ORGANIC PRODUCE PRICE FORECASTING AT A FARM LEVEL:

CRITERIA, METHODS, AND FORECAST EVALUATION

by

TATIANA GUBANOVA

(Under the direction of Luanne Lohr and Timothy A. Park)

ABSTRACT

Organic farmers, wholesalers, and retailers need price forecasts. A methodology and protocol to select the best performing method from several time and frequency domain candidates is suggested. Seasonal autoregression, the additive Holt-Winters exponential smoothing, and spectral decomposition are considered. The forecasting methods are evaluated on the basis of an aggregate accuracy measure and several out-of-sample predictive ability tests. The seasonal autoregression is found to be broadly the best performing method. The Holt-Winters method provides better forecasts in the short run; spectral decomposition is preferable for more distant periods. The price-generating process is found to have a strong autoregressive component and a clear but simple seasonal pattern. The role of better price forecasts for the agents who deal in less common organic produce is highlighted. A confirmation for the claim that the organic produce industry needs better farmgate price forecasts to grow is provided. Contracting and diversification are suggested.

INDEX WORDS:     Organic produce, Price forecasting, ARMA, Exponential smoothing,
                 Spectral decomposition, Forecast Evaluation

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## 1.1 Overview of Organic Food Markets

The last years have seen a significantly increased interest in organic food, or food grown using the principles and techniques that predated the introduction of agro-chemicals and modern intensive farming techniques. In October 2002, the U.S. Department of Agriculture fully implemented national organic standards which lay down in detail how food must be produced, processed, and packaged to qualify for the description "organic." The standards also specify detailed criteria for the inspection and subsequent certification of food producers and processors.

The National Organic Standards Board, a government-appointed panel that advises the National Organic Program, defines the organic food as a product, which

> "is produced by farmers who emphasize the use of renewable resources and the conservation of soil and water to enhance environmental quality for future generations. Organic meat, poultry, eggs, and dairy products come from animals that are given no antibiotics or growth hormones. Organic food is produced without using most conventional pesticides; fertilizers made with synthetic ingredients or sewage sludge; bioengineering; or ionizing radiation."

The level of average annual consumer food expenditures in the U.S. is stable. Since 1998, it has been accounting for 13–14 percent of the total consumer expenditures. (DOL 2004). Figure 1.1 shows the percentage of organic foods in total consumer sales. The percentage has been growing steadily, reaching 1.9 percent in 2003.

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Figure 1.1: Percentage of Organic Foods in U.S. Total Foods Consumer Sales
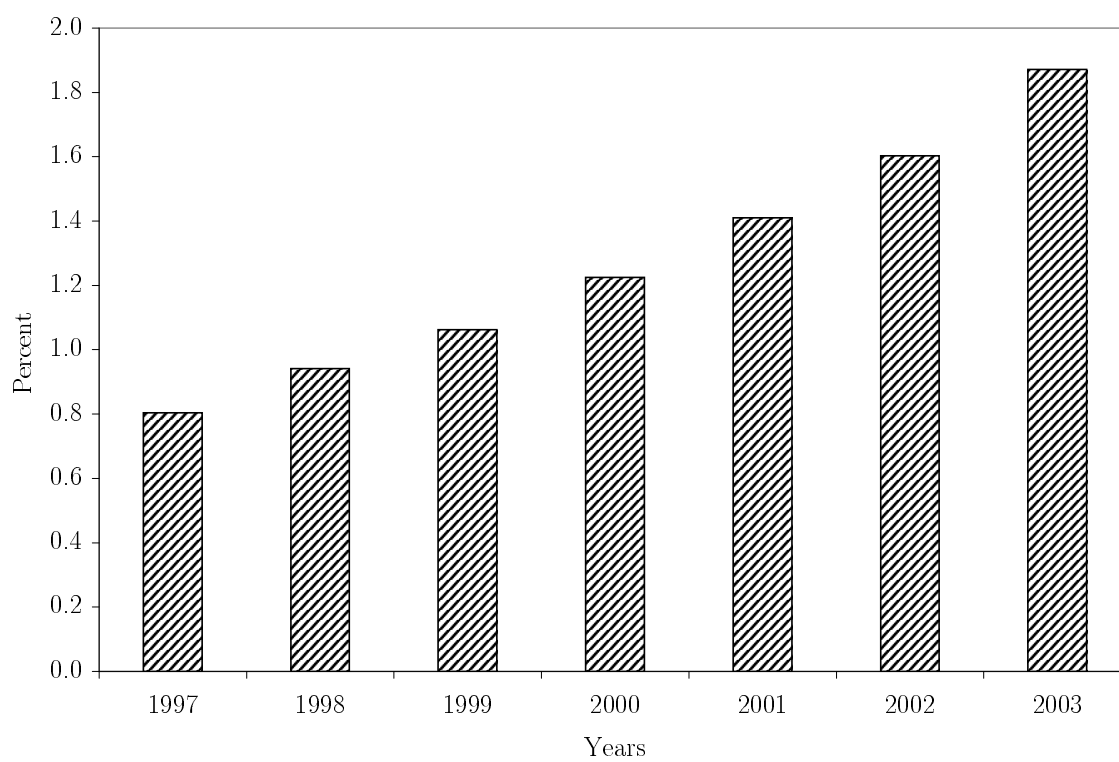


*Source*: OTA 2004 Manufacturer Survey Overview

According to the National Marketing Institute's 2003 Health and Wellness Trends Database, 38.2 percent of the general population purchased organic foods in 2003. Nearly 32 percent of the surveyed said they would increase purchases of organic products (Haumann 2004). The Whole Foods Market® Organic Foods Trend Tracker survey conducted in 2004 found that 27 percent of the Americans were eating more organic products than they did one year ago. The survey of 1,000 U.S. consumers showed that 54 percent have tried organic foods and beverages, with nearly 1 in 10 using organic products regularly or several times a week. Reasons cited for buying organic foods were the following: 58 percent think that it is better for the environment, 54 percent believe that it is better for human health, and 57 percent point out that it supports small and local farmers. In addition, 32 percent believe that organic products taste better while 42 percent believe that organic foods are of better quality (WFM 2004).

Packaged and precut organic vegetables and fruit are occupying more shelf space in the produce department as they continue to gain acceptance by consumers. By 2003, fresh produce had become the most popular category among consumers, accounting for about 42 percent of organic food sales (OTA 2004). Demand patterns are quite diverse. According to the Environmental Protection Agency, the intake of cucumbers, carrots, apples, strawberries and other berries does regularly increase by at least 100 percent of its lowest value in the peak season. The intake of corn, tomatoes, broccoli, onions, and potatoes is more or less stable all year round (EPA 1996).

As consumers become interested in organically-grown foods, organic farming in the U.S. continues to expand at a rapid pace. Almost 950,000 hectares are managed organically, which amounts to a 0.23 percent share of the total agricultural area. The U.S. is the fourth country in the world with respect to certified organic farmland acreage, following Australia, Argentina, and Italy. The number of certified organic growers has increased by 38 percent since 1997. In 2001, there were 6,949 organic farms in the country (Yussefi 2004).

Farmers nation-wide allocated 2.3 million acres of cropland and pasture to organic production systems in 2001, which is 74 percent more than in 1997. Over 1.3 million acres were used for growing crops versus over 1 million acres that were used for pasture and rangeland. The percentage of cropland acres versus pasture in 1997 was 63 percent to 37 percent, respectively. Colorado, California, North Dakota, Montana, Minnesota, Wisconsin, and Iowa have the largest share of organic cropland. Colorado, Texas, and Montana have the largest expanses of organic pasture and rangeland.

Organic grain crop acreage accounted for the largest 19.4 percent of total organic acreage in 2001. Organic fruit and vegetable acreage constituted 2.4 and 3.1 percent of the total organic acreage, respectively.

According to the Fourth National Organic Farmer's Survey, conducted by the Organic Farming Research Foundation (OFRF) in 2001, organic production grows constantly in the U.S. and little by little substitutes for conventional food production. As Figure 1.2 indicates, 51 percent of organic producers reported a market expansion of 10 percent or more in 2001. Survey results revealed that 39 percent of respondents confirmed a steady market while 9 percent of farmers contracted the market. Two thirds of those who scaled down operations (6 percent versus 3 percent) suffered a price drop of more than 10 percent during the year. Two thirds (39 percent to 12 percent) of the farmers who expanded enjoyed a price increase of 10 percent and more.

As Figure 1.3 shows, 56 percent of the OFRF survey respondents indicated that prices held steady in 2001, 28 percent indicated that prices went up, and 16 percent said prices went down. The price decreases reported were both small, less than 10 percent for 7 percent of the survey respondents, and large — more than 10 percent for 9 percent of farmers. Price increases were distributed less equally as 18 percent of farmers faced an increase of less than 10 percent. Prices went up by more than 10 percent for only 10 percent of producers.

Figure 1.2: Market Expansion for Organic Farmers, 2001
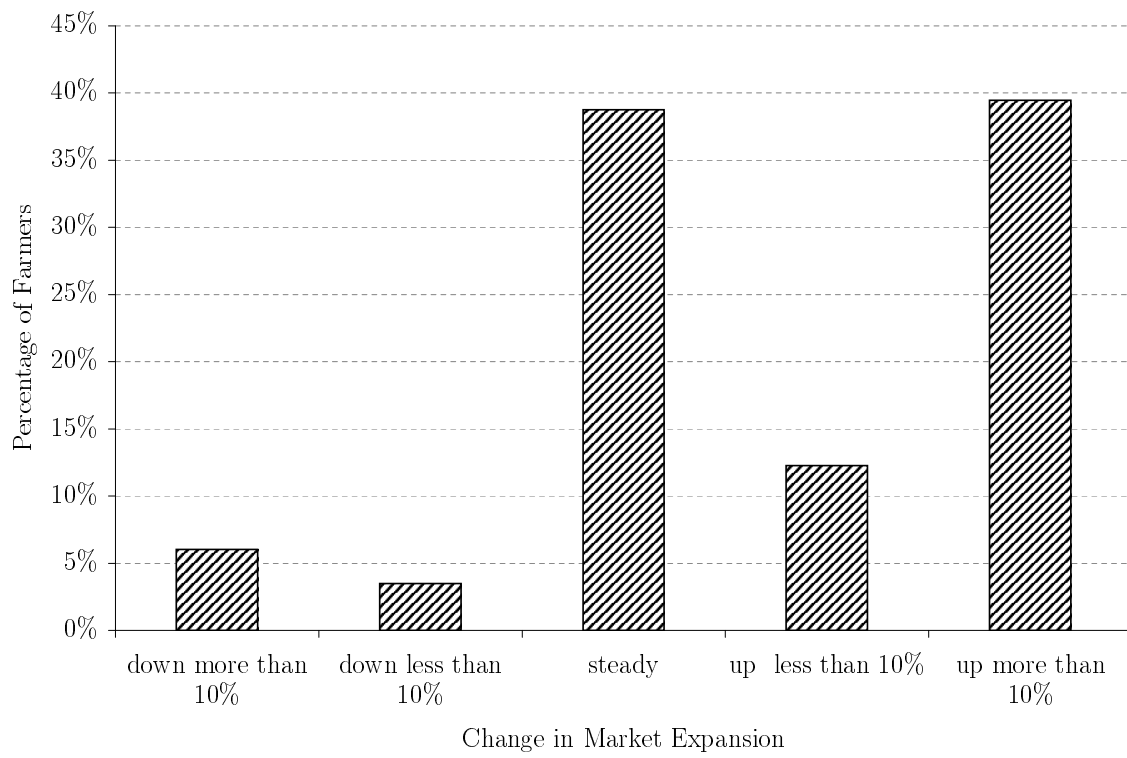


*Source*: Fourth National Organic Farmers Survey, OFRF

Figure 1.3: Average Price Change for Organic Farmers, 2001
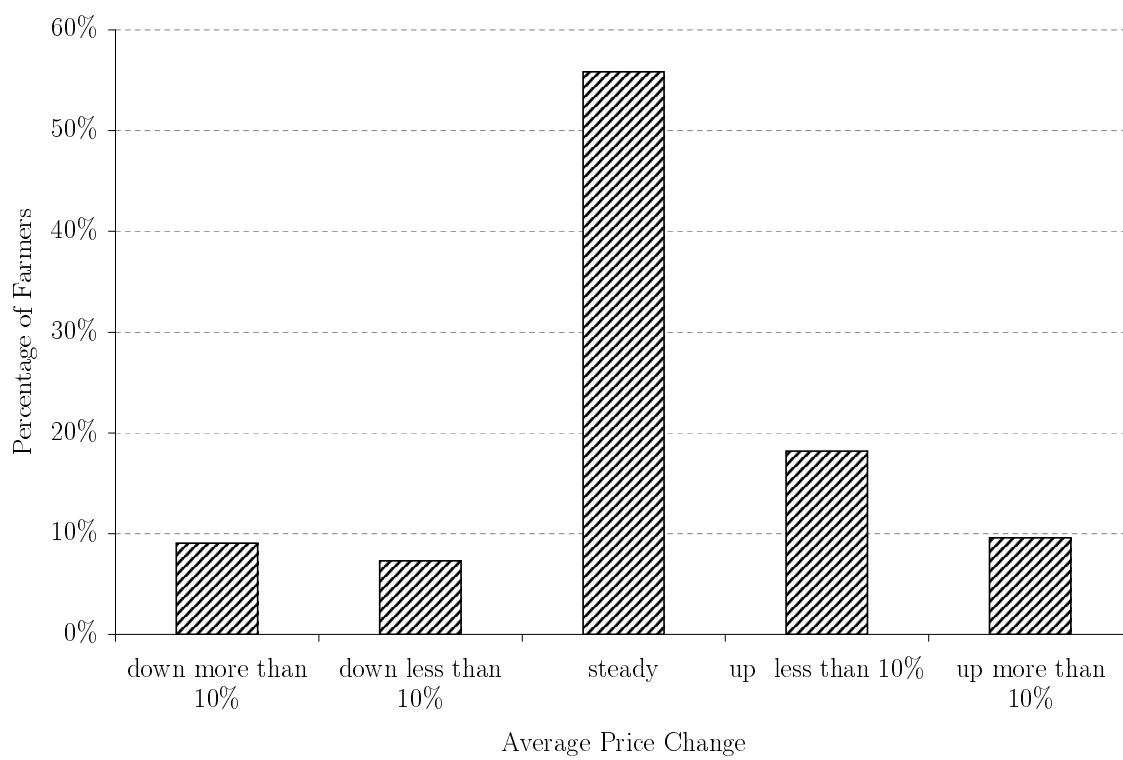


*Source*: Fourth National Organic Farmers Survey, OFRF

Figure 1.4: Average Price Change and Farmer Income, 2001
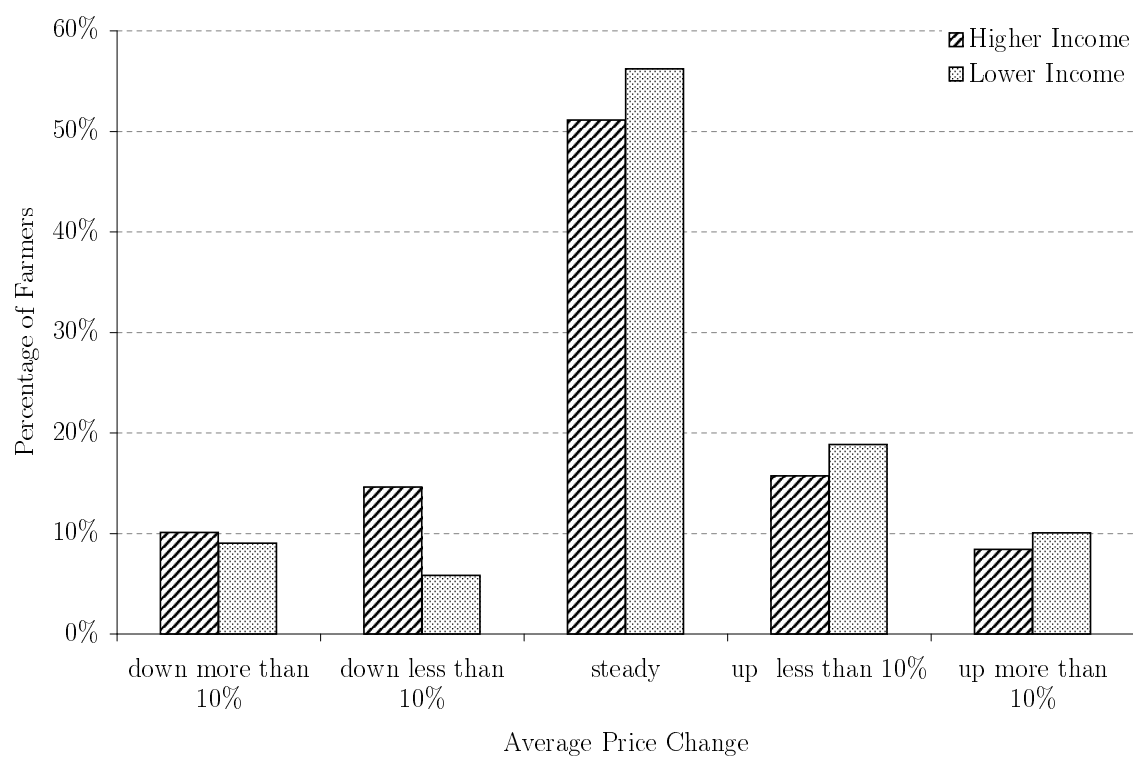


*Source*: Fourth National Organic Farmers Survey, OFRF

Figure 1.4 presents average price changes for farmers of different income. The distribution implies more favorable growth conditions for smaller farms as high-income farmers faced more price decreases than lower-income farmers.

Ninety two percent of survey respondents were able to obtain organic price premiums: 41 percent obtained organic premiums on 100 percent of their organic product and 30 percent obtained premiums on at least half of their organic product (Walz 2004).

Though organic food markets are growing, farmers indicate some barriers to expansion. These are lack of information on prices and unavailability of price forecasts. The availability of future prices is important to decision-making for it helps farmers to make production decisions. Figure 1.5 illustrates the point by combining the market expansion and price change information. A year-long decrease by more than 10% in the received price has caused almost a half of farms to contract as shown in Panel (a). From Panel (b) we see that smaller decreases bring this percentage down to a quarter. Figure 1.6 shows that three out of four farms have responded to price increases by scaling up their operations. A seemingly small change in price expectations can thus have a profound effect on the farmer's market expansion.

The state of organic fresh produce markets varied for commodity groups. Fruit producers experienced worse growth conditions in 2001 when compared to vegetable producers. Sixty four percent of fruit producers contracted when facing a price decrease of more than 10 percent, while this share was only 32 percent for the farmers that specialize in vegetables. (We define farmers who specialize in vegetables as those having more than 50 percent of their land allocated to vegetable production). The picture is similar for smaller price decreases, 58 percent versus 20 percent, and for price increases.

Figure 1.7 displays farmers' concentration plotted against the price change categories. The concentration index on the value axis represents acreage percentages dedicated to fruit and vegetable production, summed up across all survey participants that grow either fruit or vegetables, or both. One can see that fruit production makes about three fourths of those

Figure 1.5: Price Effect on Market Contraction, 2001

(a) Down by more than 10%

16%

43%

41%
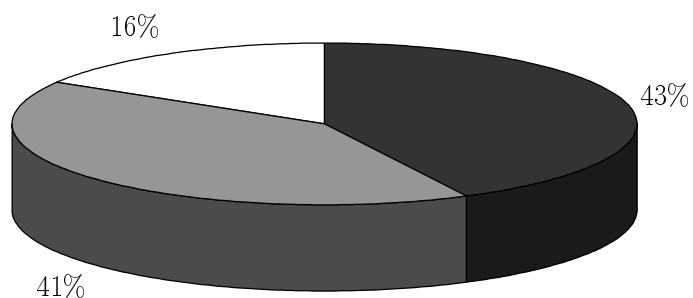
■ Market expansion is down    ■ Market expansion is constant
□ Market expansion is up

(b) Down by less than 10%
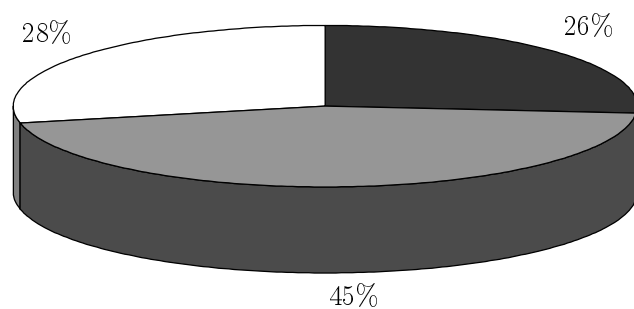
28%

26%

45%

■ Market expansion is down    ■ Market expansion is constant
□ Market expansion is up

*Source*: Fourth National Organic Farmers Survey, OFRF

Figure 1.6: Price Effect on Market Expansion, 2001

(a) Up by less than 10%

4%

25%

71%
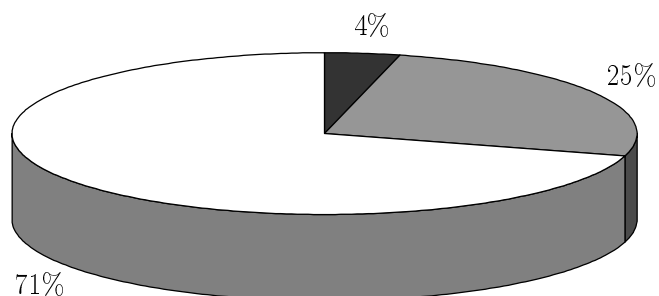
- Market expansion is down   - Market expansion is constant
- Market expansion is up

(b) Up by more than 10%
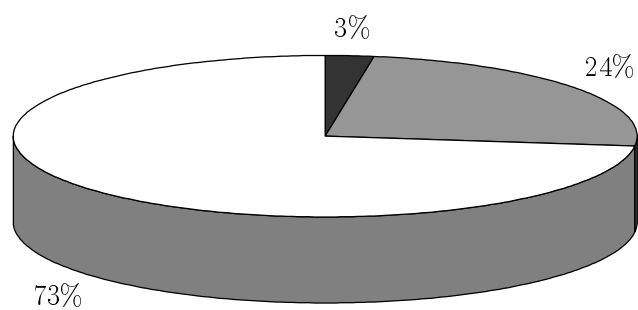
3%

24%

73%

- Market expansion is down   - Market expansion is constant
- Market expansion is up

*Source*: Fourth National Organic Farmers Survey, OFRF

Figure 1.7: Production Concentration Versus Price Change, 2001
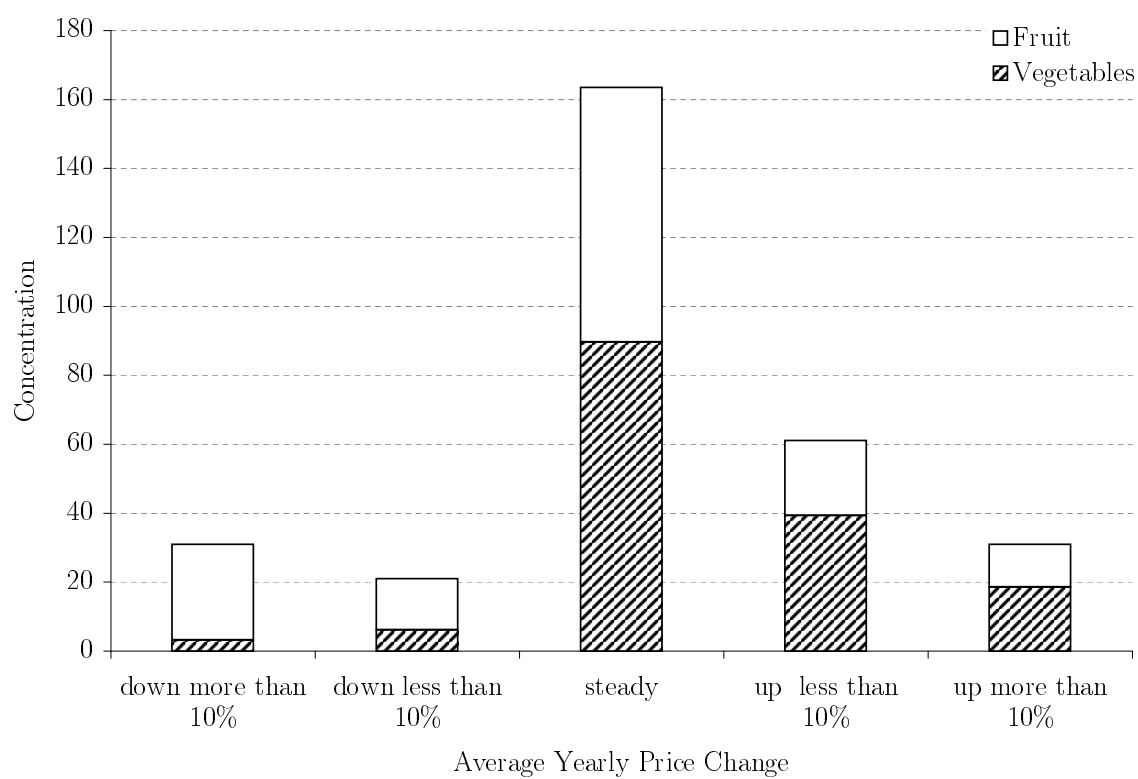
farms that faced a price decrease over the year, while vegetable production makes two thirds of those farms that enjoyed an increase in the received price.

As a summary, the brief exploratory analysis of organic produce markets reveals several important market trends:

- A small change in the received price can have a large effect on the farmer's expansion or contraction.

- There are favorable growth conditions for lower-income, smaller farmers, since they receive higher prices for their produce.

- Market growth differs significantly across different types of organic produce.

## 1.2  PROBLEM STATEMENT

Farmgate prices play an important role in the product life cycle. Guided by farm-level commodity price expectations, farmers make production decisions each year. The better the price information is, the more efficient decisions will be made. This effects the producer's welfare. The analysis from the previous section clearly shows that the farmgate price dynamics is significantly related to the farmer's scale of operations and income. At the same time, the farmgate price is the point of origin for the final price at which the commodity is purchased by the consumer.

Fresh produce is the most popular group among consumers. Americans increasingly embrace national health authorities' recommendation of consuming at least five fruit and vegetables a day. Fruit and vegetables accounted for the largest portion of consumer sales of organic foods at 42 percent in 2003. Fresh produce prices are among the most volatile of any food product (McLaughlin 2004). A complicated distribution system, a broad spectrum of varieties, perishability, weather conditions, all these factors make fresh produce prices hard to predict. Particular importance is placed on price information for organic fresh produce.

Little research is currently conducted to analyze price risk for organic commodities. Developing accessible resource materials for farmers and agribusiness professionals to systematically compare the price risk of crop planning and marketing options will greatly improve the chance of successful marketing. To provide market participants with accurate price expectations, several established forecasting methods will be compared. The best performing method will be sought. The focus of the present research is forecasting farm-level prices for organic fresh produce.

A price forecast is inextricably linked with two difficult choices. First, one must decide on how to generate the forecast. Even when a forecast is done well, its usefulness and value for the decision-maker must be established. Before one starts forecasting, it is useful to ask some questions. Who is the one to use the forecast and what are the decisions to be made on the basis of the forecast? Which factors affect the variable of interest and in what manner? When and with what frequency are the forecasts to be generated? What data are needed and what data are available? Once these questions are answered, a price forecasting process can begin.

Every agent in the marketing channel of organic produce relies on farmgate price expectations in the decision-making. Farmers can rarely make forecasts by themselves, but they form the largest group of price forecast users. They need to make production and marketing decisions that may have financial repercussions many months in future. Once committed to a product, farmers are price-takers. They produce goods that are homogeneous or highly substitutable with the goods of their competitors. It is very important to farmers to have a reliable forecast of future prices. Both wholesalers and retailers use price forecasts for their product mix decisions. They decide how many organic products should be purchased from a particular farmer. Incorrect price expectations bring about wrong decisions, and, as a result, profit losses.

The second question is about the usefulness of forecasts. Farmers want price forecasts when it is time to make a planting or breeding decision. They want to know the future price

of the produce at harvest. In this case, the lead—the interval between now and the forecast time—depends on product rotation. It constitutes about six to nine months for fresh fruit and vegetables. During and after the harvest, the producer is more likely to be interested in more frequent price forecasts; that is, every month or even every ten-days period. Wholesalers and retailers need future price forecasts by the time they make their product mix decisions. The frequency of price forecast for wholesalers and retailers depends on how often they need to restock. Taking into account that consumer demand for fresh produce does not have a clear-cut seasonal pattern and that produce deteriorates quickly, wholesalers and retailers would prefer to have a small but constant supply of fresh fruit and vegetables over the year. Hence, they might need price forecasts for every ten days.

The last two questions address the possibility of price forecasting by industry decision-makers. They may wish to make a regular price forecasting by themselves, with some changes in the initial parameters. In this case, forecasting methods to use should be easy to implement and forecasts should be obtained expediently. A prime criterion for such forecasting methods is that they be self-contained, or that they should require no additional information other than the past values of the price series. At least three methods—autoregressive and moving average model (ARMA), exponential smoothing, and spectral decomposition—satisfy these criteria.

There is no universally optimal forecasting method. Instead, a number of competing suboptimal methods can be used. A problem that decision-makers might face is how to select the best forecasting method from a set of several rivaling ones. This is why an agricultural forecaster needs to have a tool to compare methods.

Forecast quality can be evaluated using the root mean squared error (RMSE) criterion for point forecasts, and the Henriksson-Merton test for a direction-of-change comparison. For comparing forecasting techniques, a test of conditional predictive ability recently proposed by Giacomini and White (2003), is presented along with a derivative of quantile analysis.

Once some results on method performance across forecasting technics are presented, the method performance across commodities might be of interest. This part of the study answers two questions: is there any difference in method performance across commodities and, if so, what are the reasons?

The overall purpose of this study is to find an industry-oriented forecasting method which steadily gives the best price forecasts, as compared to a reasonable number of other alternative techniques. The following are the objectives of the study:

- Determine the users of organic produce price forecasts and establish price forecast assessment criteria;

- Select several forecasting methods which meet the criteria established;

- Choose a method for price forecasting technique evaluation; and

- Apply the selected methods, compare forecasting techniques, and develop recommendations based on the results.

Chapter 2 looks at potential users of organic produce price forecasts. It establishes several criteria for the selection of farm-level price forecasting methods. A review of agricultural price forecasting methods is presented in Chapter 3. Forecasting techniques are selected according to the established criteria. Chapter 4 describes the modern techniques for comparing predictive ability of several competing models. It also discusses an approach to comparing price forecasting methods. A detailed data set description and empirical results of having compared three forecasting methods are presented in Chapter 5. Chapter 6 concludes the study and outlines directions for future research.

PRICE IN ORGANIC PRODUCTION DECISIONS

This chapter pursues two objectives. The first is to reveal potential users of price forecasts for organic fresh fruit and vegetables. The second objective to provide an insight into the structure of organic produce markets, with a view to establishing criteria for the assessment of forecasting methods.

## 2.1 ORGANIC PRODUCE MARKETING CHAIN

"Organic produce" covers a wide range of commodities, including fresh produce, processed vegetables, fruit and grains, meat, egg and dairy products, livestock feed, fiber and textiles, herbs, and more. In terms of market channels, consumers, and handling and labelling requirements, each commodity shares characteristics of its conventional counterpart, occupying its niche in the organic marketplace. The present research focuses on fresh fruit and vegetables. Next in this section, a marketing chain for fresh produce will be discussed briefly.

Counting the stages in the product handover, there are three possible forms of marketing chain for fruit and vegetables. The full marketing channel includes the production and preparation of fresh produce for shipment to the wholesaler, with a subsequent sale to the retailer:

$$\boxed{\text{Farmer} \;\rightarrow\; \text{Wholesaler} \;\rightarrow\; \text{Retailer} \;\rightarrow\; \text{Consumer}}$$

When a specific variety, quality or quantity is desired, large retailers can sometimes buy fruit and vegetables directly from the farmer:

$$\boxed{\text{Farmer} \ \rightarrow \ \text{Retailer} \ \rightarrow \ \text{Consumer}}$$

Organic fruit and vegetables must be delivered to the consumer as quickly as possible because fresh foods deteriorate rapidly. Organic produce can be sold directly to consumers by the farmer, that is:

$$\boxed{\text{Farmer} \ \rightarrow \ \text{Consumer}}$$

The most common ways to deliver organic produce to its consumers are direct-to-consumer and through wholesale market channels. According to the Fourth National Organic Farmer's Survey, 80 percent of respondents who produced vegetables sold them through consumer-direct channels in 2001. For respondents producing organic fruit this figure was 58 percent. Nearly 70 percent of respondents producing vegetables sold them through wholesale market channels, as did 50 percent of fruit producers. Fifty four percent of respondents sold vegetables and 38 percent sold fruit through direct-to-retail channels. A majority of respondents indicated that they were planning market channel increases in direct-to-consumer and direct-to-retail markets (Walz 2004).

Some characteristics of agents in an organic produce marketing channel are described below, with the focus on the linkage of product, price, and market decisions.

An organic farmer is the basic agent in an organic produce channel. Problems faced by organic farmers are similar to those conventional farmers face and include what to produce, what prices to charge, and where to market the output. The first decision that a farmer makes is about the production level. This usually is a decision about what and how much to produce. At the same time, there is a regional specialization in the U.S. in terms of food production. If a farmer chooses to specialize in a unique or unusual crop, there may be limited facilities, expertise, or readily available markets to handle the new product. If the farmer opts for the products which are commonly grown in his/her region, then facilities, expertise, and market opportunities are already in place.

The key decision for many farmers is not what to produce, but how much. The decision about the quantity is closely related to the expected price of the product. An accurate future price forecast would help the farmer find the quantity that maximizes the profits. Overestimation and underestimation of future prices alike entail a loss of potential revenues. This is the main reason why farmers may pay special attention to the quality of price forecasts.

Knowledge about future prices is not the sole factor that influences the farmer's level of profit. No matter how good the product is or how reasonable is the price, the farmer cannot succeed unless the product gets to the consumer on time.

There are two basic problems in coordinating the supply and demand for organic goods. First, there is a time difference between when organic foods are produced and when they are demanded. Fresh fruit and vegetables have no seasonal consumption pattern. The only constraint is the production cycle. Second, there is a spatial difference between where organic foods are produced and where they are demanded. The Fourth National Organic Farmers' Survey indicated that organic farmers predominantly sold fruit and vegetables locally. In their sample of respondents, 79 percent of vegetable and 43 percent of fruit products were sold within 100 miles of the farm (Walz 2004).

Along with the problems that are similar to those facing conventional farmers, there are unique problems impacting organic farmers. The choice of methods to adopt suggests that farmers face at least two major barriers. First, farmers must make a dramatic change in their production methods. This aspect is especially important for those who have been in farming for a while. The land under organic production must be free of prohibited chemicals during some transition period, usually three years. During this time the land remains a frozen asset. Secondly, farmers must acquire information on organic production methods and become professional in using it. In the decision to adopt new agricultural methods, farmers typically seek information from other organic farmers, local chemical dealers, local government agencies (Duram 1999), magazines and newsletters on organic farming, and on-

farm experiments. Another problem that influences the organic farmer's decision is insects and diseases. Some farmers have decided not to grow crops susceptible to insects or diseases because the cost and risks associated with growing these crops exceeded potential returns from selling them (Baker and Smith 1987).

Organic farms are often unable to produce enough to meet the local demand primarily because their operations are small. Even though the numbers of organic farms and acres farmed using organic techniques have increased rapidly, organic farms remain much smaller than their conventional counterparts. Organic farmland acreage constitutes less than 1 percent of the total agricultural area in the U.S. Organic fresh produce acreage accounted for about 5 percent of the total organic acreage in 2001.

As Dimitri and Richman (2000) report, organic produce farmers usually lack two things that make good marketing possible: financial means and the knowledge of marketing institutions. They are accustomed to marketing to a relatively small group of people who have already converted to eating organic and other sustainably-grown products. Farmers understand that they have a much larger group to appeal to, but are unused to working with advertising consultants and firms. In many cases they do not have money to do so, even if they wish to.

In the Fourth National Organic Farmers' Survey, 75 percent of respondents used a word-of-mouth method to sell organic produce, 48 percent used organic certification label/seal on products, and 31 percent made telephone calls to potential buyers (Walz 2004). Another financial problem is that farmers who want to increase organic acreage may not be able to afford to purchase more land. Even if they could, farmers would still be unable to earn organic revenues from the land during the time required to convert it from conventional to organic use (assuming the land had not already been certified for organic production). The loss of revenue during this period may be not as severe as in previous years, since transitional products having recently begun appearing in natural foods stores.

Nearly all commodities pass through the hands of at least one intermediary on their way from farmer to retailer. For fruit and vegetables, this intermediate stage consists of packing and sorting. There are two basic types of wholesalers — merchant wholesalers and brokers. The majority of wholesalers are merchant wholesalers who take title to the product that they handle. Brokers do not take ownership of the produce but rather serve as an intermediary on behalf of either a farmer or a wholesale/retail buyer. Wholesalers do not produce products, but do make product mix decisions. The target market for the wholesaler is the retailer. Product mix decisions for merchant wholesalers and brokers are aimed at satisfying the retail demand.

Dimitri and Richman (2000) report that many wholesalers face an insufficient market supply. Except for a certain amount of organic products which retailers ask distributors to provide, farmers cannot sell this amount to the wholesalers at a particular point in time. Even if organically-operated farms could quickly step up and down their production output, it would not be enough to improve the flow of the desired organic food to retailers.

Wholesalers are the primary intermediaries between farmers and retailers because they procure food in large quantities at low prices, consolidate their purchases in warehouses, and then resell and deliver these products to retailers at lower costs than any other procurement and delivery option. Taking into account that the prices wholesalers charge to retailers are largely administered with allowances and discounts, the basic wholesaler's aim is to minimize the cost of buying organic foods from a farmer and transporting them to a retailer.

The traditional operating system used by wholesalers to minimize the cost of delivering products to the retailer consists of receiving, storage and replenishment, order selection, and shipping. Farmgate price expectations affect not only production decisions at a farm level, but also the wholesaler's profit and product mix decisions. Knowing a farmgate price forecast for a commodity, the wholesaler can adjust the delivery options and price charged to retailers, in order to maximize profits.

Organic foods are sold to consumers through three main venues: organic foods stores, conventional grocery stores, and direct-to-consumer markets. A small amount is exported to foreign markets (Dimitri and Greene 2002). Combined with the largest natural food chains — Whole Foods Market and Wild Oats — the entire natural foods/specialty retail channel still represented the largest portion of the U.S. organic sales of 47 percent in 2003. The mass market channel, which includes supermarkets, grocery stores, mass merchandisers, and club stores, accounted for 44 percent of sales, with direct sales through farmer's markets and coops, food service and exports making up the remaining 9 percent. Forty nine percent of all organic products were sold in conventional supermarkets in 2000. Conventional supermarkets comprise 99 percent of all food stores. Forty eight percent of organic products were sold in health and natural products stores. Natural product retailers account for 1 percent of all food stores. About 3 percent of organic food went through direct-to-consumer methods. In 1990, 7 percent of all organic products were sold in conventional supermarkets, 68 percent were sold in health and natural product stores, and 25 percent were sold by direct-to-consumer methods (Dimitri and Greene 2002).

Retailers in the organic foods industry behave much in the way their counterparts from other industries do. They choose the product mixes, quantities, and prices that result in optimal returns. The target market for the retailer is the consumer. Retailers make product decisions within the context of the type of retail format operated. They look at a merchandise variety to determine which product categories to carry, for example, perishables, dry grocery food, general merchandise, and/or health and beauty products. Retailers make merchandise assortment decisions to determine how many brands to carry in each category. These decisions must be consistent with the level of quality demanded by the retailers' customers.

Retailers dealing in fresh produce operate in a high price volatility environment. To withstand the uncertainty and compete, they resort to a variety of pricing techniques. An interesting aspect is a "to have the cake and eat it, too" strategy. At one hand, retailers have to keep up with competition, so that they have to charge according to what the suppliers

charge. At the other, they insulate themselves from production price volatility by not basing their prices directly on what they pay to the supplier (McLaughlin 2004).

According to the survey conducted by Jolly and Norris (1991), an insufficient supply, quality concerns, and high prices for organic foods were identified as the most important problems that affect retailers' decisions to carry organic products. Organic retailers want to have a dependable supply of products. They also need to be able to assure their customers that their organic food is truly organic. Consequently, they have made a point of establishing long-term relationships with wholesalers, who keep the retailers needs in mind when purchasing organic commodities from farmers. Prices set by retailers are generally an attempt to meet a particular profit objective. Many retailers point out that retail price differentials between organic and conventional foods may be lowered when organic foods become widely accepted.

This summary information has identified who the main users of price forecasts are and what interactions among them drive the farmgate prices. The next step is to choose the adequate forecasting methods. These methods should be readily understood and convenient to work with for industry decision-makers. The agricultural economics and forecasting literature offers a broad range of methods to apply to commodity price forecasting. Before considering particular methods, we should take a closer look at a general model of commodity price and quantity determination to see what quantitative processes would need to be taken into account.

## 2.2 Conventional Structural Model

Agricultural product markets are commonly assumed to be competitive and in equilibrium (Tomek and Myers 1993). In an equilibrium, the quantity and farm-level price of a commodity are determined simultaneously. Both quantity and price are endogenous variables. Endogenous variables are determined by supply and demand shocks, which are the exogenous variables in the system. Supply shocks may include the levels of land, labor,

and other input costs. Input prices are assumed to be known and exogenous at the decision time. Conventional commodity prices are an important supply shifter. Supply shocks for specific farm commodities differ considerably because of their different characteristics, different sets of substitute and complement goods, and the varying extent of government support programs. Demand shifters impose demand theory restrictions on the system. The inverse demand specification is very common in agriculture. An inverse demand function characterizes the price as a function of quantity and other exogenous variables. Most demand shocks are represented by consumer demand variables, such as personal income, prices for substitute and complement commodities, personal preferences that have a quantitative representation. Both quantity and price equations are treated simultaneously in order to get equilibrium values.

Organic producers are faced with the problem of output price uncertainty. But prices of organic produce are inherently more volatile in comparison to its intensive agriculture counterparts. In a long-established market, there is a well-functioning information infrastructure and the availability of hedging facilities reduces the risk in the whole chain. As yet, organic farming is hardly a full-fledged industry. Such mechanisms are not yet in place for the emerging organic produce market. This leads to a high degree of uncertainty about future revenues and, accordingly, to a sub-optimal output and pricing decision.

Both intensive and organic farming are dependent upon many natural processes, which are periodic either seasonally or on a multi-annual basis. Similarities between the two production concepts include land preparation, planting, cultivation, and irrigation. Clearly, such natural inputs as soil processes and rainfall play an important role in production technology.

Organic certification schemes specify that land must be free from chemical inputs for a number of years prior to organic production, and organic production must avoid the use of man-made fertilizers, pesticides, growth regulators and livestock feed additives. Moreover, organic farming systems foster the cycling in resources, and rely on practices such as cultural and biological pest control. Organic production primarily relies on natural processes and

makes beneficial uses thereof. The metabolism of organic fertilizers — manure and compost — depends mainly on soil and climatic conditions. Cover crops are additionally used, whose growth is subject to a wide range of climatic phenomena. So it is with harmful insect and rodent populations, which are suppressed by breaking their development cycles. There is also role for social cycles. For example, the use of labor-intensive hand weeding may depend on the availability of seasonal (potentially immigrant) workforce. Thus, cyclical natural and social phenomena bring about an output uncertainty that amplifies the price uncertainty.

Park and Lohr (1996) estimate a system of reduced-form equations to establish supply and demand factors that influence equilibrium farm price and quantity for a number of organic produce items. The dynamic supply and demand equations from their partial adjustment model can be written, with a change of notation, as

$$q_t = [1 \ y_t \ q_{t-1} \ \sin(\omega t) \ \cos(\omega t) \ y_t^* \ \boldsymbol{W}_t]\boldsymbol{\beta}_s + \epsilon_s \tag{2.1a}$$

and

$$y_t = [1 \ q_t \ y_{t-1} \ \sin(\omega t) \ \cos(\omega t) \ \boldsymbol{D}_t]\boldsymbol{\beta}_d + \epsilon_d \tag{2.1b}$$

where $y_t$ and $q_t$ are the equilibrium price and quantity for the organic item at time $t$, respectively, $\sin(\omega t)$ and $\cos(\omega t)$ are harmonic terms of a preset angular frequency $\omega$ to account for seasonal effects, $\boldsymbol{W}_t$ is a vector of weather variables, $y_t^*$ is the supply-shifting price of the conventional counterpart to the organic item, $\boldsymbol{D}_t$ are demand-shifting factors that include a price premium for the organic item on the wholesale market, wholesaler's transportation and labor costs, etc., and $\boldsymbol{\beta}_s$ and $\boldsymbol{\beta}_d$ are the supply and demand coefficients to estimate, respectively.

A simultaneous equations model requires a large array of data. The researcher must have information about all exogenous variables that have been found to exert a significant influence on the endogenous variable. Industry price forecast users usually do not have this kind of information readily available. Price series are in most case the only data at someone's disposal. While useful to explain the equilibrium price and quantity, the system in Equation (2.1) cannot be applied for price forecasting. The model contains factors that either need

to be forecast, such as the price premium and the wholesaler's costs. In addition, the information for the values of quantity supplied/demanded in the recent past will be unavailable at the time the forecast is to be made.

There is a class of forecasting methods that only use past information on the variable of interest to generate forecasts. These methods are termed "self-contained" methods. The issue is whether the output of a self-contained price forecaster can be as accurate as that of a large, equilibrium-based system. This depends on how well the "self-contained" one detects any systematic changes in the price; that is, how well it is suited to work with the main components of the data-generating process. We will now attempt to single out those components.

## 2.3 Data-Generating Process for Price Series

The approach we employ to obtain a structural forecasting model of price determination is to rewrite the supply/demand system in Equation (2.1) in a geometric lag form for price. Substituting repeatedly the supply equation (2.1a) into the demand in (2.1b) and regrouping terms, we obtain

$$y_t = \mu + \theta \sum_{i=1}^{\infty} \lambda^i y_{t-i} + s(t, \boldsymbol{\theta_s}) + g(t) + \epsilon_t \qquad (2.2)$$

or, in a compact form

$$B(L)y_t = \mu + s(t, \boldsymbol{\theta}_s) + g(t) + \epsilon_t$$

where $\mu$ is the mean of the series; $\lambda$ and $\boldsymbol{\theta} = [\theta, \boldsymbol{\theta}_s]$ are parameters that depend on $\boldsymbol{\beta}_s$, $\boldsymbol{\beta}_d$, and also parameters of the $y_t^*$ process; $s(t, \boldsymbol{\theta}_s)$ is a cyclical signal that incorporates $\sin(\omega t)$, $\cos(\omega t)$ as well as extracted periodic components from future levels of other variables in Equation (2.1); $g(t)$ is an unknown aperiodic stochastic process that reflects the cumulative effect of all explanatory variables that cannot be forecast; and $B(L)$ is the lag operator.

Assuming that the changing nature of the organic sector breaks the infinite memory geometric lag process and, accordingly, that the order of the polynomial $B(L)$ becomes

finite, the structural model in Equation (2.2) clearly identifies three major components of the price-determination process. These elements are: an ARMA component in $y_t$ and $\epsilon_t$; a seasonal component $s(t)$; and an aperiodic stochastic process $g(t)$ of unknown form.

We have already seen that different agents in the marketing chain would be eager to know future farmgate price for a product. Farmers use price forecast for production decisions. Wholesalers and retailers make product mix decision partly based on farm-level expected prices. Incorrect price expectations lead to profit losses for all agents involved. The forecast lead time will differ, depending on the type of the price forecast user. Farmers might be interested in 6–9 months price forecast at the time of planting and 10–30 days price forecast at harvest.

In turn, a periodical, 1–2 months-ahead price forecast would be the likely need of wholesalers and retailers, depending on their product replenishment strategy. Producers are likely to be interested in getting accurate forecasts in both magnitude and direction-of-change sense. Retailers that attempt to isolate themselves from the supply-size price volatility may look more for better directional quality of forecasts.

Price forecasting methods for industry application should be easy to implement and automate. Organic market participants are unlikely to afford forecasting systems that have high development and operation costs. At the same time, the industry would require quick and relatively accurate forecasts. The discussion in the next chapter is about the availability of forecasting methods than have such features.

Price Forecasting Methods

Economic forecasting in agriculture shares some of its features with business forecasting and macroeconomic forecasting. But it has developed over time a focus of its own. Agricultural economists have committed considerable effort to the methodology of commodity price forecasting. Consequently, a variety of methods, from sophisticated multiple-equation regression techniques to rather naive extrapolations or intuitive estimates, have been developed. The aim of this chapter is to provide a summary of the main approaches used by agricultural forecasters to predict commodity prices and select those that are most appropriate for a use by industry decision-makers.

## 3.1 Overview of Price Forecasting Methods

Forecasting can be performed in either time domain or frequency domain. All existing methods for commodity price forecasting fall into one of these two groups.

The time series approach, which uses autocorrelation and partial autocorrelation functions to study the evolution of a time series through parametric models, covers about all of the most extensively used time domain techniques. The time domain methods include a regression method, decomposition method, exponential smoothing, and the Box-Jenkins methodology.

Regression models assume that the relationship between the dependent, or endogenous, variable and independent, or exogenous, variables can be approximated by a known function of an arbitrary form. This group of methods contains both single equation econometric models and sectoral models that include, as the very minimum, a supply equation and

a demand equation for a single commodity. In general, regression methods reveal those exogenous variables that significantly influence the response of the endogenous variable.

A two-equation integrated demand and markup model was applied to markets for organic broccoli and carrot in a study by Lohr and Park (1999). The purpose of the study was to determine the organic wholesaler behavior to reduce price uncertainty. In Park and Lohr (1996), a sectoral model of reduced-form supply and demand equations was estimated. The average total supply and demand effects on long-run equilibrium quantities and prices of organic broccoli, carrots, and lettuce were calculated.

Decomposition models have little theoretical basis — they are more of an intuitive approach. However, the decomposition method has been found useful when the parameters describing a time series are not changing over time. The basic idea behind the method is to decompose the time series into several factors: trend, seasonal, cyclical, and irregular components. Estimates of these factors are used to describe the series. X-12-ARIMA is a decomposition method used by the Bureau of the Census of the U.S. Department of Commerce (Bowerman et al. 2005). One can see, recalling Equations (2.1) and (2.2), that the approach taken in the present study has a definite imprint of the decomposition method.

Exponential smoothing is a method of forecasting based on a simple statistical model of a time series. Unlike regression models, exponential smoothing does not make use of information from series other than the one being forecast. It is a method that weights the observed time series values unequally. More recent observations receive larger weights than more remote observations; that is, exponential smoothing assigns exponentially decreasing weights as the observations get older. Nerlove (1958) used the exponential smoothing method in estimation of farmers' response to agricultural prices. Jarrett's (1965) forecast of Australian wool prices marked the first application of the method in agriculture. Monthly forecasts of six grades of wool using Winters multiplicative model were compared with a simple moving average.

Modern commodity price forecasts are largely made with the use of Box-Jenkins methods, which include stationary autoregressive moving average (ARMA) models, nonstationary autoregressive moving average (ARIMA) models, and stationary and nonstationary vector ARMA models. In a study by Gil and Albisu (1993), three methods for the monthly maize price one-step-ahead forecast were considered: an econometric model, exponential smoothing, and ARIMA. Monthly maize prices lagged two periods, lagged maize ending stock, lagged maize import, and lagged monthly barley price were used as explanatory variables in the econometric model. Holt's exponential smoothing method was applied, with level and trend being the only factors considered. ARIMA (2,1,0) forecasts were obtained following the traditional approach. It was concluded that the ARIMA model generated the most accurate forecasts among the three models, and the econometric model was found to be the worst one. Kohzadi et al. (1996) compared ARIMA and neural network price forecasting performance for live cattle and wheat monthly prices. It was found that ARIMA was able to capture a significant number of turning points for wheat only, while the neural network did equally well for both wheat and cattle.

A data analysis procedure that measures the fluctuations in a time series by comparing them with sinusoids is known as frequency domain analysis. Fourier analysis is fundamental for the frequency domain analysis. The basic idea of Fourier analysis, or spectral decomposition of a time series, is a decomposition of a series into the sum of sinusoidal components, the harmonics, to search for periodic patterns in the data.

There are two studies in agricultural economics literature that contain a Fourier analysis application to price forecasting. A study by Myers (1972) applies spectral analysis to hog price forecasting. A combination of spectral analysis, autoregression and multiple regression analysis, and a recursive system is used in the empirical model. By attempting to keep the constructed equation within manageable proportions and produce useful information, several statistical properties were violated or fell outside the bounds of conventional acceptability. It was found that the forecasting model can only be evaluated by its ability to provide ade-

quate answers to pricing problems and only incidentally by its internal statistical properties. Weiss (1970) used spectral analysis of cocoa prices to establish an effective potential price stabilization policy for the cocoa market. Spectral analysis was used to identify empirically cyclical patterns in world cocoa prices. An indicated lag that was thought to represent a production cycle was compared with those used in several regression analyses of supply. In addition to seasonal variations, he found that there existed periodic fluctuations in cocoa prices attributable to lags in production response and in consumption response to price changes with different average lengths.

Data availability can be limited in some instances. In such cases, a combination of forecasts generated by different models takes advantage of error structures in the joint pattern of forecasts. Price forecasts using composite methods are presented in papers by Bunn (1989) and Gil and Albisu (1993). From a perspective of minimizing error variance, forecasts from a combined model are never worse than those of the best individual model.

When two or more forecasts of the same uncertain event are in hand, a composite forecast can be formed as a weighted average of the forecasts available. There are several approaches to combining forecasts. Clemen and Winkler (1986) suggest a simple average of available forecasts. The weights are assumed to be constant over the time period analyzed, ignoring the relative performance of the individual forecasts. Bates and Granger (1969) suggest deriving weights that minimize the composite forecast variance, where the variance is estimated from historical forecast performance of the individual forecasts. Bessler and Chamberlain (1987) and McIntosh and Bessler (1988) have proposed a Bayesian approach to forming composite forecasts.

The highlight of the next section is how to choose forecasting methods based on the assessment criteria we established in the previous chapter.

## 3.2 Industry-Oriented Forecasting Methods

Two classes of forecasting methods, time domain and frequency domain, were reviewed in the previous section. For the sake of variety, it is logical to implement methods from each class.

### 3.2.1 Exponential Smoothing

Industry-oriented forecasting methods remain the focus of our attention. These methods are easy to implement, they give quick price forecasts with limited analytical input, and they do not require more information than is contained in the series being forecast. Exponential smoothing and ARMA methods satisfy these criteria among time domain methods. Spectral decomposition, a frequency domain representative, also fits the industrial application criteria.

Exponential smoothing has been thought of as a way of getting accurate point predictions. There are three main advantages to the exponential smoothing method. First, smoothing forecasting equations are easy to understand and compute. Second, the method is often as well-performing as far more sophisticated one. And, finally, it may work on short series with possible structural changes. An arbitrary choice of smoothing constants and the impossibility of its adaptation to certain types of data are usually referred to as the most serious drawbacks of the exponential smoothing method.

The workhorses of the exponential smoothing family are the simple, or single exponential smoothing, Holt's (double) exponential smoothing, and Holt-Winters, or triple, exponential smoothing. Simple exponential smoothing is used when the data are nonseasonal, or seasonally detrended, and have a time-varying mean without a consistent trend. Holt's exponential smoothing was found to work well when data are nonseasonal and feature time-varying local trends. It usually works quite well with the data that are "smoother" in appearance — that is, less noisy — than what would be better handled by simple exponential smoothing.

The Holt-Winters exponential smoothing is used when data are trended and seasonal, and one wishes to decompose it into local level/trend/seasonal factors. There are two versions of

the Holt-Winters exponential smoothing models: additive and multiplicative. Normally, the multiplicative version is used for nonstationary data. Similarly, the additive version of the Holt-Winters exponential smoothing is a better choice for stationary data.

The simple exponential smoothing method is used for forecasting a time series when there is no trend or seasonal pattern but the mean of the time series is slowly changing over time. The simple exponential smoothing gives the most recent observation the most weight. Older observations are given successively smaller weights. The estimate for the mean of the series in time period $T$, $l_T$, is given by the smoothing equation

$$l_T = \alpha y_T + (1 - \alpha)l_{T-1} \tag{3.1}$$

where $\alpha$ is a smoothing constant, $0 < \alpha < 1$, $y_T$ is the observation in time period $T$, and $l_{T-1}$ is the estimate of the mean of the time series in time period $T - 1$.

In the simple exponential smoothing method, a point forecast at time $T$ of any future value $y_{T+\tau}$ of a time series is the last estimate $l_T$ for the mean of the series, that is

$$\widehat{y}_{T+\tau} = l_T \tag{3.2}$$

where $\widehat{y}_{T+\tau}$ is a point forecast made in time period $T$ for $\tau$ periods ahead, $\tau = 1, 2, ...\infty$.

Holt's exponential smoothing is appropriate when both the mean, $\beta_0$, and the regression coefficient, or the growth rate, $\beta_1$, are changing for the series that is described by the linear trend model,

$$y_t = \beta_0 + \beta_1 t + \epsilon_t \tag{3.3}$$

where $t$ represents the time trend, and $\epsilon_t$ is an error at time period $t$.

The estimate $l_T$ for the mean of the series and the estimate $g_T$ for the growth rate of the series in time period $T$ are given by the following smoothing equations

$$l_T = \alpha y_T + (1 - \alpha)[l_{T-1} + g_{T-1}] \tag{3.4}$$

$$g_T = \gamma[l_T - l_{T-1}] + (1 - \gamma)g_{T-1} \tag{3.5}$$

where $\gamma$ is smoothing constant, $0 < \gamma < 1$, and $l_{T-1}$ and $g_{T-1}$ are estimates at time $T - 1$ for the mean and the growth rate, respectively.

In Holt's exponential smoothing, a point forecast at time $T$ of any future value $y_{T+\tau}$ of a time series can be represented as

$$\widehat{y}_{T+\tau} = l_T + \tau g_T. \tag{3.6}$$

The additive Holt-Winters method is appropriate when a time series has a linear trend with an additive seasonal component for which the mean, the growth rate, and the seasonal pattern may be changing. Additive seasonal pattern is usually true for stationary series. The estimate $l_T$ for the mean, the estimate $g_T$ for the growth rate, and the estimate $s_T$ for the seasonal factor of the series in time period $T$ are given by the following smoothing equations:

$$l_T = \alpha[y_T - s_{T-\lambda}] + (1 - \alpha)[l_{T-1} + g_{T-1}] \tag{3.7}$$

$$g_T = \gamma[l_T - l_{T-1}] + (1 - \gamma)g_{T-1} \tag{3.8}$$

$$s_T = \delta(y_T - l_T) + (1 - \delta)s_{T-\lambda} \tag{3.9}$$

where $\lambda$ denotes the number of seasons in a year ($\lambda = 12$ for monthly data, and $\lambda = 4$ for quarterly data), $s_{T-\lambda}$ is the estimate for the seasonal factor in time period $T - \lambda$, and $\delta$ is smoothing constant, $0 < \delta < 1$.

In the additive Holt-Winters exponential smoothing method, a point forecast at time $T$ of any future value $y_{T+\tau}$ of a time series is

$$\widehat{y}_{T+\tau} = l_T + \tau g_T + s_{T+\tau-\lambda} \tag{3.10}$$

where $s_{T+\tau-\lambda}$ is the "most recent" estimate of the seasonal factor for the season corresponding to time period $T + \tau$.

The multiplicative Holt-Winters method is appropriate when a time series has a linear trend with a multiplicative seasonal component for which the mean, the growth rate, and the seasonal pattern may be changing. The presence of multiplicative seasonal pattern is

commonly true for nonstationary series. The estimate $l_T$ for the mean, the estimate $g_T$ for the growth rate, and the estimate $s_T$ for the seasonal factor of the series in time period $T$ are given by the following smoothing equations:

$$l_T = \alpha \left[ \frac{y_T}{s_{T-\lambda}} \right] + (1 - \alpha)[l_{T-1} + g_{T-1}] \tag{3.11}$$

$$g_T = \gamma[l_T - l_{T-1}] + (1 - \gamma)g_{T-1} \tag{3.12}$$

$$s_T = \delta \left[ \frac{y_T}{l_T} \right] + (1 - \delta)s_{T-\lambda}. \tag{3.13}$$

In the multiplicative Holt-Winters, a point forecast at time $T$ of any future value $y_{T+\tau}$ of a time series can be represented as

$$\widehat{y}_{T+\tau} = [l_T + \tau g_T]s_{T+\tau-\lambda}. \tag{3.14}$$

### 3.2.2 Box-Jenkins Model

The Box-Jenkins model is the second method from the time domain group that we consider for industry-oriented price forecasting. The Box-Jenkins approach has different versions for stationary and nonstationary time series.

In time series analysis, a weaker sense of stationarity in terms of the moments of the process is often used. A process is said to be $n$-th order weakly stationary if all its joint moments up to the order $n$ exist and are time invariant, that is, independent of a time origin.

A stationary process can be represented either in a moving average form

$$(1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p)y_t = \epsilon_t \tag{3.15}$$

or in an autoregressive form

$$y_t = (1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q)\epsilon_t \tag{3.16}$$

where $B$ denotes the lag operator which power coefficient represents the number of lags. The autoregressive and moving average coefficients are represented by $\phi$ and $\theta$, while $p$ and $q$ denote the order of autoregressive and moving average terms, respectively.

A problem with both representations is that there may be too many parameters. This is true even for a finite order moving average and a finite order autoregressive model as it often takes a high order model for good approximation. A large number of parameters frequently reduces efficiency in estimation. It may be necessary in building the model to include both autoregressive and moving average terms in a model. This leads to the following mixed autoregressive moving average (ARMA) model:

$$(1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p)y_t = (1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q)\epsilon_t. \tag{3.17}$$

A stochastic ARMA model can be extended to the following seasonal ARMA model:

$$\phi_p(B)\Phi_P(B^\lambda)y_t = \theta_q(B)\Theta_Q(B^\lambda)\epsilon_t \tag{3.18}$$

where $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p$ is autoregressive operator, while $\Phi_P(B^\lambda) = 1 - \Phi_1 B^\lambda - \Phi_2 B^{2\lambda} - ... - \Phi_p B^{p\lambda}$ indicates seasonal autoregressive operator. $\lambda$ denotes periodicity in the seasonal pattern, where $\lambda = 12$ for monthly seasonal pattern, and $\lambda = 4$ for quarterly seasonal pattern. $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q$ represents moving average operator, and $\Theta_Q(B^\lambda) = 1 - \Theta_1 B^\lambda - \Theta_2 B^{2\lambda} - ... - \Theta_q B^{q\lambda}$ denotes seasonal moving average operator.

If the series is not stationary, it must be first transformed to be stationary. One possible transformation is differencing, that is the value of the previous period is subtracted from the value of the current period. More sophisticated and, in most cases, economically meaningful transformation is the Box-Cox transformation. The stationary process resulting from a properly differenced nonstationary series can be represented by the following autoregressive integrated moving average (ARIMA) model:

$$(1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p)(1 - B)^d y_t = (1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q)\epsilon_t \tag{3.19}$$

where $(1 - B)^d y_t$ term represents $d$-order differencing of the initial time series in order to make the nonstationary series stationary.

There are several statistical tests for stationarity. The augmented Dickey-Fuller test, Phillips-Perron test, and the weighted symmetric test can be applied to the null hypothesis

of nonstationarity in the form of a unit root process (see Chapter 5). The rejection of the null hypothesis would imply that the series is stationary and does not need to be differenced.

The Box-Jenkins seasonal ARIMA model takes the following form:

$$\phi_p(B)\Phi_P(B^\lambda)(1-B)^d(1-B^\lambda)^D y_t = \theta_q(B)\Theta_Q(B^\lambda)\epsilon_t \tag{3.20}$$

where $(1-B^\lambda)^D$ denotes the $D$-order seasonal differencing factor.

### 3.2.3 SPECTRAL DECOMPOSITION

The spectral decomposition method is a representative frequency domain approach for modelling data. It can be used to look for periodicities or cyclical patterns in the data.

The basic idea of spectral decomposition is the representation of data in terms of weighted sinusoidal functions — sine and cosine — to search for periodic components in empirical data. The intuition behind the choice of these particular functions is described in Bloomfield (2000).

The simplest use of sinusoids in data analysis is to describe and isolate the periodic part of a series when the periods are known. The data $\{y_1, y_2, ..., y_t, ..., y_T\}$ are modelled as

$$y_t = s_t + \epsilon_t = \mu + \sum_{k=1}^{r}[a_k cos(\omega_k t) + b_k sin(\omega_k t)] + \epsilon_t \tag{3.21}$$

where $s_t$ represents the seasonal cycle, $\epsilon_t$ is an error at time $t$, and $\mu$ denotes the mean of the series. The cosine and sine coefficients are represented by $a_k$ and $b_k$, respectively. Functions of the Fourier coefficients $a_k$ and $b_k$ can be plotted against frequency $\omega_k$ or against wave length to form periodograms. The amplitude periodogram $J_k$ is defined as follows:

$$J_k = \frac{T}{2}(a_k^2 + b_k^2). \tag{3.22}$$

For the decomposition of the process into two-degree-of-freedom components for each of the $r$ frequencies, the periodogram can be interpreted as the contribution of the $k$-th harmonic to the total sum of squares, in an analysis of variance sense. When $T$ is even, $sin(\omega_{\frac{T}{2}})$ is zero, and thus the last periodogram value is a one-degree-of-freedom component.

The periodogram is a volatile and inconsistent estimator of the spectrum. The spectrum shows statistical regularity and is characteristic of the series as a whole. The spectral density estimate is produced by smoothing the periodogram. Smoothing reduces the variance of the estimator but introduces a bias.

### 3.2.4   Method Strengths and Weaknesses

Exponential smoothing, ARMA, and spectral decomposition are among the simplest methods available today. They can be implemented with mainstream statistical or all-purpose software, do not contain any proprietary algorithms, and do not require intense computing power. This makes the methods broadly qualify as the industry-oriented tools we seek. On the basis of accuracy, the three methods are quite different in how they can handle the components of the data-generating process in Equation (2.2).

As its name suggests, ARMA is to work with the ARMA component. While it is moderately robust to noisy data, its capabilities in terms of modelling seasonality and cyclical patterns are limited to seasonal coefficients.

Spectral decomposition can extract a periodic signal of complex form from the data. However, the method cannot handle autoregressive processes and therefore may produce very poor results for short-run forecasts.

Exponential smoothing encompasses some kinds of ARMA process and can account for a simple seasonal pattern and trends. Apart from this, the method is capable of producing satisfactory predictions in the presence of a considerable amount of noise.

Summing up the discussion: a set of candidate methods — exponential smoothing, ARMA, and spectral decomposition — are chosen for our forecasting of organic fresh produce prices. A problem that economic forecasters often face is how to select the best forecasting method from a set of available ones. The next chapter offers an overview of techniques one can consider when comparing forecasting methods on the basis of performance.

Evaluation and Comparison of Forecasting Methods

Reliable and practically useful forecasting methods are needed for organic producers. Once we have selected a set of candidate methods, we need to address two problems that economic forecasters inevitably face. First, one needs to make sure that each method generates forecasts that are of some economic value to the agents. Second, the best performing method needs to be chosen out of the set in a statistically valid way. The objective of this chapter is to provide an overview of techniques for the evaluation and comparison of forecasting methods.

## 4.1 Review of Method Evaluation and Comparison

The economic solution to the problem of forecast valuation is to calculate the profit loss from using the forecast, compared to the ideal forecast — the actual price. A commonly used measure of economic performance, based on agricultural producers' response to expected prices is a calculation of the actual income losses suffered by the producers as a result of their forecasting errors. Economists generally assume that farmers use forecasts because the latter add to profits. Thus, a more appropriate test of forecast accuracy is profitability.

In particular, DeCanio (1980) expresses the loss from forecasting error as a percentage of gross real income from production of two crops. The analysis in this study shows that the loss from forecasting error is proportional to the squared forecasting error and inversely related to the absolute curvature of the transformation surface. Havlicek and Seagraves (1962) focus on applications of more precise information about one input factor that influences production, assuming that other determinants of optimum production are known. There is an optimal level of production and a net revenue function which permits computing the reduction in net

revenue due to a wrong decision, that is, due to the use of wrong assumptions. The "cost of the wrong decision" is defined as the reduction in producer's net income.

Another common measure of comparing forecasting models is a utility-based metric, illustrated in papers by McCulloch and Rossi (1990) and by West et al. (1993). It is designed to assess forecasting models in terms of direct utility gains rather than statistical significance. Unfortunately, the economic loss associated with a forecast may be poorly assessed by common statistical metrics. That is, forecasts are used to guide decisions, and the loss associated with a forecast error of a particular sign and size is induced directly by the nature of the decision problem in hand.

In order to describe the accuracy of a method in repetitive trials, an aggregate measure may be needed. Literature abounds in numerous aggregate measures of forecast accuracy. The most popular is the mean squared error (MSE), which is calculated as

$$MSE = \frac{1}{N} \sum_{i=1}^{N} e_i^2 \tag{4.1}$$

where $e_i$ denotes the prediction error, and is calculated as the difference between the forecast value, $\widehat{y_i}$, and the actual value, $y_i$. $N$ is the number of forecasts. Some other measures — mean squared percent error (MSPE), root mean squared error (RMSE), and root mean squared percent error (RMSPE) — are derivatives of the MSE.

Mean absolute error (MAE) is another aggregate statistical measure of forecast accuracy, which is derived as

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |e_i|. \tag{4.2}$$

Likewise, the mean absolute percent error (MAPE) is a derivative of the MAE.

While all these measures are related to minimizing a particular loss function, they have considerable limitations. The measures are descriptive. They do not convey by themselves any meaningful information. Statistically, these aggregate measures have been subject to intense criticism. The RMSE is particularly affected by outliers that are common in economic data. Neither of the measures is naturally scale-independent except when applied to percentage

changes, that is the measures can be significantly changed by scaling the raw data (Armstrong and Collopy 1992; Fildes 1992). The measures involve an averaging of errors over observations that have different degrees of variability (Fair 1980; Jenkins 1982). The issue of scaling is also critical when one is to analyze a number of data series. Some measurements of forecast accuracy, such as RMSE, can change if the the variables to predicted are transformed.

Clements and Hendry (1993) have proposed a generalization of the RMSE that takes into account the correlations between errors when more than one time series is being analyzed, to ensure invariance to linear transformations. The practicality of their measure has been questioned because a typical forecast evaluation is bound to be based on a sample of non-normal data with autocorrelation and contemporaneous correlation between errors from competing forecasts (Baillie 1993; Armstrong and Fildes 1995).

However, the main problem with the common aggregate measures of forecast accuracy lies in the very fact of aggregation. Method comparisons that are based on point estimates of forecast accuracy are essentially an attempt to describe a whole distribution on the basis of a single draw from it. The proper econometric approach to the problem of forecast valuation and comparison is to develop tests for comparing the predictive ability of several alternative forecast models, given the forecaster's loss function. The sampling prediction error distribution is examined, which distinguishes this approach from merely comparing point estimates.

A number of scholars have proposed econometric techniques for forecast comparison under a general loss function, known as out-of-sample predictive ability testing. The discussion on the topic was initiated by Diebold and Mariano (1995) and further extended by West (1996), West and McCracken (1998), McCracken (2000), and Corradi et al. (2001).

When parametric forecasts and forecast errors are used to estimate moments or conduct inference there are two sources of uncertainty. There is uncertainty that exists even when the model parameters are known, and there is uncertainty due to the estimation of parameters. Diebold and Mariano (1995) show how to construct asymptotically valid out-of-sample tests of predictive ability when there is no parameter uncertainty. They propose and evaluate

several tests of a null hypothesis of no difference in the accuracy of two competing forecasts. The approach allows forecast errors to be non-normal, nonzero mean, serially correlated, and contemporaneously correlated.

The tests reviewed by Diebold and Mariano (1995) are valid for a wide class of loss functions, including non-quadratic, non-symmetric, and non-continuous loss functions. A simple F-test — testing the equal variance hypothesis — can be applied if forecast errors are independently and identically distributed Gaussian variates. An asymptotic test exploits the asymptotic normality of forecast error difference provided the errors are covariance-stationary. The test they (ibid.) refer to as the Morgan-Granger-Newbold applies an orthogonalizing transformation to forecast errors: two new variables are their sum and difference. One can then test the equal predictive ability hypothesis by testing the one of zero correlation between the transformed errors. An extension of this test is considered in Meese and Rogoff (1988).

Non-parametric tests can also be applied. Diebold and Mariano (1995) discuss an application of the sign test and Wilcoxon's signed-ranks test (Conover 1999). The former is a simple test for correlation in a bivariate pair. In the sign test, the actual differences are replaced with their signs and then the number of positive (or negative) differences is compared to tabulated critical values. The second (Wilcoxon's) test builds upon this idea by using signed ranks of differences and has a higher asymptotic relative efficiency.

Diebold and Mariano (1995) provide a review and extension of procedures to perform inference about predictions do not rely on parameter estimates; for example, when parameters are known. When parameters are unknown and must be estimated, parameter uncertainty can play a role in out-of-sample inference. West (1996) shows how the uncertainty due to parameter estimation can affect the asymptotic distribution of moments of differentiable functions of out-of-sample forecasts and forecast errors. Procedures for asymptotic inference about the moments of smooth functions of predictions and out-of-sample prediction errors were suggested. These asymptotic procedures allow for a wide class of linear and nonlinear techniques to estimate the models used to make the predictions, such as least

squares method, maximum likelihood method, and generalized method of moments. They allow for serial correlation and conditional heteroscedasticity in the regression disturbances and prediction errors as long as inference about moments in general, nonlinear functions of single or multi-period predictions and prediction errors.

Using standard regularity conditions, West (1996) establishes consistency and asymptotic normality of the estimators of the moments and shows that the asymptotic variance-covariance matrix may be estimated by familiar methods, including kernel techniques that allow for unknown forms of serial correlation and heteroscedasticity in prediction errors.

The study by West and McCracken (1998) is a revisited and renewed version of West's work. The usual tests of predictive ability account for the uncertainty that would be present if the underlying parameter vector were known rather than estimated, but ignore uncertainty resulting from error in estimation of that parameter vector. West and McCracken (1998) establish conditions under which the second type of uncertainty is asymptotically negligible. They show that such uncertainty is sometimes asymptotically nonnegligible and suggest computationally convenient ways to obtain test statistics that account for both types of uncertainty.

McCracken (2000) presents analytical, empirical, and simulation results concerning inference about the moments of nondifferentiable functions of out-of-sample forecasts and forecast errors. The work by Diebold and Mariano (1995) is extended by showing that parameter uncertainty can affect out-of-sample inference regarding moments of nondifferentiable functions. The previous findings by West and McCracken (1998) are extended by providing sufficient conditions for asymptotic normality of sample averages of nondifferentiable functions of parametric forecasts and forecast errors.

The crucial object in measuring forecast accuracy is the loss function. In addition to the loss function, the forecast horizon is of great importance. Ranking of forecast accuracy may vary across different loss functions and/or different horizons. Corradi et al. (2001) show that the test proposed by Diebold and Mariano (1995) can be used in the cases where either the

loss function is quadratic or the length of the prediction period grows at a slower rate than the length of the regression period. For the case of a generic loss function, when the length of the prediction period grows at a higher rate than the length of the regression period, the asymptotic normality result obtained by West (1996) no longer holds.

The studies on forecast evaluation that we have briefly reviewed focus solely on the forecast model. The forecast model is the only entity which is considered to affect method performance. A far more realistic situation when a good model produces bad forecasts because its parameters have been badly estimated or change over time remains largely an uncharted territory.

Giacomini and White (2003) propose an alternative approach to the conventional out-of-sample predictive ability testing, called a test of conditional predictive ability. The object of the valuation is the *forecasting method*, which includes the forecast model, the estimation procedure, and the choice of an estimation window. Apart from this fundamental difference, there are at least three features that make this test preferred over the model-based evaluation. These are important for the present research.

First, Giacomini and White (2003) suggest using a rolling estimation window instead of an expanding estimation window. This allows the estimation window to be a component of the forecasting method. The use of a rolling window avoids the arbitrary sample division problem between estimation and evaluation parts of the data set. The rolling window cuts off all dated information, which may keep contaminating results when the data-generating process has already changed. Second, their predictive ability test is conditional on the values of parameter estimates in the model, not their dubious probability limits. This matters when the researcher is unsure about the model itself. Finally, the conditional predictive ability test is easily computed using standard regression packages.

No matter how theoretically valid or general a particular comparison test is, it takes it for granted that the two or more competitors already generate forecasts of some economic value. An assumption is made that the decision-maker is better-off using either method, and

the problem reduces to selecting the best one. But how can one judge on whether or not a single method generates useful predictions, to begin with?

Suppose the decision-maker considers the price series in question to be a martingale. A martingale belongs to the class of first-order Markov processes; that is, only the most recent realization of the variable of interest affects the location of the next draw: $E[y_{T+\tau}|y_0, y_1, \ldots, y_T] = E[y_{T+\tau}|y_T]$. The process is a martingale if $E[y_{T+\tau}|y_T] = y_T$. In this case, the forecast for any horizon will be the last observed price. The actual price at that time in the future will fall either below or above its last observed value. If an alternative method cannot consistently predict this direction of change, then the method is clearly either useless or even counterproductive in terms of reducing profit losses.

A well-known test of sign predictability was developed in papers by Merton (1981) and Henriksson and Merton (1981). They were interested in whether or not the sign of the forecast would be useful as a predictor of the sign of the realization. We will describe the nonparametric test later in this study. Another sign test was suggested by Cumby and Modest (1986), who argue that their test of sign predictability is more powerful than the one suggested by Henriksson and Merton (1981). An extension of the nonparametric Henriksson-Merton test for a multivariate case can be found in Pesaran and Timmermann (1994).

The next section introduces an experimental design for price forecast evaluation with several competing forecasting methods. Details of the Giacomini-White and Henriksson-Metron tests will be presented in greater detail.

## 4.2    Forecasting Experiment Design

There are two approaches to building a forecasting experiment—an in-sample and out-of-sample forecasting. An in-sample forecasting experiment implies using the whole data set to estimate a chosen forecasting model and to obtain forecasts for at least one period ahead. This forecast cannot be compared with the actual value until it realizes in the value observed the

next time period. McCracken and West (2002) suggest reasons to believe that models which seem to fit well by conventional in-sample criteria do poorly in out-of-sample prediction.

An out-of-sample forecasting experiment is essential in determining whether a proposed forecasting model is potentially useful for forecasting the variable of interest. The idea behind out-of-sample forecasting is to divide the available data set into two parts: the in-sample data and the out-of-sample data. Applied economists usually recommend to include 75–80 percent of the data in the in-sample part and the remaining 20–25 percent in the out-of-sample part.

The in-sample data set ought to encompass the complete cyclical patterns of the series. Practitioners recommend the size of the in-sample data to be even and cover one-year period at the very least. The length of our organic price data is sufficient to allow a 2-years period as the in-sample part of the data. The out-of-sample part is the difference between the length of the whole time series and the in-sample data length for a particular commodity.

An appropriate forecast horizon and loss function should be chosen according to the needs of the forecast user. The forecast horizon is the number of steps ahead that one is most interested in forecasting the target variable for. For example, if a farmer is making a production decision, he/she would be interested in the product price at harvest time. The forecast horizon in this case depends on the growing period of that particular commodity. If the farmer has already gathered the harvest and is about to decide whether to sell it or to store for a while, one week or one month-ahead price forecast would be more appropriate. Wholesalers and retailers want to have a constant supply of fresh produce during the whole year. Hence, they might be interested in six months ahead price forecast. Ten days, one, two, and six months forecast horizons have been chosen for the purpose of this study as reasonably representing the short-, medium-, and long-run forecasting needs.

The loss function is a function that is minimized to achieve the desired outcome. Absolute error, squared error, and predictive log-likelihood are some examples of loss functions. Often econometricians minimize the sum of squared errors in making an estimate of a function or a

slope. In this case, the loss function is the sum of squared errors. Following the mainstream choice, the squared prediction error is used throughout the rest of the study.

Once several competing forecasting methods are chosen, and the in-sample data has been decided upon, price forecast competition is run. Each model is estimated on the in-sample part of the data of size $m$ and the price forecasting is made for the chosen number of periods ahead ($\tau$); see Figure 4.1. Then it is rolled through the out-of-sample data in one-period increments. Each model is reestimated and another price forecasting is made. This process continuous up to the end of the out-of-sample part of the data.

In this case, the in-sample data set is called the "estimation window." The two types of estimation window are expanding and rolling windows. An expanding window always starts with the first observation and gets wider over time. A rolling window retains its constant width. Older observations are shed as the competition progresses. When one new observation is added to the estimation window, the oldest observation gets dropped and each forecasting model must be re-estimated. This means that coefficients are re-estimated and prediction errors are obtained.

The main disadvantage of the expanding window is the influence of old observations on the parameter estimates. This is particularly troublesome when the industry — the data-generating process — is rapidly changing (Giacomini and White 2003). The organic sector in the U.S. is changing and growing, and so are the organic produce prices. Based on this premise, the present research uses a rolling estimation window technique rather than an expanding estimation window.

While competing models are rolling through the out-of-sample data set, prediction errors of each model are recorded each time the forecast is made. At the end of the forecasting procedure, there are a number of prediction errors recorded for each model.

We have earlier reviewed the two main approaches to comparing the forecast accuracy. The conventional approach assumes the mean squared prediction error or any other aggregate statistical measure. While the alternative approach examines the distribution of prediction

Figure 4.1: Rolling Window Design
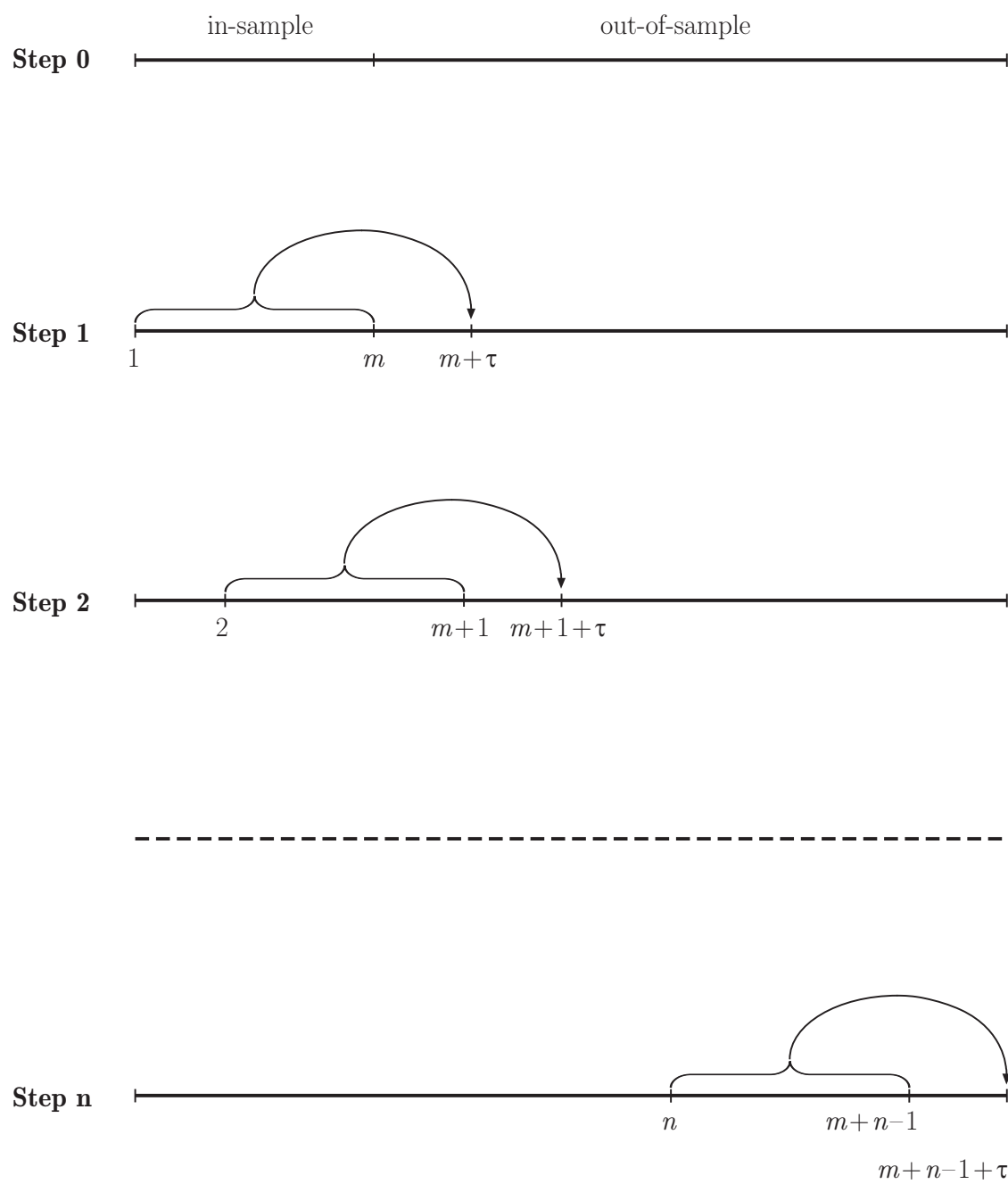
errors. The conditional predictive ability test proposed by Giacomini and White (2003) is in line with the latter approach.

The test by Giacomini and White (2003) consists of testing the null hypothesis of equal accuracy of the two forecasts, given the current information set. The null hypothesis is formulated as

$$H_{0,\tau}: \quad E[L_{t+\tau}(y_{t+\tau} - f_t(\widehat{\varphi}_t)) - L_{t+\tau}(y_{t+\tau} - g_t(\widehat{\upsilon}_t))|I_t] = 0 \equiv E[\triangle L_{t+\tau}|I_t] = 0 \qquad (4.3)$$

against the alternative hypothesis of unequal accuracy of the two forecasts. $y_{t+\tau}$ is a $\tau$ periods ahead forecast for the variable of interest, $L_{t+\tau}$ is a loss function, $\widehat{\varphi}_t$ and $\widehat{\upsilon}_t$ are the parameter estimates at time $t$ for two competing forecasting models, $f_t$ and $g_t$, and $I_t$ is the information set available at time $t = 1, 2, ...\infty$.

Let $T$ be the size of the sample available. Since the data indexed $1, ..., m$ are used for estimation of the first set of parameters, the first $\tau$-step ahead forecasts are formulated at time $m$ and compared to the realization $y_{m+\tau}$. The second set of forecasts is produced by moving the estimation window forward one step and estimating the parameters on data indexed $2, ..., m+1$. These forecasts are compared to the realization $y_{m+1+\tau}$. The procedure is thus iterated and the last forecasts are generated at time $T-\tau$, by estimating the parameters on data indexed $T - \tau - m + 1, ..., T - \tau$, and they are compared to $y_T$. This rolling window procedure yields a sequence of $n \equiv T - \tau - m + 1$ forecasts and relative forecast errors.

The sequence of out-of-sample forecasts thus produced is evaluated by selecting a loss function $L_{t+\tau}$, which depends on the forecasts and on the realizations of the variable.

For a fixed maximum estimation window length, $m$, conditional predictive ability test statistic is a Wald-type test statistic of the following form

$$T^h_{n,m,\tau} = n\overline{Z}'_{m,n}\widehat{\Omega}_n^{-1}\overline{Z}_{m,n} \qquad (4.4)$$

where $\overline{Z}_{m,n} = n^{-1}\sum_{t=m}^{T-\tau} h_t\triangle L_{t+\tau}$, $\triangle L_{t+\tau}$ is the difference of loss functions at $t + \tau$, $h_t$ is a vector of test functions, and $\widehat{\Omega}_n$ is the estimated covariance matrix of $\overline{Z}_{m,n}$. In practice, the test function is chosen by the researcher to embed elements of the information set that are

believed to have potential explanatory power for the future difference in predictive ability. In the present research, the test function is $h_t = (1, \triangle L_t)$, corresponding to the difference of squared residuals in the last period in the window.

A level $\alpha$ rejects the null hypothesis of equal conditional predictive ability whenever $T^h_{n,m,\tau} > \chi^2_{q,1-\alpha}$, where $q = 2$ is the size of $h_t$ and $\chi^2_{q,1-\alpha}$ is $(1 - \alpha)$-quantile from the $\chi^2_q$ distribution.

In order to assess the economic value of forecasts, the direction-of-change test proposed by Merton (1981) and Henriksson and Merton (1981) was conducted. The null hypothesis of the Henriksson-Merton test is that the probability limit of the Henriksson-Merton criterion is one:

$$\text{H}_0 : \text{plim}_{n\to\infty} \left( \frac{n_{ii}}{n_i} + \frac{n_{jj}}{n_j} \right) = 1 \tag{4.5}$$

against the alternative of the left-hand side being greater than one. $i$ denotes the "up" state (an increase from the last observed value) and $j$ indicates the "down" state (a decrease) into which forecasts and realizations fall. $n_i$ and $n_j$ are the numbers of actual price "ups" and "downs," respectively, recorded by moving the data window $n$ times. $n_{ii}$ and $n_{jj}$ are the numbers of correctly forecast price realizations. Under $\text{H}_0$, $n_{jj}$ follows a Hypergeometric distribution with parameters $(n_j, n, n_{.j})$, where $n_{.j}$ is the number of forecast "downs." Henriksson and Merton (1981) assert that a forecast has an economic value if their criterion is greater than one.

Once the experimental design for price forecasting and forecast evaluation is fixed, the actual competition can be run and statistical analysis performed. A description of the price data set and empirical results of having evaluated and compared the three selected methods are presented in the next chapter.

CHAPTER 5

STATISTICAL ANALYSIS AND DISCUSSION

## 5.1 DATA SET DESCRIPTION

Nine produce items, presented in Table 5.1, were chosen for implementing price forecasting methods. The choice was based on the knowledge of consumption levels, demand patterns, and the frequency of purchase for conventional fresh produce; see Appendix A. Potatoes, lettuce, tomatoes, and apples are the most demanded products among fresh produce. They are purchased two to four times per month by consumers all over the U.S. Being generally popular among consumers, onions are more consumed in the Western states. Whereas, it is less consumed in the Northeast. Cabbage is also largely demanded nation-wide. Consumers purchase it at least once a month.

Farm-level price series of organic commodities are currently available from three sources—Hotline Printing and Publishing, Inc. (Hotline), the Rodale Institute, and the Organic Farmers Agency for Relationship Marketing (OFARM). Hotline is the only for-profit firm providing weekly organic price information at the national level. According to the mail survey of existing and prospective subscribers to the Hotline Organic Commodity FAX Service (Lohr 2005), more than half of the respondents are satisfied with the overall quality of the information provided. Most of those who are able to make a comparison with other price reporting services rate the Hotline service as either "good" or "excellent."

The price data for the study were collected by Hotline through weekly telephone interviews of brokers and farmers throughout the United States. The list of sources is confidential and cannot be disclosed. Weekly prices were averaged for all locations from which data has been collected. The methods used to assess representativeness were based on statistical

Table 5.1: Commodity Description[†]

| Item | Description | Series Length | Missing Observations | Data Availability |
|------|-------------|--------------|---------------------|-------------------|
| APPLES | Red Delicious, $/lb | 479 | 28 | August 1994–June 2004 |
| AVOCADOS | Hass, $/lb | 454 | 90 | April 1995–June 2004 |
| CABBAGE | Green, $/lb | 418 | 2 | January 1996–June 2004 |
| LEMONS | $/lb | 451 | 22 | April 1995–June 2004 |
| LETTUCE | Romaine, $ each | 479 | 1 | August 1994–June 2004 |
| ONIONS | Yellow, $/lb | 521 | 31 | January 1991–June 2004 |
| POTATOES | Red, A grade, $/lb | 479 | 8 | August 1994–June 2004 |
| STRAWBERRIES | $/pint | 455 | 146 | August 1990–June 2004 |
| TOMATOES | Roma, $/lb | 408 | 37 | March 1996–June 2004 |

[†] The entries are related to the initial data.

testing and qualitative comparison of the states in the source list with geographic distribution of production acreage and brokers (Lohr 2005).

In order to allow for a seasonality adjustment, series of weekly price observations were regrouped into ten-days periods. Observations available for dates 1 through 10, 11 through 20, and from 21 until the end of the month were placed into the group 1, 2, and 3, respectively. If only one observation was available for a ten-days period, it was used itself; if two observations were available, their average was used. If weekly observations were missing to obtain a ten-days period value, the value was set to missing as well. As a result, 36 observations per year were made available for estimation and forecasting. Regrouping weekly data into ten-days periods were utilized to avoid the unevenly-spaced data problem that plagued the initial series.

All data sets had some missing values. None of the standard software packages allows to work with data contained missing values. There are many methods for handling missing data. When a series does not have too many missing observations, it is possible to perform some missing data replacement. A crude missing data replacement method is to plug in the mean for the overall series. Another approach is to take the mean of the adjacent observations. Missing values in exponential smoothing are replaced with their one-step-ahead forecasts and so used in smoothing (Yaffee and McGee 2000). The last approach was found inappropriate because three different forecasting methods were applied to the same data. As a practical solution, missing ten-days values were linearly interpolated using the available boundary points. Missing observations at the beginning and end of a series were cut off.

Each series was tested for white noise with Bartlett's version of the Kolmogorov-Smirnov test. The test involves examining a random sample from some unknown distribution in order to test the null hypothesis that the unknown distribution is in fact the white noise. The maximum vertical distance between the empirical distribution function and the hypothesized distribution function serves as a measure of how well the functions resemble each other. The

main advantage of this test is that it does not require any assumptions about the distribution function of the organic price series.

With all commodities, p-values of the Kolmogorov-Smirnov statistic were reported to be less than $10^{-4}$; see Appendix B. This lead to the rejection of the white noise null hypothesis in every case.

Additionally, each series was tested for stationarity with the Augmented Dickey-Fuller test at the maximum lag order $p = 18$. The Dickey-Fuller test checks whether the series is stationary or non-stationary. The unit root process is a particular form of non-stationary process. A simple unit root model with zero mean, and white noise errors (random walk) is given by $y_t = \gamma y_{t-1} + \epsilon_t$, where $\gamma$ denotes the autoregressive coefficient. If $\gamma = 1$, the process has a unit root and the non-stationarity null hypothesis cannot be rejected. The Dickey-Fuller statistic is constructed as the conventional t-statistic for the null hypothesis $\gamma = 1$ in a regression of $\triangle y_t = y_t - y_{t-1}$ on $y_t$ and its $p$ lags. The asymptotic distribution of the test statistic is a peculiar one and is tabulated in many econometric textbooks.

The p-values of the Augmented Dickey-Fuller statistic all fell in the range of $10^{-3}$ to $10^{-2}$; see Appendix C. This resulted in having rejected the non-stationarity null hypothesis for all commodities and the series having been considered stationary.

A series being non-white noise warrants that its expected future value is not the overall mean of the series. Since the series were considered stationary, its expected future value would not be the last observed value. No transformation would have been needed before forecasting.

## 5.2 Model Specification and Statistical Results

A preliminary analysis of price series conducted with the use of SAS Time Series Forecasting System, revealed autoregressive and seasonal components in the series. No significant moving average process was detected. The high density of ten-days data allows using a set of individual forecasting methods rather than a combination of approaches. All three method classes

discussed in Chapter 3 are able to deal with data featuring seasonal variation. A seasonal autoregressive (AR) model was chosen out of the autoregressive-moving-average (ARMA) class of models. The additive version of the Holt-Winters (HW) exponential smoothing was chosen out of the exponential smoothing family.

The width of the rolling estimation window was set at two years ($m = 72$ observations) so that every observation in the year cycle would have its year-long lag included in the estimation data set. Thus, for a series of length $T$ and a specified lead of $\tau$ periods ahead, $T-m+1-\tau = T-71-\tau$ forecasts could be obtained for competition. Four forecast horizons: next ten days with $\tau = 1$, next month with $\tau = 3$, two months ahead with $\tau = 6$, and six months ahead with $\tau = 18$, were selected as being reasonable for the purpose of comparing method performance in short-, mid-, and relatively long-term planes. The squared forecast error was used as the loss function with all methods and lags. The squared prediction error is a point estimator of variance. It reflects the philosophy of mean-variance analysis, is related to the economic loss (DeCanio 1980), and therefore is more economically meaningful than other types of loss function. Details of method implementation are set out below and the SAS code is given in Appendix F.

Estimation of the AR model was performed in two stages. In the first stage, monthly constants were estimated by regressing the price on a set of 12 month indicators. Residuals from the first stage regression were used to estimate the autoregressive part of the model. The latter was estimated by least squares, the least squares computation was performed by using the Householder transformation method. The appropriate autoregressive order, up to 3 lags, was chosen in each case by using the minimum Akaike Information Criterion (AIC) method. Once the optimum lag order was identified, the forecast was produced by recombining the first-stage monthly constant estimate and the predicted value from the autoregression part of the model. SAS IML/TIMSAC modules were used to program the method (SAS Institute Inc. 1999b).

Estimation of the spectral decomposition (SD) model was performed by using the Finite Fourier Transform (FFT) of the series and obtaining smoothed spectral density estimates. The estimation window of length $m$ allows obtaining $m/2$ Fourier cosine and sine coefficients. These were used to obtain the respective values of the amplitude periodogram according to Equation 3.22. Since the periodogram is a volatile and inconsistent estimator of the spectrum, spectral density estimates were produced by smoothing the periodogram. A triangular symmetric kernel with 3 points on each side was used for smoothing. A simple form of model identification in the frequency domain was chosen, based on the identification of peaks in spectral density. A spectral density estimate $\widehat{s}_k$, $k = 1 \ldots m/2$ was considered to be a peak if its value was greater than its neighbors, that is, if $\widehat{s}_k > \widehat{s}_{k-1}$ and $\widehat{s}_k > \widehat{s}_{k+1}$. Correspondingly, amplitude coefficients for all non-peak harmonics were set to zero. Thus modified coefficients were used to obtain the forecast value. In case the spectral density was found monotone, only the series mean (the leading term in Equation 3.21) was used as the forecast for all periods. SAS ETS/SPECTRA procedure was employed to program the method (SAS Institute Inc. 1999a).

Monthly seasonal factors were used for the HW method, one for each month in the year. The starting values for the seasonal factors were computed from seasonal averages over the first complete seasonal cycle of 36 observations. The weights for updating the seasonal factors were set at $\omega_3 = \omega_2 = 0.25$ and $\omega_1 = 0.2$. SAS ETS/FORECAST procedure was employed to program the method (SAS Institute Inc. 1999a).

After a forecast was generated at any position of the rolling window, the following information was stored:

a. The squared residual for the last observation $m$ in the estimation window $L_m = (\hat{y}_m - y_m)^2$;

b. The squared forecast error at the specified lead $L_{m,\tau} = (\hat{y}_{m+\tau} - y_{m+\tau})^2$; and

c. The direction of change for the forecast price $\hat{d}_{m+\tau} = 1[\hat{y}_{m+\tau} - y_m > 0]$ and the actual price $d_{m+\tau} = 1[y_{m+\tau} - y_m > 0]$.

The output (a) and (b) was used to conduct the Giacomini-White test of conditional predictive ability. The squared forecast errors from (b) were used to obtain quantiles from their distribution for a derivative of quantile analysis. The indicators (c) were used for the Henriksson-Merton test of the direction-of-change.

Forecast quality was evaluated using the root mean squared error (RMSE) for point forecast (Table 5.2), and the Henriksson-Merton test for direction-of-change comparison (Table 5.3).

The precision of AR forecasts is notably better in both magnitude and direction-of-change sense. RMSE of AR forecasts are smaller, for all commodities and all horizons, than those for SD and WH forecasts, sometimes by two or three times. Values of RMSE increase as the forecast horizon increases; that is, the precision of relatively long-term forecasts is lower than that for short-term forecasts. RMSE for avocados and strawberries are higher as compare to the rest of organic items. One of the possible reasons is larger number of missing observations in the series relative to the number of missing price values for another commodities. It is impossible to make deeper analysis about the difference in the RMSE magnitude for different commodities.

Values of the Henriksson-Merton criterion are significantly greater than unity for most commodities, with both AR and SD model, while those for WH model were often found insignificant. The reason for mostly poor fits with WH model appears to be an autoregressive rather than moving-average nature of the data-generating process and problems with the automatic choice of smoothing weights.

Although RMSE does point at the best performing method for the considered data series, this aggregate measure does not allow formal testing. Therefore, a statistical technique, such as the Giacomini-White test, must be employed to verify if the method yielding the minimum RMSE can indeed boast a better predictive ability.

Table 5.2: Root Mean Squared Error for Organic Produce

| | FORECAST HORIZON | | | | | | | | | | | |
| | TEN DAYS | | | ONE MONTH | | | TWO MONTHS | | | SIX MONTHS | | |
| | AR | SD | HW | AR | SD | HW | AR | SD | HW | AR | SD | HW |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| APPLES | 0.094 | 0.152 | 0.112 | 0.120 | 0.138 | 0.145 | 0.139 | 0.154 | 0.166 | 0.163 | 0.190 | 0.273 |
| AVOCADOS | 0.254 | 0.387 | 0.272 | 0.339 | 0.348 | 0.344 | 0.369 | 0.378 | 0.386 | 0.405 | 0.412 | 0.469 |
| CABBAGE | 0.081 | 0.120 | 0.116 | 0.118 | 0.121 | 0.153 | 0.134 | 0.140 | 0.176 | 0.153 | 0.172 | 0.290 |
| LEMONS | 0.150 | 0.341 | 0.172 | 0.204 | 0.344 | 0.218 | 0.216 | 0.378 | 0.243 | 0.214 | 0.326 | 0.346 |
| LETTUCE | 0.178 | 0.232 | 0.218 | 0.226 | 0.240 | 0.279 | 0.245 | 0.267 | 0.321 | 0.252 | 0.277 | 0.456 |
| ONIONS | 0.080 | 0.143 | 0.111 | 0.115 | 0.139 | 0.145 | 0.135 | 0.157 | 0.167 | 0.152 | 0.157 | 0.231 |
| POTATOES | 0.085 | 0.124 | 0.105 | 0.102 | 0.122 | 0.133 | 0.114 | 0.141 | 0.153 | 0.118 | 0.148 | 0.223 |
| STRAWBERRIES | 0.400 | 0.737 | 0.559 | 0.592 | 0.720 | 0.760 | 0.709 | 0.834 | 0.895 | 0.892 | 0.919 | 1.435 |
| TOMATOES | 0.148 | 0.201 | 0.188 | 0.205 | 0.218 | 0.238 | 0.214 | 0.242 | 0.263 | 0.214 | 0.260 | 0.346 |

The entries are root mean squared errors for seasonal autoregression (AR), spectral decomposition (SD), and the additive Holt-Winters (HW) method.

Table 5.3: Henriksson–Merton Criterion for Organic Produce

| | FORECAST HORIZON | | | | | | | | | | | |
| | TEN DAYS | | | ONE MONTH | | | TWO MONTHS | | | SIX MONTHS | | |
| | AR | SD | HW | AR | SD | HW | AR | SD | HW | AR | SD | HW |
| APPLES | 1.04 | 1.06 | 1.04 | 1.17** | 1.12** | 1.08* | 1.24** | 1.20** | 1.13** | 1.53** | 1.31** | 1.09* |
| AVOCADOS | 1.04 | 1.03 | 1.03 | 1.24** | 1.17** | 1.13** | 1.42** | 1.35** | 1.33** | 1.35** | 1.36** | 1.27** |
| CABBAGE | 1.24** | 1.10** | 1.07 | 1.33** | 1.28** | 1.06 | 1.41** | 1.35** | 1.16** | 1.45** | 1.30** | 0.87 |
| LEMONS | 1.07 | 1.01 | 1.06 | 1.36** | 1.11** | 1.24** | 1.68** | 1.19** | 1.58** | 1.82** | 1.79** | 1.75** |
| LETTUCE | 1.15** | 1.19** | 1.11** | 1.27** | 1.22** | 1.11** | 1.18** | 1.08* | 0.95 | 1.36** | 1.21** | 0.93 |
| ONIONS | 1.04 | 1.08** | 0.99 | 1.28** | 1.28** | 1.12** | 1.42** | 1.44** | 1.31** | 1.63** | 1.54** | 1.31** |
| POTATOES | 1.22** | 1.21** | 1.20** | 1.28** | 1.26** | 1.28** | 1.46** | 1.35** | 1.39** | 1.58** | 1.44** | 1.30** |
| STRAWBERRIES | 1.14** | 1.19** | 0.90 | 1.34** | 1.24** | 1.00 | 1.42** | 1.20** | 1.16** | 1.58** | 1.41** | 1.29** |
| TOMATOES | 1.17** | 1.23** | 1.14** | 1.37** | 1.35** | 1.24** | 1.56** | 1.42** | 1.35** | 1.45** | 1.37** | 1.08 |

**—significant at 5% level; *—significant at 10% level.

The entries are the Henriksson–Merton criteria for seasonal autoregression (AR), spectral decomposition (SD), and the additive Holt-Winters (HW) method.

In order to select the best performing method, the formal Giacomini-White test of equal conditional predictive accuracy was conducted. The table in Appendix E contains the results of pairwise tests of equal conditional predictive ability of AR, SD, and HW for all price series, with the squared error loss function.

The Giacomini-White test is a new approach in predictive ability comparison. That is why, in addition to it, a derivative of quantile analysis was implemented. The stochastic dominance principle was used for quantile analysis.

With two alternative states of nature present, state A stochastically dominates state B (in the first degree) if the probability of obtaining no more than a given level of wealth for state A is less than or equal to the probability of obtaining no more than the same level of wealth for state B. Taking this definition of stochastic dominance as the basis for comparison, a forecasting method A dominates (in the first degree) method B, for a selected loss function, if the probability of getting a loss less or equal to some value with method A is higher than with method B, for any loss value.

The comparison was performed using the squared prediction error as the statistical criterion of loss and quantiles from the empirical distribution function of squared prediction errors. Quantiles are essentially points taken at regular vertical intervals from the cumulative distribution function of a random variable. In our study, quantiles represent the percentage of data points below a given RMSE magnitude; see Figure 5.1.

Since it is generally hard to attain the first order stochastic dominance in samples of moderate size, the dominance requirements were relaxed so as to apply to a number of key quantiles, instead of all quantiles. The key quantiles were chosen to be 2.5%, 20%, 50% (the median), 75%, and 97.5%. Quantile tables are presented in Appendix D.

Tables 5.4 and 5.5 summarize test results, which are fully presented in Appendix E. Table 5.4 presents combined results of both quantile analysis and the Giacomini-White test. Eighty three percent of cases where the method could be chosen on the basis of quantile analysis were confirmed by the Giacomini-White test. According to both quantiles and the

Figure 5.1: Quantile Analysis
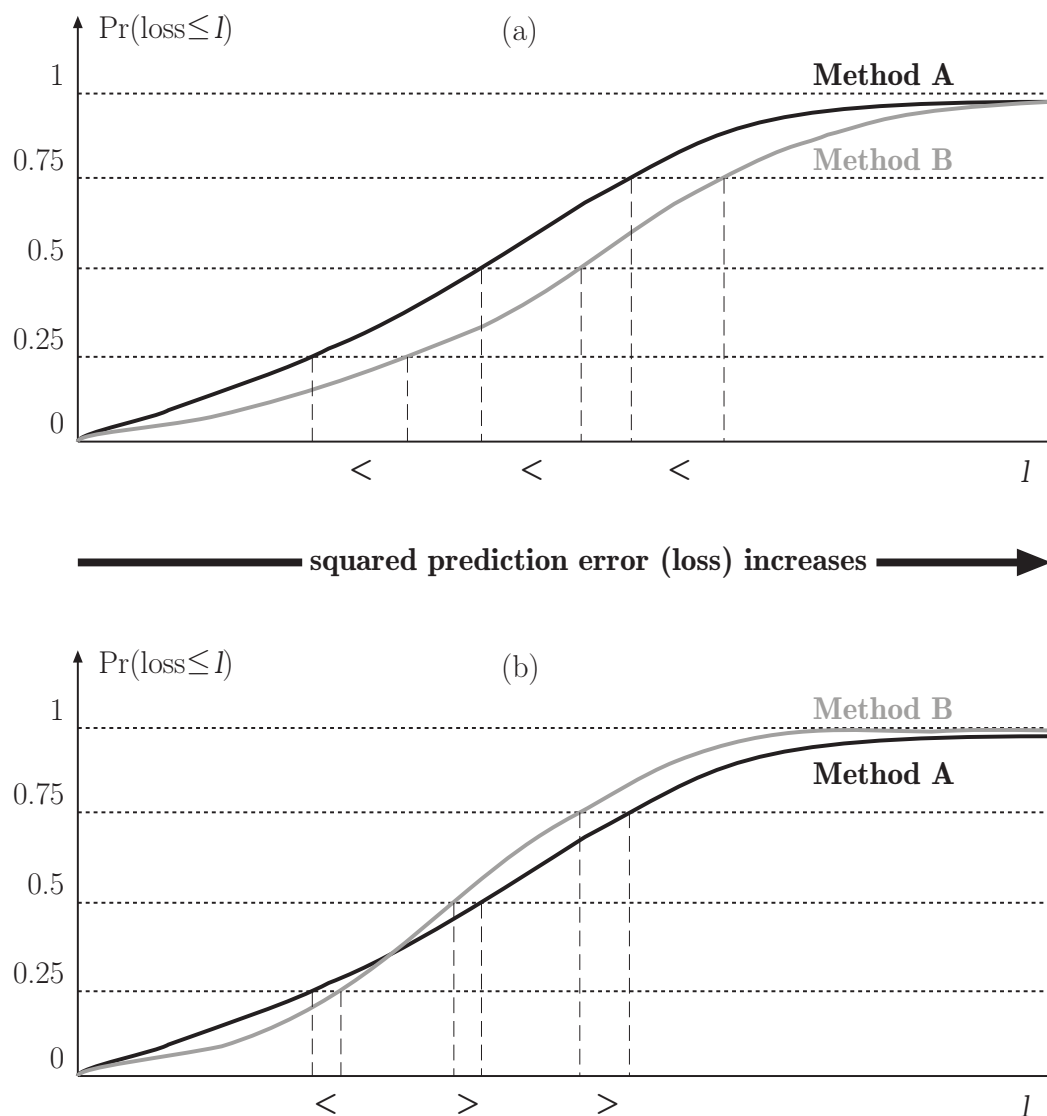


In Panel (a), Method A dominates Method B for the selected 25%, 50%, and 75% quantiles because their values are all smaller with Method A than Method B. Panel (b) presents a case of no clear (first-degree) dominance relationship between Methods A and B for these quantiles.

Table 5.4: Comparison of Quantile Analysis and Giacomini-White Tests

| | FORECAST HORIZON | | | |
| | TEN DAYS | ONE MONTH | TWO MONTHS | SIX MONTHS |
| --- | --- | --- | --- | --- |
| APPLES | AR<br>(AR) | AR<br>(AR) | AR<br>(AR) | —<br>(AR) |
| AVOCADOS | —<br>(—) | —<br>(—) | —<br>(—) | —<br>(—) |
| CABBAGE | AR<br>(AR) | —<br>(—) | —<br>(—) | AR<br>(AR) |
| LEMONS | AR<br>(AR) | AR<br>(—) | AR<br>(AR) | AR<br>(AR) |
| LETTUCE | AR<br>(AR) | —<br>(—) | AR<br>(—) | AR<br>(AR) |
| ONIONS | AR<br>(AR) | AR<br>(AR) | AR<br>(AR) | AR<br>(—) |
| POTATOES | AR<br>(AR) | AR<br>(AR) | AR<br>(AR) | AR<br>(AR) |
| STRAWBERRIES | AR<br>(AR) | —<br>(AR) | AR<br>(AR) | —<br>(AR) |
| TOMATOES | AR<br>(AR) | AR<br>(—) | AR<br>(AR) | AR<br>(AR) |

The entries without parentheses denote the best performing method among seasonal autoregression, spectral decomposition, and the additive Holt-Winters based on quantile analysis. Letters in parentheses indicate the best performing method according to the Giacomini-White test. "—" symbolizes the equivalence of the three forecasting methods.

Giacomini-White test results, AR is broadly the best forecasting method as compared to both SD and HW methods for all produce items and all horizons.

Results of pairwise comparisons of SD and HW can be found in Table 5.5. Seventy eight percent of the quantile analysis results were confirmed by the Giacomini-White test. Based on both quantiles and the Giacomini-White test results, HW appears to be the best forecasting method for the ten-days-ahead forecast horizon. SD outperforms HW for mid-term and relatively long-term forecasts.

Given the available data and the quadratic loss function, the results indicate that a forecast user would be better off using the seasonal autoregressive model as a forecasting technique for all forecast horizons. For the purpose of short-term forecasting, such as ten days ahead, the additive Holt-Winters method can be reasonably employed along with a seasonal autoregressive model, whereas spectral decomposition would likely have resulted in decreased forecast accuracy. For mid-term and long-term forecasts, however, spectral decomposition along with a seasonal autoregressive model would promise better forecasts than the additive Holt-Winters method.

In order to see the complete picture, one should also look at method performance across commodities. The question we pose is: are there any commodities for which the methods perform better and, if so, what might be the reason?

To answer the first part in a statistically valid way, the Friedman test (non-parametric ANOVA) was performed. This test (Conover 1999) is similar to the usual parametric method of testing the null hypothesis of no treatment difference (two-way ANOVA). Friedman's method makes use of only ranks of observations within each block, not their actual values. This makes their distribution immaterial. For the purpose of the test, commodities were considered treatments and methods played the role of blocks. Commodity RMSE were averaged across all forecast horizons and normalized by average commodity prices. The Friedman test allows for correlation between treatment effects, which is useful when dealing with complement or substitute goods.

The $\chi^2[8]$ distributed test statistic was 21.51, which leads to the rejection of the null hypothesis of no forecast quality difference among the nine commodities. The null hypothesis is rejected at any reasonable confidence level, since it has the p-value of 0.006. Therefore, we can conclude that prices for some commodities can be better predicted with any method than others.

To see how the performance differs across commodities, Dunn's post-test pairwise comparisons (Conover 1999) were conducted. This particular implementation of the post-test makes use of the asymptotic t-distribution of the absolute difference of ranks across blocks. At the borderline tolerance of 0.006 above, three commodity groups can be identified by forecast quality:

- apples and potatoes; (the highest precision)

- cabbage, lemons, onions, and tomatoes;

- avocados, strawberries, and lettuce (the lowest precision).

The post-test comparison results showed that price forecast quality differs across commodities. The discussion about some options to manage price risk is followed.

The grouping of commodities by their forecast quality does not lend itself to any evident explanation. It does not align with the OFRF survey results, where it may appear that fruit producers who experienced more market shrinkage than vegetable producers should be facing more unpredictable prices; see Figure 5.2. A significant relationship comes to light when analyzing the correlation between normalized commodity RMSE and commodity-specific factors.

It was found that the correlation between the normalized RMSE and the consumption share of the commodity in total consumption of fresh produce is $-0.6$. The correlation of the normalized RMSE and the standard deviation of price series is 0.5. Both values indicate the presence of relatively high correlation.

Table 5.5: Comparison of Spectral Decomposition and Holt-Winters Method

|  | FORECAST HORIZON | | | |
| --- | --- | --- | --- | --- |
|  | TEN DAYS | ONE MONTH | TWO MONTHS | SIX MONTHS |
| APPLES | HW<br>(HW) | —<br>(SD) | SD<br>(—) | SD<br>(SD) |
| AVOCADOS | HW<br>(HW) | —<br>(—) | —<br>(—) | —<br>(SD) |
| CABBAGE | HW<br>(HW) | SD<br>(SD) | SD<br>(SD) | SD<br>(SD) |
| LEMONS | HW<br>(HW) | HW<br>(HW) | HW<br>(HW) | —<br>(—) |
| LETTUCE | —<br>(—) | SD<br>(SD) | SD<br>(SD) | SD<br>(SD) |
| ONIONS | HW<br>(HW) | —<br>(SD) | SD<br>(—) | SD<br>(SD) |
| POTATOES | HW<br>(HW) | SD<br>(SD) | SD<br>(SD) | SD<br>(SD) |
| STRAWBERRIES | HW<br>(HW) | —<br>(SD) | —<br>(SD) | SD<br>(SD) |
| TOMATOES | HW<br>(HW) | —<br>(—) | SD<br>(—) | SD<br>(SD) |

The entries without parentheses indicate the best performing method among spectral decomposition and the additive Holt-Winters by quantile analysis. Letters in parentheses denote the best performing method as found through the Giacomini-White test. "—" symbolizes the equivalence of the two forecasting methods.

Figure 5.2: Price Effect on Market Expansion by Commodity Category, 2001

(a) Market Shrinkage
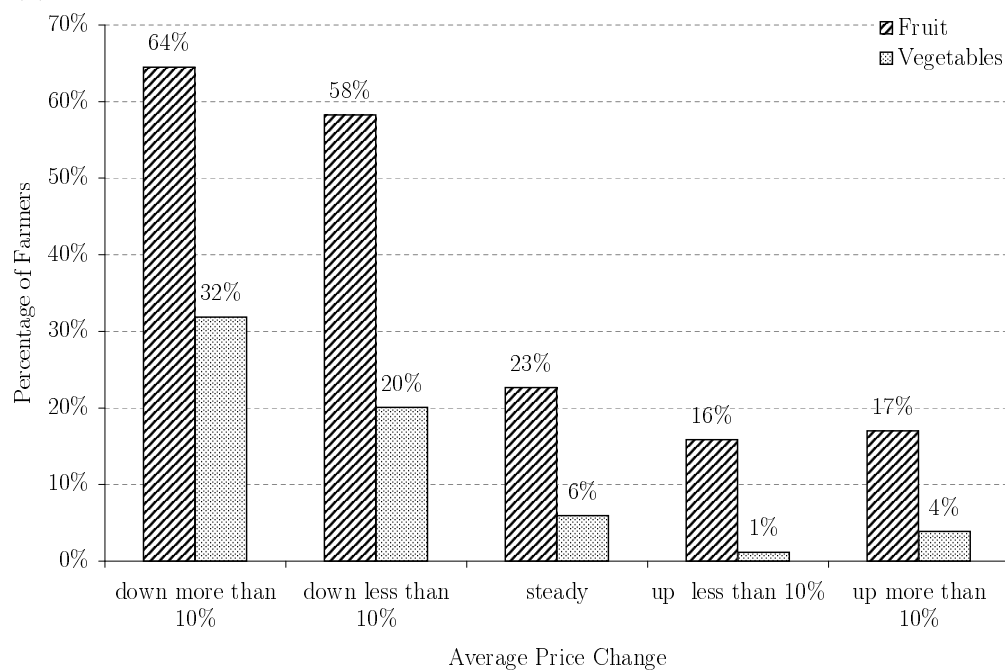


(b) Market Expansion
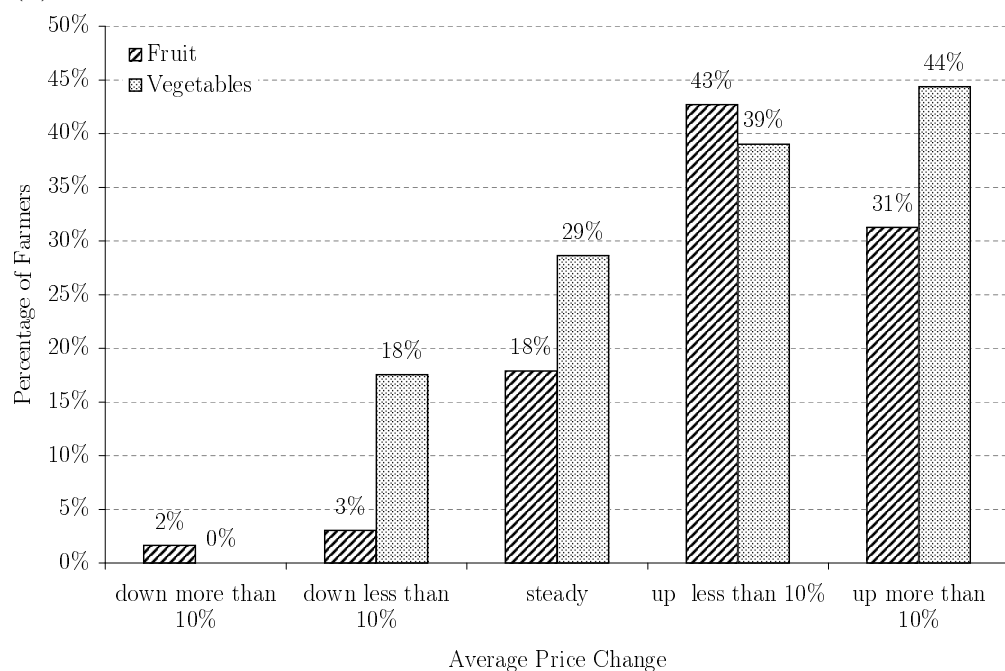


*Source*: Fourth National Organic Farmers Survey, OFRF

Larger organic produce markets appear to have less price volatility and behave in a more predictable way. This result is broadly in line with economic theory which states that larger markets with many agents more resemble the perfect competition environment (Ferris 1997). Information is more freely available in larger markets. Farmers that supply to large markets are less subject to the oligopsonic market control by retailers (McLaughlin 2004).

Another factor is the varying perishability of produce. Table 5.6 reveals a relationship between perishability and forecast quality. Apparently, supply and demand for more perishable commodities experience more sporadic shocks, which boosts price volatility in these markets and makes the prices less predictable. It was mentioned in Chapter 2 that buyers and sellers of fresh produce generally tend to be averse to opportunistic transactions and do engage in contractual agreements. This stabilizes prices. One can therefore recommend producers of the commodities in the least predictable group to consider forward contracting to damp down shocks and improve their profits.

The OFRF survey results show that only 14 percent of vegetable product produced was sold under forward contracts in 2001. While 86 percent of vegetable product was delivered on the spot market. Fruit producers, on the contrary, prefer reducing price risk. Sixty one percent of fruit product produced was sold under forward contracts versus 39 percent delivered on the spot market (Walz 2004).

Alternatively, farmers can participate in marketing order programs in order to manage price risk. Marketing orders assist farmers in allowing them to collectively work to solve marketing problems. Marketing orders are binding on all individuals and businesses who are classified as "handlers" in a geographic area covered by the order. In 2002, only 9 percent of organic farmers participated in marketing order programs (Walz 2004).

The predictability of price is positively related to the commodity's market size. This emphasizes the role of better price forecasts for the agents—farmers and traders—who deal in less common organic produce. Economic theory tells us that better price information improves profits of the producer. This confirms the claim made at the very beginning of

Table 5.6: Forecast Quality and Produce Perishability

| Item | Forecast Quality[†] | | | Perishability[‡] |
|------|------|------|------|------|
| | AR | SD | HW | |
| APPLES | 1 | 1 | 1 | low |
| POTATOES | 2 | 2 | 3 | low |
| LEMONS | 3 | 7 | 2 | low |
| TOMATOES | 5 | 3 | 4 | high |
| ONIONS | 4 | 4 | 5 | low |
| CABBAGE | 6 | 5 | 6 | moderate |
| LETTUCE | 7 | 6 | 7 | high |
| STRAWBERRIES | 8 | 8 | 8 | high |
| AVOCADOS | 9 | 9 | 9 | no data |

[†] For each method, forecast quality is given by within-method ranks of normalized commodity RMSE. The highest forecast quality is 1; the lowest quality is 9. Commodities are arranged in descending order according to their average ranks.

[‡] Relative produce perishability (Hardenburg et al. 1986); categories "very low" and "low," "very high" and "high" merged to simplify exposition.

the study: organic producers do need better farmgate price forecasts to grow. Diversification could also be instrumental. Farmers can be recommended to hedge themselves against price volatility risks by adding a commodity from a better predictable group to their production assortment. Diversification across a range of marketing channels — consumer-direct, direct-to-retail, and wholesale-market — can be employed by organic fresh producers as well. Alternatively, farmers can diversify delivery of the product across geographic regions.

The influence of commodity consumption share also reveals an important role of demand factors in the farmgate price formation. This study deals with the prediction of farm-level prices only. The downstream effects of pricing behavior of wholesalers and retailers are not considered. Forecasting prices at a wholesale and retail level coupled with the farmgate price may thus improve the general accuracy of forecasts.

More than half of farmers that participated in the OFRF survey stated that they had not experienced much price volatility. This was demonstrated with Figure 1.3 in Chapter 1. It is reasonable to conclude that based on the positive correlation between the forecast accuracy and price volatility, at least 50 percent of the OFRF survey respondents would receive price forecasts of relatively high quality. Since the distribution of farmers income is roughly symmetric in volatility categories (Figure 1.4), one cannot expect price forecasts to influence a particular income category of organic farmers.

CHAPTER 6

CONCLUSIONS

The organic food market is one of the most promising emerging sectors of the U.S. economy. A substantial consumer demand for organic produce leads to an increasing interest in this sector by farmers, wholesalers, and retailers. This emphasizes the importance of farm-level price information in decision-making.

Simultaneous equations models, being the most popular method of equilibrium price determination, require a wide range of data. Commodity price series are usually the only information available to industry forecast users. Self-contained forecasting methods were found to be as reliable as large, equilibrium-based models operated by governmental agencies. To be considered for industry application, self-contained price forecasting methods should be easy to implement and give quick and relatively accurate price forecasts. The following passages are a brief recap of what this study set out to do, what was done, and what was achieved.

Three forecasting methods — seasonal autoregression, spectral decomposition, and the additive Holt-Winters exponential smoothing — were selected, implemented and extensively tested at four planning horizons with nine produce items. A problem was considered that decision-makers face: how to select the best forecasting method from a set of several competing ones. Forecast quality is evaluated by using the RMSE for the comparison at an aggregate level, and the Henriksson-Merton test for the direction-of-change comparison. For comparing several forecasting techniques, a test of conditional predictive ability, proposed by Giacomini and White (2003), along with a derivative of quantile analysis were discussed and implemented.

The best performing method was found among these three industry-oriented forecasting techniques. Based on both quantile analysis and the Giacomini-White test, seasonal autoregression is the best forecasting method, compared to spectral decomposition and the Holt-Winters exponential smoothing for all produce and all horizons. Choosing between spectral decomposition and the Holt-Winters exponential smoothing, the latter provides better forecasts for the ten days horizon, while spectral decomposition is preferable for one, two, and six months horizons.

A significant positive correlation between the forecast precision and market size and a negative one between the precision and commodity price volatility were found. This emphasized the role of better price forecasts for agents who deal in less common organic produce and more perishable items. A confirmation for the claim that the organic produce industry needs better farmgate price forecasts to grow was provided. Organic farmers were recommended to consider contracting, marketing order programs, and diversification. The relevance of joint forecasting of prices in the whole marketing channel of the product was underlined.

Price risks were found to be significant and forecasting models had varying degrees of success across different commodities. The study demonstrated the validity of a key set of models and tools. Market participants, however, need more sophisticated models and forecast evaluation tools, to compare and assess the value of forecasts from a range of models.

As a result of the study, market participants were provided with a methodology of application, evaluation, and comparison of price forecasting methods for organic fresh produce. Factors that influenced the forecast performance across commodities were discussed. Considering those factors can help the market participants evaluate the riskiness of various crops and crop combinations.

A seemingly simple matter of choosing between several forecasting methods is not so simple indeed. It requires a large scope of analysis to select a good forecaster's tool, provided that one approaches the issue thoroughly and rigorously. The present study is yet a small

step toward supplying the organic industry with a set of forecasting tools and guides. Below are some of the directions for future study, as were identified throughout the present study:

- Adaptation of forecasting methods for cases when the data are unevenly-spaced. This kind of data is more common in agricultural economics rather than data sets of evenly-spaced observations.

- Missing data are a common problem not only for agricultural data but for economic data in general. More effective techniques need to be implemented instead of linear spline interpolation used in the present research. A kernel approach with varying weights may be one of them.

- Instead of applying a forecasting method to one commodity at a time, prices for a group of products can be forecast jointly, in order to account for an effect of substitution amongst commodities. Spectral decomposition and multivariate ARMA allow to conduct such a kind of analysis.

- Combining several methods. Even though the seasonal ARMA was found to be the best performing method, ARMA forecasts can be combined with those from the Holt-Winters method and spectral decomposition to further improve the forecast quality. Various statistical and heuristic methods exist to combine forecasts, and those are worth a closer look.

- A more in-depth analysis of forecast performance across commodities. Such an analysis would require more information about production technologies and costs.

Another direction for future research comes from the insufficiency of price forecasts for the farmgate level only. Three price spreads (differentials) matter in the decision-making by organic industry agents; these are: farm-wholesale, wholesale-retail, and farm-retail spreads. The analysis in this study shows the importance of demand-driven factors in the farmgate price formation. This means that the above spreads should better be forecast together with

the farm-level price rather than considering the latter in isolation. Such a joint forecasting would necessitate the development of an extensive forecasting system that takes into account mathematically the interaction between the farm, wholesale, and retail stages.

Finally, it is important to find the channels through which results of the study can be disseminated among market participants. Future work should include liaison with the farm organizations or trade associations which organic market participants belong to, in order to enhance models and improve forecasting techniques.

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APPENDIX A

CONVENTIONAL FRESH PRODUCE CHARACTERISTICS

| Item | Frequency of purchase | Region[†] | Percentage of consumption[‡] |
|---|---|---|---|
| POTATOES | twice a month | U.S. | 14.6 |
| LETTUCE | no data | U.S. | 7.3 |
| TOMATOES | once a week | U.S. | 6.0 |
| ONIONS | no data | West/Northeast | 6.0 |
| APPLES | twice a month | U.S. | 5.2 |
| CABBAGE | once a month | U.S. | 2.7 |
| CUCUMBERS | twice a month | Northeast/West | 2.2 |
| STRAWBERRIES | no data | no data | 1.5 |
| LEMONS | no data | no data | 1.1 |
| AVOCADOS | no data | West/Northeast | 0.8 |
| CAULIFLOWER | once a month | Midwest/South | 0.5 |
| ASPARAGUS | once a month | West/South | 0.3 |
| BLUEBERRIES | less once a month | Northeast/West | 0.3 |

[†] The entries indicate the regional impact on produce purchases. "U.S." stands for a product purchased nationwide; "West/South" indicates that western part of the U.S. is the dominating region in product consumption while the southern part is the least-consuming region (FT 2003).

[‡] The entries are the percentage of product consumption in total fresh produce consumption (USDA/ERS 2004). Commodities are arranged in descending order according to their consumption share.

Kolmogorov-Smirnov Test Results

| Commodity | Test statistic[†] |
|---|---|
| APPLES | 0.717 |
| AVOCADOS | 0.715 |
| CABBAGE | 0.654 |
| LEMONS | 0.790 |
| LETTUCE | 0.547 |
| ONIONS | 0.787 |
| POTATOES | 0.685 |
| STRAWBERRIES | 0.776 |
| TOMATOES | 0.578 |

[†] All tests are significant at 1% level.

Augmented Dickey-Fuller Test Results

| Commodity | Test statistic[†] |
| --- | --- |
| APPLES | -4.09 |
| AVOCADOS | -4.51 |
| CABBAGE | -5.04 |
| LEMONS | -4.82 |
| LETTUCE | -5.60 |
| ONIONS | -5.25 |
| POTATOES | -4.49 |
| STRAWBERRIES | -5.01 |
| TOMATOES | -6.06 |

[†] All tests are significant at 1% level.

# Appendix D

## Quantiles of Squared Prediction Errors

| Forecasting | Quantiles, % | | | | |
|---|---|---|---|---|---|
| Method | 97.5 | 75.0 | 50.0 | 20.0 | 2.5 |
| **APPLES** | | | | | |
| | | HORIZON = TEN DAYS | | | |
| AR | 0.050 | 0.011 | 0.003 | 0.001 | 0.000 |
| SD | 0.106 | 0.029 | 0.016 | 0.006 | 0.000 |
| HW | 0.066 | 0.013 | 0.005 | 0.002 | 0.000 |
| | | HORIZON = ONE MONTH | | | |
| AR | 0.073 | 0.019 | 0.007 | 0.002 | 0.000 |
| SD | 0.089 | 0.026 | 0.011 | 0.004 | 0.000 |
| HW | 0.125 | 0.023 | 0.009 | 0.003 | 0.000 |
| | | HORIZON = TWO MONTHS | | | |
| AR | 0.082 | 0.027 | 0.011 | 0.002 | 0.000 |
| SD | 0.121 | 0.031 | 0.013 | 0.003 | 0.000 |
| HW | 0.158 | 0.031 | 0.013 | 0.003 | 0.000 |
| | | HORIZON = SIX MONTHS | | | |
| AR | 0.108 | 0.039 | 0.013 | 0.004 | 0.000 |
| SD | 0.168 | 0.047 | 0.018 | 0.003 | 0.000 |
| HW | 0.275 | 0.108 | 0.048 | 0.014 | 0.000 |
| **AVOCADOS** | | | | | |
| | | HORIZON = TEN DAYS | | | |
| AR | 0.404 | 0.066 | 0.019 | 0.005 | 0.000 |
| SD | 0.817 | 0.205 | 0.063 | 0.014 | 0.000 |
| HW | 0.287 | 0.093 | 0.034 | 0.009 | 0.000 |
| | | HORIZON = ONE MONTH | | | |
| AR | 0.628 | 0.153 | 0.055 | 0.011 | 0.000 |
| SD | 0.647 | 0.156 | 0.051 | 0.011 | 0.000 |
| HW | 0.498 | 0.172 | 0.054 | 0.013 | 0.000 |
| | | HORIZON = TWO MONTHS | | | |
| AR | 0.636 | 0.175 | 0.065 | 0.016 | 0.000 |
| SD | 0.655 | 0.202 | 0.069 | 0.014 | 0.000 |
| HW | 0.599 | 0.213 | 0.073 | 0.017 | 0.000 |
| | | HORIZON = SIX MONTHS | | | |
| AR | 0.665 | 0.258 | 0.082 | 0.014 | 0.000 |
| SD | 0.619 | 0.258 | 0.114 | 0.032 | 0.000 |
| HW | 0.920 | 0.326 | 0.093 | 0.020 | 0.000 |

| Forecasting | Quantiles, % | | | | |
|---|---|---|---|---|---|
| Method | 97.5 | 75.0 | 50.0 | 20.0 | 2.5 |

**CABBAGE**

HORIZON = TEN DAYS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.053 | 0.005 | 0.002 | 0.000 | 0.000 |
| SD | 0.072 | 0.017 | 0.005 | 0.001 | 0.000 |
| HW | 0.070 | 0.017 | 0.005 | 0.001 | 0.000 |

HORIZON = ONE MONTH

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.101 | 0.012 | 0.004 | 0.001 | 0.000 |
| SD | 0.086 | 0.019 | 0.005 | 0.001 | 0.000 |
| HW | 0.110 | 0.029 | 0.009 | 0.003 | 0.000 |

HORIZON = TWO MONTHS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.112 | 0.017 | 0.005 | 0.001 | 0.000 |
| SD | 0.102 | 0.030 | 0.007 | 0.001 | 0.000 |
| HW | 0.157 | 0.044 | 0.012 | 0.004 | 0.000 |

HORIZON = SIX MONTHS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.126 | 0.023 | 0.006 | 0.001 | 0.000 |
| SD | 0.149 | 0.035 | 0.010 | 0.001 | 0.000 |
| HW | 0.438 | 0.114 | 0.026 | 0.008 | 0.000 |

**LEMONS**

HORIZON = TEN DAYS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.138 | 0.023 | 0.008 | 0.001 | 0.000 |
| SD | 0.395 | 0.171 | 0.086 | 0.025 | 0.000 |
| HW | 0.153 | 0.037 | 0.011 | 0.002 | 0.000 |

HORIZON = ONE MONTH

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.246 | 0.052 | 0.014 | 0.003 | 0.000 |
| SD | 0.401 | 0.163 | 0.080 | 0.030 | 0.000 |
| HW | 0.246 | 0.063 | 0.018 | 0.004 | 0.000 |

HORIZON = TWO MONTHS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.291 | 0.060 | 0.015 | 0.003 | 0.000 |
| SD | 0.551 | 0.196 | 0.081 | 0.031 | 0.001 |
| HW | 0.301 | 0.078 | 0.025 | 0.005 | 0.000 |

HORIZON = SIX MONTHS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.274 | 0.059 | 0.019 | 0.004 | 0.000 |
| SD | 0.547 | 0.156 | 0.061 | 0.018 | 0.000 |
| HW | 0.447 | 0.160 | 0.076 | 0.019 | 0.000 |

| Forecasting | Quantiles, % | | | | |
|---|---|---|---|---|---|
| Method | 97.5 | 75.0 | 50.0 | 20.0 | 2.5 |

**LETTUCE**

HORIZON = TEN DAYS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.183 | 0.030 | 0.009 | 0.002 | 0.000 |
| SD | 0.273 | 0.060 | 0.023 | 0.004 | 0.000 |
| HW | 0.230 | 0.064 | 0.015 | 0.004 | 0.000 |

HORIZON = ONE MONTH

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.315 | 0.059 | 0.020 | 0.005 | 0.000 |
| SD | 0.261 | 0.072 | 0.026 | 0.005 | 0.000 |
| HW | 0.382 | 0.097 | 0.035 | 0.005 | 0.000 |

HORIZON = TWO MONTHS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.327 | 0.074 | 0.025 | 0.006 | 0.000 |
| SD | 0.374 | 0.092 | 0.035 | 0.006 | 0.000 |
| HW | 0.439 | 0.149 | 0.045 | 0.010 | 0.000 |

HORIZON = SIX MONTHS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.302 | 0.074 | 0.022 | 0.005 | 0.000 |
| SD | 0.443 | 0.091 | 0.036 | 0.010 | 0.000 |
| HW | 0.664 | 0.303 | 0.131 | 0.028 | 0.000 |

**ONIONS**

HORIZON = TEN DAYS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.043 | 0.007 | 0.002 | 0.000 | 0.000 |
| SD | 0.140 | 0.023 | 0.008 | 0.002 | 0.000 |
| HW | 0.076 | 0.015 | 0.005 | 0.001 | 0.000 |

HORIZON = ONE MONTH

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.076 | 0.016 | 0.004 | 0.001 | 0.000 |
| SD | 0.128 | 0.022 | 0.008 | 0.002 | 0.000 |
| HW | 0.116 | 0.029 | 0.008 | 0.001 | 0.000 |

HORIZON = TWO MONTHS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.113 | 0.021 | 0.007 | 0.001 | 0.000 |
| SD | 0.158 | 0.026 | 0.010 | 0.002 | 0.000 |
| HW | 0.186 | 0.037 | 0.012 | 0.002 | 0.000 |

HORIZON = SIX MONTHS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.162 | 0.022 | 0.007 | 0.001 | 0.000 |
| SD | 0.166 | 0.026 | 0.010 | 0.003 | 0.000 |
| HW | 0.402 | 0.060 | 0.022 | 0.005 | 0.000 |

| Forecasting | Quantiles, % | | | | |
|---|---|---|---|---|---|
| Method | 97.5 | 75.0 | 50.0 | 20.0 | 2.5 |

**POTATOES**

HORIZON = TEN DAYS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.045 | 0.008 | 0.002 | 0.001 | 0.000 |
| SD | 0.084 | 0.020 | 0.007 | 0.002 | 0.000 |
| HW | 0.066 | 0.013 | 0.005 | 0.001 | 0.000 |

HORIZON = ONE MONTH

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.051 | 0.013 | 0.005 | 0.001 | 0.000 |
| SD | 0.088 | 0.019 | 0.006 | 0.001 | 0.000 |
| HW | 0.102 | 0.021 | 0.007 | 0.001 | 0.000 |

HORIZON = TWO MONTHS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.068 | 0.017 | 0.005 | 0.001 | 0.000 |
| SD | 0.097 | 0.028 | 0.007 | 0.001 | 0.000 |
| HW | 0.139 | 0.029 | 0.008 | 0.002 | 0.000 |

HORIZON = SIX MONTHS

| | | | | | |
|---|---|---|---|---|---|
| AR | 0.077 | 0.015 | 0.006 | 0.001 | 0.000 |
| SD | 0.102 | 0.026 | 0.010 | 0.003 | 0.000 |
| HW | 0.235 | 0.073 | 0.022 | 0.005 | 0.000 |

**STRAWBERRIES**

HORIZON = TEN DAYS

| | | | | | |
|---|---|---|---|---|---|
| AR | 1.158 | 0.150 | 0.027 | 0.005 | 0.000 |
| SD | 2.905 | 0.639 | 0.203 | 0.035 | 0.001 |
| HW | 2.767 | 0.228 | 0.055 | 0.020 | 0.000 |

HORIZON = ONE MONTH

| | | | | | |
|---|---|---|---|---|---|
| AR | 1.790 | 0.452 | 0.127 | 0.026 | 0.001 |
| SD | 3.128 | 0.544 | 0.155 | 0.030 | 0.000 |
| HW | 3.466 | 0.413 | 0.114 | 0.037 | 0.001 |

HORIZON = TWO MONTHS

| | | | | | |
|---|---|---|---|---|---|
| AR | 2.399 | 0.619 | 0.147 | 0.029 | 0.001 |
| SD | 4.412 | 0.818 | 0.248 | 0.036 | 0.001 |
| HW | 5.684 | 0.666 | 0.166 | 0.046 | 0.000 |

HORIZON = SIX MONTHS

| | | | | | |
|---|---|---|---|---|---|
| AR | 3.716 | 1.081 | 0.236 | 0.057 | 0.002 |
| SD | 3.983 | 1.218 | 0.251 | 0.038 | 0.000 |
| HW | 11.183 | 3.618 | 0.336 | 0.064 | 0.000 |

| Forecasting | Quantiles, % | | | | |
|---|---|---|---|---|---|
| Method | 97.5 | 75.0 | 50.0 | 20.0 | 2.5 |

**TOMATOES**

| | | | HORIZON = TEN DAYS | | |
|---|---|---|---|---|---|
| AR | 0.110 | 0.028 | 0.008 | 0.002 | 0.000 |
| SD | 0.215 | 0.049 | 0.017 | 0.004 | 0.000 |
| HW | 0.170 | 0.045 | 0.014 | 0.004 | 0.000 |
| | | | HORIZON = ONE MONTH | | |
| AR | 0.230 | 0.058 | 0.011 | 0.003 | 0.000 |
| SD | 0.257 | 0.062 | 0.019 | 0.004 | 0.000 |
| HW | 0.244 | 0.084 | 0.025 | 0.006 | 0.000 |
| | | | HORIZON = TWO MONTHS | | |
| AR | 0.248 | 0.059 | 0.014 | 0.003 | 0.000 |
| SD | 0.329 | 0.077 | 0.022 | 0.005 | 0.000 |
| HW | 0.332 | 0.105 | 0.028 | 0.006 | 0.000 |
| | | | HORIZON = SIX MONTHS | | |
| AR | 0.263 | 0.056 | 0.014 | 0.003 | 0.000 |
| SD | 0.459 | 0.093 | 0.020 | 0.004 | 0.000 |
| HW | 0.530 | 0.180 | 0.047 | 0.017 | 0.000 |

## Appendix E

## Giacomini-White Test Results

| | TEN DAYS | | ONE MONTH | | TWO MONTHS | | SIX MONTHS | |
| | AR | SD | AR | SD | AR | SD | AR | SD |
|---|---|---|---|---|---|---|---|---|
| **APPLES** | | | | | | | | |
| SD | 0.000 (AR) | | 0.005 (AR) | | 0.035 (AR) | | 0.000 (AR) | |
| HW | 0.000 (AR) | 0.000 (HW) | 0.000 (AR) | 0.000 (SD) | 0.000 (AR) | 0.063 (—) | 0.000 (AR) | 0.000 (SD) |
| **AVOCADOS** | | | | | | | | |
| SD | 0.000 (AR) | | 0.029 (AR) | | 0.245 (—) | | 0.131 (—) | |
| HW | 0.091 (—) | 0.000 (HW) | 0.657 (—) | 0.167 (—) | 0.211 (—) | 0.765 (—) | 0.000 (AR) | 0.000 (SD) |
| **CABBAGE** | | | | | | | | |
| SD | 0.000 (AR) | | 0.338 (—) | | 0.422 (—) | | 0.003 (AR) | |
| HW | 0.000 (AR) | 0.000 (HW) | 0.000 (AR) | 0.000 (SD) | 0.000 (AR) | 0.000 (SD) | 0.000 (AR) | 0.000 (SD) |
| **LEMONS** | | | | | | | | |
| SD | 0.000 (AR) | | 0.000 (AR) | | 0.000 (AR) | | 0.000 (AR) | |
| HW | 0.000 (AR) | 0.000 (HW) | 0.138 (—) | 0.000 (HW) | 0.004 (AR) | 0.000 (HW) | 0.000 (AR) | 0.344 (—) |
| **LETTUCE** | | | | | | | | |
| SD | 0.000 (AR) | | 0.132 (—) | | 0.055 (—) | | 0.001 (AR) | |
| HW | 0.000 (AR) | 0.166 (—) | 0.000 (AR) | 0.000 (SD) | 0.000 (AR) | 0.000 (SD) | 0.000 (AR) | 0.000 (SD) |

| | FORECAST HORIZON | | | | | | | |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| | TEN DAYS | | ONE MONTH | | TWO MONTHS | | SIX MONTHS | |
| | AR | SD | AR | SD | AR | SD | AR | SD |
| **ONIONS** | | | | | | | | |
| SD | 0.000 (AR) | | 0.000 (AR) | | 0.000 (AR) | | 0.178 (—) | |
| HW | 0.000 (AR) | 0.000 (HW) | 0.000 (AR) | 0.000 (SD) | 0.000 (AR) | 0.241 (—) | 0.000 (AR) | 0.000 (SD) |
| **POTATOES** | | | | | | | | |
| SD | 0.000 (AR) | | 0.000 (AR) | | 0.000 (AR) | | 0.000 (AR) | |
| HW | 0.000 (AR) | 0.000 (HW) | 0.000 (AR) | 0.002 (SD) | 0.000 (AR) | 0.010 (SD) | 0.000 (AR) | 0.000 (SD) |
| **STRAWBERRIES** | | | | | | | | |
| SD | 0.000 (AR) | | 0.000 (AR) | | 0.000 (AR) | | 0.010 (AR) | |
| HW | 0.001 (AR) | 0.000 (HW) | 0.000 (AR) | 0.000 (SD) | 0.000 (AR) | 0.000 (SD) | 0.000 (AR) | 0.000 (SD) |
| **TOMATOES** | | | | | | | | |
| SD | 0.000 (AR) | | 0.227 (—) | | 0.013 (AR) | | 0.000 (AR) | |
| HW | 0.000 (AR) | 0.000 (HW) | 0.000 (AR) | 0.177 (—) | 0.000 (AR) | 0.096 (—) | 0.000 (AR) | 0.000 (SD) |

The table shows the best performing method among seasonal autoregression (AR), spectral decomposition (SD), and the additive Holt-Winters (HW) methods according to the Giacomini-White test. The entries are the p-values of the test of equal conditional predictive accuracy for the methods in the corresponding row and column. The letters within parentheses indicate the better performing method. "—" denotes the equivalence of the corresponding methods. Tests were conducted at a 5% significance level.

SAS Code for Rolling Window Forecasting

```
dm out 'clear' continue; dm log 'clear' continue; options nocenter
nodate pageno=1 ls=255;

%macro app;
/*++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++*/
%let nme=Tomatoes; /*set commodity name*/
%let sl = 0.05;    /*set significance level*/
%let wnd=72;       /*set size of rolling window WND*/
/*++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++++*/
%let ld=1;

proc iml;
  start main;
    use work.Timeline; read all into T; close work.Timeline;
    TN = nrow(T);

    do i=1 to TN; T[i]=datepart(T[i]); end;

    use work.Prices_in; read all into X; close work.Prices_in;
    N = nrow(X);

    do i=1 to N;
       X[i,1]=datepart( X[i,1]);
       if (X[i,2]=0) then X[i,2]=.;
    end;

    X1 = T||j(TN,2,0);
    do i=1 to (TN-1);
       do j=1 to N;
          if (X[j,1]>=X1[i,1] & X[j,1]<X1[i+1,1]) then do;
             X1[i,2] = X1[i,2]+X[j,2];
             X1[i,3] = X1[i,3]+1;
          end;
       end;
    end;
```

```
flag = 1;
do i=1 to TN while(flag=1);
   if X1[i,3]^=0 then flag=0;
end;
lo = i-1;

flag = 1;
do i=TN to 1 by -1 while(flag=1);
   if X1[i,3]^=0 then flag=0;
end;
up = i+1;

X = X1[lo:up,];
N = nrow(X);
call symput("dsize",char(N));

do i=1 to N;
   if (X[i,2]^=0 & X[i,3]^=0) then X[i,2]=X[i,2]/X[i,3];
   else X[i,2]=.;
end;

X = X[,1:2];

do i=2 to (N-1);
   if X[i,2]=. then do;
      lo = X[i-1,2];
      flag = 1;
      do j=(i+1) to N while(flag=1);
         if X[j,2]^=. then flag=0;
      end;
      j=j-1;
      up = X[j,2];
      nn = j-i+1;
      if up^=lo then do;
         tmp = do(lo,up,(up-lo)/nn)`;
         tmp = tmp[2:nn];
      end;
      else do;
         tmp = j(j-i,1,lo);
      end;
      X[i:(j-1),2]=tmp;
   end;
end;

X = (do(1,N,1))`||X;

varnames = {ind date price};
```

```
    create Prices_tmp from X [colname=varnames];
    append from X;
    close;

  finish main;
  run main;

quit;

data Prices_out;
  set Prices_tmp;
  format date date8.;
  run;

proc datasets nolist;
  delete Prices_tmp;
  run;

/*+++++++++++++++Data format complete+++++++++++++++*/

%do %while(&ld>0);
%do i=&wnd %to (&dsize-&ld);
%let lo=&i-&wnd+1;
%let up=&i;

/*+++++++++++++++Winters-Holt method+++++++++++++++*/

proc forecast data=Prices_out interval=tenday
              method=addwinters seasons=month lead=&ld
              out=WH outresid;
  where ind between &lo and &up;
  id date;
  var price;
  run;

proc iml;
  start main;

    use work.WH;
    read all into X;
    close work.WH;

    use work.Prices_out;
    read all into Y;
    close work.Prices_out;

    LWH = j(1,2,0);
```

```
    LWH[2] = X[&wnd,3]##2;
    LWH[1] = (X[&wnd+&ld,3]-Y[&up+&ld,3])##2;

    HMWH = j(1,2,0);
    HMWH[1] = ((Y[&up+&ld,3]-Y[&up,3])>0);
    HMWH[2] = ((X[&wnd+&ld,3]-Y[&up,3])>0);

    create WH1 from LWH;
    append from LWH;
    close;

    create WH2 from HMWH;
    append from HMWH;
    close;

  finish main;
  run main;
  quit;

proc datasets library=work nolist;
  append base=work.WHcum data=work.WH1;
  append base=work.WHHMcum data=work.WH2;
  delete WH;
  run;
  quit;

/*++++++++++++++++Spectral Analysis+++++++++++++++*/

proc spectra data=work.Prices_out out=sp coef s;
  where ind between &lo and &up;
  var Price;
  weights 1 2 3 4 3 2 1;
  run;
  quit;

proc iml;
  start main;
    use work.sp;
    read all into X;
    close work.sp;
    N = nrow(X);

    nk = (&wnd/2)+1;

    toleave=j(nk,1,0);
    toleave[1]=1;
    do k=2 to nk;
```

```
    if k=2 then do;
        if (X[k,5]>X[k+1,5]) then toleave[k]=1;
    end;
    else if k=nk then do;
        if (X[k,5]>X[k-1,5]) then toleave[k]=1;
    end;
    else do;
        if (X[k,5]>X[k+1,5] & X[k,5]>X[k-1,5]) then toleave[k]=1;
    end;
end;
X[,3]=X[,3]#toleave;
X[,4]=X[,3]#toleave;

Ppred = j(&wnd,1,0);
do t=1 to &wnd;
    cum = 0;
    do k=2 to (&wnd/2+1);
        cum = cum+X[k,3]#cos(X[k,1]#(t-1))+X[k,4]#sin(X[k,1]#(t-1));
    end;
    cum = cum+X[1,3]/2;
    Ppred[t]=cum;
end;

Predict = j(1,2,0);
HMFD = j(1,2,0);

use work.Prices_out;
read all into tmp;
close work.Prices_out;

Predict[1] = (Ppred[&ld]-tmp[&up+&ld,3])##2;
Predict[2] = (Ppred[&wnd]-tmp[&up,3])##2;

HMFD[1] = ((tmp[&up+&ld,3]-tmp[&up,3])>0);
HMFD[2] = ((Ppred[&ld]-tmp[&up,3])>0);

create FD from Predict;
append from Predict;
close;

create FD2 from HMFD;
append from HMFD;
close;

finish main;
run main;
quit;
```

```
proc datasets library=work nolist;
  append base=work.FDcum data=work.FD;
  append base=work.FDHMcum data=work.FD2;
  delete Sp;
  run;
  quit;

%end;

proc datasets library=work nolist;
  delete WH1 WH2 FD FD2;
  run;
  quit;

/*+++++++++++++++Box-Jenkins ARIMA+++++++++++++++*/

proc iml;
  start main;
    use work.Prices_out;
    read all into X;
    close work.Prices_out;
    N = nrow(X);
    X1 = X;
    X = X[,3];

    opt = {0 1};
    constant = 0;
    nma = 0;
    maxlag = 3;

    results = j(1,2,0);
    HMBJ = j(1,2,0);

    do i=&wnd to (N-&ld);
        lo = i-&wnd+1;
        up = i;

        Xr = X1[lo:up,];
        Tr = j(&wnd,12,0);
        do j=1 to &wnd;
            Tr[j,month(Xr[j,2])]=1;
        end;
        Xr = X[lo:up,];
        X2 = (I(&wnd)-Tr*inv(Tr`*Tr)*Tr`)*Xr;
        Br = inv(Tr`*Tr)*Tr`*Xr;
```

```
        call TSUNIMAR(arcoef,ev,nar,aic,X2,maxlag,opt);
        call TSPRED(forecast,impulse,mse,X2,arcoef,nar,nma,ev,&ld,,constant);

        addrow = j(1,2,0);
        addrow[1,1]=(forecast[&wnd+&ld]+Br[month(X1[up+&ld,2])]-X[up+&ld])##2;
        addrow[1,2]=(forecast[&wnd]+Br[month(X1[up,2])]-X[up])##2;
        results=results//addrow;

        addrow[1,1]=((X[up+&ld]-X[up])>0);
        addrow[1,2]=((forecast[&wnd+&ld]+Br[month(X1[up+&ld,2])]-X[up])>0);
        HMBJ = HMBJ//addrow;

    end;
    results = results[2:nrow(results),];
    HMBJ = HMBJ[2:nrow(HMBJ),];

    create BJcum from results;
    append from results;
    close;

    create BJHMcum from HMBJ;
    append from HMBJ;
    close;

  finish main;
  run main;
  quit;

/*++++++++++++++++The Giacomini-White Test++++++++++++++++*/

proc iml;
  reset noname;
  start main;

    use work.BJcum;
    read all into bj;
    close work.BJcum;

    use work.FDcum;
    read all into sa;
    close work.FDcum;

    use work.WHcum;
    read all into wh;
    close work.WHcum;

    nm = {&nme};
```

```
use work.BJHMcum;
read all into bjhm;
close work.BJHMcum;

use work.FDHMcum;
read all into sahm;
close work.FDHMcum;

use work.WHHMcum;
read all into whhm;
close work.WHHMcum;

print "+++++++++++++++++++++++++++++++";
print "Commodity: " nm;
print "Lead: " &ld;
print "Alpha value: " &sl ,;

print "+++++ Descriptive & HM tests +++++";
print "+++++ BJ Forecast:";
RMSE = sqrt(bj[:,1]);
print "RMSE: " RMSE;
tmp = bj[,1];
ntmp = nrow(bj);
tmp2 = tmp;
tmp[rank(tmp)]=tmp2;
q975 = tmp[ceil(ntmp#0.975)];
q75  = tmp[ceil(ntmp#0.75)];
q50  = tmp[ceil(ntmp#0.5)];
q25  = tmp[ceil(ntmp#0.25)];
q025 = tmp[ceil(ntmp#0.025)];
print "Sq. Error Quantiles (97.5 75 50 20 2.5):";
print q975 q75 q50 q25 q025;

XHM  = bjhm;
HMS  = ((XHM[,+]=0)[+]);
N1   = (nrow(XHM)-XHM[+,1]);
N2   = (XHM[+,1]);
m    = (nrow(XHM)-XHM[+,2]);
HMC  = HMS/N1 + ((XHM[,+]=2)[+])/N2;
print "HM criterion: " HMC;
pval = 1-CDF('HYPER',HMS,N1+N2,N1,m);
print "P-value: " pval;

print "+++++ SA Forecast:";
RMSE = sqrt(sa[:,1]);
print "RMSE: " RMSE;
```

```
tmp = sa[,1];
ntmp = nrow(sa);
tmp2 = tmp;
tmp[rank(tmp)]=tmp2;
q975 = tmp[ceil(ntmp#0.975)];
q75  = tmp[ceil(ntmp#0.75)];
q50  = tmp[ceil(ntmp#0.5)];
q25  = tmp[ceil(ntmp#0.25)];
q025 = tmp[ceil(ntmp#0.025)];
print "Sq. Error Quantiles (97.5 75 50 20 2.5):";
print q975 q75 q50 q25 q025;

XHM  = sahm;
HMS  = ((XHM[,+]=0)[+]);
N1   = (nrow(XHM)-XHM[+,1]);
N2   = (XHM[+,1]);
m    = (nrow(XHM)-XHM[+,2]);
HMC  = HMS/N1 + ((XHM[,+]=2)[+])/N2;
print "HM criterion: " HMC;
pval = 1-CDF('HYPER',HMS,N1+N2,N1,m);
print "P-value: " pval;

print "+++++ WH Forecast:";
RMSE = sqrt(wh[:,1]);
print "RMSE: " RMSE;
tmp = wh[,1];
ntmp = nrow(wh);
tmp2 = tmp;
tmp[rank(tmp)]=tmp2;
q975 = tmp[ceil(ntmp#0.975)];
q75  = tmp[ceil(ntmp#0.75)];
q50  = tmp[ceil(ntmp#0.5)];
q25  = tmp[ceil(ntmp#0.25)];
q025 = tmp[ceil(ntmp#0.025)];
print "Sq. Error Quantiles (97.5 75 50 20 2.5):";
print q975 q75 q50 q25 q025;

XHM  = whhm;
HMS  = ((XHM[,+]=0)[+]);
N1   = (nrow(XHM)-XHM[+,1]);
N2   = (XHM[+,1]);
m    = (nrow(XHM)-XHM[+,2]);
HMC  = HMS/N1 + ((XHM[,+]=2)[+])/N2;
print "HM criterion: " HMC;
pval = 1-CDF('HYPER',HMS,N1+N2,N1,m);
print "P-value: " pval;
```

```
print "+++++ Predictive ability pairwise tests +++++";

print "Testing BJ versus WH:";
dL = (bj[,1]-wh[,1])`;
dL1 = (bj[,2]-wh[,2])`;
n = ncol(dL);
h = j(1,n,1)//dL1;
Z = h#repeat(dL,2,1);
Omega = (1/n)#(Z*Z`);
T = n # (Z[,:])`*inv(Omega)*(Z[,:]);
pval=1-probchi(T,2);
dff = dL[:];
if (dff<0 & pval<&sl) then dff2="BJ is better";
if (dff>0 & pval<&sl) then dff2="WH is better";
if pval>=&sl then dff2="Tests Equivalent";
print "Test statistic (chi-sq, df=2): " T;
print "p-value: " pval;
print "Indication: " dff2 ,;

print "Testing BJ versus SA:";
dL = (bj[,1]-sa[,1])`;
dL1 = (bj[,2]-sa[,2])`;
n = ncol(dL);
h = j(1,n,1)//dL1;
Z = h#repeat(dL,2,1);
Omega = (1/n)#(Z*Z`);
T = n # (Z[,:])`*inv(Omega)*(Z[,:]);
pval=1-probchi(T,2);
dff = dL[:];
if (dff<0 & pval<&sl) then dff2="BJ is better";
if (dff>0 & pval<&sl) then dff2="SA is better";
if pval>=&sl then dff2="Tests Equivalent";
print "Test statistic (chi-sq, df=2): " T;
print "p-value: " pval;
print "Indication: " dff2 ,;

print "Testing WH versus SA:";
dL = (wh[,1]-sa[,1])`;
dL1 = (wh[,2]-sa[,2])`;
n = ncol(dL);
h = j(1,n,1)//dL1;
Z = h#repeat(dL,2,1);
Omega = (1/n)#(Z*Z`);
T = n # (Z[,:])`*inv(Omega)*(Z[,:]);
pval=1-probchi(T,2);
dff = dL[:];
if (dff<0 & pval<&sl) then dff2="WH is better";
```

```
      if (dff>0 & pval<&sl) then dff2="SA is better";
      if pval>=&sl then dff2="Tests Equivalent";
      print "Test statistic (chi-sq, df=2): " T;
      print "p-value: " pval;
      print "Indication: " dff2 ,;

      /*LIST OF LEADS*/
      lds = {1 3 6 18};
      if ((&ld)=18) then do;
         ldset = -1;
      end;
      else do;
         ldset = loc(lds=(&ld))+1;
         ldset = lds[ldset];
      end;
      call symput("ld",char(ldset));

   finish main;
   run main;
   quit;

proc datasets library=work nolist;
   delete BJcum BJHMcum FDcum FDHMcum WHcum WHHMcum;
   run;
   quit;

dm log 'clear' continue;

%end;

proc datasets library=work nolist;
   delete Prices_out;
   run;
   quit;

%mend app;

%app;
```