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A LINEAR RATIONAL EXPECTATIONS MODEL OF THE U.S. SOYBEAN OIL MARKET

By

Ernesto Santiago Liboreiro

A THESIS

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ABSTRACT

A LINEAR RATIONAL EXPECTATIONS MODEL
OF THE U.S. SOYBEAN OIL MARKET

By

Ernesto Santiago Liboreiro

In this study a linear rational expectations storage model of the U.S. soybean oil market is estimated. An inventory demand equation is specified to linearly depend on the expected appreciation in stocks value. Model estimation requires the solution of an expectational difference equation and computation of the multi-step ahead forecasts of exogenous variables. The later are solved analytically by repeated substitution, making use of the stochastic processes governing exogenous variables. The simultaneous nature of prices and inventories determination requires the use of FIML estimation method. Results obtained show statistical significance in the speculative inventory demand slope parameter and demonstrate that good results can be obtained for soybean oil storage using a linear model. A test of the rational expectation cross-equation restrictions only gave a p-value of 0.01, suggesting that these restrictions would be rejected at conventional significance levels.

To Ernesto (Dad), Cristina (Mom),
Mariana and Christine

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TABLE OF CONTENTS

	Page
LIST OF TABLES	vi
INTRODUCTION	1
CHAPTER 1, THE U.S. SOYBEAN COMPLEX	11
1.1. Soybean market	11
1.2. Soybean oil market	15
1.3. Soybean meal market	21
CHAPTER 2, LITERATURE REVIEW	24
2.1. Soybean complex structural models	24
2.2. Rational expectations inventory models	32
2.3. Applications of dynamic programming to soybean markets	38
2.4. Crushing rates and margins	41
CHAPTER 3, ECONOMIC MODELS OF COMMODITY MARKETS	43
3.1. Demand	43
3.2. Supply	48
3.3. Inventory demand	50
3.3.1. Speculative motivation	51
3.3.2. Convenience yield	57
3.4. Commodity market model	60
CHAPTER 4, MODEL SPECIFICATION	62
CHAPTER 5, ESTIMATION RESULTS	75
5.1. Data	75
5.2. Exogenous variables processes	76
5.3. The complete model	78
5.4. Econometric procedures	78
5.5. Results	80
5.6. A test of the rational expectations restrictions	83
5.7. Limitations of the study	84
Chapter 6, Conclusions	87
Annex I	90
Annex II	101
Annex III	105
Bibliography	107

LIST OF TABLES

Table 1	U.S. Oils and fats usage, 1996	16
Table 2	1995/96 Quarterly U.S. Soybean Oil Balance	21
Table 3	Own Price elasticities	27
Table 4	Inventory demand studies	36
Table 5	U.S. Soybeans: Own Price elasticities	49
Table 6	Exogenous variable AR(1) processes	76
Table 7	ADF test on EXPEN, CRCAP and RFFR variables	77
Table 8	FIML parameter estimates	80
Table 9	R^2 and residuals tests	81

INTRODUCTION

Much of the research in commodity price analysis during the last twenty years has been devoted to understanding the role of inventory demand on price determination. Importantly, there is a simultaneous determination of prices and inventories: inventory demand affects current prices and current prices affect inventory levels.

Inventories, in turn, are not just the mere consequence of current production and consumption imbalances, but are affected by specific factors like speculative stockholding and "convenience yield".

If prices are expected to climb, storers may look for increased stockholding in order to profit by carrying goods forward in time while bidding up current period prices. Thus, expectations about future prices affect current prices through inventory demand (Muth, 1961; Gosh, Gilbert and Hughes-Hallett, 1987; Wright and Williams, 1991).

Convenience yield is also considered an important factor. Agents may want to hold stocks even with the expectation of decreasing prices because the costs associated with a "stock-out" are greater than the expected speculative losses (Working, 1949; Brennan, 1959). Thus, some minimum (pipeline) stocks would be held as a cautionary measure.

This is important because much of the policy efforts aimed at to price stabilization in commodity markets has been made on the assumption that private inventory demand does not play a significant price stabilizing role. Much of the research of the 1950's and 1960's provided theoretical support to buffer schemes on the assumption that there was no private storage industry at all (Waugh, 1944; Oi, 1961).

A major concern in these research efforts has been how to model price expectations. Much of the debate has centered on whether expectations about future prices are constructed looking backward in time or looking forward. Muth (1961) provided reasonable arguments favoring forward looking behavior (i.e. "rational" expectations). The success of Muth's idea lies in the "elegance" of the concept, in the sense that it provides a sensible approach to making expectations endogenous. If agents are assumed rational in choosing decision variables, they should also be rational in making forecasts, thus using all knowledge available about the actual model that determines market price and quantity behavior. Much recent econometric work has assumed that agents form expectations consistent with the model (rational expectations).

Papers by Wallis (1980), Hoffman and Schmidt (1981) and Chow (1981) provided the statistical underpinning for rational expectations econometric models in a linear framework. Since then, much econometric effort has been devoted to studying inventory demand effects on market equilibrium, implementing the so-called "linear rational expectations inventory model" (Hwa, 1985; Gosh, Gilbert and Hughues-Hallett, 1987; Trivedi, 1990; Gilbert and Palaskas, 1990, Lord, 1991; Thurman, 1993; and Gilbert, 1995). The goal of these studies has been to show that the speculative component of inventory demand plays a role in spot price determination. The basis for all of these studies has been Muth's (1961) commodity price model with inventories.

The linear approach is subject to the criticism that it does not account for the non-negative stocks constraint. Although based on theoretical considerations it is possible to argue that speculative inventory demand increases linearly in respect to expected price appreciation of stocks, it is also true that if the expected price appreciation is zero or negative, speculative inventory demand would be zero. Because stocks cannot be negative for physical reasons, there is a nonlinear relationship between expected price appreciation in stocks and inventory demand levels.

Consequently, a linear representation of inventory demand may not fit the actual characteristics of a storable commodity market. This is sometimes blamed for poor econometric results from linear rational expectations storage models of commodity markets (Glauber and Miranda, 1993). Specifically, it has been rather difficult to obtain statistically significant parameter estimates on the speculative component of inventory demand. Researchers have repeatedly failed to obtain statistically significant evidence of inventory demand's role in commodity price determination (Gilbert and Palaskas, 1990; Trivedi, 1990).

Algorithms for estimating non-linear rational expectations models appeared in the early eighties (Fair and Taylor, 1983, 1991). The non-linearities in many economic models do not allow a closed form solution. Thus, numerical optimization techniques are required. The implementation of these techniques in estimating commodity market models that include non-linear inventory demand has been successful (Miranda and Glauber, 1993).

However, the costs involved in this approach in terms of computer power required and its intractability are quite high. The computational costs grow quite rapidly as the number of state variables increase. This has lead many researchers to continue working in a linear framework consistent with Muth's work. In fact, stock-out episodes are rare and researchers should expect to find evidence of speculative inventory demand (Deaton and Laroque, 1990).

There are other problems besides a linear specification that might explain poor econometric results from rational expectations commodity storage models. In particular:

1) Most studies used annual data (Gilbert and Palaskas, 1990, Trivedi 1990, Lord, 1991; Gilbert 1995). It may be difficult to capture the inventory demand effect using annual data. Although some commodities can be stored for more than one year, it is reasonable to argue that speculative demand is mostly a short run phenomena (Trivedi, 1990). If this is the case, the use of expected appreciation in annual prices as an explanation of the end-of-period inventories may not be a sensible approach. It is difficult to argue that speculators base their storage decisions on expectations of annual average price appreciation.

Also, when using annual data, the number of observations may be small thus making it difficult to uncover statistical evidence of relationships among variables. Making use of long data series is an issue in itself because the non-linear cross equation restrictions implied by the rational expectations hypothesis clearly calls for the use of non-linear estimation methods. If maximum likelihood methods are used, large samples are required, since standard errors are biased when working with small samples.

2) The econometric implementation of the rational expectations hypothesis has also brought problems in previous studies. Much of the focus has been placed on the price behavior implications of the model without considering the remaining structural equations as informative (Gosh, 1987; Gilbert and Palaskas, 1990; Trivedi 1990). None (with the exception of Gilbert, 1995) estimate a complete commodity market model imposing the rational expectations cross-equations restrictions nor do they recover the underlying structural parameter estimates.

3) Some studies (Gilbert and Palaskas, 1989) have relied on Ordinary Least Squares or Non Linear Least Squares methods instead of Full Information Maximum Likelihood. This fails to account for price and stock simultaneity and

results in biased and inconsistent parameter estimates. The simultaneous nature of price and stock level determination requires the use of simultaneous equation estimation methods.

4) Other studies have essentially estimated/applied the same model to different commodities, thus failing to take account of the unique features of different commodity markets (Gilbert and Palaskas, 1990; Trivedi 1990; Lord 1991). The unique features of each market must be addressed in order to obtain good econometric results. "One size fits all" is not a sensible approach because misspecification in one equation may spill over and affect parameter estimates in other equations when using simultaneous estimation methods.

5) Other studies have estimated models for commodities that have faced a great deal of government intervention, such as price stabilization schemes (Trivedi, 1990). Modeling these markets without accounting for government actions may result in poor results

The present study estimates a model of the U.S. soybean oil market assuming price expectations are rational. The attempt is to study whether, overcoming many difficulties of other studies, a statistically significant and economically meaningful estimate of the parameter on expected price appreciation can be obtained under a linear specification of inventory demand. We show that the linearity issue is not a major obstacle to obtain statistically significant empirical estimates of the inventory demand equation.

The U.S. soybean oil market is suitable for conducting this study because there is evidence of stock-out events and forward looking behavior among stock holders (Lence, Hayes and Meyers, 1995).

Much of the existing empirical work on the soybean oil market has relied on inventory demand specifications that are not well supported by economic theory. In particular, models of the soybean oil market have specified inventory demand equations as a function of several variables that enter in linear and unrestricted form, without imposing rational expectations restrictions (Vandeborre, 1967; Houck, Ryan and Subotnik, 1972; Meyers and Hacklander, 1979; Wesscott and Hull, 1985; Meyers, Helmar and Devadoss, 1986). Some studies have introduced an explicit price expectation variable in soybean oil models and assumed rational expectations. However, these studies (eg. Lence, Hayes and Myeres, 1995) use futures prices to model price expectations and assume futures prices as exogenous. The present study is the first one to apply full linear rational expectations storage model with endogenous price expectations to the U.S. soybean oil market.

Our study also represents an improvement over previous studies of linear speculative inventory demand for several reasons. In this study we make use of a long data series of 71 quarterly observations, and directly estimate all structural parameters of the model. Both the model and the exogenous variables stochastic processes are estimated simultaneously, thus imposing the cross equation restrictions and obtaining efficiency gains in parameter estimates. We make use of FIML estimation methods to account for simultaneity. In the course of estimation, we impose the implied root restriction and we model supply and demand taking into account the particular features of the soybean oil market (contemporaneous supply response, no partial adjustment, etc.).

Estimating such a model calls for the solution of an expectational difference equation in prices. Prices end up being a function of the stable root of the polynomial in the lag operator and the multi-step ahead forecast of exogenous variables. The latter are turned into observable variables by making use of the stochastic properties of the variables. Multi-step ahead forecasts of exogenous variables are computed by repeated substitution.

The approach followed in this study is subject to the criticism that it is not "truly rational" in the sense that expectations about the future path of exogenous variables depend only on their past (their stochastic time series properties). It has been suggested (Wright and Williams, 1991), however, that this approach generates consistent parameter estimates.

The study starts with a description of the U.S. soybean complex focusing particularly on the soybean oil market. The second chapter presents a review of the literature. The third chapter covers commodity market modeling and the fourth outlines the model specification used in this study. Chapter five presents the estimation results. In the last chapter we summarize and draw conclusions. Annexes I and II present mathematical work, and Annex III, introduces data descriptive statistics.

CHAPTER 1

THE U.S. SOYBEAN COMPLEX

1.1 Soybean market

Although soybeans have been cultivated in the U.S. since the early 20th century, it was not until the early 1950's when they became an important part of American agriculture, accounting for more than 10% of total agricultural land devoted to corn, wheat and soybeans. By 1995 that share rose to 31% (U.S. Statistics Annuary, 1999), production value reached 14.6 billion dollars and US soybean production represented 47.4% of world soybean production (USDA, Oil Crops Yearbook, 1999).

Soybeans are an annual crop, cultivated at the end of spring-early summer and harvested by the end of summer and early fall. After harvest, the crop is consumed throughout the year on a season that extends from September to August. Good soil fertility, timely rains and good moisture conditions are required for proper plant growth. Those conditions are met in several U.S. states, including Illinois, Iowa, Indiana, Michigan and Minnesota.

Soybean production has doubled every ten years from the 1950's until the 1980's and in the first half of 1990's has stagnated at near 2 billion bushels (bill. bu.). This stagnation is, in part, due to the growth in south American soybean production. More recently, worldwide income growth and China's import demand sparked renewed growth in American soybean plantings and production which reached an all time high level of 2.75 bill. bu. in the 1998/89 season.

As for any storable good, soybean demand sources include demand for current consumption and storage demand. The bulk of current consumption demand comes from the crushing industry. Soybeans are the main input for the simultaneous production of crude soybean oil and soybean meal, both of which are produced in almost fixed proportions: 18% and 80% respectively (i.e. one soybean ton crushed yields 180 kilos of oil and 800 kilos of meal).

Crushing is a rather simple process that originally extracted the oil and meal content of soybeans using a hydraulic pressing technique (mechanical extracting) and latter evolved towards chemical extraction (solvent extraction). Soybeans are cracked and de-hulled before they are crushed and flaked. When crushed, some portion of the oil contained by soybeans is extracted, although some oil still remains in the flakes. The remaining oil is then removed from the flakes by solvent extraction after which, the flakes are de-solventized, toasted and ground to obtain

48% protein soybean meal. Lower protein contents are obtained by mixing back the hulls into the meal. As part of the process the oil is degummed to obtain degummed soybean oil ready for refining. Hulls are mostly sold as feed material and gums obtained from degumming are sold to lecithin producers. Both hulls and gums represent a very small portion of soybean crusher's revenue. In 1995/96 crushing accounted for 54.4% of total soybean demand in US, with the remaining going to exports (33.8%), seed use (2.8%), residual usage/shrinkage (1.4%) and inventories (7.2%) according to USDA data (Oils Crops Yearbook, 1999).

The two main products obtained from soybean crushing have very different characteristics regarding production and inventory demand compared to the soybeans themselves. First, although soybeans are an annual crop, both oil and meal are continuously produced goods, since crushing extends throughout the season. Second, while soybean oil is a storable commodity, soybean meal is non-storable.

It is also very important to note that, since both products (oil and meal) are the simultaneous result of soybean crushing, not only soybean availability impacts the supply of products (and their prices) but also demand conditions in one product have an impact in the supplies of the other product. To illustrate, an increase in soybean meal demand would generate an increase in prices along the supply curve of soybean meal, inducing expanded crushing rates which in turn yields increases in soybean oil supply and consequently lower oil prices.

Crushing takes place in very specialized factories. Given the additional investment costs to be incurred for a multi-seed operation, most soybean crushing facilities can only crush one seed type, making it difficult to use alternative inputs (cottonseed, sunseed, rapeseed, etc.).

Processing returns along with crushing capacity drive crushing rates. Returns are composed of the difference between revenue generated by sales of soybean oil and meal minus the acquisition costs of beans. This difference is usually called Gross Crushing Margin. Once processing costs are deducted the Net Crushing Margin (the actual profit of the operation) appears. Variable processing costs include mainly labor, fuel, solvent and power.

Gross crushing margins averaged 95 cents per bushel crushed over the 1988/89 to 1997/98 seasons based on 44% protein soybean meal. The relative importance of oil and meal sales in total annual revenue can be measured by the oil share of product value, which averaged 34.8% and fluctuated between 28% and 47% in the same period (USDA, Oil Crops Yearbook, 1999).

Crushing capacity has grown since the sixties but the number of crushing facilities has fallen, according to ERS and Census data. Total annual soybean crushing capacity in 1995 was 1.8 billion bushels which compared to 1.4 billions bushels in 1980, based on National Oilseed Processors Association. Both years recorded utilization ratios near 74%.

Soybean price determination is the result of many forces including carry-in stocks, current period's soybean production, exports, seed usage, crushing capacity, oil and meal demand, and storage demand. Product prices are the result of supply and demand forces evolving from each of these different components of the soybean complex. Most important is the issue that soybeans are the main input for producing soybean oil. As such, soybean prices have a strong impact on soybean oil supply.

1.2. Soybean oil market

In calendar year 1996 a total of 15,447 million pounds (mill. lbs.) of crude soybean oil were produced of which 1,256 were exported and 13,658 were consumed domestically (an increase of 618 mill. lbs. in stocks took place and 94.1 mill. lbs. were imported in the period). A total of 996 mill. lbs. were consumed in several other non-refined uses and the remaining 12,662 mill. lbs. were consumed in crude refining. That is, more than 90% of crude oil domestic use is in the manufacture of refined oil products for food consumption. Production of refined soybean oil reached 12,274 mill. lbs. (there is about 5% weight loss in refining). A total of 12,322 mill. lbs. were used in the manufacture of end products (more refined oil was used than produced because of a slight reduction in refined oil stocks). Major soybean oil uses are shown in table 1.

Table 1

U.S. Oils and fats usage, 1996
(in million pounds)

Usage	Manufacture of	Oils and fats use	Soybean oil use	Percentage
Salad and Cooking oils	6,641	6,717	5,508	81
Baking and frying oils	5,823	5,935	4,690	77
Margarine	2,480	1,847	1,694	91
Other		361	125	51
Inedible		6,018	305	5
Total			12,322	

Source: USDA, Oil Crops Yearbook, 1996 and Census Bureau of Statistics, Industrial Reports, M20K9613

Table 1 shows the great importance of soybean oil in the manufacture of salad and cooking oils, baking and frying oils and margarine producing as it accounts for about 80% of input usage in the manufacture of these products. In fact, the mentioned products represent 84% of total fats and oils domestic consumption in food products (18,187 mill. lbs.).

Growth in domestic soybean oil consumption has been due to population and per capita income growth, but also has been fueled by the increasing use of vegetable fats as a source of caloric intake. The increased consumption of poultry and fish in place of red meats has reduced animal fat intake.

Total domestic crude soybean oil consumption rose from 9,113 to 13,465 mill. lbs. in 1980/81-1995/96 seasons period. Increased consumption was paralleled by increased domestic production which rose by an accumulated annual rate of 2% in the same period (USDA, Oil crops Yearbook, 1999).

Soybean oil faces competition from seed oils (cottonseed oil and peanut oil mostly), as well as from corn oil, olive oil and palm oil in the manufacturing of salad and cooking oils. These same goods compete with soybean oil in the making of baking and frying fats, as also do lard and edible tallow. To a much lesser extent soybean oil competes with other oils in manufacturing margarine and the fabrication of paints, soaps, resins, lubricants, etc.

The degree of substitution in the oils and fats markets seems to be quite small. In particular, studies by Chern and Yen (1992) and Chern, Loehman and Yen (1995) show very low cross-price demand elasticities for soybean oil.

Exports are an important demand source although their role has decreased in the last twenty years due to fast production and export growth in South America. In the 1970-74 period, exports represented 16.6% of total usage while in 1990-94 period only 10%. Export demand variability, however, appears to be an important source of price instability in U.S. soybean oil.

After degumming (removing non-fatty materials), processing crude soybean oil into refined soybean oil consists of neutralizing the free fatty acids with caustic acid (an alkali) and removing the resultant soap stock (which is used in glycerin and soap production). Further processing may include blanching, winterizing, hydrogenation and deodorization. An Alkali refining process is the most common in US, accounting for 96% of total refining capacity in 1975 and 95% in 1983 (USDA, Oil Crops, Outlook and Situation Report, May 1985).

Stocks of soybean oil are therefore held in the form of crude soybean oil by soybean crushers (as end product) as well as soybean oil refiners (as inputs). Stocks of refined soybean oil are held by refiners (as end products) and brand product makers (as inputs). Many crushers, however have integrated operations that reach the consumer in supermarket stores. Consequently they hold stocks of refined soybean oil also.

Crushers hold crude soybean oil for speculative purposes and due to opportunity costs. The former involves the expectation of price appreciation from which a speculative gain can be earned. The latter relates to the "logistics" aspect of product distribution. Lacking storage space involves the risk of stopping the crushing process. It is not uncommon to face discontinuities in sales, not only due to demand variability but also because of the lack of coordination between production rates and current demand rates. It is necessary to increase stockholding when sales slow down because of the opportunity cost related to stopping the factory, which in turn results in making no profit on current operations.

Similar reasons motivate crude soybean oil refiner's stockholding. The "convenience yield" associated with storing provides support to stockholding that otherwise would not take place for purely speculative reasons.

No stockholding of soybean oil takes place in the hands of the Government. Government intervention has been limited to export donations and credit subsidies in the form of the PL-480 program and Export Enhancement Program (EEP).

Some (small) portion of stocks is kept out of reported statistics, the so called "invisible" stocks, that take place while some portion of materials are in transportation vehicles such as trucks, railroad, barges, etc.

During the last twenty years the soybean oil end-of-season stocks to full-season-usage ratio averaged 10.8% with a high of 16.3% in 1987 and a low of 5.5% in 1984. On a quarterly basis, soybean oil stocks represented an average of 35% of total demand with a high of 47% and a low of 19% (according to USDA data). Table 2 shows 1995/96 quarterly and annual soybean oil balance.

Table 2

1995/96 Quarterly U.S. Soybean Oil Balance
(in million pounds)

	Quarter				
Concept	1	2	3	4	Total
Beg.Stocks	1,103	1,409	1,654	1,888	1,103
Production	4,096	3,888	3,677	3,578	15,239
Imports	11	34	36	14	95
Exports	371	354	155	112	992
Consumption	3,430	3,324	3,323	3,353	13,430
End Stocks	1,408	1,654	1,888	2,015	2,015
Demand	5,209	5,332	5,336	5,480	16,437
Usage	3,801	3,678	3,478	3,465	14,422
Stocks/Dem.	27	31	35	37	12
Stocks/Usage	37	45	55	58	14

Source: USDA, Oil Crops Yearbook, Oct. 1999

1.3 Soybean meal market

In the 1995/96 season, total domestic feed usage was 200.42 million short tons (mst.) of which high protein feedstuff was 35.6 mst. and soybean meal 26.5 mst. Soybean meal use represented 33% of total domestic feed use and 74% of high protein concentrates (USDA, Oil Crops Yearbook, 1998). Soybean meal feeding is the most important use although it can also be used as food and fertilizer. Soybean meal feed use is 98% of total soybean meal usage in the US.

Soybean meal protein content can vary according to product quality requirements. However, its variability is limited between 43% and 50% per pound of weight, constituting the highest protein content in all meal-feeds available after groundnut meal. These features make soybean meal feasible for livestock and poultry feeding in varied proportions depending on the animal absorption capabilities. Soybean meal is usually mixed with other components in the ration depending on the animal, protein content, nutritional content of other materials, and prices. Given the varied characteristics of feeding materials, they are not close substitutes. Moreover, a case can be made for complementarity between soybean meal and corn for example.

In the 1995/96 season, soybean meal production reached a level of 32.5 mst. Domestic usage and exports were 26.6 and 6.0 mst., respectively (USDA, Oil Crops Yearbook, 1999).

Domestic soybean meal consumption has increased rapidly in the last 20 years as a consequence of increased livestock population and average weight per animal reaching slaughter, but also has been fueled by increased poultry consumption as part of the change in population's eating habits regarding meats.

Exports have increased from 4.5 mst. in 1970-74 to 6.1 mst. in 1990-94 for a 35% increase. Faster South American production growth prevented exports from having a higher share in total usage. In 1970-74 exports represented 26% of total annual usage whereas in 1990-94 that percentage was 20%.

Soybean meal stocks are held by mills mostly. However, they do not represent a major component of current demand. During the period 1970-1995 end-of-season stocks to season-usage ratio averaged less than 1% with a high of 1.8% in 1982 and a low of 0.4% in 1993. These numbers suggest soybean meal non-storability.

Soybean meal pricing thus depends entirely on factors affecting current supply and demand. Since inventories are not a major source of demand, soybean meal prices depend on crushing rates and demand factors such as number of animals, feeding substitutes, export demand, etc. These considerations are important as soybean meal is a major output of soybean processing. Soybean meal prices determine crushing rates to a great extent and consequently impact on soybean oil supply and prices also.

CHAPTER 2

LITERATURE REVIEW

2.1. Soybean complex structural models

Vandenborre (1967) may be considered the first attempt to estimate a complete model of the soybean complex. He estimated an annual model, for the period 1948-1963. A soybean supply response function was not estimated, and supplies of soybean oil and meal were assumed to be given each year. Soybean oil consumption demand was specified to depend negatively on prices and availability of butter and lard, and positively on cottonseed oil price. A time variable was included to capture the effects of population and taste changes. Soybean meal consumption demand was specified to depend negatively on prices and availability of other high protein feeds, positively on livestock prices and high protein animal units. A time trend was added to reflect technological change. Soybean oil ending stocks were supposed to depend negatively on PL-480 exports and positively on time and price of soybean oil. Soybean oil beginning stocks plus current production were also included. Soybean meal ending stocks were specified to depend on time and prices of oil and meal. Crushing margins were endogenous to the model, depending on a time trend (standing for technological improvement) and prices of oil and meal.

Results, from Vandenborre's study were to a large extent poor and suggested several specification errors, with exception of the soybean meal equation which resulted in a good fit. Crushing margins for example did not include any variable referring to crushing capacity or soybean availability. An equation for soybean meal ending stocks was modeled in spite of existing evidence of non-storability. Ending soybean oil stocks were modeled on prices without providing any convincing reason for doing so and this variable failed to be statistically significant.

Houck, Ryan and Subotnik (1972), Meyers and Hacklander (1979) and Meyers, Helmar and Devadoss (1986) used annual data in the soybean complex in an attempt to provide improvements over previous efforts.

Houck, Ryan and Subotnik (1972) using data from 1946 to 1966, introduced an equation for soybean supply response, although they assumed crushing margins to be exogenous. Meyers and Hacklander (1979) built a model in which crushing margins are endogenous for the period 1955-1975. Meyers, Helmar and Devadoss (1986) expanded the model by modeling the soybean complex in foreign countries and introducing explicit export demand equations, for the period 1966-1982. These models have in common several specification features that are worthy of comment.

Soybean supply response is usually specified to depend on expected own prices and expected prices of competing products. Expected prices in turn are specified to depend on previous period (observed) prices. Linear adjustment costs are also modeled, which leads to a lagged dependent variable in the model. Performance of this equation is generally good with supply elasticities ranging between 0.60 and 0.84 (see table 3). These results suggest supply adjustments do not totally occur in one period but are spread out over several, and also suggest that farmer's price expectation mechanism is backward looking.

Crushing rates (resulting in oil and meal supply) are modeled to depend on soybean prices, prices of oil and meal products, and crushing capacity. Although no other input prices are included as explanatory variables, results are remarkably good and conform with theory. An important conclusion derived from these results is that crushing rates respond instantaneously to prices of products and soybeans (crushing margin).

Table 3

Own Price elasticities

Study	Period	Supply Response	Soyoil Consump.	Soymeal Consump.	Crushing Demand
Vanden	(48-63)	-	-0.45	-0.28	-
HSR	(46-66)	0.84	-0.28	-0.18	-0.21
MH	(55-75)	0.60	-0.06	-0.21	-1.25
MHD	(66-82)	0.71	-0.45	-0.41	-2.08
WH	(66-81)	-	-0.33	-0.09	-
Henry	(65-81)	-	-0.08	-0.23	-

Source: Vandenborre (1967); Houck, Ryan and Subotnik (1972); Meyers and Hacklander (1979); Meyers, Helmar and Devadoss (1986); Wesscott and Hull (1985) and Henry (1981)

Explanatory variables used in soybean oil consumption demand equations are similar and include own price, income and price of substitutes, although the actual specification diverges to some extent. Houck, Ryan, and Subotnik (1972) modeled consumption as a function of soybean oil price, real food expenditures, cottonseed oil consumption and wholesale price index of butter and lard obtaining statistically significance in all variables but cottonseed oil consumption. Meyers and Hacklander (1979) specified the same equation to depend on real soybean oil price, real consumer expenditures in non-durables and services, and all other fats and oils consumption. Meyers, Helmar and Devadoss (1986) used the same specification, although expenditures are expressed in logarithmic terms.

Several issues can be mentioned related to the soybean oil consumption equations specified in previous research. Firstly, it is important to note refiner's demand for soybean oil comes from consumer's demand for refined oil products. Modeling crude soybean oil demand by introducing some income variable as an explanatory implies demand originates from consumers and thus should be conceived as a derived demand form. Secondly, modeling soybean oil consumption depending on all other oils and fats consumption may be the source of biased estimators as long as consumption of soybean oil and other oils and fats are simultaneously determined. But most importantly, this modeling approach fails to comply with economic theory. It is not consistent to model the consumption of one good as a function of the quantity consumed of another good. Yet, introducing close substitutes prices instead of quantities to account for substitution effects often results in multicollinearity problems. In this sense it has been difficult to obtain good estimates of the consumption demand equation.

Soybean meal consumption demand equations included own price, livestock prices, livestock units and price or quantities of substitute products as explanatory variables, with very minor differences in specification. The remarks made above in respect to soybean oil also apply here. Simultaneity bias can also be suspected in this equation as quantities are used as explanatory variables.

Soybean and soybean oil end-of period stocks are modeled in similar fashion in all three studies commented above: 1) in an attempt to capture expectations about future prices, next period's soybean production is included as a proxy variable; 2) present period prices of the stored good are included as an explanatory variable; 3) current period production is included to capture convenience yield effects; 4) stocks held by government are included as an additional explanatory variable; 5) partial adjustment in inventories is modeled; 6) dummy variables accounting for outliers are also included; 7) all variables are specified in linear form.

Although econometric results from the above specification of the inventory demand equation seem to be satisfactory from a purely statistical point of view, it is difficult to reconcile them with theory. For a start, there is no solid theoretical argument to support partial adjustments in inventory demand. Second, specifying expected price as a linear function of expected production does not acknowledge the fact that prices also depend on demand shifts. Third, it is evident that current period production has a positive statistical relationship with end-of-period inventories. To attribute the statistical significance of this relationship to convenience yield may be misleading. Fourth, although current prices are included in the equation, this slope parameter is not restricted to equal the one on expected price, thus the specification does not enforce the speculative behavior of stockholders during the estimation.

The inclusion of many variables with few restrictions may very well result in a good statistical fit. For example, the explanatory power of these equations, as measured by its R^2, is relatively high. In the case of soybean oil equation, R^2 figures are 0.80, 0.62 and 0.72 in Houck, Ryan and Subotnik (1972), Meyers and Hacklander (1979) and Meyers, Helmar and Devadoss (1986) studies respectively. However, the actual economic relevance of these results may be difficult to assess and accept. If speculative inventory demand is to be modeled, the specification should be based in solid economic theory and the restrictions enforced.

Quarterly soybean complex models have also been estimated. Wesscott and Hull (1985) modeled the soybean sector using quarterly data for the period 1966-81. Although soybean oil consumption demand follows a similar specification to earlier works some seasonality was found. Soybean meal consumption demand is specified as a function of own price lagged one period, corn price, livestock prices and seasonals variables. The Wesscott and Hull (1985) study also specifies soybean meal demand as a function of cattle placements and sows farrowings lagged one and two periods. No inventory demand equation was modeled since ending stocks were assumed to result from the balance identity.

Monthly econometric models of the soybean sector have also been estimated. Henry (1981) developed a partial adjustment model for soybean oil and meal consumption in a monthly model. Similar explanatory variables as in previous studies were used in this work. Seasonal components were found in both consumption equations. A very interesting result, however, is that oil and meal expected prices were found to be not statistically significant in explaining crushing variability, in what seems to be a confirmation that crushing rates depend on current product prices (not the expected ones). Henry's (1981) work on the inventory demand equations concluded that the speculative component was irrelevant in both equations, thus challenging previous efforts.

2.2. Rational expectations inventory models

Even though the origins of the rational expectations hypothesis is dated to forty years ago with the seminal work of Muth (1961), its application to agricultural markets has taken place more recently. Until the late seventies supply response analysis was dominated by several backward-looking expectations formation hypotheses (naive, extrapolative, adaptive, etc.) out of which adaptive expectations was the one most commonly used. Nerlove's adaptive expectations supply response model seemed to provide a good explanation of the data in many applications (see Askari and Cummings, 1979).

In the beginning of the 1980's a shift in the literature took place towards the use of the rational expectations hypothesis as an alternative to Nerlove's model. The attempts made by Sheffrin and Goodwin (1982) and Eckstein (1984) showed that an alternative explanation was able to explain the data without relying on ad hoc mechanisms such as the partial adjustment process and adaptive expectations.

In view of the U.S. government efforts to achieve stabilization of grain prices in the mid 1980's, a major part of the literature was devoted to estimating the "bounded price variation" model in which farmers' expectations were modeled to include their expectations about government actions and its effects on prices. Shonkwiler and Maddala (1985), Holt and Johnson (1989) and Holt (1992) are characteristic examples of this type of research.

In the late 1980's the rational expectations hypothesis was also implemented to explain prices in markets where inventories play a role in price determination. The efforts in this area used the basic specification in Muth's inventory model of three structural equations and one equilibrium identity, in which previous period inventory levels plus current production must equal the current usage plus inventories carried into next period. Following this basic structure several studies were conducted: Hwa (1985), Gosh, Gilbert and Hughes-Hallet (1987), Thurman (1988), Gilbert and Palaskas (1990), Trivedi (1990) and Gilbert (1995).

Hwa (1985) made a first attempt to estimate a rational expectations model in coffee, cocoa, sugar, copper, rubber and tin. His model, however, modeled the "rational price expectations" in a manner not consistent with the notion of agents knowing the model. Hwa (1985) also introduced ad hoc mechanisms such as partial adjustment in stocks and a price equation implying that inventory holders incur in unplanned storage.

Gosh, Gilbert and Hughes-Hallet (1987) who studied the copper market found evidence of speculative behavior without introducing convenience yield in their specification nor enforcing the non-linear cross equation restrictions. Thurman (1988) rejected the rational expectations restrictions in a monthly copper model but the model made better out-of sample forecasts than competing models.

Gilbert and Palaskas (1990) (who investigated the same commodities that Hwa worked on) confirmed previous results in copper in an annual model but were unable to replicate results on the other five commodities. They argued that maybe the "production and consumption models were insufficiently realistic to pick up future supply/demand balances" and that the other five commodities had a great deal of government market intervention. It should also be noted that they only used twelve observations in their empirical model.

The latter three studies mentioned, studied a simplified version of Muth's basic model structure, i.e. that current production (supply equation) depends on current price rather than expected prices as it is common to assume in agricultural commodities. Significantly, these models only estimated the pseudo-reduced form of the price equation, not the full structural models.

Table 4 briefly summarizes the major characteristics of studies mentioned here and their results.

Trivedi (1990) who worked with annual data in tea, cocoa and palm oil generated improvements over earlier approaches. He modeled inventory demand to include a speculative component and a transactions component, the former specified as the expected change in prices and the latter depending on expected consumption demand which produced a positive convenience yield. He also modeled supply to depend on current prices and expected prices which is a specification that is rather difficult to interpret. The results showed no evidence of a significant relationship between inventory demand and expected prices. An interesting conclusion of this study is that better modeling of the process driving the exogenous variables may be needed to provide a better fit. Based on his results the author suggested that neglect of speculative inventory

Table 4

Inventory demand studies

Study	Period	Frequency	Commodity	C.Yield	Results	Restrictions enforced
GGH (1987)	1961-1978	Quarterly	Copper	No	Evidence found (*)	No
Thurman (1988)	1975-1984	Monthly	Copper	Yes	Inconclusive	Yes
GP (1990)	1963-1975	Annual	Coffee,Cocoa, Rubber,Copper, Tin and Sugar	No	Evidence found in copper (*)	No
Trivedi (1990)	1958-1983	Annual	Tea, Cocoa, Palm Oil	Yes	No evidence found	No
Gilbert (1995)	1966-1991	Annual	Aluminum	No	Evidence found (*)	Yes

* Evidence was found of speculative behavior in inventory demand

behavior in annual models may not be a serious misspecification, while it may be important in the short term.

Gilbert (1995) attempted to estimate an annual model of the aluminum market. This study is the only one that enforced the non-linear cross equation restrictions and estimated the full market model. The study fails to reject the rational expectations restrictions. The parameter on expected appreciation of stocks value is significantly different from zero. For estimation, the author constructed estimates of expected long-term and short-term fundamental imbalances, to account for the multi-step ahead forecasts of exogenous variables, instead of exploiting the stochastic properties of exogenous variables. Furthermore the root restrictions implied by the second order expectational difference equation was not imposed. Importantly, his results critically depend on the fact that the market that he studied does not show any evidence of stock-out events. Gilbert's work is the only study, of the several reviewed here, that obtained sound evidence (in a linear framework) of inventory demand being explained by expected price changes.

2.3. Applications of dynamic programming to soybean markets

More recently, the non-linearities involved in inventory demand drove many researchers to the use dynamic programming techniques.

Many researchers have studied the properties of price stabilization in the context of dynamic programming when a competitive storage industry exists (Helmberger and Akinyosoye, 1984; Miranda and Helmberger, 1988; Glauber, Helmberger and Miranda, 1989). A great majority of these studies used the soybean market for those simulations. Wheat to a lesser extent was also used.

The basic building block for these simulations is a supply response function and a current consumption demand function. From the parameters of those equations, a measure of the inventory demand sensitivity to expected price appreciation can be deduced. Convenience yield is mostly not introduced in these models, however, since the main goal is to analyze the effects of speculative storage decisions on prices.

For the purposes of the simulations, estimation of the above mentioned supply and demand functions were carried out in many studies. The main feature of these supply response estimations is that, instead of assuming backward-looking expectations (as in almost every structural study mentioned in section 2.1) they assume forward looking behavior and consequently try to capture the response of farmers to expected future prices. Because the best proxy for future price expectations are provided by the consensus of the futures markets, futures prices of deferred contracts were used in almost all studies and showed statistical significance. The results of these estimations are summarized in Table 5.

Table 5

U.S. Soybeans: Own Price elasticities

Study	Supply Response	Crushing Demand
Gardner (1976)	0.73	-
AH (1984)	1.02	-0.45
Lowry (1984)	0.89	-0.55
Glauber(1984)	0.64	-0.56
LGMH (1987)	0.89	-0.56
GHM (1989)	0.89	-0.61
MG (1993)	0.44	-0.55

Source: Gardner (1976); Akinyosoye and Helmberger (1984); Lowry (1984); Glauber (1984); Lowry, Glauber, Miranda and Helmberger (1987); Glauber, Helmberger and Miranda (1989); Miranda and Glauber (1993)

These studies are important because they place a question mark on previous econometric work in the soybean complex using less sophisticated expectation formation assumptions.

Irwin and Thraen (1994) reviewed several studies with the objective of assessing how relevant is the rational expectations hypothesis. The results of these studies are mixed. Soybean farmers may use adaptive mechanisms as pointed by Giles, Goss and Chin (1985), a perfect foresight model according to Orazem and Miranowski (1980), the naïve model based on Shideed and White (1989), or the rational conditional forecast or AR(2) model as stated by Holt (1992).

The article by Miranda and Glauber (1993) provided very interesting results in this respect because the estimated elasticity of private stocks demand with respect to expected price appreciation in the value of stocks was 4.78 (and statistically different from zero), which means that storage decisions are very sensitive to changes in current price, expected price and interest rates. The results suggest that rational price expectations in soybean inventory demand and acreage response functions may be a very useful way to proceed. Also, a trend variable showed statistical significance in the inventory demand equation in what can be interpreted as a signal of the "scale of the market" effect suggested by Muth (1961).

Gardner and Lopez (1996) carry on specific modeling of convenience yield for their dynamic programming simulations. For this purpose, a storage cost function was fitted in soybean market, obtaining the best result with a cubic representation on stocks levels.

2.4. Crushing rates and margins

Several articles have also been devoted to the analysis of soybean crushing firms behavior, with special focus on marketing margins.

Boyd, Brorsen and Grant (1985) worked on explaining crushing margin as a function of non-soybean input prices (a weighted average of natural gas and wages), a risk variable, the amount crushed and a trend variable. Input prices did not show explanatory power on crushing margins. They found the risk variable to be statistically significant. Increased risk measured by monthly product price variability increased marketing margins. They concluded that soybean crushing firms are risk averse.

Lence, Hayes and Meyers (1992) implemented a cash crushing margins equation in which they included the amount of soybeans crushed, risk variables and crushing capacity as explanatory variables. They argued that previous analysis was invalid since it ignored the risk management possibilities existing by using futures markets. Making use of a specification in which futures crushing margins are used as dependant variable confirmed results of a sizable effect of risk in marketing margins. Their work on crushing rates shows that crushing margins and crushing capacity are statistically significant explanatory variables of annual crushing volume.

Lence, Hayes and Meyers (1995) argued that hedging in the futures markets should reduce the risk on output decisions. They concluded that futures prices had little effect on crushing rates but a significant impact on inventory levels suggesting that firms try to obtain profits on basis speculation. Their analysis concluded that soybean crushing firms do have forward looking expectations which determine their storage decisions.

CHAPTER 3

ECONOMIC MODELS OF COMMODITY MARKETS

Microeconomic theory provides the theoretical underpinnings for commodity market modeling. Since our study requires the specification of demand and supply equations, sections 3.1. and 3.2. are devoted to these topics. In section 3.3. we review the relevant stockholding theory for our model and in section 3.4. we present a summary of a commodity market model for a storable commodity.

3.1. Demand

Resource endowment, an individual's utility function and prevailing prices of goods determine consumer choices between goods. Consequently, consumer demand is modeled to depend on own prices, prices of other goods, consumer resources and tastes and preferences. Market demand is the addition of individual consumer's demands. Equation (1) depicts this relationship.

$$Q^d = f\ (RP,\ OP,\ R,\ NI,\ TP,\ u) \qquad (1)$$

where Q^d = Consumer's quantity demanded

RP	=	Retail price of the good
OP	=	Retail prices of other goods
R	=	Resource endowment
NI	=	Number of individuals
TP	=	Tastes and Preferences
f	=	Functional relationship
u	=	Random error term

Several other factors such as income distribution among individuals and demographics also affect market demand. These (not included in above equation) factors are usually collapsed into a random error term. The random error term may also account for optimization errors, and errors in the functional form.

In specifying the above equation, it is common practice among econometricians to use a per capita income variable to measure resource endowments. Taxes play a role in determining the amount of resources available for consumption, thus a measure of disposable income is usually used. Disposable income can be devoted to savings and consequently be affected by interest rates. To avoid introducing interest rates in the model specification it is often the case that an expenditure variable is used instead of an income variable.

The number of individuals is proxied by the population. However, in order to simplify the specifications, both the expenditure variable and population number are generally collapsed into one single per capita variable. Usually an aggregate measure of per capita expenditure is used.

Consumer choices are made in the presence of an immense array of goods available at different prices. Because it is not usually feasible in econometric work to introduce the prices of all goods, economists often revert to the simplification of specifying the "other prices" with the inclusion of close substitutes and complementary goods prices only. However, in order to account for the existence of an enormous amount of other goods, prices are usually deflated by a general (consumer) price index.

Tastes and preferences are quite difficult to measure and so the common econometric approach is to assume that tastes and preferences change smoothly and relatively slowly in time. It is common practice to proxy these changes with a trend variable in linear or quadratic form.

The functional specification of the above relationship is still subject of debate among economists, given that the true consumer's utility function is unknown. A linear specification in the parameters is often used. To ensure theoretical consistency in the parameter estimates, homogeneity is often imposed in the course of estimation.

Many goods, however, are not directly consumed by individuals but rather by firms, as intermediary goods (inputs). These firms "transform" intermediary goods to obtain a product suitable for retail consumption. The firm's demand for the intermediary good is then a derived demand from consumers.

Assuming that the firm's objective is to maximize profits, input demand is modeled to depend on input price, output price, other input prices, technology and the number of firms in the market. This relationship is shown in equation (2).

$$Q^d = g\ (RP,\ WP,\ AWP,\ NP,\ T,\ v) \tag{2}$$

where Q^d = Processor quantity demanded

RP = Retail price of the good

WP = Wholesale input prices

AWP= Alternative wholesale input prices

NP = Number of firms

T = Technology

g = Functional relationship

v = Random error term

The theoretical developments presented above are key in deriving the wholesale commodity demand. The usual procedures to obtain a complete description of wholesale demand for an intermediary good is: a) to invert equation (1) in order to obtain an expression for the retail price as a function of the remaining variables, b) to substitute the resulting expression into (2) in order to derive a "reduced' form demand for an intermediate product at the firm level. This results in an equation (3).

$$Q^d = h\ (WP,\ AWP,\ NP,\ T,\ OP,\ R,\ NI,\ TP,\ s) \qquad (3)$$

where Q^d = Quantity demanded

WP = Wholesale input price

AWP= Alternative wholesale input prices

NP = Number of processors

T = Technology

OP = Retail prices of other goods

R = Resource endowment

NI = Number of individuals

TP = Tastes and Preferences

h = Functional relationship

s = Random term

It is clear from equation (3) that all exogenous variables contained in equation (1) and (2) are also contained in equation (3). The functional relationships f and g of both equations are transformed into a new functional relationship h. Also the random terms u and v are now replaced by a new term s.

3.2. Supply

Based on output prices, firms choose the optimal amount of inputs required to produce the planned output. The profit maximization assumption leads to a model of output supply that depends on output prices, input prices, alternative output prices and technology. Market supply is the addition of individual firm's supplies. Equation (4) depicts this relationship.

$$Q^s = i\ (WP,\ AP,\ IP,\ N,\ T,\ w) \tag{4}$$

where Q^s = Quantity supplied

WP = Wholesale output price

AWP = Alternative wholesale output prices

IP = Input prices

N = Number of firms

su

us

ma

fu

re

in

ca

wh

A

d

s

e

a

a

s

g

t

T	=	Technology
i	=	Functional relationship
w	=	Random error term

Other factors such as weather also affect output supply. These (not included in above equation) factors are usually collapsed into a random error term. The random term may also stand for optimization errors or errors in the functional form.

Some firms may produce different outputs depending on relative output prices and select different combinations of inputs to accomplish their production objectives. In these cases (a plot of land suitable to producing either corn or wheat, for example), several output prices are introduced. Also, once the output decision is made, an input allocation decision is required. Several input prices are generally specified.

To empirically implement the above equation, econometricians have assumed that physical characteristics and technological standards (including manager's knowledge) are similar among firms. Market supply is the addition of single firms outputs. Processing capacity has been of general use as a proxy variable for the number of firms in the market.

Technological improvement is understood to mean a change in the relationship between output produced and input usage. If a higher output level can be reached with no change in the input usage, it is said that a technological improvement took place. Technological changes are generally assumed to occur slowly, or at least to spread slowly in the market (economy). This effect has consequently been specified as a linear or quadratic trend.

The functional relationship of equation (4) largely depends on the production function. Many different functional specifications have been used to implement (4) empirically.

3.3. Inventory demand

Stocks are held by producers, merchants, speculators and consumers for precautionary, transactions, and speculative motives. Stockholding theory attempts to provide an explanation for why producers hold stocks of end-products and merchants, processors and consumers hold inventories of inputs. Speculators hold inventories with the purpose of making speculative profits by changing the temporal allocations of goods.

3.3.1. Speculative motivation

In its simplest representation, stockholding depends on the difference between current and expected future prices. Anyone (producers, processors or speculators) might want to own stocks and carry them into the future for speculative purposes. Producers and processors may want to accumulate stocks in the anticipation of increased prices. In such an event, producers would sell their products at higher prices and processors would buy them at lower prices than otherwise. Professional speculators would hold stocks with the sole aim of making capital gains.

Modeling speculative activities is not different to modeling any other economic activity. A risk-neutral speculator will seek to maximize expected profits as the difference between expected revenue and costs involved in the storing operation. Since storing of non-perishable goods is only a temporal reallocation of commodities, no "physical transformation" takes place. Consequently the expected revenue is nothing else but the expected future value of stored goods.

Storing operations require monetary resources to acquire inputs, of which the raw material is the main cost. Physical costs of storage include payments for insurance of storage facilities and stored goods, rent, wages, energy, and loading and unloading costs. Other costs of storage are physical deterioration and opportunity costs, i.e. the returns that could be achieved by allocating storage resources to alternative uses.

Agricultural commodities may experience some deterioration of their physical condition, or may very well loose (by vaporization) some of their moisture content to yield a product with no different characteristics than the one originally stored but of lesser weight. These losses are costs that should also be modeled.

In the short run, a risk neutral speculative firm that maximizes expected profit in a competitive market for storage would maximize:

$$E_t\phi_{t+1} = [(1-a)\ E_tP_{t+1} - (1+r_t)P_t]S_t - (1+r_t)C(S_t,w_t) \qquad (5)$$

where $E_t\phi_{t+1}$ = expected profits at time t

E_tP_{t+1} = expected future price at time t

P_t = price at time t

S_t = stock level at time t

r_t = interest rate at time t

a = deterioration factor $(0<a<1)$

$C(S_t,w_t)$ = total physical cost of storage function

w_t = vector of input prices

t = time

Total physical costs of storage may be classified into fixed costs and variable costs, the latter depending on the total amount of stocks held:

$$C(S_t,w_t)= FC + VC(S_t,w_t) \tag{6}$$

where FC = fixed costs of physical storage

$VC(S_t,w_t)$ = variable costs of physical storage

The first order condition (FOC) to maximizing (5) is:

$$(1-a)\ E_tP_{t+1} - P_t = r_tP_t + (1+r_t)C'(S_t,w_t) \tag{7}$$

where $C'(St,w_t))$ = marginal physical costs of storage

If <u>a</u> is assumed to be zero, equation (7) can be expressed as:

$$\beta_t\ E_tP_{t+1} - P_t = C'(S_t,w_t) \tag{8}$$

where $\beta_t = 1 / (1 + r_t)$

The left hand-side of (8) is referred to as the "cost of carry". Equation (8) says that in equilibrium the firm m

d

S

f

f

l

u

l

a

B

w

w

p

p

i

c

c

m

maximizes profits at the stock level where expected discounted marginal revenue equals storing marginal costs.

From (8) we can solve for the optimal level of storage S_t, obtaining a functional relationship that depends on the form of $C'(S_t)$. $VC(S_t)$ is usually considered to be a linear function, and so, marginal storage costs are constant, at least until total warehouse capacity is almost fully utilized. If total physical costs of storage are assumed linear (and consequently marginal costs of storage are assumed constant), (8) can be expressed as:

$$\beta_t\ E_tP_{t+1} - P_t = c_0\ ;\ S_t > 0 \tag{9}$$

where c_0 = marginal physical costs of storage

which states that when speculative storage levels are positive, the cost of carry should equal the constant (per period of time) marginal physical costs of storage. That is, marginal revenue must equal marginal costs, the usual condition for profit maximization.

This condition implies that when stocks are positive carrying charges would be positive and equal to the marginal physical storage cost

Implicitly, equation (9) also says that whenever $\beta_t E_tP_{t+1} - P_t$ is greater than c_0 storers would choose to store an infinite amount of the commodity whereas zero levels would be stored when $\beta_t E_tP_{t+1} - P_t < c_0$. In reality we see, however a much smoother inventory behavior (which may be explained by convenience yield).

If marginal physical costs of storage are linearly increasing, the optimal level of storage can be obtained as follows:

$$\beta_t E_tP_{t+1} - P_t = m_0 + m_1 S_t \quad ; \text{ or} \qquad (10)$$

$$S_t = c_0 + c_1 (\beta_t E_tP_{t+1} - P_t) \qquad (11)$$

where $c_0 = -m_0/m_1$

$c_1 = (1/m_1)$

which says that the storage level depends linearly on the expected discounted price appreciation.

Assuming risk neutrality, however, may not be a realistic assumption since speculative storage is in fact a risky activity. Thus modeling speculative demand for inventories may require the assumption that firms maximize expected utility instead.

A similar expression for inventory demand equation (11) can be obtained when risk aversion plays a role in speculative behavior. Under uncertainty a risk averse firm would maximize expected utility of profits EU [ϕ_{t+1}]. It is possible to show that under EU decision making, inventory demand can be expressed as a linear function of expected price appreciation if certain assumptions are made (constant conditional variance of prices and constant risk aversion) (Muth, 1961, Gosh, Gilbert and Hughes-Hallett, 1987).

In many instances, risk averse speculators can manage price risk by hedging with futures contracts. Under an EU decision framework, a similar result to equation (11) can be obtained as long as we assume no basis risk and unbiased futures markets (Chavas and Helmberger, 1996). When price risk can be hedged in futures markets a risk averse firm would choose the amount to store as a linear function of expected appreciation in cash prices.

Although it may be difficult to provide support for an equation of the type depicted in equation (8) on the grounds of constant conditional variance of prices and constant risk aversion, it is no less true that price risk management is a sensible possibility in U.S. soybean oil market. Soybean oil futures contracts have traded in U.S.

since 1958 at the Chicago Board of Trade and have grown in volume through the years. In fact, Lence, Hayes and Meyers (1995) provide evidence that futures prices play a role in determining soybean oil inventory levels. On these grounds, explicit modeling of price risk aversion can be avoided.

3.3.2. Convenience yield

Stocks are also held by producers, processors and consumers for transactions and precautionary reasons. It is well documented that goods may be carried into the future even in the expectation of price depreciation. When such a thing happens it is said that stocks are held not for speculative purposes but because of the "convenience" return from holding stocks.

The functional form of the relationship between convenience yield and stock levels is assumed to increase at a decreasing rate as the level of stocks increase. Therefore, at high levels of stocks held, marginal convenience yield approaches zero and at low levels of stocks marginal convenience yield is very high.

Given the enormous variability of firm sales rates, a commodity producer firm looks to have as many outlets as possible to sell their products. Creating new commercial relationships requires time to evaluate the financial conditions of buyer and seller and contract execution performance. Typically, building confidence between each other to reach a successful commercial relationship takes years. Once it is established, a consistent flow of commercial transactions are required to keep relationships "going on". The availability of product to sell is therefore a key to maintaining "good" commercial relationships.

A crusher might want to hold high stock levels of end-products, because this would allow sales of big quantities to clients with which commercial deals can only be done on that basis. The stock levels should not be as high, however, as to reach the maximum storage capacity, due to its implications for the production process. Full storage impedes production from continuing. To prevent this, a permanent flow of sales must be possible, the only guarantee being a diversified portfolio of clients. On the other side, crushers may not want to have stocks lower than a certain "working" level, because there are clients whose product needs must be fulfilled, at least in small volumes.

A refiner might want to keep input stock levels above a certain "working level", due to the costs of running under capacity, or having to stop the production process in the case of a stock-out. This may evolve into an inability to provide refined material to customers, which in turn must look for other supply sources. This may jeopardize a commercial relationship and, most important, reduce profits from the refining operation. In brief, some level of stocks are held not for speculative purposes but to allow continuos transactions to take place.

Convenience yield is therefore a function of the stocks level. The exact nature of the functional relationship is one that must be determined empirically. Formally:

$$CY = f\ (S) \tag{12}$$

where CY = Convenience yield

Convenience yield modeling has differed among researchers. Some researchers have reasoned that including a trend variable in the inventory demand equation would account for "coverage yields" a related concept to the "transactions" motivation for stockholding (Lord, 1991). As a matter of fact Muth (1961) had suggested that inventory demand would also depend on the "size of the market".

A more realistic approach (Trivedi, 1990) specified that inventory demand would linearly depend on expected consumption. In his own terms this factor would "reflect transactions demand for inventories which produce a positive convenience yield".

The two sources of inventory demand introduced in section 3.3. may be integrated into a single framework. Producers and processors would hold stocks of products and input materials for either of both reasons, making it difficult to determine the exact reason why some portion of stock is held. Suffice to say that in what follows we assume that some portion of stocks is held for one reason and the remaining portion for the second reason, to obtain an additive formulation to obtain:

$$S_t = c_0 + c_1 (\beta_t E_t P_{t+1} - P_t) + CY \tag{13}$$

which says that expected profits are the result of expected speculative profits plus convenience yields.

3.4. Commodity market model

On the grounds of the work presented above, a commodity market model would include a demand equation, a supply equation, an inventory demand equation and a market clearing condition. The latter, when dealing with non-storable commodities is usually expressed as the equality between quantity supplied and demanded. When dealing with storable commodities the condition transforms to include inventory demand. That is, beginning inventories plus current's period output supplied must equal current's period demand for consumption plus demand for storage. If the market is open to foreign trade, imports and exports should be modeled and be included in the market clearing condition. The market model then consists of equations (3), (4), (13) and the market clearing condition (15).

Market model

$$Q^d = h\ (WP,\ AWP,\ NP,\ T,\ OP,\ R,\ NI,\ TP,\ s) \qquad (3)$$

$$Q^s = i\ (WP,\ AWP,\ IP,\ N,\ T,\ w) \qquad (4)$$

$$S_t = c_0 + c_1\ (\beta_t\ E_tP_{t+1} - P_t) + CY \qquad (13)$$

$$S_{t-1} + Q^s = Q^s + S_t \qquad (15)$$

In our work, the wholesale price refers to crude soybean oil price.

CHAPTER 4

MODEL SPECIFICATION

On the grounds of the literature review conducted in Chapter 2, the work developed in Chapter 3, and Muth's (1961) inventory model, we specify the following model of the U.S. soybean oil market:

$$DISS_t = a_0 + a_1\ RSBOP_t + a_2\ EXPEN_t + a_3\ RLARDP + e_{1t} \tag{1}$$

$$\begin{aligned} PROD_t = b_0 &+ b_1\ RSBOP_t + b_2\ RSBMP_t + \\ &b_3\ RSBP_t + b_4\ CRCAP_t + \\ &s_1\ D_1 + s_2\ D_2 + s_3\ D_3 + e_{2t} \end{aligned} \tag{2}$$

$$\begin{aligned} CO_t = c_0 &+ c_1\ [E_t\ RSBOP_{t+1} - RSBOP_t] + \\ &c_2{}^{*}\ T + c_3\ RFFR_t \end{aligned} \tag{3}$$

$$CO_{t-1} + PROD_t = DISS_t + X_t + CO_t \tag{4}$$

where

where	DISS	= Domestic soybean oil consumption
	RSBOP	= Real crude soybean oil price
	EXPEN	= Personal consumption expenditures
	RLARD	= Real wholesale lard price
	PROD	= Soybean oil production
	RSBMP	= Soybean meal price
	RSBP	= Real soybean price

CRCAP = Crushing capacity

D1,D2,d3 = Seasonal dummy variables

CO = End-of-period soybean oil stocks

E = Expectations operator

RFFR = Real interest rate

T = Trend variable

X = Soybean oil exports

e = error term

t = time, quarter

$E_t \; RSBOP_{t+1}$ = $E_t \; [RSBOP_{t+1} \mid \Omega_t]$

= The expectation formed about $RSBOP_{t+1}$ conditional on information available at time t. Expectations are rational.

The model resembles the typical structure of Muth's model and includes three behavioral equations, (1) to (3) (consumption demand, production and inventory demand), and one market clearing condition (4) (the material balance identity). Behavioral equations are specified linearly in levels as is the material balance identity. All price variables are real as they are deflated by the Census Bureau of Statistics producer price index.

Equation 1, stands for current period consumption demand, which is modeled to depend on soybean oil prices lard prices and personal consumption expenditures. Although it is reasonable to believe that prices of other oils would affect soybean oil demand, several aspects leads us to the simplification of including only a not-so close substitute.

Firstly, it is important to recall that equation (1) refers to demand at a wholesale level, which derives from demand at a retail level. In this sense retail prices of bottled soybean oil competing products might be included such as bottled rapeseed oil and bottled corn oil. Also retail prices of margarine competing products like butter might be included and retail prices baking and frying fats alternatives to soybean oil, such as lard and edible tallow. We opted for including lard prices in our specification. We used wholesale lard prices as a proxy variable for retail prices.

On the other hand, wholesale prices of alternative inputs to soybean oil might also be included. The representation of processor's input demand introduced in Chapter 3, fits well to different processing activities in the soybean oil market such as refining and bottling, the making of salad dressings, margarine, products for industrial use (paints and lubricants) and others.

In the making of margarine, soybean oil inputs only marginally compete with cottonseed oil and corn oil. More important is the substitution effect that may take place between soybean oil and cottonseed in the making of baking and frying fats. But still, out of the total oil usage in the manufacturing of baking and frying fats, soybean oil constituted 80 % of total input demand.

Salad dressing, and cooking oils also use soybean oil in their makings. Salad dressings use alternative vegetable oils according to their prices and as is the case in the production of blended bottled oils. However, it is important to note that institutional factors (regulations) and consumer tastes severely limit the range of substitutions among alternative inputs. In brief, although soybean oil may be substituted for other inputs, it is limited to a narrow range.

Second, the inclusion of many other wholesale oil prices would introduce a high degree of multicollinearity. As a matter of fact, soybean oil is the major oil consumed in the U.S. so its supply and demand conditions are the major factor explaining edible oil price variability.

The literature review conducted in Chapter 2, on the other hand, suggests modeling consumption demand should depend on some income measure. However, some work also proved satisfactory with the specification of an expenditure variable as a proxy variable for resource endowments. In this study we follow the latter approach.

There is no available data for the number of refiners (processors) thus we were unable to include this variable in the course of estimation. We also considered it inappropriate to include a trend line accounting for such a variable, as a trend would be correlated with the expenditure variable. We have also assumed that there has been no major technological change.

We have also assumed, following previous research, that demand contemporaneously responds to prices and expenditures. No lag structure is specified.

The signs in equation 1 are expected to be negative on prices, and positive on expenditures and lard prices.

The seasonal behavior of consumption demand seems to be fairly well explained by prices. That is, seasonality in consumption demand is induced by supply through the price mechanism thus no seasonal dummy variables are incorporated in the specification of this equation.

Equation 2, specifies current period production as a function of output prices (oil and meal) input prices (soybeans), and crushing capacity (proxy variable for the number of firms).

Soybean oil is produced in almost fixed proportions from soybean crushing. About 180 kilos of oil are obtained per 1,000 kilos of soybeans crushed. This relationship marginally varies through the years according to soybean vegetative growth conditions (temperatures, moisture, etc). Thus we may substitute soybean oil production for crushing rates and maintain the same equation specification used for soybean crushing rates.

Soybean crushing rates, depend largely on crushing margins, i.e. the difference between product value and soybean prices. Product value is the revenue from oil and meal sales weighted by their production yields. Although there are many other inputs related to soybean crushing, soybeans account for the bulk of them. In our specification we assume other input costs are fixed.

Most work on crushing rates assumes a specification of crushing margins that we do not fully enforce in this study. The need for a specific soybean oil price in the supply equation (in order to study soybean oil inventory demand), requires that each component of the crushing margin (soybean oil price, soybean meal price and soybean price) be specified separately. Still, the specification losses no theoretical support.

No technological change took place in the last 20 years in the soybean oil extraction industry. Solvent extraction factories were the standard production technology then as now.

In specifying equation (2) we follow previous research in modeling contemporaneous supply response without partial adjustments mechanisms. Soybean oil output decisions depend on current prices, not expected prices. The literature has consistently shown that this specification is a good representation of reality. Also, as mentioned in Chapter 2, no study has been conducted to asses whether partial adjustment mechanisms play a role in soybean oil output (i.e. soybean processing). However, the presumption is that if they exist they are marginal and are not modeled here.

Most soybean crushing facilities do not have the ability to crush other types of seeds, so alternative output prices are not specified.

We make used of crushing capacity as the proxy variable for the number of firms in the market. The literature reviewed in Chapter 2, has placed a big emphasis on the explanatory power of crushing capacity on annual crushing rates. In this study we incorporate crushing capacity as an explanatory variable of soybean oil output.

The strong seasonal component in soybean oil production is captured by specifying seasonal dummy variables.

Equation (3), the soybean oil inventory demand equation, specifies a linear functional relationship between inventory demand and the expected appreciation in stocks value. Although it has been shown that inventory demand may depend as well on higher moments of the price probability distribution, we have assumed that price risk management is possible in the soybean oil market.

In equation (3) we assume that price expectations are formed rationally. Although it is still a matter of debate whether rational expectations properly depicts the formation of expectations by agents, there is evidence supporting this hypothesis in soybean inventory demand (Glauber and Miranda, 1993) and soybean oil inventory demand (Lence, Hayes and Meyers, 1995).

Given that convenience yields are in essence non-monetary (and non-observable) benefits to stockholdings it may be difficult to find any variable that properly captures the convenience yield effect. Thus researchers have oriented their efforts to hypothesize about the actual shape of the storage function cost by introducing quadratic, cubic and hyperbolic functions. The result of this effort has been the introduction of a nonlinear relationship between expected appreciation of stocks value an the inventory level (Gardner and López, 1996; Glauber and Miranda, 1993).

The trade-off between the two approaches is high. The econometric tractability of a linear specification is hurt by its lack of realism. On the other hand, a non-linear specification of convenience yield would require the use of non-linear rational expectations estimation techniques. As discussed in the Introduction of this study we have opted for the first approach.

Inventory demand is also affected by the size of the market as pointed out by Muth (1961). A linear trend variable was included to capture the effect of "scale of the market" growth. The linear specification allows for negative stocks. Previous research has considered that this specification accounts for "transactions" convenience yield and we take this to be the specification for convenience yield.

We specify equation (3) to depend linearly on interest rates. Although the work conducted here, leads to a specification where the discounting factor is multiplicative in respect to expected prices, the non-linearities introduced by such a representation, leads to model complexities that could not be solved in a linear framework. We thus opted for including the discounting factor in a linear fashion.

Equation (4) is the material balance condition where initial inventories plus current period's production must equal current period's consumption plus export demand and current period's inventory demand.

Import demand is not modeled because they are almost non-existent. Export demand, on the other hand is assumed exogenous at every period in order to reduce the complexity of the model. The exogeneity assumed here allows us to avoid modeling government actions in the form of PL-480 donations and the Export Enhancement Program (EEP).

When expectations about future prices are assumed rational in a rational expectations model a solution for the expectations variable is needed, i.e. an expression for the non-observable variable E_t $RSBOP_{t+1}$.

By substituting equations (1), (2) and (3) into the market clearing condition (4) and after rearranging terms an expectational difference equation results. Solving this equation results in an expression for E_{t-1} $RSBOP_t$ as a function of the stable root (λ) of the polynomial in the lag operator, the structural equations parameters and the multi-step ahead forecasts of exogenous variables (see Annex I and II for procedures).

$$
\begin{aligned}
E_{t-1}\ RSBOP_t = {} & \lambda\ RSBOP_{t-1} + c_1^{-1}(b_0 - a_0)\lambda\ /\ (\lambda-1) \\
& - c_1^{-1}\ b_2\ \lambda\ \Sigma_{i=0}\ \lambda^i\ E_{t-1}\ RSBMP_{t+i} \\
& - c_1^{-1}\ b_3\ \lambda\ \Sigma_{i=0}\ \lambda^i\ E_{t-1}\ RSBP_{t+i} \\
& - c_1^{-1}\ b_4\ \lambda\ \Sigma_{i=0}\ \lambda^i\ E_{t-1}\ CRCAP_{t+i} \\
& + c_1^{-1}\ a_2\ \lambda\ \Sigma_{i=0}\ \lambda^i\ E_{t-1}\ EXPEN_{t+i} \\
& + c_1^{-1}\ a_3\ \lambda\ \Sigma_{i=0}\ \lambda^i\ E_{t-1}\ RLARDP_{t+i} \\
& + c_1^{-1}\ \lambda\ \Sigma_{i=0}\ \lambda^i\ E_{t-1}\ X_{t+i} \\
& + c_1^{-1}\ c_2\ \lambda\ \Sigma_{i=0}\ \lambda^i\ E_{t-1}\ T_{,t+i} \\
& + c_1^{-1}\ c_3\ \lambda\ \Sigma_{i=0}\ \lambda^i\ E_{t-1}\ RFFR_{t+i} \\
& + c_1^{-1}\ s_1\ \lambda\ \Sigma_{i=0}\ \lambda^i\ E_{t-1}\ D1_{t+i} \\
& + c_1^{-1}\ s_2\ \lambda\ \Sigma_{i=0}\ \lambda^i\ E_{t-1}\ D2_{t+i} \\
& + c_1^{-1}\ s_3\ \lambda\ \Sigma_{i=0}\ \lambda^i\ E_{t-1}\ D3_{t+i} \qquad (5)
\end{aligned}
$$

In order to obtain an observable form for $E_t\ RSBOP_{t+1}$ we compute the multi-step ahead forecasts of exogenous variables by repeated substitution. This requires a previous assessment of the stochastic processes governing each of the exogenous variables. Once this is assessed and an expression for $E_t\ RSBOP_{t+1}$ is obtained, it is substituted into equation (3) and estimated simultaneously. In Annex I and II we go over mathematical procedures.

If we specify that RSBMP, RSBP, CRCAP, EXP, RLARD and X follow autoregressive processes of order one and that RFFR follows a random walk with no drift, we obtain an estimable expression for E_t $RSBOP_{t+1}$ which we substitute into the inventory demand equation:

$$
\begin{aligned}
CO_t = {} & c_0 + (b_0-a_0-c_2)\lambda \,/\, (\lambda-1) \;+\; c_1 \,(\lambda-1)\; RSBOP_t \\
& - b_2\, \lambda\, h_{10} \,/((1-\lambda)(1-\lambda h_{11})) \;-\; (b_2\, \lambda\, h_{11} \,/(1-\lambda h_{11}))\; RSBMP_t \\
& - b_3\, \lambda\, h_{20} \,/((1-\lambda)(1-\lambda h_{21})) \;-\; (b_3\, \lambda\, h_{21} \,/(1-\lambda h_{21}))\; RBP_t \\
& - b_4\, \lambda\, h_{30} \,/((1-\lambda)(1-\lambda h_{31})) \;-\; (b_4\, \lambda\, h_{31} \,/(1-\lambda h_{31}))\; CRCAP_t \\
& + a_2\, \lambda\, h_{00} \,/((1-\lambda)(1-\lambda h_{01})) \;-\; (b_3\, \lambda\, h_{01} \,/(1-\lambda h_{01}))\; EXPEN_t \\
& + a_3\, \lambda\, h_{50} \,/((1-\lambda)(1-\lambda h_{51})) \;+\; (a_3\, \lambda\, h_{51} \,/(1-\lambda h_{51}))\; RLARDP_t \\
& + \quad \lambda\, h_{40} \,/((1-\lambda)(1-\lambda h_{41})) \;+\; (\;\lambda\, h_{41} \,/(1-\lambda h_{41}))\; X_t \\
& + c_2\, T_t \\
& + c_3\, RFFR_t \\
& - s_1\, \lambda \,/\, (1-\lambda^4) \\
& - s_2\, \lambda^2 \,/\, (1-\lambda^4) \\
& - s_3\, \lambda^3 \,/\, (1-\lambda^4) + e_{3t} \qquad (6)
\end{aligned}
$$

As is common in rational expectations models, the structural equation (inventory demand) containing expectations variables (expected prices) not only contains its own shifters but also the solution for the multi-step ahead forecasts of those shifters (both of them in terms of t time). It is immediately clear from equation (6) that the rational expectations hypothesis leads to imposing non-linear cross equation constraints in the estimation. This obviously also leads to the use of non-linear estimation methods.

Testing whether the restrictions hold (are supported by the data) calls for a likelihood ratio test comparing the unrestricted maximum likelihood to the restricted one. An alternative procedure is a Wald test. An estimation of the unrestricted model is needed. Then, it is studied how much the unconstrained estimates fail to satisfy the restrictions. For that purpose analytical expressions of the restrictions are required, these being quite complex to obtain. In Chapter 5 we estimate the model and conduct a likelihood ratio test.

CHAPTER 5

ESTIMATION RESULTS

The linear rational expectations inventory model specified in Chapter 4 was estimated for the U.S. soybean oil market and a test of the rational expectations restrictions was conducted. In what follows we present the results of this analysis.

5.1. Data

Quarterly data are used, starting in the first quarter of 1980 and ending in the third quarter of 1997 for a total of 71 observations. Table 6 details the variables names, units of measurement and the corresponding sources. Price variables are real (in dollar/cents of October 1997), deflated by the Producer Price Index (PPI); personal consumption expenditures are in billions of (1996) dollars and interest rates are real, computed by subtracting the quarterly inflation rate (as per PPI) from the nominal interest rate. Quarterly crushing capacity (three month agregate) is reported in million bushels by the National Oilseed Processors Association. In Annex III data descriptive statistics are presented.

5.2. Exogenous variables processes

Of great importance for model estimation is the determination of the data generating processes for exogenous variables. Exploratory work conducted with different stochastic processes specifications lead us to the conclusion that, for most variables, autoregressive processes of order one are appropiate representations of the data generating processes. Table 6 shows OLS estimates of AR(1) processes for all (seven) exogenous variables.

Table 6. Exogenous variable AR(1) processes

Param	EXPEN	RSBMP	RBP	CRCAP	X	RFFR	RLARD
Const	-0.81	28.76	115.22	1.71	257.08	0.77	272.4
	(-0.04)	(2.08)	(2.43)	(0.20)	(5.70)	(1.74)	(2.23)
AR(1)	1.00	0.88	0.84	1.00	0.27	0.88	0.87
	(211.5)	(15.0)	(13.5)	(47.3)	(2.4)	(15.9)	(15.5)
Q(10)	14.12	12.48	12.06	12.57	7.30	9.83	13.15

Note: t statistics are in parenthesis. Q is Box-Pierce statistic at the 5% level. The chi-square critical value is 18.30

Results obtained also leads us to conclude that all but three (EXPEN, CRCAP and RFFR) exogenous variables follow stationary autoregressive processes of order one. For the three mentioned variables it is not possible to reject the hypothesis of pure random walks. In Table 7 results of Augmented Dickey-Fuller for the mentioned variables are presented. The test included a constant, trend variable and one period lagged first differences.

Table 7. ADF test on EXPEN, CRCAP and RFFR variables

Param	EXPEN	CRCAP	RFFR
Slope	-0.04	-0.15	-0.10
ADF Stat.	-1.19	-1.60	-2.75

Note: MacKinnon critical value is -3.47 at 5% significance level

We modeled EXPEN, CRCAP as AR(1) and allowed for the AR parameter estimates to be generated in the course of the estimation. In contrast, the RFFR stochastic process restriction was analytically imposed.

The seasonal component in the supply equation, as well as the trend component in inventory demand equation were assumed to be known with certainty and the multi-step ahead forecasts drawn upon these variables were computed using this assumption.

5.3. The complete model

The model estimated is:

Structural equations

$$DISS_t = a_0 + a_1\ RSBOP_t + a_2\ EXPEN_t + a_3\ RLARD + e_{1t} \tag{1}$$

$$PROD_t = b_0 + b_1\ RSBOP_t + b_2\ RSBMP_t + b_3\ RBP_t + b_4\ CRCAP_t + s_1\ D1 + s_2\ D2 + s_3\ D3 + e_{2t} \tag{2}$$

$$CO_t = c_0 + c_1\ [E_t\ RSBOP_{t+1} - RSBOP_t] + c_2\ T + c_3\ RFFR + e_{3t} \tag{3}$$

Exogenous variable processes

$$EXPEN_t = h_{00} + h_{01}\ EXPEN_{t-1} \tag{4}$$

$$RSBMP_t = h_{10} + h_{11}\ RSBMP_{t-1} \tag{5}$$

$$RBP_t = h_{20} + h_{21}\ RBP_{t-1} \tag{6}$$

$$CRCAP_t = h_{30} + h_{31}\ CRCAP_{t-1} \tag{7}$$

$$X_t = h_{40} + h_{41}\ X_{t-1} \tag{8}$$

$$RLARD_t = h_{50} + h_{51}\ RLARD_{t-1} \tag{9}$$

Market clearing condition

$$CO_{t-1} + PROD_t = DISS_t + X_t + CO_t$$

5.4. Econometric procedures

Price expectations are non-observable which calls for transformation of the model into an estimable form based only on observed data, as described in Chapter 4. Once this is done econometric estimation of the model is possible. In this study, due to the simultaneous nature of the model, the Full Information Maximum Likelihood (FIML) method was used applying GAUSSX software.

In the course of the estimation, the model and the processes governing exogenous variables were simultaneously estimated. Also, and importantly, the root restriction implied by the model was imposed in the course of the estimation, according to following formula:

$$\lambda = 1+0.5(b_1-a_1)/c_1-0.5((b_1-a_1)/c_1)(1+4c_1/b_1-a_1))^{0.5} \tag{10}$$

Starting parameter values of equations (1) and (2) are based on OLS estimates. Starting values for equations (4) to (9) are based on FIML estimates of these equations. Starting parameter values in equation (3) are 1670 (mean carry over), 0.5, 0 and 0 for the constant term, c_1, c_2 and c_3 respectively. Several combinations of different starting values in this equation resulted in similar results in all cases.

5.5. Results

In Table 8 we report results of the model estimation.

Table 8. FIML parameter estimates

Variable	No.	Param.	Estimate	p Value
Consumption				
Constant	1	a0	506.21	0.08
RSBOP	2	a1	-0.170	0.00
EXPEN	3	a2	0.584	0.00
RLARD	4	a3	0.137	0.03
Production				
Constant	5	b0	-304.50	0.66
RSBOP	6	b1	0.889	0.00
RSBMP	7	b2	15.670	0.00
RBP	8	b3	-7.558	0.00
CRCAP	9	b4	8.509	0.00
D1	10	s1	-47.225	0.62
D2	11	s2	-371.167	0.00
D3	12	s3	-608.317	0.00
Inventories				
Constant	13	c0	3340.595	0.00
Price Aprec.	14	c1	18.117	0.00
Trend	15	c2	-17.974	0.14
RFFR	16	c3	-100.112	0.03
Processes				
Constant	17	h00	1.805	0.93
EXPEN	18	h01	1.007	0.00
Constant	19	h10	11.108	0.10
RSBMP	20	h11	0.952	0.00
Constant	21	h20	8.167	0.63
RBP	22	h21	0.986	0.00
Constant	23	h30	3.504	0.76
CRCAP	24	h31	0.996	0.00
Constant	25	h40	253.871	0.00
X	26	h41	0.378	0.00
Constant	27	h51	332.627	0.11
RLARD	28	h52	0.885	0.00

A total of 28 parameters were estimated. The estimation reached convergence in 95 iterations with a tolerance level of 0.001 and a log-likelihood value of -3514.192.

All structural parameter estimate signs are in accordance with economic theory. The own price elasticity of demand is -0.159 computed when computed at the means, which is in the range of previous studies.

The crucial parameter in the model, c_1, which measures the inventory demand response to expected price appreciation in stocks is positive at 18.12 and is statistically significant at a 5% significance level. The parameters c_2 on the Trend variable is negative but not statistically significant. The parameter c_3 on the interest rates is also statistically significant at a 5% significance level.

Table 9. R^2 and residuals tests

Equation	R^2	D.W.	Order
DISS	0.85	1.537	-
PROD	0.84	0.927	1
CO	0.79	1.566	-

Table 9 shows R^2 statistics for equations (1), (2) and (3) at 0.85, 0.84 and 0.79 respectively. Results on equation (3) show the important explanatory relevance of speculative inventory demand. Our results compare favorably to about an average R^2 of 0.71 in previous studies (Houck, Ryan, and Subotnik, 1972; Meyers and Hacklander, 1979; and Meyers, Helmar and Devadoss, 1986). The results are not strictly comparable as these studies used different specifications and data.

Table 9 also show Durbin-Watson statistics. There is no strong evidence of autocorrelation on equations (1) and (3) as the test statistics lie in the indecisive area. There is, however, evidence of serial autocorrelation in equation (2). Correlogram analysis leads us to believe residuals are follow an AR(1) process.

The inventory demand elasticity with respect to expected price is 28.26 when computed at data means.

The root parameter was estimated, based on the restrictions implied by formula (10), at 0.147. The estimate is consistent with a priori expectations (higher than zero and lower than one) and is consistent with a low degree of serial autocorrelation in quarterly prices.

The results obtained are consistent with economic theory and support the hypothesis that expected future price appreciation plays a role in spot price determination, through inventory demand in the soybean oil market.

5.6. A Test of the rational expectations restrictions

A likelihood ratio test was conducted to test whether the data and our model specification support the rational expectations hypothesis imposed in this study.
The likelihood ratio test as described by Wallis (1980) and Hoffman and Schmidt (1981) consists of comparing the log-likelihood of the restricted and unrestricted model. Specifically, the test statistic is two times the difference between the unrestricted and restricted log likelihood values, under the null that the rational expectations hypothesis is true. The asymptotic distribution of the test statistic is Chi-square with degrees of freedom equal to the number of restrictions being tested. Importantly, the test is a joint test of the rational expectations restrictions and the proposed model specification (the structural equations and exogenous variables stochastic processes).

We conducted an estimation of the unrestricted model under FIML. A total of 34 parameters were estimated. Convergence was achieved in 89 iterations. The log-likelihood is -3506.12.

The critical Chi-square value for 6 degrees of freedom (the number of restrictions) is 12.59 at a 5% significance level. The test statistic value is 16.08, and rejects the null of rational expectations and model specification. The computed test statistic p-value is 1.4%

The test result suggest that the model specification and the rational expectations hypothesis jointly are not supported by the data.

5.7. Limitations of the study

The most important limitations of this study are related to model specification. In particular, the variables are in levels not logs, the latter being the norm in previous studies. The need for consistency between the structural equations and the material balance identity forced our research effort to assume linearity in the levels of the variables. Some studies, however, have relied on log-linear specifications of consumption demand and supply equations.

The convenience yield specification that we used is a very simplified one. Although assuming that inventory levels should increase as the market size increases (in the long run) is a reasonable representation of reality, convenience yield also has short run implications that our simple trend-line specification may not have captured.

Exports were assumed exogenous, in spite of evidence suggesting that they are endogenous.

There is also a limitation on the supply equation. Research efforts tend to show that crushing margins have explanatory power over supply of soybean oil. Our specification, although in line with this approach, did not impose the corresponding parameter restrictions in the supply equation (i.e. b_1= m 0.225, b_2= m 0.011 and b_3=-m). This may explain the resulting autocorrelation evidence.

Finally, our results may be subject to simultaneous equations bias as the prices of soybeans and soybean oil are simultaneously determined with soybean oil prices.

These aspects may explain why the rational expectation restrictions were rejected even though significant parameter estimates in the inventory demand equation were obtained.

Given that rejection of the rational expectations restrictions is a common feature in econometric work it might be worth to explore alternative ways to judge the model performance.

In particular, we have not conducted a test of how well the estimated model predicts (out of sample) price behavior compared to models where inventory demand is not specified or simpler models based on the stochastic properties of the time series. This would also help to assess the model's practical use as a predictive instrument.

CHAPTER 6

CONCLUSIONS

In this study we estimated a linear rational expectations storage model following the tradition of Muth (1961). Our study is the first one to apply this analytic framework to the estimation of a model of the U.S. soybean oil market.

The estimation of such a model requires an observable form of the rational expectation of future prices. To do so in a model-consistent framework, an expectational difference equation must be solved. This results in expected prices depending on multi-step ahead forecasts of exogenous variables. To obtain the later we exploit the time series properties of exogenous variables.

Estimation results are in agreement with theory. Most importantly, the parameter on expected price appreciation of stocks value in the inventory demand equation is of the correct sign and statistically significant, providing evidence of speculative inventory demand. Also, a good fit of the inventory demand equation was obtained.

The results support the hypothesis that expected future prices impact on current prices through inventory demand. This finding contradicts claims made by previous studies indicating that anticipated future market conditions may be unimportant in assessing price prospects for primary commodities.

Our work supports the view that soybean oil inventory demand behavior contributes to price stability.

However, a likelihood ratio test rejected the rational expectations restrictions. It is our view that, although this fact casts doubts on whether the rational expectations hypothesis is a sensible way to model expectations in the soybean oil market, the specification limitations commented in Chapter 5 may be at least part of the explanation.

Importantly, this study shows that statistically significant estimates of the relevant inventory model parameters can be obtained in a linear framework while imposing the rational expectations restrictions in the course of estimation. The non-linearity issue is not a major obstacle to getting reasonable results.

Further work might include an assessment of out-of-sample forecasting power compared to simpler model specifications, since it is important to assess the extent to which price forecasting improves when inventories are modeled. Work should also be oriented towards the estimation of the non-linear inventory model making use of the stochastic dynamic programming algorithm embeded in the maximum likelihood estimator. It would be important to compare results of both estimates of the c_1 parameter and check whether the claim made in the introduction of this study (about the approach implemented in this study to be a reasonable estimator) is actually correct.

ANNEX I

Model

$$Q^d_t = a_0 + a_1 P_t + a_2 X1_t + v_t \tag{1}$$

$$Q^s_t = b_0 + b_1 P_t + b_2 X2_t + u_t \tag{2}$$

$$I_t = c_0 + c_1 [E_t P_{t+1} - P_t] + c_2 X3_t + c_3 X4_t \tag{3}$$

$$I_{t-1} + Q^s_t = Q^d_t + X0_t + I_t \tag{4}$$

where

Q^d_t : Consumption demand

Q^s_t : Production

I_t : Inventory demand

$X1_t$: Consumption demand shifters

$X2_t$: Production shifters

$X3_t$: Inventory demand shifter

$X4_t$: Inventory demand shifter

$X0_t$: Exports

v_t : Random error term

u_t : Random error term

t : Time

To obtain an estimable form of the model we:

<u>substitute (1), (2) and (3) into (4)</u>

$$c_0+c_1[E_{t-1}P_t-P_{t-1}]+c_2X_{3t-1}+c_3X4_{t-1}+b_0+b_1P_t+b_2X2_t+u_t \quad =$$

$$a_0+a_1P_t+a_2X1_t+v_t+X0_t+c_0+c_1[E_tP_{t+1}-P_t]+c_2X3_t+c_3X4_t$$

<u>and operate</u>

$$c_1E_{t-1}P_t-c_1P_{t-1}+c_2X_{3t-1}+c_3X4_{t-1}+b_0+b_1P_t+b_2X2_t+u_t \quad =$$

$$a_0+a_1P_t+a_2X1_t+v_t+X0_t+c_0+c_1E_tP_{t+1}-c_1P_t+c_2X3_t+c_3X4_t$$

<u>We rearrange</u>

$$c_1E_{t-1}P_t-c_1P_{t-1}+b_1P_t-a_1P_t-c_1E_tP_{t+1}+c_1P_t \quad =$$

$$a_0-b_0-c_2X_{3t-1}-c_3X4_{t-1}-b_2X2_t+a_2X1_t+X0_t+c_2X3_t+c_3X4_t-u_t+v_t$$

<u>And regroup</u>

$$c_1E_{t-1}P_t-c_1E_tP_{t+1}+(b_1-a_1+c_1)P_t-c_1P_{t-1} \quad =$$

$$a_0-b_0-c_2X_{3t-1}-c_3X4_{t-1}-b_2X2_t+a_2X1_t+X0_t+c_2X3_t+c_3X4_t-u_t+v_t$$

<u>We take expectations as of t-1</u>

$$c_1E_{t-1}[E_{t-1}\ P_t]-c_1E_{t-1}\ P_{t+1}+(b_1-a_1+c_1)E_{t-1}P_t-c_1E_{t-1}P_{t-1} \quad =$$

$$a_0-b_0-c_2E_{t-1}X_{3t-1}-c_3E_{t-1}X4_{t-1}-b_2E_{t-1}X2_t+a_2E_{t-1}\ X1_t+E_{t-1}X0_t+c_2E_{t-1}\ X3_t$$

$$+c_3E_{t-1}X4_t-E_{t-1}u_t+E_{t-1}v_t$$

By the law of iterative expectations

$$c_1E_{t-1}P_t-c_1E_{t-1}P_{t+1}+(b_1-a_1+c_1)E_{t-1}P_t-c_1E_{t-1}P_{t-1} =$$

$$a_0-b_0-c_2E_{t-1}X_{3t-1}-c_3E_{t-1}X4_{t-1}-b_2E_{t-1}X2_t+a_2E_{t-1}X1_t+E_{t-1}X0_t+c_2E_{t-1}X3_t$$

$$+c_3E_{t-1}X4_t-E_{t-1}u_t+E_{t-1}v_t$$

Rearranging

$$-c_1E_{t-1}P_{t+1}+(b_1-a_1+2c_1)E_{t-1}P_t-c_1E_{t-1}P_{t-1} =$$

$$a_0-b_0-c_2E_{t-1}X_{3t-1}-c_3E_{t-1}X4_{t-1}-b_2E_{t-1}X2_t+a_2E_{t-1}X1_t+E_{t-1}X0_t+c_2E_{t-1}X3_t$$

$$+c_3E_{t-1}X4_t$$

which is

$$E_{t-1}P_{t+1}-c_1^{-1}(b_1-a_1+2c_1)E_{t-1}P_t+E_{t-1}P_{t-1} =$$

$$c_1^{-1}(b_0-a_0)+c_1^{-1}c_2E_{t-1}X_{3t-1}+c_1^{-1}c_3E_{t-1}X4_{t-1}+c_1^{-1}b_2E_{t-1}X2_t-c_1^{-1}a_2E_{t-1}X1_t -$$

$$c_1^{-1}E_{t-1}X0_t-c_1^{-1}c_2E_{t-1}-X3_t-c_1^{-1}c_3E_{t-1}X4_t$$

We operate on the LHS with lagged polynomials

$$E_{t-1}P_{t+1} = L^{-1}E_{t-1}P_t$$

$$E_{t-1}P_{t+1} = L\ E_{t-1}P_t$$

to obtain:

$$L^{-1}E_{t-1}P_t-c_1^{-1}(b_1-a_1+2c_1)E_{t-1}P_t+LE_{t-1}P_t = (L^{-1}+\Theta+L)\ E_{t-1}P_t$$

where

$$c_1^{-1}\ (b_1-a_1+2c_1) = \theta$$

We pre-multiply in both sides of the equation by L

$$\begin{aligned} L\ (L^{-1}+\theta+L)E_{t-1}P_t \ =\ & Lc_1^{-1}(b_0 - a_0) \\ & + c_1^{-1}c_2LE_{t-1}X_{3t-1}+c_1^{-1}c_3LE_{t-1}X4_{t-1} \\ & + c_1^{-1}b_2LE_{t-1}X2_t - c_1^{-1}a_2LE_{t-1}\ X1_t - c_1^{-1}LE_{t-1}X0_t \\ & - c_1^{-1}c_2LE_{t-1}X3_t - c_1^{-1}c_3LE_{t-1}X4_t \end{aligned}$$

to obtain

$$\begin{aligned} (L+\theta L+L^2)E_{t-1}P_t \ =\ & Lc_1^{-1}(b_0-a_0) \\ & + c_1^{-1}c_2E_{t-1}X_{3t-2}+c_1^{-1}c_3E_{t-1}X4_{t-2} \\ & + c_1^{-1}b_2E_{t-1}X2_{t-1}-c_1^{-1}a_2E_{t-1}\ X1_{t-1}-c_1^{-1}E_{t-1}X0_{t-1} \\ & - c_1^{-1}c_2E_{t-1}X3_{t-1}-c_1^{-1}c_3E_{t-1}\ X4_{t-1} \end{aligned}$$

The LHS can be expressed as:

$$(1-\lambda_1L)(1-\lambda_2L)E_{t-1}P_t$$

where

$\lambda_1+\lambda_2 = \theta$ and $\lambda_1\lambda_2 = 1$

which implies

$$\lambda_1 = \lambda_2^{-1}$$

Thus

$$(1-\lambda_1 L)(1-\lambda_2 L)E_{t-1}P_t = Lc_1^{-1}(b_0-a_0)$$

$$+ \quad c_1^{-1}c_2E_{t-1}X3_{t-2}+c_1^{-1}c_3E_{t-1}X4_{t-2}$$

$$+ \quad c_1^{-1}b_2E_{t-1}X2_{t-1}-c_1^{-1}a_2E_{t-1}\,X1_{t-1}-c_1^{-1}E_{t-1}X0_{t-1}$$

$$- \quad c_1^{-1}c_2E_{t-1}X3_{t-1}-c_1^{-1}c_3E_{t-1}\,X4_{t-1}$$

Pre-multiplying both sides by $-(\lambda_2 L^{-1})/(1-\lambda_2 L^{-1})$ yields

$$(1-\lambda_2 L)E_{t-1}P_t = -\lambda_2 L^{-1}Lc_1^{-1}(b_0-a_0)/(1-\lambda_2 L^{-1})$$

$$+(\lambda_2 c_1^{-1}c_2)/(1-\lambda_2 L^{-1})E_{t-1}X3_{t-2}+(\lambda_2 c_1^{-1}c_3)/(1-\lambda_2 L^{-1})E_{t-1}X4_{t-2}$$

$$+(\lambda_2 c_1^{-1}b_2)/(1-\lambda_2 L^{-1})E_{t-1}X2_{t-1}-(\lambda_2 c_1^{-1}a_2)/(1-\lambda_2 L^{-1})E_{t-1}\,X1_{t-1}$$

$$-\ (\lambda_2 c_1^{-1})/(1-\lambda_2 L^{-1})E_{t-1}X0_{t-1}-(\lambda_2 c_1^{-1}c_2)/(1-\lambda_2 L^{-1})E_{t-1}X3_{t-1}$$

$$-(\lambda_2 c_1^{-1}c_3)/(1-\lambda_2 L^{-1})E_{t-1}X4_{t-1}$$

Note that:

$$-(\lambda_2 L^{-1})(1-\lambda_2 L)/(1-\lambda_2 L^{-1}) = 1$$

Also that:

$$-\lambda_2 L^{-1}Lc_1^{-1}(b_0-a_0)/(1-\lambda_2 L^{-1}) = c_1^{-1}(b_0-a_0)\lambda_2/(\lambda_2-1)$$

Thus we obtain (dropping the subscript on λ_2)

$$
\begin{aligned}
E_{t-1}P_t = \lambda\ P_{t-1} &+ c_1^{-1}(b_0-a_0)\lambda/(\lambda-1) \\
&+ \lambda c_1^{-1}a_2 \textstyle\sum_{i=0} \lambda^i\ E_{t-1}\ X1_{t+i} \\
&- \lambda c_1^{-1}b_2 \textstyle\sum_{i=0} \lambda^i\ E_{t-1}\ X2_{t+i} \\
&+ \lambda c_1^{-1}c_2 \textstyle\sum_{i=0} \lambda^i\ E_{t-1}\ X3_{t+i} \\
&+ \lambda c_1^{-1}c_2 \textstyle\sum_{i=0} \lambda^i\ E_{t-1}\ X4_{t+i} \\
&+ \lambda c_1^{-1} \textstyle\sum_{i=0} \lambda^i\ E_{t-1}\ X0_{t+i} \\
&- \lambda c_1^{-1}c_2 \textstyle\sum_{i=0} \lambda^i\ E_{t-1}\ X3_{t+i-1} \\
&- \lambda c_1^{-1}c_3 \textstyle\sum_{i=0} \lambda^i\ E_{t-1}\ X4_{t+i-1}
\end{aligned}
$$

If we assume that X0, X1 and X2 follow AR(1) processes such that:

$$X0_t = h_{40} + h_{41}\ X0_{t-1} + e_{0t}$$

$$X1_t = h_{10} + h_{11}\ X1_{t-1} + e_{1t}$$

$$X2_t = h_{20} + h_{21}\ X2_{t-1} + e_{2t}$$

then (see Annex II):

$$
\begin{aligned}
\lambda c_1^{-1} \textstyle\sum_{i=0} \lambda^i\ E_{t-1}\ X0_{t+i} = &\ (\lambda c_1^{-1}h_{40})/((1-\lambda)(1-\lambda h_{40})) \\
&+ ((\lambda c_1^{-1}h_{41})/(1-\lambda h_{41}))X0_{t-1}
\end{aligned}
$$

$$
\begin{aligned}
\lambda c_1^{-1}a_2 \textstyle\sum_{i=0} \lambda^i\ E_{t-1}\ X1_{t+i} = &\ (\lambda c_1^{-1}h_{10}a_2)/((1-\lambda)(1-\lambda h_{10})) \\
&+ ((\lambda c_1^{-1}h_{11}a_2)/(1-\lambda h_{11}))X1_{t-1}
\end{aligned}
$$

$$\lambda c_1^{-1}b_2 \sum_{i=0} \lambda^i E_{t-1} X2_{t+i} = (\lambda c_1^{-1}h_{20}b_2)/((1-\lambda)(1-\lambda h_{20}))$$

$$+ ((\lambda c_1^{-1}h_{21}b_2)/(1-\lambda h_{21}))X2_{t-1}$$

<u>If a component of the $X2_t$ vector is a seasonal dummy variable (see Annex II), then:</u>

$$\lambda c_1^{-1}s_1 \sum_{i=0} \lambda^i E_{t-1} D1_{t+i} = \lambda c_1^{-1}s_1/(1-r^4)$$

<u>If we assume that X3 is a trend variables and X4 follows a random walk (see Annex) then:</u>

$$\lambda c_1^{-1}c_2 \sum_{i=0} \lambda^i E_{t-1} X3_{t+i} = (\lambda c_1^{-1}c_2)/(1-\lambda)^2$$

$$+ ((\lambda c_1^{-1}c_2)/(1-\lambda))X3_{t-1}$$

$$\lambda c_1^{-1}c_2 \sum_{i=0} \lambda^i E_{t-1} X3_{t+i-1} = (\lambda^2 c_1^{-1}c_2)/(1-\lambda)^2$$

$$+ ((\lambda c_1^{-1}c_2)/(1-\lambda))X3_{t-1}$$

$$\lambda c_1^{-1}c_3 \sum_{i=0} \lambda^i E_{t-1} X4_{t+i} = ((\lambda c_1^{-1}c_2)/(1-\lambda))X4_{t-1}$$

$$\lambda c_1^{-1}c_3 \sum_{i=0} \lambda^i E_{t-1} X4_{t+i-1} = ((\lambda c_1^{-1}c_2)/(1-\lambda))X4_{t-1}$$

<u>Thus we obtain following expression for $E_{t-1}P_t$</u>

$$E_{t-1}P_t = \lambda P_{t-1} + c_1^{-1}(b_0-a_0)\lambda/(\lambda-1)$$

$$+ (\lambda c_1^{-1}h_{10}a_2)/((1-\lambda)(1-\lambda h_{10})) + ((\lambda c_1^{-1}h_{11}a_2)/(1-\lambda h_{11}))X1_{t-1}$$

$- (\lambda c_1^{-1}h_{20}b_2)/((1-\lambda)(1-\lambda h_{20})) - ((\lambda c_1^{-1}h_{21}b_2)/(1-\lambda h_{21}))X2_{t-1}$

$+ (\lambda c_1^{-1}h_{40})/((1-\lambda)(1-\lambda h_{40})) + ((\lambda c_1^{-1}h_{41})/(1-\lambda h_{41}))X0_{t-1}$

$- (\lambda c_1^{-1}s_1/(1-r^4))$

$+ (\lambda c_1^{-1}c_2)/(1-\lambda)^2 - (\lambda^2 c_1^{-1}c_2)/(1-\lambda)^2$

which we lead one period

$E_tP_{t+1} = \lambda P_t + c_1^{-1}(b_0-a_0)\lambda/(\lambda-1)$

$+ (\lambda c_1^{-1}h_{10}a_2)/((1-\lambda)(1-\lambda h_{10})) + ((\lambda c_1^{-1}h_{11}a_2)/(1-\lambda h_{11}))X1_t$

$- (\lambda c_1^{-1}h_{20}b_2)/((1-\lambda)(1-\lambda h_{20})) - ((\lambda c_1^{-1}h_{21}b_2)/(1-\lambda h_{21}))X2_t$

$+ (\lambda c_1^{-1}h_{40})/((1-\lambda)(1-\lambda h_{40})) + ((\lambda c_1^{-1}h_{41})/(1-\lambda h_{41}))X0_t$

$- (\lambda c_1^{-1}s_1/(1-r^4))$

$+ (\lambda c_1^{-1}c_2)/(1-\lambda)^2 - (\lambda^2 c_1^{-1}c_2)/(1-\lambda)^2$

Note that

$(\lambda c_1^{-1}c_2)/(1-\lambda)^2 - (\lambda^2 c_1^{-1}c_2)/(1-\lambda)^2$

$= -(\lambda c_1^{-1}c_2)/(\lambda-1)$

We substitute E_tP_{t+1} in equation (3) to obtain

$I_t = c_0 + c_1[\lambda P_t + c_1^{-1}(b_0-a_0)\lambda/(\lambda_2-1)$

$+ (\lambda c_1^{-1}h_{10}a_2)/((1-\lambda)(1-\lambda h_{10})) + ((\lambda c_1^{-1}h_{11}a_2)/(1-\lambda h_{11}))X1_t$

$- (\lambda c_1^{-1}h_{20}b_2)/((1-\lambda)(1-\lambda h_{20})) - ((\lambda c_1^{-1}h_{21}b_2)/(1-\lambda h_{21}))X2_t$

$+ \ (\lambda c_1^{-1}h_{40})/((1-\lambda)(1-\lambda h_{40})) \ + \ ((\lambda c_1^{-1}h_{41})/(1-\lambda h_{41}))X0_t$

$- \ (\lambda c_1^{-1}s_1/(1-r^4)) \ -((\lambda c_1^{-1}c_2)/(\lambda-1)) \ - \ Pt]$

$+ \ c_2X3_t \ + \ c_3X4_t$

<u>which is</u>

$I_t \ = c_0 + c_1\lambda P_t \ + (b_0-a_0-c_2)\lambda/(\lambda-1)$

$+ \ (\lambda h_{10}a_2)/((1-\lambda)(1-\lambda h_{10})) \ + \ ((\lambda h_{11}a_2)/(1-\lambda h_{11}))X1_t$

$- \ (\lambda h_{20}b_2)/((1-\lambda)(1-\lambda h_{20})) \ - \ ((\lambda h_{21}b_2)/(1-\lambda h_{21}))X2_t$

$+ \ (\lambda h_{40})/((1-\lambda)(1-\lambda h_{40})) \ + \ ((\lambda h_{41})/(1-\lambda h_{41}))X0_t$

$- \ (\lambda s_1/(1-r^4))$

$+ \ c_2 \ X3_t \ + \ c_3X4_t$

<u>Thus estimate the model</u>

(1) $Q^d{}_t \ = a_0 + a_1 \ P_t + a_2 \ X1_t \ + v_t$

(2) $Q^s{}_t \ = b_0 + b_1 \ P_t + b_2 \ X2_t \ + u_t$

(4) $I_t \ = c_0 + c_1(\lambda-1)P_t \ + (b_0-a_0-c_2)\lambda/(\lambda-1)$

$+ \ (\lambda h_{10}a_2)/((1-\lambda)(1-\lambda h_{10})) \ + \ ((\lambda h_{11}a_2)/(1-\lambda h_{11}))X1_t$

$- \ (\lambda h_{20}b_2)/((1-\lambda)(1-\lambda h_{20})) \ - \ ((\lambda h_{21}b_2)/(1-\lambda h_{21}))X2_t$

$+ \ (\lambda h_{40})/((1-\lambda)(1-\lambda h_{40})) \ + \ ((\lambda h_{41})/(1-\lambda h_{41}))X0_t$

$- \ (\lambda c_1^{-1}s_1/(1-r^4))$

$+ \ c_2 \ X3_t \ + \ c_3X4_t$

(5) $X0_t = h_{40} + h_{41}\, X0_{t-1} + e_{0t}$

(6) $X1_t = h_{10} + h_{11}\, X1_{t-1} + e_{1t}$

(7) $X2_t = h_{20} + h_{21}\, X2_{t-1} + e_{2t}$

and impose the root restriction

$\lambda = 1 + 0.5(b_1-a_1)/c_1 - 0.5((b_1-a_1)/c_1)(1+(4c_1/(b_1-a_1))^{0.5}$

ANNEX II

We look for an estimable form if the multi-step ahead forecasts of exogenous variables:

$\sum_{i=0} \lambda^i E_{t-1}X_{t+i}$ where $|\lambda| < 1$

If we assume that X follows an AR(1) process:

$X_t = h_0 + h_1 X_{t-1} + e_t$; where $|h_1| < 1$; $e_t \sim D(0,\sigma)$

then

$$E_{t-1}X_t = E_{t-1}[h_0 + h_1 X_{t-1} + e_t]$$

$$= h_0 + h_1 X_{t-1}$$

$$E_{t-1}X_{t+1} = E_{t-1}[h_0 + h_1 X_t + e_{t+1}]$$

$$= h_0 + h_1 E_{t-1}X_t$$

$$= h_0 + h_1[h_0 + h_1 X_{t-1}]$$

$$= h_0 + h_1h_0 + h_1^2 X_{t-1}$$

$$= h_0(1 + h_1) + h_1^2 X_{t-1}$$

$$E_{t-1}X_{t+2} = E_{t-1}[h_0 + h_1 X_{t+1} + e_{t+2}]$$

$$= h_0 + h_1 E_{t-1}X_{t+1}$$

$$= h_0 + h_1[h_0 + h_1h_0 + h_1^2 X_{t-1}]$$

$$= h_0 + h_1h_0 + h_1^2h_0 + h_1^3 X_{t-1}$$

$$= h_0(1 + h_1 + h_1^2) + h_1^3 X_{t-1}$$

$$E_{t-1}X_{t+i} = h_0(1 + h_1 + h_1^2 \ldots h_1^i) + h_1^{i+1} X_{t-1}$$

<u>Now</u>

$$\textstyle\sum_{i=0} \lambda^i E_{t-1}X_{t+i} = \sum_{i=0} \lambda^i [h_0(1 + h_1 + h_1^2 \ldots h_1^i) + h_1^{i+1} X_{t-1}]$$

$$\textstyle\sum_{i=0} \lambda^i E_{t-1}X_{t+i} = \sum_{i=0} \lambda^i [h_0(1 + h_1 + h_1^2 \ldots h_1^i)] + \sum_{i=0} \lambda^i h_1^{i+1} X_{t-1}$$

$$\textstyle\sum_{i=0} \lambda^i E_{t-1}X_{t+i} = (h_0/((1-\lambda)(1-\lambda h_1)) + (h_1/(1-\lambda h_1)) X_{t-1}$$

<u>If $X_t = h_1 X_{t-1} + e_t$; where $|h_1| < 1$; $e_t \sim D(0,\sigma)$, then</u>

$$\textstyle\sum_{i=0} \lambda^i E_{t-1}X_{t+i} = (h_1/(1-\lambda h_1)) X_{t-1}$$

<u>If $X_t = 1 + X_{t-1} + e_t$;where $e_t \sim D(0,\sigma)$, then</u>

$$\textstyle\sum_{i=0} \lambda^i E_{t-1}X_{t+i} = 1/(1-\lambda)^2 + (1/(1-\lambda)) X_{t-1}$$

<u>If $X_t = X_{t-1} + e_t$;where $e_t \sim D(0,\sigma)$, then</u>

$$\textstyle\sum_{i=0} \lambda^i E_{t-1}X_{t+i} = (1/(1-\lambda)) X_{t-1}$$

<u>The seasonal components muti-step ahead forecasts are:</u>

$$\textstyle\sum_{i=0} \lambda^i E_{t-1}D1_{t+i} =$$

$$\textstyle\sum_{i=0} \lambda^i E_{t-1}D2_{t+i} =$$

$$\textstyle\sum_{i=0} \lambda^i E_{t-1}D3_{t+i} =$$

where

$$\sum_{i=0} \lambda^i E_{t-1}D1_{t+i} = \lambda^0 E_{t-1}D1_{t+0} + \lambda^1 E_{t-1}D1_{t+1} + \lambda^2 E_{t-1}D1_{t+2}$$

$$\lambda^3 E_{t-1}D1_{t+3} + \lambda^4 E_{t-1}D1_{t+4} \dots \lambda^i E_{t-1}D1_{t+I}$$

Since D1 is defined such that

$D1_{t+0} = 1$;(first quarter)

$D1_{t+1} = 0$;(second quarter)

$D1_{t+2} = 0$;(third quarter)

$D1_{t+3} = 0$;(fourth quarter)

Then:

$$\sum_{i=0} \lambda^i E_{t-1}D1_{t+i} = \lambda^0 (1) + \lambda^1 (0) + \lambda^2 (0) + \lambda^3 (0)$$

$$\lambda^4 (1) + \lambda^5 (0)\dots$$

which is

$$\sum_{i=0} \lambda^i E_{t-1}D1_{t+i} = \lambda^0 + \lambda^4 + \lambda^8 \dots = 1/(1-\lambda^4)$$

In the same fashion we can compute

$$\sum_{i=0} \lambda^i E_{t-1}D2_{t+i} = \lambda^1 + \lambda^5 + \lambda^9\dots = \lambda/(1- \lambda^4)$$

$$\sum_{i=0} \lambda^i E_{t-1}D3_{t+i} = \lambda^2 + \lambda^6 + \lambda^{10}\dots = \lambda^2/(1- \lambda^4)$$

ANNEX III

Descriptive statistics

Variable name	Acronym	Mean	Std.Dev	Minimum	Maximum
Carry In	CI	1666.5	534.7	632.0	2893.0
Production	PROD	3235.9	454.7	2316.0	4303.0
Imports	M	3.4	7.6	0.0	36.0
Exports	X	415.7	191.6	72.0	1149.0
Dissapereance	DISS	2818.3	424.1	2064.0	3810.0
Carry Out	CO	1671.8	529.9	632.0	2893.0
Real SBO price	RSBOP	2637.8	561.0	1887.5	4365.0
Real SBM price	RSBMP	233.5	45.1	151.2	354.1
Real Bean price	RBP	750.8	129.9	581.0	1132.4
Real Lard price	RLARD	2114.4	581.2	1375.5	3725.1
Expenditures	EXPEN	4222.7	674.8	3149.2	5453.1
Crush capacity	CRCAP	407.3	32.0	347.1	482.7
Real F.F. Rate	RFFR	7.2	3.3	2.0	16.9

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