taken from the U.S. Bureau of Labor Statistics. Personal income and population were taken from the U.S. Bureau of Economic Analysis (BEA).

4.1.2 Definitions

The raw data are comprised of monthly observations on import quantities and "cost, insurance, and freight" (c.i.f.) values of oranges, clementines, and tangerines, f.o.b. price of Florida navels, personal income, the consumer price index and population. The series covers the period from January 1989 through December 2003 with a total of 180 observations.

The import quantities represent the metric ton volume of imported oranges, clementines, and tangerines for consumption. Imports for consumption measure the total of merchandise that has physically cleared through customs either entering consumption channels immediately or entering after withdrawal for consumption from bonded warehouses under customs custody or from Foreign Trade Zones.

The c.i.f. value represents the landed value of the merchandise at the first port of arrival in the United States. It is computed by adding "Import Charges[4]" to the "Customs Value[5]" and therefore excludes U.S. import duties.

The f.o.b. (free on board) price of Florida navels is the dollar value of one metric ton of navel shipments at the Florida border.

Personal income is measured in billion dollars of income received by persons from all sources. It is the sum of compensation of employees (received), proprietors' income, rental income, income receipts on assets, and current transfer receipts less contributions for government social insurance.

The consumer price index (CPI) is the seasonally adjusted U.S. city average price index for all items less food. The base year used for its calculation is 1982-84=100.

Population is the total population of the United States, including the Armed Forces overseas and the institutionalized population. The monthly estimate is the average of the estimates for the first of the month and the first of the following month.

[4] Import charges represent the aggregate cost of all freight, insurance, and other charges (excluding U.S. import duties) incurred in bringing the merchandise from alongside the carrier at the port of exportation and placing it alongside the carrier at the first port of entry in the United States. In the case of overland shipments originating in Canada or Mexico, such costs include freight, insurance, and all other charges, costs and expenses incurred in bringing the merchandise from the point of origin (where the merchandise begins its journey to the United States) in Canada or Mexico to the first port of entry.

[5] The Customs value is the value of imports as appraised by the U.S. Customs Service in accordance with the legal requirements of the Tariff Act of 1930, as amended. This value is generally defined as the price actually paid or payable for merchandise when sold for exportation to the United States, excluding U.S. import duties, freight, insurance, and other charges incurred in bringing the merchandise to the United States. The term "price actually paid or payable" means the total payment (whether direct or indirect, and exclusive of any costs, charges, or expenses incurred for transportation, insurance, and related services incident to the international shipment of the merchandise from the country of exportation to the place of importation in the United States) made, or to be made, for imported merchandise by the buyer to, or for the benefit, of the seller. In the case of transactions between related parties, the relationship between buyer and seller should not influence the Customs value.

Import prices were calculated by dividing the monthly c.i.f. value of each product by the corresponding quantity.

$$P_{t,i}^{cif} = \frac{V_{t,i}^{cif}}{Q_{t,i}}$$

where,

t is the month of the calendar year, and i is the citrus product

The data were aggregated to semi-annual observations by calculating the weighted average prices summing import quantities, and averaging income and population. Finally, import quantities were divided by population in order to calculate the per capita consumption of imported products.

4.2 The Econometric Model

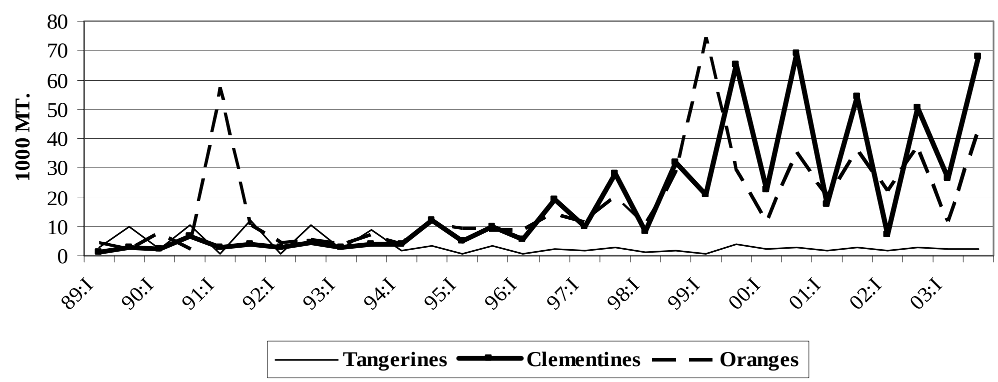
4.2.1 The Choice of Variables

The left-hand side of the models, as delineated in (3.5), is the per capita expenditure of the corresponding products. Following the approach developed by Agnew, per capita expenditures were used rather than quantities in order to avoid the potential problem of heteroscedasticity.

As for the right-hand side of the models, the LINQUAD model encompasses four types of parameters in addition to the intercept coefficients. The first type represents the parameters of demographic shifting variables. This set includes a trend and different dummy variables. The “trend” variable is a TSP-generated series of linear growth trend, and it accounts for potential growth factors that are not included in the model.

The group of dummy variables was constructed to translate some inherent aspects of the semi-annual data into the models (see graph 4.1). Tangerine imports dropped remarkably after 1993 and continued to be small in magnitude throughout the rest of the years. A dummy variable that takes a value of one for imports over the first five years and a value of zero otherwise was constructed to incorporate this structure into the model. Similarly another dummy variable was generated to account roughly for the dramatic increase in clementines imports in the last five years after abolishing the trade embargo with South Africa. Another dummy was constructed to account for import seasonality. It takes a value of one when imports occur during the second half of the year and a value of zero otherwise. The last dummy variable represents the irregular high orange imports during the first half of year 1991 and of year 1999.

Figure 4.1: Semi-Annual Import Quantities



The second group of variables contains the deflated weighted-average c.i.f. prices of the imported products, and the deflated f.o.b price of Florida navels. The c.i.f. prices of the three products are in both linear and quadratic forms, and their coefficients account for own-and cross-price effects.

The LINQUAD model by construction places the price of Florida navels within the category of demographic shifters (Agnew). This price enters the model in linear form, and its estimated parameter captures the effect of navels' price on the per capita consumption of imports. Since the incomplete import demand does not specify explicitly the demand for domestic navels, treating the price of domestic navel as a demographic variable compromises the structure of the model.

The third group consists merely of deflated income. The last group of variables includes the first- and the second-order serial correlation variables. Table 4.1 gives descriptive statistics of all variables that were used in the model.

Table 4.1 : Descriptive Statistics of the Incomplete Demand System Variables

Definition	Variable	Unit	Mean	S.E.	Minima	Maxima
Tangerine Price	p_{Tang}	$/MT	517.2	210.9	137.0	1071.7
Clementine Price	p_{Clem}	$/MT	1371.2	380.2	398.8	2120.1
Orange Price	p_{Orange}	$/MT	799.6	379.4	342.9	1590.1
Tangerine Import Quantity	x_{Tang}	MT	3345.3	3280.6	515.8	11831.9
Clementine Import Quantity	x_{Clem}	MT	18941.4	21294.4	1294.2	68969.6
Orange Import Quantity	x_{Orange}	MT	18353.2	17435.5	2121.0	74685.4
Income	y	$	6755.9	1545.6	4532.4	9285.9
Population			269574	13906	246739	291819
Florida Navel f.o.b. Price	p_{Navel}	$/MT	391.9	120.6	0.0	607.8
Trend	T		15.5	8.8	1.0	30.0
Dummy for First Five Years	D_{89-93}		0.3	0.5	0.0	1.0
Dummy for Last Five Years	D_{99-03}		0.3	0.5	0.0	1.0
Dummy for High orange Imports	D_{5-21}		0.1	0.3	0.0	1.0
Dummy for Second Half of the Year	D_2		0.5	0.5	0.0	1.0

The table shows that the prices and, to a lesser extent, the imported quantities of the three products exhibit considerable variability. They are diverse in terms of countries of origin, sub-products (the case of clementines and oranges), and time of year. The fact that clementines and oranges are groups of different varieties explains the high variance in their prices and quantities compared with those of tangerines. The minimum price value of Florida navels is zero because of one missing observation in the second half of 2003.

4.2.2. Estimation Method

The method used for estimating the LINQUAD model is based on calculating the least squares or the minimum distance estimates of nonlinear multivariate regression. The estimation was conducted using the LSQ command in TSP software.

In the case of nonlinear multivariate regression, TSP uses the maximum likelihood estimator to estimate the model's parameters. The parameter estimates are obtained by concentrating variance parameters out of the multivariate likelihood and then maximizing the negative of the log determinant of the residual covariance matrix. The estimates are consistent, efficient, and asymptotically normal if the disturbances are multivariate normal and identically distributed.

4.2.3 Likelihood Ratio test for Serial Correlation

A common practice in time series analysis is to test for a potential serial correlation between error terms. The serial correlation coefficients are estimated from the nonlinear differenced model

The likelihood ratio LR test indicates whether the original model (restricted) is significantly different from the new model(unrestricted). The LR test for large samples is given as:

$$LR = 2\left[\ln L_{unrestricted} - \ln L_{restricted}\right] \sim \chi^2(q)$$

where $ln\,L$ refers to the log likelihood value of the relevant model, and q is the number of restrictions. The LR statistic is distributed as chi-square with degrees of freedom equals the number of restrictions.

However, the semi-annual sample has only thirty observations. The previous test, therefore, may tend to over-reject the null hypothesis, and it needs to be adjusted for small sample. The adjustment for the propensity of over rejection is suggested by De Boer and Harkema as:

$$Adj.LR = \left(\frac{T * N - \left(df_{restricted} + df_{unrestricted}\right) - T(T+1)}{T * N}\right) * LR \sim \chi^2(q)$$

where T and N are the number of equations and observations, respectively, and df is the number of parameters of each model.

4.2.4 Imposition of Symmetry Restrictions

From the Marshallian demand equation (3.4), the Slutsky substitution matrix can be derived by taking the first derivatives with respect to prices

(4.1) $$\mathbf{S} = \mathbf{B} + \left[\boldsymbol{m} - \alpha'\mathbf{p}\text{-}\mathbf{p}'\mathbf{A}\ \mathbf{z}\text{-}.5\mathbf{p}'\mathbf{B}\mathbf{p} - \delta(\mathbf{z})\right]\gamma\gamma'$$

The symmetry condition of the Slutsky matrix is an important property in testing the correspondence between demand functions and utility functions, i.e. necessary condition for integrability. In LINQUAD demand models, the insertion of a quadratic term in prices increases the flexibility in Slutsky symmetry. The symmetry of **S** matrix depends on matrix **B** because $\gamma\gamma'$ is symmetric by construction. The matrix **B**, however, is not necessarily symmetric (Agnew). Nevertheless, imposing symmetry in this case is straightforward. The restrictions imply that $\mathbf{B} = \mathbf{B}'$.

4.2.5. Imposition of Concavity Restrictions

The other property that ensures quasi-concavity of the underlying expenditure function is the negative semi-definiteness of **S.** According to Agnew, the Slutsky matrix **S** from LINQUAD is guaranteed to be negative semi-definite if **B** is restricted to being negative semi-definite for all sample points. To maintain this property, **B** needs to be reparameterized with the Cholesky factorization (Fuss & McFadden) to say $\tilde{\boldsymbol{B}}$. A necessary and sufficient condition for negative semi-definiteness of **B** is that $\tilde{\boldsymbol{B}}$ can be written as $\tilde{\boldsymbol{B}} = -\boldsymbol{LL}'$, where $\boldsymbol{L} \equiv \lfloor \boldsymbol{l}_{ij} \rfloor$ is the 3×3 lower triangular matrix.

$$\boldsymbol{L} = \begin{bmatrix} l_{11} & & \\ l_{21} & l_{22} & \\ l_{31} & l_{32} & l_{33} \end{bmatrix} \qquad -\tilde{\boldsymbol{B}} = \begin{bmatrix} l_{11}^2 & & \\ l_{11}l_{21} & l_{12}^2 + l_{22}^2 & \\ l_{11}l_{31} & l_{12}l_{13} + l_{22}l_{32} & l_{13}^2 + l_{32}^2 + l_{33}^2 \end{bmatrix}$$

This reparametrization implies theoretically that if concavity is attained without imposing any restriction on any element of ***L***, the symmetry conditions imposed earlier are sufficient for imposing concavity. In empirical studies, however, the imposition of further zero restrictions on the elements of ***L*** is very common because the data may not be consistent with $\tilde{\boldsymbol{B}}$ being full rank and negative semi-definite (Moschini).

The number of zero restrictions on the elements of ***L*** is determined by the eigenvalues of $\tilde{\boldsymbol{B}}$. The necessary and sufficient condition for the Slutsky matrix to be either negative definite (globally concave) or negative semi-definite is to have negative or negative and zero eigenvalues, respectively. The negative eigenvalues indicate a consistent behavior of the expenditure function. The expenditure on a particular good increases at a decreased rate. Hence, any element of $\boldsymbol{L}$ which does not reflect the negative semi-definiteness of **S** should be eliminated. In other words, irregular price effects are restricted to the dimension that guarantees a well-behaved expenditure function. The elimination of such elements will force quasi-concave curvature in the function but at a lower rank of $\tilde{\boldsymbol{B}}$.

4.2.6 Price and Income Elasticities

The uncompensated own- and cross-price elasticities of the expenditure system given by (3.5), when $\beta_{ij} = \beta_{ji}, \forall i \neq j$, are

(4.2) $$\eta_{ii} = \left[\beta_{ii} - \gamma_i \left(\alpha_i + \mathbf{A_i z} + \mathbf{B_i p}\right)\right] p_i / x_i \,,$$

(4.3) $$\eta_{ij} = \left[\beta_{ij} - \gamma_i \left(\alpha_j + \mathbf{A_j z} + \mathbf{B_j p}\right)\right] p_j / x_i \,,$$

where $i, j \in \{Oranges, mandarines, Tangerines\}$. $\mathbf{A}_i$, and $\mathbf{B}_i$ are the corresponding rows of matrices **A** (parameters of demographic variables) and **B** (price parameters), and β_{ij} denotes the *ij*th element of matrix **B**.

The income elasticities are

(4.4) $$\varepsilon_i = \gamma_i y / x_i$$

CHAPTER FIVE

5. ESTIMATION RESULTS

The general estimation framework of the semi-annual incomplete demand system involves testing for serial correlation, the testing and imposition of symmetry and concavity restrictions, the estimation of model's parameters, and finally the calculation of price (income-compensated) and income elasticities. Therefore, the results are organized as to (*i)* check for serial correlation in the unrestricted model; (*ii)* illustrate the outcome of hypothesis testing of imposing theoretical restrictions for weak integrability; (*iii)* determine which restricted model is the most consistent and plausible; *(iv)* report and compare the estimates of unrestricted and restricted models in terms of their statistical significance and effects; (*v)* derive and compare price and income elasticities; and finally, (*vi)* depict own-price elasticity values for all sample points; and finally (vii) calculate the approximate standard errors of elasticities and compare elasticities across three different sample periods.

5.1 Serial Correlation Test Results

The Durbin-Watson (DW) and likelihood-ratio (LR) tests were conducted to check for serial correlation. The DW statistic d is a diagnostic test based on single-equation estimation. It tests the hypothesis of zero autocorrelation against the alternative of positive first-order autocorrelation. The LR test, by contrast, can test jointly for higher-order structures in multiple equations.

The corresponding $d_{k=19}^{n=30}$ [6] values for each of the three equations of the model lie between the DW established upper and lower bounds for the critical values. Hence, the DW tests for the three equations were inconclusive. LR tests were then used to test the hypothesis of zero correlation coefficients (first- and second-order) against the alternative of non-zero correlation in the unrestricted model. According to the results, in table 5.1, the null hypothesis is significantly rejected before and after adjustment for sample size for only first and for both first and second-order serial correlation. The consideration of serial correlation in addition to the imposition of theoretical restrictions will generate different models with different results. Therefore, results of these models will be displayed and compared.

Table 5.1: Likelihood Ratio Tests for First and Second-Order Serial Correlation

H_0	χ^2	DF	P-value	Result
AR(0) vs. AR(1)				
$\rho_{1,Tang} = \rho_{1,Clem} = \rho_{1,Orange} = 0$	101.06	3	0.000	Reject
Adj. $\rho_{1,Tang} = \rho_{1,Clem} = \rho_{1,Orange} = 0$	54.01	3	0.000	Reject
AR(0) vs. AR(1,2)				
$\rho_{1,Tang} = \rho_{1,Clem} = \rho_{1,Orange} = \rho_{2,Tang} = \rho_{2,Clem} = \rho_{2,Orange} = 0$	193.50	6	0.000	Reject
Adj. $\rho_{1,Tang} = \rho_{1,Clem} = \rho_{1,Orange} = \rho_{2,Tang} = \rho_{2,Clem} = \rho_{2,Orange} = 0$	96.75	6	0.000	Reject
AR(1) vs. AR(1,2)				
$\rho_{2,Tang} = \rho_{2,Clem} = \rho_{2,Orange} = 0$	92.44	3	0.000	Reject
Adj. $\rho_{2,Tang} = \rho_{2,Clem} = \rho_{2,Orange} = 0$	46.22	3	0.000	Reject

Note: Adjusted LR statistic values use the De Boer and Harkema adjustment.

5.2 Symmetry and Concavity Test Results

Symmetry restrictions were imposed by setting $\beta_{ij} = \beta_{ji} \quad \forall i \neq j$. This implies the imposition of three linear restrictions on the unrestricted model. On the other hand,

[6] n is the sample size, and k is the number of regressors of each equation.

the imposition of concavity restriction was done by applying the Cholesky factorization. The Slutsky matrix of the AR(0), AR(1) models has three negative eigenvalues whereas, that of AR(1,2) has two negative eigenvalues. This indicates negative semi-definiteness in three dimensions in the first case as appose to two dimensions in the second case. Only one restriction was imposed on the elements of $\boldsymbol{L}$. Setting $\boldsymbol{l}_{33} = 0$ reduces the rank of **S** from three to two and imposes the desired curvature.

Several LR tests were conducted. Symmetry restrictions were first tested for models with and without serial correlation correction. Second, they were jointly tested with concavity restrictions against the only symmetry- and the non-symmetry-restricted models. The null hypothesis is that the restricted and unrestricted models are not different.

P-values in table 5.2 indicate that for the model with no serial correlation correction AR(0) the symmetry restrictions are not rejected. Regarding the model with first-order serial correlation AR(1), the corresponding p-value before adjustment indicates that symmetry restrictions are rejected at 1% level of significance. However, they were not rejected at 6.5% level of significance after adjustment. Regarding the second-order serial correlation model AR(1,2), symmetry is not rejected before adjustment. The rejection is considerably strengthened after adjustment. The restrictions are not rejected at the 26% level.

The results of testing the joint imposition of symmetry and concavity restrictions against the unrestricted show that the three models fail to reject the theoretical restrictions at different levels. AR(1,2) has the highest probability of not rejecting theoretical conditions. By contrast, AR(1) has the lowest p-value.

The hypothesis tests of joint symmetry and concavity restrictions against only symmetry restrictions are also tested. For AR(1,2) model the restriction on symmetrical structure of concave curvature is not rejected. The corresponding p-value is considerably high with a 53% level of significance.

Table 5.2: LR and Adjusted LR Tests for Theoretical Restrictions

a) AR(0)

Test	DF	χ^2-statistic	p-value	Result [1%]
LR (Symmetry vs. Non-Symmetry)	3	1.09	.779	Fail to reject
Adj. LR (Symmetry vs. Non-Symmetry)	3	0.71	.871	Fail to reject
LR (Concavity vs. Symmetry)	1	7.68	.005	Reject
Adj. LR (Concavity vs. Symmetry)	1	4.65	.031	Fail to reject
LR (Concavity vs. Non-Symmetry)	4	8.76	.067	Fail to reject
Adj. LR (Concavity vs. Non-Symmetry)	4	5.16	.271	Fail to reject

b) AR(1)

Test	DF	χ^2-statistic	p-value	Result [1%]
LR (Symmetry vs. Non-Symmetry)	3	11.98	.007	Reject
Adj. LR (Symmetry vs. Non-Symmetry)	3	7.23	.065	Fail to reject
LR (Concavity vs. Symmetry)	1	8.74	.003	Reject
Adj. LR (Concavity vs. Symmetry)	1	4.87	.027	Fail to reject
LR (Concavity vs. Non-Symmetry)	4	20.72	.000	Reject
Adj. LR (Concavity vs. Non-Symmetry)	4	11.19	.025	Fail to reject

c) AR(1,2)

Test	DF	χ^2-statistic	p-value	Result [1%]
LR (Symmetry vs. Non-Symmetry)	3	8.34	.039	Fail to reject
Adj. LR (Symmetry vs. Non-Symmetry)	3	4.02	.259	Fail to reject
LR (Concavity vs. Symmetry)	1	.80	.371	Fail to reject
Adj. LR (Concavity vs. Symmetry)	1	.40	.525	Fail to reject
LR (Concavity vs. Non-Symmetry)	4	9.14	.058	Fail to reject
Adj. LR (Concavity vs. Non-Symmetry)	4	4.46	.437	Fail to reject

The non-rejection of concavity strengthens the model's theoretical consistency. In most demand applications, concavity conditions are usually rejected. The last result indicates that the three models can incorporate a local concave structure. Testing the null hypothesis of symmetry- and concavity-restricted AR(0) models against the alternative hypothesis of symmetry- and concavity-restricted AR(1) and AR(1,2) models determines the most plausible restricted model. The results of the following LR tests (table 5.3) reject significantly the null hypothesis of no serial correlation and the null of an AR(1) structure.

Table 5-3: Serial Correlation Likelihood Ratio Tests for Restricted Models

H_0	χ^2	DF	P-value	Result
Symmetry-restricted				
L.R. AR(0) vs. AR(1)	90.16	3	.000	Reject
Adj.	51.29	3	.000	Reject
L.R. AR(0) vs. AR(1,2)	187.92	6	.000	Reject
Adj.	100.67	6	.000	Reject
L.R. AR(1) vs. AR(1,2)	96.08	3	.000	Reject
Adj.	49.75	3	.000	Reject
Concavity-restricted				
L.R. AR(0) vs. AR(1)	89.10	3	.000	Reject
Adj.	51.72	3	.000	Reject
L.R. AR(0) vs. AR(1,2)	193.12	6	.000	Reject
Adj.	105.76	6	.000	Reject
L.R. AR(1) vs. AR(1,2)	104.02	3	.000	Reject
Adj.	55.10	3	.000	Reject

5.3 Parameter Estimates

The unrestricted and restricted models incorporate five types of parameters. Table 5.4 classifies and defines the entire set of model parameters. The estimation results for the three unrestricted and restricted models are presented in tables 5.5, 5.6 and 5.7.

Table 5.4: Parameters Classification

Category	Sub-Category	Parameters
Intercept		α_{Tang} α_{Clem} α_{Orange}
Demographic Shifters	*Trend*	$A_{Tang,T}$ $A_{Clem,T}$ $A_{Orange,T}$
	Dummies	$A_{Tang,89-93}$ $A_{Clem,98-03}$ $A_{Oranges,5\text{-}21}$ $A_{Tang,D2}$ $A_{Clem,D2}$ $A_{Orange,D2}$
Price	*Own*	$\beta_{Tang,Tang}$ $\beta_{Clem,Clem}$ $\beta_{Orange,Orange}$
	Cross	$\beta_{Tang,Clem}$ $\beta_{Tang,Orange}$ $\beta_{Clem,Tang}$ $\beta_{Clem,Orange}$ $\beta_{Orange,Tang}$ $\beta_{Orange,Clem}$
	Other Prices	$A_{Tang,Nav}$ $A_{Clem,Nav}$ $A_{Orange,Nav}$
Income		γ_{Tang} γ_{Clem} γ_{Orange}
Serial Correlation	*First*	$\rho_{1,Tang}$ $\rho_{1,Clem}$ $\rho_{1,Orange}$
	Second	$\rho_{2,Tang}$ $\rho_{2,Clem}$ $\rho_{2,Orange}$

Table 5.5:Parameter Estimates for the Unrestricted Model

Parameter	Estimates			p-value		
	AR(0)	***AR(1)***	***AR(1,2)***	***AR(0)***	***AR(1)***	***AR(1,2)***
α_{Tang}	-15.141	78.954	38.416	[.568]	[.026]	[.001]
α_{Clem}	348.299	56.862	56.183	[.134]	[.163]	[.135]
α_{Orange}	184.016	-64.697	-94.645	[.220]	[.000]	[.000]
$A_{Tang,Nav}$	-0.027	0.005	0.024	[.512]	[.546]	[.001]
$A_{Tang,T}$	2.449	-0.732	-0.594	[.002]	[.000]	[.001]
$A_{Tang,89-93}$	3.168	5.896	9.331	[.271]	[.000]	[.000]
$A_{Tang,D2}$	66.577	11.782	7.025	[.000]	[.223]	[.151]
$A_{Clem,Nav}$	-0.077	-0.075	-0.097	[.808]	[.178]	[.056]
$A_{Clem,T}$	-26.410	1.010	-0.248	[.000]	[.140]	[.804]
$A_{Clem,98-03}$	55.198	95.789	110.398	[.000]	[.000]	[.000]
$A_{Clem,D2}$	-322.938	52.550	9.197	[.001]	[.005]	[.733]
$A_{Orange,Nav}$	0.026	0.063	-0.016	[.898]	[.085]	[.605]
$A_{Orange,T}$	219.203	244.949	277.146	[.000]	[.000]	[.000]
$A_{Orange,D5,21}$	-13.460	4.109	4.184	[.000]	[.000]	[.000]
$A_{Orange,D2}$	-192.844	47.432	130.527	[.002]	[.007]	[.000]
$\beta_{Tang,Tang}$	-0.006	-0.168	-0.090	[.455]	[.026]	[.000]

Parameter	Estimates			p-value		
	AR(0)	***AR(1)***	***AR(1,2)***	***AR(0)***	***AR(1)***	***AR(1,2)***
$\beta_{Clem,Clem}$	0.299	-0.066	0.002	[.009]	[.108]	[.969]
$\beta_{Orange,Orange}$	0.090	-0.025	-0.057	[.070]	[.185]	[.171]
$\beta_{Tang,Clem}$	-0.020	-0.082	-0.065	[.322]	[.001]	[.000]
$\beta_{Tang,Orange}$	-0.050	-0.028	0.033	[.000]	[.453]	[.045]
$\beta_{Clem,Tang}$	0.333	8.934	7.366	[.117]	[.006]	[.000]
$\beta_{Clem,Orange}$	0.208	0.058	0.064	[.004]	[.008]	[.003]
$\beta_{Orange,Tang}$	-0.916	-2.249	-7.815	[.137]	[.454]	[.000]
$\beta_{Orange,Clem}$	0.830	1.823	1.456	[.067]	[.110]	[.051]
γ_{Tang}	0.000	0.000	0.000	[.000]	[.002]	[.000]
γ_{Clem}	0.001	0.000	0.000	[.000]	[.304]	[.439]
γ_{Orange}	0.001	0.000	0.000	[.000]	[.491]	[.061]
$\rho_{1,Tang}$		-0.908	-1.554		[.000]	[.000]
$\rho_{2,Tang}$			-0.698			[.000]
$\rho_{1,Clem}$		-0.565	-0.645		[.000]	[.000]
$\rho_{2,Clem}$			0.204			[.187]
$\rho_{1,Orange}$		-0.449	-0.314		[.000]	[.015]
$\rho_{2,Orange}$			0.589			[.000]

Table 5.6:Parameter Estimates for the Restricted Model (Symmetry Imposed)

Parameter	Estimates			p-value		
	AR(0)	***AR(1)***	***AR(1,2)***	***AR(0)***	***AR(1)***	***AR(1,2)***
α_{Tang}	-25.467	1.410	-61.771	[.285]	[.856]	[.000]
α_{Clem}	468.859	49.963	45.580	[.040]	[.221]	[.159]
α_{Orange}	249.021	-48.340	-386.778	[.093]	[.047]	[.002]
$A_{Tang,Nav}$	-0.006	0.008	-0.012	[.874]	[.251]	[.123]
$A_{Tang,T}$	1.887	-0.252	0.939	[.012]	[.183]	[.000]
$A_{Tang,89-93}$	3.448	10.334	8.997	[.272]	[.000]	[.000]
$A_{Tang,D2}$	41.364	15.803	52.642	[.000]	[.017]	[.000]
$A_{Clem,Nav}$	-0.225	-0.083	-0.128	[.526]	[.163]	[.007]
$A_{Clem,T}$	-26.226	1.446	1.798	[.001]	[.182]	[.184]
$A_{Clem,98-03}$	61.008	71.331	61.896	[.000]	[.000]	[.000]

Parameter	Estimates			p-value		
	AR(0)	***AR(1)***	***AR(1,2)***	***AR(0)***	***AR(1)***	***AR(1,2)***
$A_{Clem,D2}$	-142.421	65.068	-23.190	[.068]	[.001]	[.256]
$A_{Orange,Nav}$	-0.051	0.061	-0.165	[.821]	[.109]	[.031]
$A_{Orange,T}$	224.584	217.584	392.513	[.000]	[.000]	[.000]
$A_{Orange,D5,21}$	-13.570	3.510	14.576	[.001]	[.001]	[.002]
$A_{Orange,D2}$	-94.164	33.498	288.457	[.040]	[.150]	[.000]
$\beta_{Tang,Tang}$	-0.004	0.005	0.067	[.584]	[.484]	[.000]
$\beta_{Clem,Clem}$	0.104	-0.077	-0.005	[.000]	[.013]	[.825]
$\beta_{Orange,Orange}$	0.032	-0.023	0.096	[.088]	[.212]	[.000]
$\beta_{Tang,Clem}$	0.005	0.005	-0.006	[.708]	[.462]	[.180]
$\beta_{Tang,Orange}$	-0.034	-0.009	0.008	[.000]	[.243]	[.132]
$\beta_{Clem,Orange}$	0.104	0.018	0.040	[.000]	[.196]	[.001]
γ_{Tang}	0.000	0.000	0.000	[.001]	[.598]	[.000]
γ_{Clem}	0.001	0.000	0.000	[.000]	[.383]	[.561]
γ_{Orange}	0.001	0.000	0.001	[.000]	[.421]	[.000]
$\rho_{1,Tang}$		-0.861	-0.060		[.000]	[.071]
$\rho_{2,Tang}$			0.971			[.000]
$\rho_{1,Clem}$		-0.493	-0.382		[.000]	[.003]
$\rho_{2,Clem}$			0.579			[.001]
$\rho_{1,Orange}$		-0.310	-0.103		[.001]	[.003]
$\rho_{2,Orange}$			0.835			[.000]

Table 5.7:Parameter Estimates for the Restricted Model (Concavity Imposed)

Parameter	Estimates			p-value		
	AR(0)	***AR(1)***	***AR(1,2)***	***AR(0)***	***AR(1)***	***AR(1,2)***
α_{Tang}	7.409	10.058	-62.440	[.752]	[.270]	[.000]
α_{Clem}	-21.947	-81.543	33.061	[.718]	[.486]	[.311]
α_{Orange}	-28.894	-30.529	-394.209	[.264]	[.341]	[.002]
$A_{Tang,Nav}$	0.002	-0.005	-0.012	[.940]	[.524]	[.137]
$A_{Tang,T}$	-0.273	-0.573	0.952	[.622]	[.045]	[.001]
$A_{Tang,89-93}$	7.794	10.121	9.036	[.087]	[.000]	[.000]
$A_{Tang,D2}$	26.191	13.149	52.741	[.000]	[.030]	[.000]
$A_{Clem,Nav}$	-0.052	0.032	-0.127	[.632]	[.816]	[.007]

Parameter	Estimates			p-value		
	AR(0)	***AR(1)***	***AR(1,2)***	***AR(0)***	***AR(1)***	***AR(1,2)***
$A_{Clem,T}$	2.019	4.946	1.727	[.309]	[.104]	[.207]
$A_{Clem,98-03}$	69.024	114.255	58.897	[.043]	[.006]	[.000]
$A_{Clem,D2}$	55.460	136.929	-28.591	[.006]	[.013]	[.132]
$A_{Orange,Nav}$	0.064	0.068	-0.167	[.126]	[.137]	[.029]
$A_{Orange,T}$	167.962	185.038	395.687	[.000]	[.000]	[.000]
$A_{Orange,D5,21}$	2.052	2.527	14.510	[.025]	[.046]	[.002]
$A_{Orange,D2}$	-10.001	3.119	299.687	[.109]	[.883]	[.000]
$l_{Tang,Tang}$	0.131	0.072	0.259	[.000]	[.084]	[.000]
$l_{Clem,Clem}$	-0.104	-0.046	-0.118	[.627]	[.933]	[.000]
$l_{Clem,Tang}$	-0.027	0.005	-0.023	[.749]	[.954]	[.142]
$l_{Orange,Tang}$	-0.142	-0.068	0.029	[.035]	[.499]	[.152]
$l_{Orange,Clem}$	-0.066	-0.043	-0.299	[.747]	[.889]	[.000]
γ_{Tang}	0.000	0.000	0.000	[.957]	[.043]	[.000]
γ_{Clem}	0.000	0.000	0.000	[.791]	[.077]	[.484]
γ_{Orange}	0.000	0.000	0.001	[.084]	[.223]	[.000]
$\rho_{1,Tang}$		-0.835	-0.060		[.000]	[.075]
$\rho_{2,Tang}$			0.972			[.000]
$\rho_{1,Clem}$		-0.540	-0.353		[.000]	[.009]
$\rho_{2,Clem}$			0.619			[.000]
$\rho_{1,Orange}$		-0.203	-0.101		[.117]	[.002]
$\rho_{2,Orange}$			0.838			[.000]

Note: $l_{Orange,Orange}$*=0 in all models*

Table 5.8 summarizes the significance of parameter estimates for all models with or without restrictions. Two important conclusions can be inferred from these results. AR(1,2) models produce more significant estimates than AR(0) and AR(1). The significance of the estimates deteriorates with the imposition of theoretical restrictions in the case of AR(0) and AR(1) models. Whereas that of AR(1,2) maintains its level even after imposing symmetry and concavity restrictions. These conclusions reconfirm the strong performance of AR(1,2) model.

Table 5.8: Number of Significant Parameter Estimates

Model	**AR(0)**		**AR(1)**		**AR(1,2)**	
Significance Level	*5%*	*1%*	*5%*	*1%*	*5%*	*1%*
Unrestricted	0	14	3	15	0	20
Symmetry-Restricted	3	11	3	8	1	20
Concavity-Restricted	3	4	5	5	1	20

Table 5.9 show the consistency of the marginal effects of the demographic shifters in the two restricted models. These estimates indicate that there are no substitution effects between any of the three products and the domestic navels.

Table 5.9: Demographic Marginal Effects of AR(1,2) Models

Demographic Effects	**AR(1,2)**	**Sym. AR(1,2)**	**Con. AR(1,2)**
$A_{Tang,Nav}$	+	-	-
$A_{Clem,Nav}$	-	-	-
$A_{Orange,Nav}$	-	-	-
$A_{Tang,T}$	-	+	+
$A_{Clem,T}$	-	+	+
$A_{Orange,T}$	+	+	+
$A_{Tang,89-93}$	+	+	+
$A_{Clem,98-03}$	+	+	+
$A_{Orange,D5,21}$	+	+	+
$A_{Tang,D2}$	+	+	+
$A_{Clem,D2}$	+	-	-
$A_{Orange,D2}$	+	+	+

The per capita consumption of imported products increases over time. The marginal effects associated with the dummy variables which reflect some structural changes and irregular imports are all positive. The per capita consumption of tangerines and oranges increases in the second half of the year as opposed to that of clementines which decreases during these periods.

5.4 Price and Income Elasticity Estimates

5.4.1 Elasticities at Sample Means

Price and income elasticities are computed from the Slutsky matrix of the AR(1,2) concavity-restricted model. The Marshallian elasticity estimates [7] and their approximate standard errors were evaluated at the sample means. Approximate standard errors of the elasticities are calculated using the delta method.

Table 5.10: Price & Income Elasticities of Concavity-Restricted AR(1,2) Model

	Price			Income
	Tangerines	**Clementines**	**Oranges**	
Tangerines	-1.71 (0.01)**	0.40 (0.03)**	-0.15 (0.05)**	0.0001 (0.00003)**
Clementines	0.02 (0.02)	-0.18 (0.01)**	-0.32 (0.08)**	0.00004 (0.00005)
Oranges	0.10 (0.01)**	-0.48 (0.10)**	-0.12 (0.22)	0.0004 (0.00004)**

Values in parentheses and in italic form represent the approximate standard errors
** Indicates statistical significance at the 0.01 level.
* Indicates the statistical significance at the 0.05 level.

All elasticity estimates are significant at the 1% level except for orange own-price elasticity, the cross-price elasticity of clementines and tangerines, and clementine income elasticity. The t-statistic of these estimates indicate that they are not different from zero.

Tangerines are own-price elastic, while clementines are own-price inelastic. The cross-price responses suggest heterogeneous substitution relationships between

[7] Elasticity estimates are the Marshallian (uncompensated) elasticities. The calculation of the Hicksian (compensated) elasticities is not pursued because of the inability to calculate precise budget shares of the imported commodities

tangerines, clementines, and oranges. Tangerines and clementines are potential substitutes. They are, though, cross-price inelastic. There are no substitution effects between oranges and clementines. They are also cross-price inelastic.

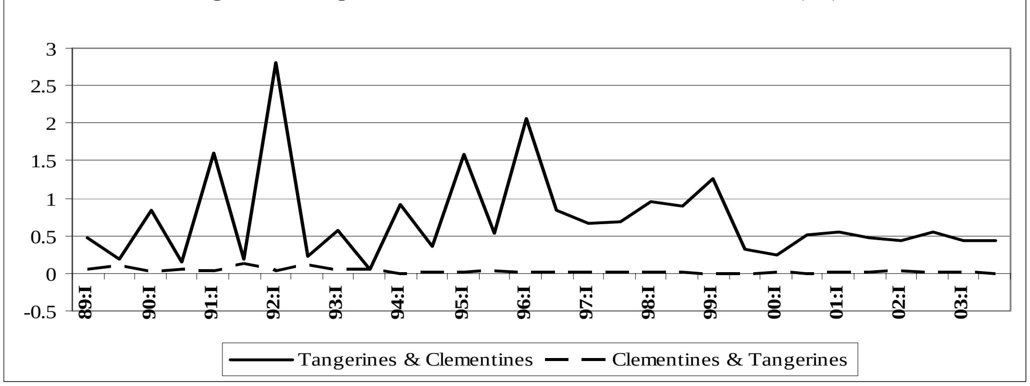
An important observation is the different signs of the cross-price elasticities for tangerines and oranges. As Marshallian elasticities, the signs are not constrained to be the same.

The income effects on per capita consumption for the three imported products are quite small. The small magnitude of income elasticities is expected because fresh citrus products account for a very small share of consumer's consumption bundle. It is worth emphasizing that incomplete demand systems use income rather than citrus expenditure.

5.4.2 Elasticities at All Sample Points

Evaluating elasticities at sample means hides the variability in elasticities throughout the sample period. Cross-price elasticities at all sample points reveal an asymmetry between cross-price elasticities. This situation is most pronounced when comparing the cross-price elasticity of tangerines with clementines or with oranges (figures 5.1 and 5.2). By contrast, cross-price elasticities of oranges with clementines display less dispersion and irregularity (figure 5.3).

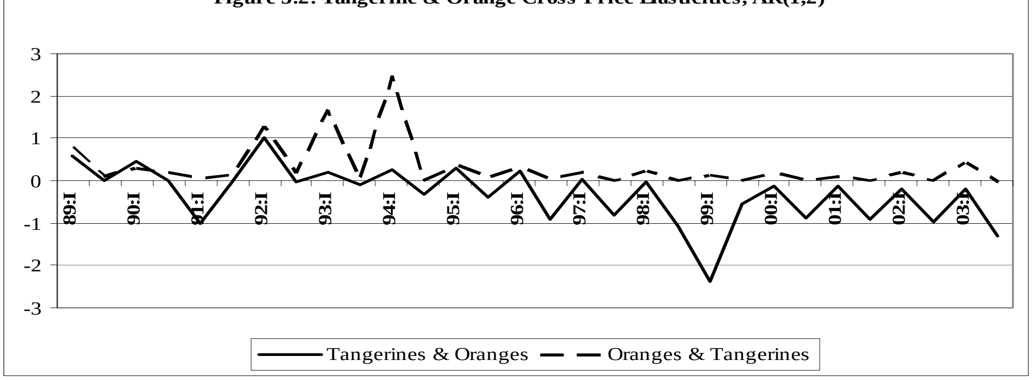
Figure 5.1: Tangerine & Clementine Cross-Price Elasticities, AR(1,2)



From a different perspective, positive cross-price[8] elasticity values of tangerines and clementines over the entire period confirm substitutability between the two products. The consumption of tangerines has indeed decreased while that of clementines has increased. Recent changes in consumer taste have occurred favoring seed-free and juicy citrus products such as clementines, hybrids, and navel oranges over tangerines which have high seed content.

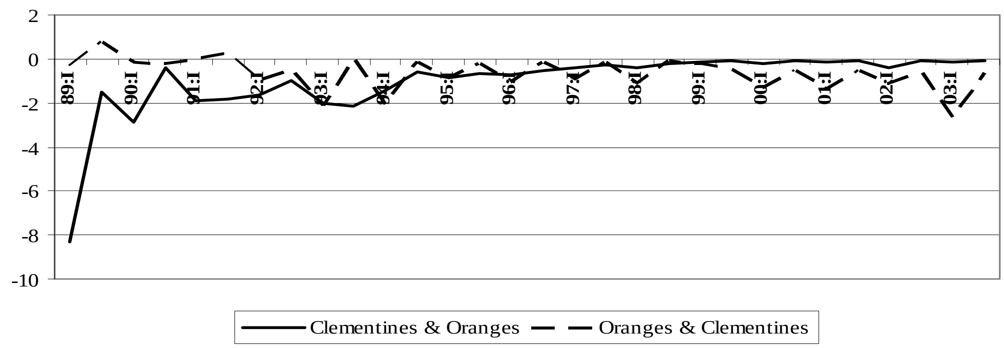
On the other hand, tangerines and oranges are more likely to be complements particularly in the last eight years. Also clementines and oranges tend to remain complements over time.

Figure 5.2: Tangerine & Orange Cross-Price Elasticities, AR(1,2)



[8] By convention, cross price elasticities refer to the change in the quantity of the first product due to the change of the price of the second product.

Figure 5.3: Clementine and Orange Cross-Price Elasticities, AR(1,2)



Clementine and orange own-price elasticities over the sample points exhibit odd behavior during the first five years with big elasticity values (see figures 5.5 and 5.6). These values are even positive in the case of oranges. They start to approach zero or take small negative values later in the sample. This discrepancy between values could be the result of heterogeneous composition of clementines and oranges products in terms of varieties and sources. Oranges, for instance, consist, among others, of navels and valencia oranges. The shares of these varieties have changed through the last fifteen years. valencia oranges accounted for most orange imports in the first five years, while in the following years navels have been increasingly imported because of their low seed and high juice content. On the other hand, sources for clementine imports have changed over time. Countries from the southern hemisphere have become important importers in recent years. These aspects are not accounted for in the model nor do the data allow these aspects to be analyzed explicitly.

As for tangerines, elasticity values are relatively consistent and show no irregularities throughout the entire period. The following figures show own-price elasticities at all sample points for the three products.

Figure 5.4 : Tangerine Own-Price Elasticity Over Sample Points

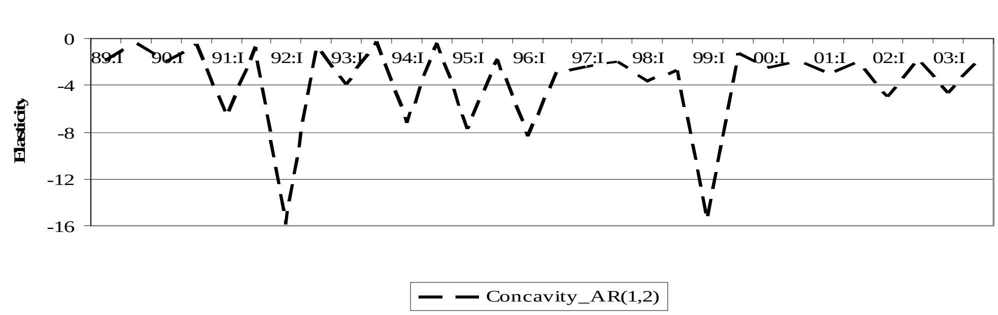


Figure 5.5 : Clementine Own-Price Elasticity Over Sample Points

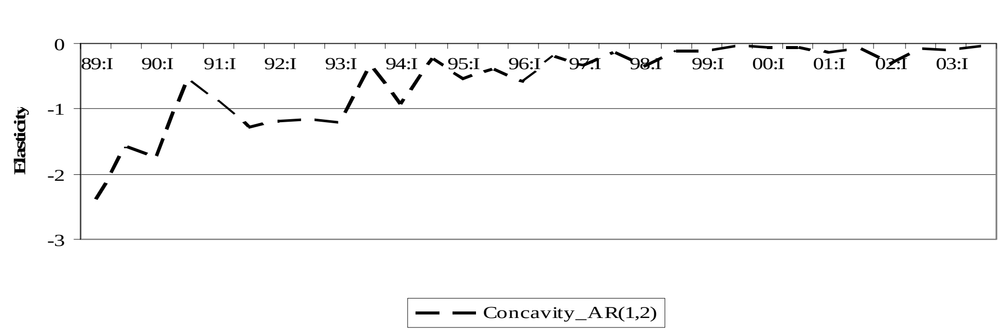


Figure 5.6 : Orange Own-Price Elasticity Over Sample Points

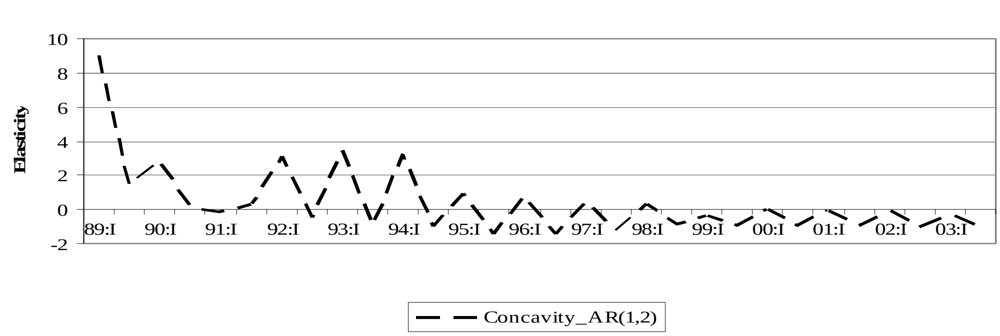
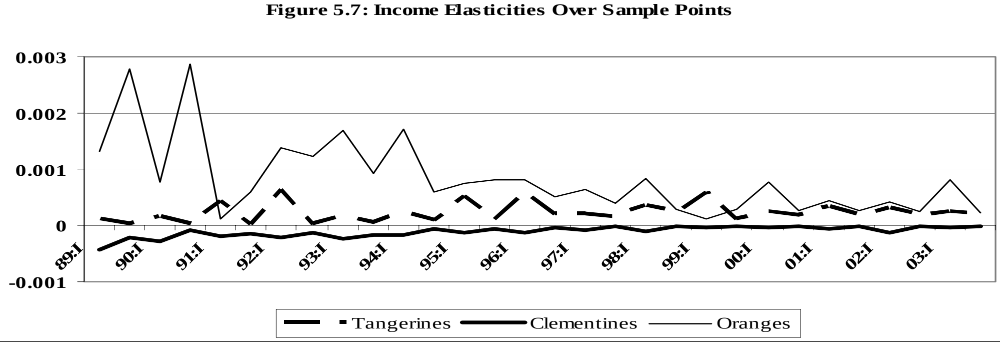


Figure 5.7: Income Elasticities Over Sample Points



The values of income elasticities over the sample points were very small in general (figure 5.7). Income elasticity of oranges were relatively higher at the beginning of the period than the end. The income elasticity of clementines, although negative at early sample points, became infinitesimal at the end of the period. The income elasticity of tangerines does not show any big changes over the entire sample.

5.4.3 Elasticities at Different Means

The changing behavior of own-price elasticity values of clementines and oranges over time, and the small cross-price elasticities for all products make information about statistical significance at different sample points important. The p-values in table 5.11 demonstrate that the own-price elasticity for tangerines became much more elastic in the last ten years of the sample.

Clementines, by contrast, are own-price elastic in the first five years but have become quite inelastic later in the sample. As for oranges, they are own-price inelastic in the last five years of the sample. However, positive elasticity estimates in the early sample periods are not significantly different from zero. The cross-price elasticity of clementines and oranges was negatively elastic in the first five years. However, later in the sample it has become inelastic. The substitution between tangerines and clementines is relatively higher during the second period when tangerine imports began to decrease and those of clementine started to augment. The other elasticity measures show no significant changes over time.

Table 5.11: Price and Income Elasticity Estimates and P-Values at Different Sample Means

Elasticity	Estimate			p-value		
	First 5[9] Years	Second 5 Years	Last 5 Years	First 5 Years	Second 5 Years	Last 5 Years
$\varepsilon^{p}_{Tang,Tang}$	<u>-0.99</u>	<u>-2.84</u>	<u>-2.88</u>	[.000]	[.000]	[.000]
$\varepsilon^{p}_{Clem,Clem}$	<u>-1.06</u>	<u>-0.26</u>	-0.07	[.000]	[.000]	[.042]
$\varepsilon^{p}_{Orange,Orange}$	0.87	0.01	<u>-0.54</u>	[.235]	[.983]	[.000]
$\varepsilon^{p}_{Tang,Clem}$	<u>0.26</u>	<u>0.75</u>	<u>0.46</u>	[.000]	[.000]	[.000]
$\varepsilon^{p}_{Clem,Tang}$	0.08	0.02	0.01	[.510]	[.427]	[.245]
$\varepsilon^{p}_{Tang,Orange}$	0.02	<u>-0.22</u>	<u>-0.60</u>	[.643]	[.047]	[.000]
$\varepsilon^{p}_{Orange,Tang}$	<u>0.21</u>	<u>0.14</u>	<u>0.04</u>	[.000]	[.000]	[.000]
$\varepsilon^{p}_{Clem,Orange}$	<u>-1.79</u>	<u>-0.50</u>	<u>-0.11</u>	[.017]	[.000]	[.000]
$\varepsilon^{p}_{Orange,Clem}$	-0.15	<u>-0.46</u>	<u>-0.67</u>	[.443]	[.001]	[.000]
ε^{y}_{Tang}	<u>0.0001</u>	<u>0.0002</u>	<u>0.0002</u>	[.000]	[.000]	[.000]
ε^{y}_{Clem}	-0.0002	0.0001	0.00002	[.484]	[.484]	[.484]
ε^{y}_{Orange}	<u>0.0006</u>	<u>0.0006</u>	<u>0.0003</u>	[.000]	[.000]	[.000]

Note: p-values are based on the t-test for the elasticity being equal to zero, using the approximate standard errors of the elasticities. The significant estimates are underlined.

[9] Splitting the sample into three pieces of equal size characterizes visible differences in quantity and price behavior (refer to variable construction in chapter 4). Splitting the sample into smaller pieces would compromise degrees of freedom. Although the sample could be split elsewhere, there does not seem any compelling reason for doing so.

CHAPTER SIX

6. SUMMARY AND CONCLUSION

6.1 Summary

This study departs from conventional demand studies of key agricultural and food products by focusing on specific fresh citrus products namely, tangerines, clementines, and oranges which have different consumption patterns. The scope of research is also narrowed by focusing only on import demand relationships for these products.

Fresh citrus import data are characterized with high variability and apparent irregularities. The data variability is the result of seasonal and discontinuous availability of imports. Seasonality is a main characteristic of fresh citrus imports. Orange imports peak noticeably twice each year due to imports from both northern and southern hemisphere countries. Clementine and tangerine importing seasons are from September through February. In recent years, clementine imports have begun as early as May due to the increasing imports from Australia and South Africa.

Import prices are highly variable and heterogeneous because of factors such as variety, origin, quality, and trade policies. Tangerine imports and prices are more uniform and less variable than those of clementines and oranges. Clementines and oranges, as classified by the harmonized tariff schedule, consist of different varieties with different attributes. This fact influences the interpretation of results for these two products.

U.S. total fresh import volume of citrus products grew in the last 15 years due to the growth in orange and clementine imports. Clementine imports have the highest share of citrus products. The increase in imports of oranges and clementines is due to the expansion of counter-seasonal, non-traditional imports of oranges from Australia and South Africa, and the remarkable growth of Spanish clementine imports. Such countries in addition to Mexico and Morocco account for 98% of U.S. total imports of these products. By contrast, tangerine imports have dropped considerably in the last decade and a half. Mexico has dominated the U.S. import market of tangerines during the last 15 years. The diversity of import sources, particularly those of clementines and oranges, has contributed to the variability in import c.i.f. prices within any given year or over many years. The demand estimation in this study, however, does not address the issue of imports origin.

The incomplete demand system is a convenient and theoretically plausible approach to estimate the import demand of a small group of closely related products. The LINQUAD model, which is linear in income and linear and quadratic in prices, is one common form of incomplete demand system. LINQUAD demand equations are consistent with weak integrability conditions that ensure the recovery of the underlying expenditure function.

One major problem with the monthly import data is the sub-sample of zero import quantities and unobservable relevant prices of tangerines and clementines. This sub-sample is the outcome of import feasibility constraints or selection criteria that determine whether tangerines and clementines are imported in a particular month. Three different regimes emerge from the double selection rule of imports. These regimes reflect a partial truncation in the data and create a non-random sample. The estimation of import demand with non-random sample results in biased parameter estimates. Econometric remedies for this particular problem range from simple approaches such as temporal aggregation to complicated methods such as maximum likelihood or two-stage estimation of truncation-correction models. The aggregation to semi-annual data avoids the problem of truncation and preserves some of the main features of the monthly data. Aggregation, however, reduces the sample size and reduces some variability of the original monthly data.

The import demand equations of the incomplete demand system are susceptible to serial correlation. Import quantities of a particular good in a particular time period seem to be significantly correlated to the imports from two previous periods. In semi-annual time series, this means that import quantities during the high season for example are influenced by the imports that have occurred during the preceding low season and the those that took place in the high season one year earlier.

The model that accounts for first- and second-order of serial correlation performs relatively better than the model with first-order serial correlation coefficient and the no-correlation restricted model. The imposition of symmetry and concavity conditions of the Slutsky matrix is not rejected at higher level of significance than those of other models. The non-rejection of theoretical restrictions strengthens the credibility of the model. The number of significant parameter estimates was higher in this model, and did not decline after imposing the restrictions.

The price and income elasticity estimates evaluated at the sample means showed that tangerines are own-price elastic. Meanwhile, clementines and oranges are own-price inelastic. Cross-price elasticities suggest heterogeneous substitution effects among the three products. Clementines and tangerines are substitutes. However, this substitution effect is relatively small. There is no substitution relationship between oranges and clementines, and there is no clear inference about the substitution relationship between tangerines and oranges.

The behavior of elasticity values over the entire sample period differs across products. Those of tangerines are negative throughout the entire period and display no irregular behavior. Tangerines, though, have become more own-price elastic in the last ten years. By contrast, clementines and oranges own-price elasticity values at the beginning of the period differ from those later in the sample. Clementines are own-price elastic only during the first five years. Oranges are own-price inelastic throughout the entire period.

Finally, the income effect on the consumption of the imported products is very small since these products make up a very minor share of consumers' total consumption.

6.2 Conclusion

The results of this study are very useful from the policy analyzing perspective. Exact welfare measures such as the equivalence variance (EV) or the compensation variation (CV) can be calculated due to the strong theoretical consistency of the semi-annual incomplete demand system. Examples include the welfare impacts of price-distorting policies. The welfare impacts of current or future trade concessions that are or will be granted to the U.S. main exporting countries of tangerines, clementines, and oranges are possible applications.

Apart from welfare measurement, elasticity and flexibility estimates (the inverse of elasticity estimates) can be evaluated at certain periods when quantitative restrictions or technical barriers to trade such as sanitary and phyto-sanitary measures were imposed.

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