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Structural and forecasting softwood lumber models with a time series approach

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STRUCTURAL AND FORECASTING SOFTWOOD LUMBER MODELS WITH A TIME SERIES APPROACH

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Abstract

The development of cointegration theories and the presence of nonstationarity in time series raised serious concerns about possible spurious estimations in forest products models. Based on the results of Hsiao (1997a, 1997b), all the virtues of two-stage least square (2SLS) hold if there are sufficient cointegration relations. Stationary null and nonstationary null unit root tests and monthly seasonal unit root tests were applied to the time series used in this dissertation. Cointegration tests with exogenous variables were performed to justify the 2SLS. A regional error correction model (ECM) with four regional lumber supply and demand equations and a U.S.-Canada supply and demand ECM were estimated. CUSUM tests did not find any structural changes. Both estimated models showed that the imported Canadian lumber and the U.S. lumber are substitutes. The estimated long-run and short-run own-price elasticities for demand and supply are inelastic for all the equations but the short-run supply equation for the West Coast. The long-run lumber supply equations have significant trends: annually -3% for the Inland West and 2% for the other regions. The popular maximum likelihood estimation for the restricted ECM cannot pass the test for the restrictions and is, therefore, not used for the regional structural lumber model.

A series of univariate and multi-equation models were used as forecasting models. A combination of univariate model were shown to be the best forecasting models for lumber prices, and a combination of univariate and multi-equation models were shown to be the best forecasting models for lumber quantities. The selected combinations of models were shown to be the best with additional observations. It was also shown that lumber quantities could be forecasted better than lumber prices.

Chapter 1 Introduction

Lumber is timber, also called roundwood, sawn into convenient sizes of beams, planks and boards. Lumber dominates the forest product market in the United States. Half of all the timber produced in the United States has been sawn into lumber. In 2002, 10 out of the total 20 billion cubic feet of timber consumed and 7 out of the 16 billion cubic feet of timber produced in the United States were sawn into lumber (Howard, 2003, Table 5a).

This research will study only the softwood lumber market of the United States. “Lumber” hereafter means softwood lumber unless otherwise stated. In 2002, 8 out of 13 billion cubic feet of softwood timber consumed and 5 out of 10 billion cubic feet of softwood timber produced in the United States were sawn into softwood lumber (Howard, 2003, Table 6a). Softwood lumber is mainly used for housing construction in the United States. The softwood lumber supply of the United States comes from four major regions--the West Coast, the Inland West, the South, and Canada. The West Coast and the Inland West contribute about one third of the total softwood lumber supply. The South and Canada each provide about the other one third of the total softwood lumber supply of the United States.

The West Coast comprises the coastal region of Washington and Oregon, west of the Cascade Range, and coastal California. The West Coast mainly produces lumber from Douglas-Fir (*Pseudotsuga menziesii*) and hem-fir, which is a mix of western hemlock (*Tsuga heterophylla*) and several kinds of true firs (genus *Abies*). In addition, the West Coast produces a significant amount of redwood (*Sequoia sempervirens*). The Inland

West includes eastern Oregon, eastern Washington, California (except the redwood region), Nevada, Idaho, Montana Wyoming, Utah, Colorado, Arizona, New Mexico, and a portion of South Dakota. Main species of the Inland West are pines, spruces, true firs, and Douglas-Fir. Pines include Ponderosa pine (*Pinus ponderosa*), lodgepole pine (*Pinus contorta*), and western white (Idaho) pine (*Pinus strobes*). The South covers Alabama, Arkansas, Florida, Georgia, Kentucky, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, and Virginia. The South mainly produces lumber of southern pines, which includes loblolly pine (*Pinus taeda*), slash pine (*Pinus elliottii*), longleaf pine (*Pinus palustris*), and shortleaf pine (*Pinus echinata*). These southern pines have similar wood properties and are thus almost completely substitutable. Collectively, they are also called the "southern yellow pines." According to Camp (2005), about 69% of the cost of southern pine lumber production is timber cost; 18% of the cost is labor cost.

Lumber imported from Canada is mostly Spruce-Pine-Fir (SPF). It is a mixture of spruces, pines and firs. They come mainly from British Columbia and Alberta. Properties of SPF from Canada are similar to those of the lumber from the Inland West.

The lumber market of the United States is a highly competitive market with several thousand sawmills each having a small market share. According to the 2002 Economic Census published in 2005 (accessible at http://www.census.gov/prod/ec02/ec0231i321113.pdf), there were a total of 3807 lumber companies with 1099 of them, less than a third, having 20 or more employees in 2002. Canadian suppliers are generally larger, but the market power of these companies in the international market is limited. The demand for lumber was determined largely by housing construction. Lumber

production and consumption of the United States have been closely following the fluctuation in housing starts over time.

There are two different approaches in studying the softwood lumber market. One is the stationary approach based on the assumption that all variables are stationary, and the other is the nonstationary approach based on cointegration theories. Examples of the stationary approach include Buongiorno (1979), Haji-Othman (1991), Lewandrowski et al. (1994), Bernard et al. (1997), Zhang and Sun (2001), and Rao et al. (2004). In the stationary approach, Ordinary Least Squares (OLS) was the basic method although data series used may be nonstationary. However, Granger and Newbold (1974) suggested that estimates of OLS with nonstationary data are spurious and may result in misleading conclusions. Integration and cointegration theories have been developed to solve this problem. Models based on newly developed theories of time series may greatly improve results of the regression and provide a better insight into lumber demand and supply.

Past research on lumber using the cointegration approach includes papers on cointegration tests of the "law of one price" for softwood lumber (e. g. Jung and Doroodian, 1994, Nanang, 2001, Yin et al. 2005). Although these papers on the law of one price for softwood lumber considered unit root and cointegration, they only tested cointegration among prices.

Since a specific model may be better than others for making forecasts of a specific number of steps ahead, it is necessary to find the best combination of forecasting models for forecasts of different number of steps ahead of the estimation period. Quantities and prices have different properties, the best models for two groups of variables should be chosen separately. Past forecasting models (Adam and Haynes, 1980; Kallio et al. 1987;

Sedjo and Lyon, 1990; Abt et al. 2000) used one model to forecast for any steps ahead of sample data, and the nonstationary was not considered.

One purpose of the dissertation is to find models and regression methods that will best explain dynamic and long-run relationships among variables of the lumber market in the United States. With unit roots and cointegration treatments, all results will be free of any problem caused by nonstationarity and therefore be more reliable. Another purpose is to find a combination of models to forecast lumber quantities and prices. A procedure for selecting the best models for rolling forecasting will be shown in this dissertation. The third purpose of the dissertation is to present an example of the application of integration and cointegration theories in forestry. Nonstationary null and stationary null unit root tests, unrestricted and restricted cointegration tests, and estimations of restricted Error Correction Models with MLE and 2SLS will all be included. The robustness of the two-stage least squares (2SLS) will be shown.

This dissertation is the first study estimating structural models of U.S. forest products with cointegration theories. It is also the first study estimating ECM using 2SLS (Hsiao, 1997a, 1997b) in modeling forest products. The idea of finding the best model for a forecast of a specific step ahead is different from all other methods used in forecasting forest products.

Chapter 2 of the dissertation will review past studies on structural and forecasting models for lumber, and recent econometric studies on nonstationary time series. Chapter 3 will discuss relevant theories and methods. Chapter 4 will discuss sources and properties of data that will be used in this dissertation. Unit root tests will be performed in this chapter to show the nonstationarity of these time series.

Chapter 5 of the dissertation will focus on studying both supply and demand of the lumber market with regional simultaneous equations models. The Error Correction Model (ECM) will be estimated in two steps according to the results of Hsiao (1997a, 1997b). In the first step, a 2SLS will be applied to the long-run model, and long-run elasticities of lumber demand and supply of all the regions will be obtained. Residuals of estimations will be tested for possible breaking points to make sure that the estimated model is valid during the observation period. Since the long-run model will include equations for the four supply regions, substitution and complementation of the lumber from different regions will be discussed. The dynamic model will be estimated in the second step and the short-run own-price and cross-price elasticities will be discussed. In addition to the regional simultaneous equations model, a U.S.-Canada model will be analyzed for both the short-run and long-run. The Maximum Likelihood Method suggested by Johansen and Juselius (1990) will be applied to the regional structural ECM to show why this popular method does not always work.

Chapter 6 will estimate two groups of models for multi-step-forward forecasts, and then evaluate the accuracy of their out-of-sample forecasts. One group of models will be univariate models and the other group of models will be multi-equations models. The purpose of chapter 6 is to find the best combinations of forecasting models for both lumber quantities and lumber prices. The selected best combinations of forecasting models will then be used against data from the most recent two years to validate the models. Chapter 7 will present the conclusion of this study.

Chapter 2 Literature Review

This chapter will first summarize the important studies in modeling lumber and other forest products. Following the summaries will be a brief review of the developments of econometric theories about cointegration and the Error Correction Model.

2.1 Structural Models

Several models of the lumber market have been developed. The paper by Lewandrowski et al. (1994) represents by far the most accomplished study of such models. It used monthly data to model the demand and supply system. Lumber inventory was used as a shifter in the supply equations. The two-stage least squares (2SLS) method was employed to estimate the model for three regions of the United States and Canada. The autoregressive specification, the inclusion of lumber inventory and price expectation helped improve models. Most of the signs of the estimated parameters were as expected. According to its results, production was positively affected by price expectations and negatively affected by beginning inventories. Sales decisions were negatively influenced by price expectations and positively influenced by beginning inventories. The paper did not find significant cross-price effects between regions within the United States, but between Canada and regions of the United States. The idea of using an ARMA model to forecast expected prices and including the forecasted prices into the lumber model is an important contribution in modeling the market of forest products. The ARMA model produced forecasts of prices for the current month. Such forecasts helped improve the forecast of the production in the current month. The major shortcoming of this paper is its failure to consider the nonstationarity problem.

Zhang and Sun (2001) examined lumber price volatility. The volatility was measured by the standard deviation and the coefficient of variation. Exogenous variables include dummy variables for periods, changes of housing starts, and timber availability that were measured by the uncut volume contracted. The model was estimated without checking the nonstationarity that may exist for some of the variables. They concluded that the lumber prices in the 1990s were more volatile than those in the 1980s. The US-Canada Softwood Lumber Agreement and variations of housing start were said to be the source of the volatile lumber prices of the 1990s. Haji-Othman (1991) used a market share approach to assess the degree of price competitiveness of rough and dressed Malaysian lauan lumber in the import market of the United States. This model was based on the partial adjustment and adaptive expectation model. However, it was reduced to a level data model for estimation. Quarterly data for hardwood lumber price, exchange rate, quantity and value of import of the two kinds of lauan lumber, and personal income were included in the model. This paper concluded that the Malaysian lauan lumber is price competitive in the United States. Other early lumber models included that of Adams and Haynes (1980, 1986), Buongiorno et al. (1979), Chen et al. (1988), Luppold (1984), McKillop et al. (1980), Robinson (1974), and Wiseman and Sedjo (1981), but none of them employed unit root tests to check for nonstationarity.

In recent years, cointegration theories were applied to modeling forest products market. Following Johansen and Juselius (1990), Jung and Doroodian (1994) tested the law of one price for U.S. softwood lumber with a cointegration test. The time series included lumber prices of the Northeast, the North Central, the South and the West. Its results supported the hypothesis of the “law of one price”. Nanang (2001) tested the law

of one price for five regional markets of Canadian softwood lumber following the same procedure. He also conducted pair-wise tests for five prices, and concluded that the law of one price did not hold for the Canadian softwood lumber markets. His result suggested there is no single market for softwood lumber in Canada. Yin and Baek (2005) concluded that the law of one price holds for the entire U.S. softwood lumber market. Jung and Doroodian (1994), Nanang (2001), and Yin and Baek (2005) tested unit roots with the Augmented Dickey-Fuller (ADF) test and showed that all of the relevant price data for both Canada and United States are integrated of order one, or $\boldsymbol{I}(1)$.

Some papers for forest products other than lumber also tried to apply the newly developed cointegration theories. The paper by Buongiorno and Uusivuori (1992) was the first attempt to test the law of one price in U.S. exports of pulp and paper. Follow-ups include Alavalapati et al. (1997), for prices of imported Canadian pulp and U.S. pulp, and Hänninen (1998) for United Kingdom soft sawnwood imports. Buongiorno and Uusivuori (1992) and Alavalapati et al. (1997) concluded that the law of one price held with their data. Hänninen (1998) confirmed one cointegration relation, but concluded that the law of one price held only for one pair of prices. After finding that there were only three to six cointegration vectors for each of the 10-series group, Yin et al. (2002) concluded that the law of one price did not hold for both the sawtimber and pulpwood markets.

There were also applications of cointegration theories to structural models for forest products. Toppinen (1998) applied ECM to the Finnish sawlog market with monthly data and interpreted cointegration vectors as long-run equilibrium relationships between variables. All the data in his model were log-transformed before estimation. ADF tests

for five variables showed that all variables but the wood quantity (i.e. demand and supply) had unit roots. Still the stationary variable was included in the cointegration test. The cointegration test resulted in two cointegration vectors. Following Johansen and Juselius (1994), Toppinen believed that it was necessary to build the system by including at least one variable that was strongly correlated with demand and uncorrelated with supply, and vice versa. Long-run and short-run demand and supply were estimated. Heikkinen (2002) studied the co-integration of timber and financial markets by means of Vector Error Correction Model (VECM), and compared the results with Vector Autoregressive Model (VAR model). He found that, although forestry returns lacked a close relationship with the other types of assets in the short-run, in the long-run forest returns were important to predict the overall asset returns.

2.2 Forecasting Models

Only a few forecasting models have been published in the forestry literature, and they are mainly long-run forecasting models. The Softwood Timber Assessment Market Model (TAMM, Adams and Haynes, 1980), the Subregional Timber Supply Model (SRTS, Abt et al. 2000), the Center for International Trade in Forest Products Global Trade Model (CGTM, Kallio et al. 1987), and the Global Timber Supply Model (TSM, Sedjo and Lyon, 1990) are major timber forecasting models. TAMM is a part of the System of Models of the 2000 RPA[*] Assessment (http://www.fs.fed.us/pnw/sev/rpa/model.htm, accessed 2/24/2006). TAMM and CGTM are static models based on ordinary least square method with level data. The Subregional Timber Supply (SRTS)

[*] The Forest and Rangeland Renewable Resources Planning Act of 1974 (RPA) requires the Secretary of Agriculture to conduct an assessment of the Nation's renewable resources once every 10 years (http://www.fs.fed.us/pnw/sev/rpa/aboutrpa.htm, accessed 2/24/2006).

model was based on the log-linear timber demand and supply function. Although TSM is an optimal control model, parameters were either estimated by OLS or predetermined by intertemporal adjustment (i.e. those for timber supply). These models assumed that the time series data used for their estimation are stationary.

2.3 Time Series and Econometric Methods

Before the development of cointegration theory (Granger, 1981, Engle and Granger, 1987) and the maximum likelihood estimation method for Error Correction Models (Johansen, 1988, Johansen and Juselius, 1990), the most popular method for time series analysis was the Box-Jenkins method (Box and Jenkins, 1970). This method shifted the attention of time series analysis from a stationary paradigm to the autoregressive integrated moving average [ARIMA (p,d,q)] paradigm. The basics of the Box-Jenkins method can be found in textbooks (e.g. Hamilton, 1994). This method is feasible but largely dependent on the experience of the econometricians who used the methodology. Unit root tests such as the ADF test (Dickey and Fuller, 1979, Said and Dickey, 1984) and PP test (Phillips and Perron, 1988), and methods for Error Correction Models made time series analysis more efficient. Methods based on cointegration theories started a new era of estimation with time series. When some nonstationary series drift together, rather than moving apart, these time series may have equilibriums in the long run. Engle and Granger (1987) showed that, when there are cointegration relations, Error Correction Models (ECM) are the data generating functions, combining a dynamic short-run process and a long-run equilibrium. When there exist unit roots but no cointegration relations, OLS with level data is no longer valid. However, when there is a cointegration relation, the OLS estimator is super-consistent and is valid again. Johansen (1988) and Johansen

and Juselius (1990, 1992 1994) developed maximum likelihood methods that can test the number of cointegration relations for a set of data with some restrictions and estimate the ECM. Hsiao (1997a, 1997b) showed that, with integrated variables and cointegration, 2SLS estimators for structural and dynamic simultaneous equations models are consistent, and all the virtues of the relevant tests hold. Robledo (2002) attempted in his dissertation to derive a 2SLS estimator for simultaneous equations models with seasonal cointegration.

The earliest seasonal unit root method is the DHF test (Dickey, Hasza, and Fuller, 1984). It is an ad hoc test and its null was shown to imply four unit roots (Engle et al., 1993). EGHY (Engle et al., 1993) was designed to test units at different frequencies simultaneously. Two-step methods (Hylleberg et al., 1990, Engle et al. 1993) similar to Engle and Granger (1987) can test seasonal cointegration. Lee (1992) developed a maximum likelihood test on cointegration similar to Johansen (1988). Lee showed that several null hypotheses could be tested separately for each case of interest without any prior knowledge about the existence of cointegration relationships at other frequencies. Johansen and Schaumburg (1999) improved upon Lee (1992) and derived the asymptotic distribution of estimates in the context of a vector autoregressive model.

Chow (1960) developed the earliest test for structural breaks in the economic literature. Dufour (1982) extended these tests to the case of multiple regimes. Lo and Newey (1985) and Park (1991) extended these tests to simultaneous equations. Brown et al. (1975) suggested the cumulated sum of residual (CUSUM) test. Both the Chow and CUSUM tests were extended to models with unknown breaks by many studies. Quandt (1960) developed a likelihood ratio (LR) test for unknown break points. Kim and

Siegmund (1989) found the distribution of the test as a function of Wiener processes. Bai (1993) suggested a least squares estimation of a shift in linear processes to estimate unknown change point. Asymptotic distribution of the change point estimator and the rate of convergence for the estimated change point were established. Bai (1997) extended his own earlier work (Bai, 1993) to multiple breaks by estimating one break at a time. Bai and Perron (1998) developed a method for testing unknown breaks simultaneously. A generalized F test was designed for this method. By a Monte Carlo test, Perron (1989) showed that a shift of the intercept and/or slope of the trend would greatly affect the Dickey-Fuller test result. If shifts are significant, one could hardly reject the unit root hypothesis even if the series is one with a trend and an independently identical distributed (iid) distribution. To solve the problem, an extension of the Dickey-Fuller testing strategy to ensure a consistent testing procedure against shifting trend functions was designed. With a single known break, Perron (1989) proposed a modified DF test for a unit root. Percentage points of limiting distributions were tabulated for different λ with a value between 0 and 1. It determined a change point T_B with $T_B = \lambda T$. For different specifications, the critical value table for the modified DF tests should be simulated specifically.

Chapter 3 Theories and Models

This chapter will first review in detail basic theories and methods that may be applied in this dissertation. The long-run and short-run regional models, the U.S.-Canada model, and forecasting models will then be discussed.

3.1 Theories and Methods

Lumber models will be fitted with monthly regional and national observations of lumber production, lumber inventory, lumber price, housing starts, stumpage prices, labor cost, and disposable income. Most of these time series are highly likely to be nonstationary. Modeling with these data may involve unit root tests, cointegration tests, Vector Error Correction Model (VECM) and structural change. For structural models in this dissertation, this section will cover unit root tests, Box-Jenkins (i.e. ARIMA) method, cointegration, and ECM. Theories for testing structural changes will also be discussed. Spectral and VAR models will be discussed as forecasting models in additional to the structural models that will also be used for forecasting.

3.1.1 Unit Root Tests

The ADF test, the PP test, and the KPSS test (Kwiatkowski et al., 1992) are the most important three unit root tests. The ADF test is based on the Dickey-Fuller test (i.e. DF test, Dickey and Fuller, 1979) which tests the null hypothesis of the existence of unit root that may results in the stationarity of differences of series. A time series y_t is said to have an autoregressive unit root if it can be expressed as

$$\Delta y_t = w_{t,}$$

where w_t is a stationary process. To test the unit root, we can write the process as a random walk.

$$y_t = \rho y_{t-1} + \varepsilon_{t.}$$

The null hypothesis of the DF test is H_0: $\rho = 1$; the alternative is H_1: $|\rho| < 1$. The t-statistic of the OLS estimate for ρ has a limit distribution derived by Dickey and Fuller. The Dickey-Fuller test was generalized by Said and Dickey (1984) to the case when the difference was of the general ARMA form. The test method for the generalized model is called the Augmented Dickey-Fuller test (ADF test). The ADF test estimates

$$\Delta y_t = \alpha + (\rho\text{-}1)y_{t-1} + \beta_1\Delta y_{t-1} + \beta_2\Delta y_{t-2} +,\ldots,+ \beta_k\Delta y_{t-k}+ \varepsilon_{t.}$$

The null hypothesis is the same as that for the DF test. Limit distributions of the estimated parameters are similar to that for the DF test. It has been shown that the ADF test is sensitive to the value of k. Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and other criterions have been suggested to determine lag numbers of the ADF regression (Maddala and Kim, 1998, page 77). The ADF test is also applicable to models with a trend, but the distribution is modified accordingly.

The PP test (Phillips and Perron, 1988) is an alternative general unit root test with a nonparametric approach regarding nuisance parameters. It allows for a very wide class of time series models in which there is a unit root. It is an extension of the study of Phillips (1987), which could have a significant advantage in cases when there is moving average component in a time series. Drifts with and without a linear trend are included in specifications of the test. This test requires weak stationarity. Heterogeneous distribution and some extent of temporal dependence are allowed. Consider

$$Y_t = \alpha Y_{t-1} + u_t \qquad \text{with } \alpha = 1,$$

where u_t is a general random component that may be weakly stationary, heterogeneously distributed and temporal dependent to some extent. The test applies two regression equations with drift and trend.

$$Y_t = \hat{\mu} + \hat{\alpha} Y_{t-1} + \hat{\mu}_t$$

$$Y_t = \tilde{u} + \tilde{\beta}(t - \frac{1}{2}T) + \tilde{\alpha} Y_{t-1} + \tilde{u}_t ,$$

where T is the last period. The hypothesis is H_0: $\alpha=1$, $\mu = \beta = 0$.

The difficulty of this test is that distributions of the standard t-statistic depend upon nuisance parameters. This difficulty is circumvented by transforming the statistic in such a way that the critical values derived in studies of Dickey and Fuller under the assumption of independent and identically distributed errors $\{u_t\}$ may be used with the PP test (Phillips and Perron, 1988). The asymptotic power of the PP test is the same as that of the Dickey-Fuller procedure in spite of the fact that it allows for a more general class of error processes.

KPSS test was proposed by Kwiatkowski et al. (1992). The null hypothesis is that an observable series is stationary around a deterministic trend. The series is expressed as the sum of deterministic trend, random walk, and stationary error. The test is the Lagrangian Multiplier test (LM test) with the hypothesis that the random walk has zero variance. In many cases the power of the ADF and PP tests with the null hypothesis of a unit root are very low (Maddala and Kim, 1998, page 100). It is helpful to perform tests with the null hypothesis of nonstationarity as well as tests with the null hypothesis of stationarity against the alternative of a unit root. Assume a series y_t can be decomposed into the sum of a deterministic trend, a random walk, and a stationary error:

$$y_t = \xi t + r_t + \varepsilon_t,$$

where r_t is a random walk:

$$r_t = r_{t-1} + u_t,$$

ε_t is iid(0, σ_ε^2), u_t is iid(0, σ_u^2). The stationary hypothesis is simply

$$H_0: \sigma_u^2 = 0.$$

Under the assumption of stationarity (level stationary or trend stationary), the LM statistic with iid ε_t is

$$\mathrm{LM} = \sum_{t=1}^{T} S_t^2 / \hat{\sigma}_\varepsilon^2 ,$$

where $S_t = \sum_{i=1}^{t} e_i$; e_i are the residuals from the regression of y on an intercept and time trend. Autocorrelation is allowed. It can be an ARMA process with either homogeneous or heterogeneous innovation. Define long-run variance as

$$\sigma^2 = \lim_{T\to\infty} T^{-1} E(S_T^2) ,$$

and use estimator

$$s^2(\ell) = T^{-1}\sum_{t=1}^{T} e_t^2 + 2T^{-1}\sum_{s=1}^{l} w(s,\ell)\sum_{t=s+1}^{T} e_t e_{t-s}$$

to estimate σ^2. Here w(s, ℓ)=1-s/(ℓ +1) is the optional weighting function that corresponds to the choice of a spectral window. With temporal dependent series but no trend, test statistic for the KPSS test is

$$\hat{\eta}_\mu = \eta_\mu / s^2(\ell) = T^{-2}\sum_{t=1}^{T} S_t^2 / s^2(\ell).$$

The statistic converges to a distribution that is a function of a standard Brownian bridge, $V(r) = W(r) - rW(1)$.

$$\hat{\eta}_\mu \rightarrow \int_0^1 V(r)^2 dr \,.$$

With a trend the test statistic is

$$\hat{\eta}_\tau = \eta_\tau / s^2(\ell) = T^{-2} \sum_{t=1}^{T} S_t^2 / s^2(\ell) \,.$$

Its asymptotic distribution from which the critical values are obtained is given by

$$\hat{\eta}_\tau \rightarrow \int_0^1 V_2(r)^2 dr \,,$$

where the second-level Brownian Bridge $V_2(r)$ is given by

$$V_2(r) = W(r) + (2r - 3r^2)W(1) + (-6r + 6r^2)\int_0^1 W(s)ds \,.$$

The DHF test (Dickey, Hasza, and Fuller, 1984) uses the Box-Jenkins approach for testing seasonal unit roots. The DHF test analyzes

$$y_t = \varphi_4 y_{t-4} + u_t.$$

The null hypothesis is H_0: $\varphi_4 = 1$ and the alternative is H_1: $\varphi_4 < 1$. However, by the EGHY (Engle et al., 1993), the null implies that all the four unit roots by Δ_4 are unity. The EGHY is a test procedure extending the well-known Dickey-Fuller test for integration at frequency $\theta = 0$. This test is extended to monthly unit root test by Frances (Maddala and Kim, 1998, page 368).

3.1.2 Box-Jenkins Methods

The Box-Jenkins method was designed for ARIMA model estimation. It is a univariate method. The technique used in this method for checking stationarity and autocorrelation may be applied for detecting problems in the error that may arise in the

estimation of any model, including ECM model. The method consists of 5 steps (Maddala and Kim, 1998, page18-20).

1. Differencing to achieve stationarity by checking the paradigms of level and differences (one or more times of differences). Keep on differencing until the correlogram dampens.
2. Identifying a tentative model by determining the ARMA process.
3. Estimating the model.
4. Diagnostic checking. The Akaike Information Criterion (AIC) and Schwartz Bayesian Information Criterion (BIC) are used for determining the specification of the model. If an estimation of a model has p parameters and n observation

$$\text{AIC(p)} = \text{nlog}(\hat{\sigma}^2) + 2\text{p}$$

$$\text{BIC(p)} = \text{nlog}(\hat{\sigma}^2) + \text{plog(n)}$$

5. Forecasting (when necessary).

3.1.3 VAR

VAR is a vector version of the autoregressive model. A VAR may be written as

$$Y = \sum_{s=1}^{p} \Phi_s Y_{t-s} + u_t ,$$

where Y is an N-vector of variables and Φ_s is an N×N matrix. VAR models with exogenous variables are actually restricted VAR model such that equations for exogenous variables drop out. The maximum likelihood estimates of parameters of the VAR model are independent OLS estimates of each of the individual equations (Hamilton, 1994, page 309-313).

3.1.4 Integration, Cointegration and ECM

Integration is defined by Engle and Granger (1987) as:

> "A series with no deterministic component which has a stationary, invertible, ARMA representation after differencing d times, is said to be integrated of order *d*, denoted $x_t \sim I(d)$."

By this definition, an $I(d)$ series has *d* unit roots.

The definition of co-integration by Granger (1981) is:

> "The components of the vector x_t are said to be *co-integrated of order* d, b, denoted $x_t \sim CI(d,b)$, if (i) all components of x_t are $I(d)$; (ii) there exists a vector $\alpha \neq 0$ so that $z_t = \alpha' x_t \sim I(d-b)$, b>0. The vector α is called the *co-integration vector.*"

Consider the case d = b = 1, the components of x_t are $I(1)$, but z_t is $I(0)$. The idea of Error Correction Models is that the disequilibrium from one period is corrected in the next period. A vector of time series x_t has an error correction representation if it can be expressed as

$$\mathbf{A}(L)(1-L)\mathbf{x}_t = -\gamma \mathbf{z}_{t-1} + \mathbf{u}_t, \tag{1}$$

where L is the lag operator, and $\mathbf{A}(L)$ is an matrix of polynomial of L that is invertible. $\mathbf{u}_t$ is a stationary multivariate disturbance, with $\mathbf{A}(0) = \mathbf{I}$. $\mathbf{z}_t = \boldsymbol{\alpha}'\mathbf{x}_t$. $\boldsymbol{\alpha}$ is taken as an unknown vector of parameters. The vector variable $\mathbf{x}$ whose values are generated by equation (1) will be $\boldsymbol{I}(1)$ and has a cointegration vector $\mathbf{z}_t$. A pure VAR in difference will be misspecified if the variables are cointegrated. The parameter $\boldsymbol{\alpha}$ can be estimated by least squares, and this estimator converges even faster to the true value than standard

econometric estimates. This is the so-called "super consistent". Error correction models can be estimated based on the estimated cointegration vector $\hat{\alpha}$.

The two-step estimation method (Engle and Granger, 1987) is based on this property of cointegration vectors. The first step is to estimate $\hat{\alpha}$ by OLS. The second step is to calculate values for z and estimate the Error Correction Model.

The two-step estimation method by Engle and Granger is a single-equation method; the Maximum Likelihood Estimation (MLE) method is a multi-equation method. The estimates and inference of the MLE for an ECM (Johansen and Juselius, 1990) is believed to be more efficient than Granger's two-step estimation. Any VAR model may be written in an ECM form as

$$\mathbf{\Delta X_t = \Gamma_1 \Delta X_{t-1} + \ldots + \Gamma_{k-1} \Delta X_{t-k+1} + \Pi X_{t-1} + \mu + \Phi D_t + \varepsilon_t.} \qquad (2)$$

In this equation, $\boldsymbol{\varepsilon_t}$ is assumed to be stationary, and $\mathbf{X}_t$ is supposed to be $I(1)$. $\mathbf{\Delta X_t}$, $\boldsymbol{\mu}$, $\mathbf{\Phi D}_t$, $\mathbf{\Gamma_1 \Delta X_{t-1}}$,…, **and** $\mathbf{\Gamma_{k-1} \Delta X_{t-k+1}}$are all supposed to be stationary, $\mathbf{\Pi X_{t-1}}$ must be stationary. There are three cases:

1. Rank($\mathbf{\Pi}$) = p, i.e. the matrix $\mathbf{\Pi}$ has a full rank, indicating that $\mathbf{X_{t-1}}$ are functions of linear combination of stationary variables.
2. Rank($\mathbf{\Pi}$) = 0, i.e. the matrix $\mathbf{\Pi}$ is a null matrix. $\mathbf{\Pi X_{t-1}}$ drop off from the equation (2). No cointegrations exist.
3. 0<Rank($\mathbf{\Pi}$)<r<p, i.e. the matrix $\mathbf{\Pi}$ is not a full-rank matrix. There exist $p \times r$ matrices $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$[†] such that $\mathbf{\Pi} = \boldsymbol{\alpha\beta'}$. $\boldsymbol{\beta'}\mathbf{X_{t-1}}$ is stationary even though $\mathbf{X}_{t-1}$ is not.

[†] When each row of $\boldsymbol{\beta}$ is normalized so that the corresponding parameter of the lagged dependent variable is one, $\boldsymbol{\beta'}\mathbf{X_{t-1}}$ is a column of equilibrium errors, and nonzero elements of $\boldsymbol{\alpha}$, as the rates of adjustment, must be negative if only the corresponding equilibrium errors are included in each of the equations of (2).

The parameters, including $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ of model (2) can be estimated simultaneously by the maximum likelihood method. A corresponding test for the cointegration is offered by the Johansen's method.

An alternative for the MLE multi-equation method is 2SLS. In a simultaneous equations model, exogenous variables are generated by an integrated process if exogenous variables are nonstationary, and endogenous variables are generated by autoregressive linear functions of lags of endogenous variables and levels of exogenous variables when there are cointegration relations (Hsiao, 1997b). Since exogenous variables are nonstationary, the endogenous variables are also nonstationary. A vector of autoregressive linear equations can be expressed as:

$$\boldsymbol{\Gamma}(L)\mathbf{y}_t + \mathbf{B}(L)\mathbf{x}_t = \boldsymbol{\varepsilon}_t,$$

where $\boldsymbol{\Gamma}(L)$ and $\mathbf{B}(L)$ are vectors of functions of the lag operator L; $\mathbf{y}_t$, and $\mathbf{x}_t$ are vectors of G endogenous and K exogenous variables respectively; $\boldsymbol{\varepsilon}_t$ is a vector of stationary error term with mean zero. This expression can be transformed into error-correction form as

$$\boldsymbol{\Gamma}^*(L)\Delta\mathbf{y}_t + \mathbf{B}^*(L)\Delta\mathbf{x}_t + \boldsymbol{\Gamma}(1)\mathbf{y}_{t-1} + \mathbf{B}(1)\mathbf{x}_{t-1} = \mathbf{u}_t,$$

in which $\boldsymbol{\Gamma}^*(L)\Delta\mathbf{y}_t + \mathbf{B}^*(L)\Delta\mathbf{x}_t$ and $\boldsymbol{\Gamma}(1)\mathbf{y}_{t-1} + \mathbf{B}(1)\mathbf{x}_{t-1}$ may be explained as the short-run and long-run relations between $\mathbf{y}$ and $\mathbf{x}$.

When there are G linearly independent cointegration relations for the system, the roots of $|\boldsymbol{\Gamma}(L)| = 0$ lie outside the unit circle, and $\boldsymbol{\Gamma}(L)^{-1}$ exists. Therefore, $\mathbf{y}$ is a function of $\mathbf{x}$, and $\mathbf{y}_t = -\boldsymbol{\Gamma}(L)^{-1}\mathbf{B}(L)\mathbf{x}_t + \boldsymbol{\Gamma}(L)^{-1}\boldsymbol{\varepsilon}_t$. Hsiao (1997b) showed that conditions for the stationary case also hold. The gth equation is identified if and only if

$$\text{rank}(\mathbf{A}\boldsymbol{\Phi}_g) = G - 1,$$

where $\mathbf{A} = [\boldsymbol{\Gamma}(L) \;\; \mathbf{B}(L)]$; $\boldsymbol{\Phi}_g$ is a restriction matrix for the gth equation, and $\boldsymbol{\alpha}'_g\boldsymbol{\Phi}_g = \mathbf{0}$. $\boldsymbol{\alpha}'_g$ is the gth row of $\mathbf{A}$. Equivalent conditions are

$$\mathrm{rank}(\mathbf{A}^*\boldsymbol{\Phi}^*_g) = G - 1, \text{ or } \mathrm{rank}(\mathbf{A}^*_1\boldsymbol{\Phi}^*_{g1}) = G - 1, \text{ or } \mathrm{rank}(\mathbf{A}^*_2\boldsymbol{\Phi}^*_{g2}) = G - 1.$$

In the above conditions $\mathbf{A}^* = [\boldsymbol{\Gamma}^*(L) \;\; \mathbf{B}^*(L) \;\; \boldsymbol{\Gamma}(1) \;\; \mathbf{B}(1)]$, $\mathbf{A}^*_1 = [\boldsymbol{\Gamma}^*(L) \;\; \mathbf{B}^*(L)]$, and $\mathbf{A}^*_2 = [\boldsymbol{\Gamma}(1) \;\; \mathbf{B}(1)]$; $\boldsymbol{\Phi}^*_g$, $\boldsymbol{\Phi}^*_{g1}$, and $\boldsymbol{\Phi}^*_{g2}$ are restriction matrices for the gth equations of the ECM, the short-run dynamics, and long-run equilibrium relations**.** These equivalent conditions imply that the error correction model, the long-run equilibrium relations and short-run dynamics have equivalent conditions for identification. Hsiao showed that the 2SLS and 3SLS estimators for the normalized autoregressive form and the least square estimator for the long-run reduced form are consistent, and the Wald type test statistic can be applied.

Hsiao concluded that with G cointegration relations and integrated variables, it is optimal to estimate the long-run simultaneous equations by 2SLS, which, in turn, allows an ECM model system to be estimated in the second step. The cointegration and nonstationarity “do not call for new estimation methods or statistical inference procedures” (Hsiao, 1997b) for structural models, and conventional 2SLS methods for estimating and testing simultaneous equations models with stationary variables are still valid. As such, the demand and supply models of the lumber market will be estimated. However both the long-run and the short-run models will be examined for identification since they are estimated in two separate steps.

If a long-run equilibrium is observed in the real world, there must be a cointegration when the time series are integrated. This dissertation research will try different

specifications to find possible equilibriums in the lumber market so that the structural models may be estimated consistently.

3.1.5 Spectral Forecasting Methods

Like ARIMA, spectral forecasting methods are also univariate forecasting methods. They require stationary data, and the time series data have to be differenced if they are integrated. The basis of the methods is the moving average representation,

$$Y_t = C(L)\varepsilon_t,$$

where $C(L)$ is a polynomial of L, and L is the lag operator; ε_t is a stationary random variable. Box-Jenkins techniques will represent C in a mathematically rational function. However, Spectral methods will estimate the Fourier transform of C. The spectral density of Y can be written as the z-transform (RATS, 2003, page 447).

$$f_y(z) = C(z)C(z^{-1})\sigma^2.$$

Hamilton (1994, page 171) has an example of such an expression. Under some reasonable conditions, $\log(f_y)$ has a Laurent expansion:

$$\text{Log}[f_y(z)] = d(z) + d(z^{-1}) + d_0,$$

where d is a one-sided polynomial in positive powers of z. Take the exponent of both sides of the above equation, one obtains

$$C(z)C(z^{-1})\sigma^2 = e^{d(z)}e^{d(z^{-1})}e^{d_0}.$$

RATS first compute the log spectral density of Y, then mask the negative and zero frequencies to get the Fourier transform of d. Finally, take its exponent frequency by frequency to get the Fourier transform of C. Filter the input series Y by $1/C(L)$ to get residuals, and mask it outside the data range. Forecasts are then obtained by filtering the

forecasted residual with C (RATS, 2003, page 448). Since the methods do not use data efficiently, it requires more data.

3.1.6 Simulation

Simulation will be applied to show whether a forecasting model is better in forecasting for a certain number of steps beyond the sample. Possible dynamic rolling forecasting process was simulated, and then statistics for accuracies of forecasts will be calculated through forecasts and observed values. The virtue of simulation is that it leads to an intuitive conclusion without any sophisticated mathematics. The econometric software RATS will be used.

3.2 Structural Models

In this dissertation lumber models will be estimated for two purposes. One is for demand and supply analysis; the other is for forecasting. For different purposes, the best models obtained may be different. Consistent estimates with smaller variances will be pursued for demand and supply models. Simultaneous equations models may be suitable in this case. Accurate forecasts are the targets of forecasting models, and any model may be a candidate for forecasting.

3.2.1 The Long-Run Model

The restricted cointegration relation can be represented by a long-run demand and supply model. The demand and supply equations for a market k of the model can be expressed simultaneously as

Demand: $Q_{kt} = f(\mathbf{X}_{k1t}, \mathbf{P}_{\mathbf{t}}) + u_{dt}$

Supply: $Q_{kt} = g(\mathbf{X}_{k2t}, P_{kt}) + u_{st}$,

where t is the subscript for time; Q_k is the quantity for market k; **P** includes all simultaneous determined prices; P_k is the price for market k, and included in **P**. Q_k, P_k, and **P** are endogenous variables. f() and g() are functions for demand and supply respectively. $\mathbf{X}_{k1}$ and $\mathbf{X}_{k2}$ include some different exogenous variables so that the system is identified. $u_{s,}$ and u_d are stationary disturbance terms. The two error terms are stationary only if there is enough number of cointegration relations among the involved time series.

According to Lewandrowski et al. (1994), the demand equation is mainly determined by lumber prices, housing starts, and dummy variables. Supply is mainly determined by the lumber price, production costs, and the lagged inventory. Production cost for lumber may includes stumpage prices and labor cost. Since the disposable personal income (DPI) may contribute to the consumption of lumber, DPI may be included in the demand equations. So, $\mathbf{X}_1$ may include housing starts, DPI and dummy variables; $\mathbf{X}_2$ may include the lagged inventory, timber prices, labor cost, trend and dummy variables.

The amount of monthly production and shipments of lumber are usually not equal. Furthermore, the monthly lumber inventory in a month is usually greater than the lumber production or shipments in the same month. For example, in 1998, the average monthly lumber production, shipments, and inventory of the West Coast were 807, 803, and 1005 million board feet (mmbf) respectively. Typically, firms have plenty of stock to meet changes in the market. Thus the demand and supply in each month are measured by shipments instead of by production whenever possible.

As mentioned above, U.S. lumber supply comes from four major regions--the West Coast, the Inland West, the South, and Canada. For each of the supply regions, the demand has its regional characteristics. Based on the U.S. regional housing starts and the

Table 3-1 Definitions of log-transformed variables

Regions	Variable	Definition	Exogeneity
The West Coast	LSH1	The log-transformed lumber shipment of the West Coast	
	LP1	The log-transformed lumber price of the West Coast	
	Linv1_1	The lagged-one-month log-transformed lumber inventory in the West Coast	exogenous
	LTP1_1	The lagged-one-month log-transformed timber price of the West Coast	exogenous
The Inland West	LSH2	The log-transformed lumber shipment of the Inland West	
	LP2	The log-transformed lumber price of the Inland West	
	Linv2_1	The lagged-one-month log-transformed lumber inventory of the Inland West	exogenous
	LTP2_1	The lagged-one-month log-transformed timber price of the Inland West	exogenous
The South	LY3	The log-transformed lumber production of the South	
	LP3	The log-transformed lumber price of the South	
	LTP3_1	The lagged-one-month log-transformed timber price of the South	exogenous
Canada	LSH4	The log-transformed lumber import from Canada	
	LP4	The log-transformed price of the Canadian imported lumber	
	Linv4_1	The lagged-one-month log-transformed lumber inventory of Canada	exogenous
	LTP4_1	The lagged-one-month log-transformed timber price of Canada	exogenous
Housing Starts	LH	The log-transformed U.S. housing starts	exogenous
	LHWM	The log-transformed housing starts of the West and Midwest	exogenous
	LHS	The log-transformed U.S. South housing starts	exogenous
Others	LDPI	The log-transformed disposable personal income	exogenous
	LLC	The unit labor cost	exogenous

production, the West Coast and the Inland West are assumed to sell lumber mainly to the census region West (roughly identical to the Inland West and West Coast) and the Midwest (Appendix A). The South is assumed to sell mainly to the South. Canada is assumed to supply the entire United States. The DPI of the United States and dummy variables are included in the demand equations for all the supply regions. Each of the

supply regions has its own regional lumber inventory except region 3 (the South) where the inventory data is not available. All the supply regions have their own timber prices included in the corresponding supply equations. The lag of the inventory is used since it is the inventory at the end of the last period that matters. The unit labor cost of manufacturing industry is used as the labor cost for the three U.S. lumber supply regions. Log-transformed variables are used in the models.

The long-run model includes a pair of demand and supply equations for each of the four regions. There are 8 equations with eight endogenous variables.

Region 1

Demand: $LSH1_t = f_1(LP1_t, LP2_t, LP3_t, LP4_t, LHWM_t, LDPI_t, \mathbf{D}_t) + u_{d1t},$ (3.1)

Supply: $LSH1_t = g_1(LP1_t, LInv1\_1_t, LTP1\_1_t, LLC_t, \mathbf{D}_t, trend) + u_{s1t}.$ (3.2)

Region 2

Demand: $LSH2_t = f_2 (LP1_t, LP2_t, LP3_t, LP4_t, LHWM_t, LDPI_t, \mathbf{D}_t) + u_{d2t},$ (3.3)

Supply: $LSH2_t = g_2(LP2_t, LInv2\_1_t, LTP2\_1_t, LLC_t, \mathbf{D}_t, trend) + u_{s2t}.$ (3.4)

Region 3

Demand: $LY3_t = f_3(LP1_t, LP2_t, LP3_t, LP4_t, LHS_t, LDPI_t, \mathbf{D}_t) + u_{d3t},$ (3.5)

Supply: $LY3_t = g_3(LP3_t, LTP3\_1_t, LLC_t, \mathbf{D}_t, trend) + u_{s3t}.$ (3.6)

Region 4

Demand; $LSH4_t = f_4 (LP1_t, LP2_t, LP3_t, LP4_t, LH_t, LDPI_t, \mathbf{D}_t) + u_{d4t},$ (3.7)

Supply; $LSH4_t = g_4(LP4_t, LInv4\_1_t, LTP4\_1_t, \mathbf{D}_t, trend) + u_{s4t}.$ (3.8)

In these equations, f_i and g_i represent the functions of the demand and supply equations for the i th region respectively. The definitions of the variables are explained in Tables 3-1. t is the subscript for time. **D** is a vector of dummy variables, possibly

including monthly dummy variables for January, November, and December. Since shipments and inventory for the South (Region 3) are not available, production instead is used as the lumber quantity for the supply and demand equations of region 3. LSH1, LSH2, LY3, LSH4, LP1, LP2, LP3, and LP4 are endogenous variables. They are simultaneously determined in the lumber market. All the other variables in the model are exogenous variables.

All eight equations must satisfy both the order condition and the rank condition to be identified. Table 3-2 demonstrates the parameter structure of the simultaneous equations model. Each equation in the simultaneous equations model has more exogenous variables excluded than the number of endogenous variables included on the right-hand side (RHS) of the equation. Therefore, the order conditions are satisfied for all the equations (Greene, 2002, page 392).

The rank condition is verified following the procedure, outlined in Greene (2002, page 393), that is an equivalence for the identification condition described by the condition 3.10 in Hsiao (1997b). For example, for the demand equation for region 1 (the West Coast), the rank condition is determined by the shaded columns in Table 3-3. Since all 7 columns are uniquely defined, the matrix consisting of the shaded columns has a rank of 7.

Given the 8 endogenous variables, the rank required for identification is 8-1 = 7. Thus the rank condition is satisfied. Similar procedures were followed to verify that the rank conditions are satisfied for the other 7 equations. Since both order and rank conditions are satisfied the structural model is fully identified.

Table 3-2 The parameter structure of the long-run simultaneous equations model

	LSH1 (demand)	LSH1 (supply)	LSH2 (demand)	LSH2 (supply)	LY3 (demand)	LY3 (supply)	LSH4 (demand)	LSH4 (supply)
Variable								
LSH1	x	x						
LSH2			x	x				
LY3					x	x		
LSH4							x	x
LP1	x	x	x		x		x	
LP2	x		x	x	x		x	
LP3	x		x		x	x	x	
LP4	x		x		x		x	x
LHWM	x		x					
LHS					x			
LH							x	
LDPI	x		x		x		x	
LTP1_1		x						
LTP2_1				x				
LTP3_1						x		
LTP4_1								x
LInv1_1		x						
LInv2_1				x				
LInv4_1								x
LLC		x		x		x		
trend		x		x		x		x
Constant	x	x	x	x	x	x	x	x
D1	x	x	x	x	x	x	x	x
D11	x	x	x	x	x	x	x	x
D12	x	x	x	x	x	x	x	x
Exogenous variables excluded	11	9	11	9	11	10	11	10
Endogenous variables included on RHS	4	1	4	1	4	1	4	1
Rank condition	satisfied	satisfied	satisfied	satisfied	satisfied	satisfied	satisfied	satisfied

3.2.2 The Short-Run Model

A vector ECM of eight equations can be established with equilibrium errors and differences of variables. Each equation includes the differences of the variables included in the corresponding long-run equations and the errors (lagged-one-month) from these corresponding equations. These errors are the estimated stationary linear combinations of nonstationary time series. Corresponding to the eight long-run equations there are eight short-run equations.

$$dLSH1_t = f_1(dLP1_t, dLP2_t, dLP3_t, dLP4_t, dLHWM_t, dLDPI_t, Z1d\_1_t, d1, d11, d12) + \varepsilon_{1dt}$$

$$dLSH1_t = f_1(dLP1_t, dLTP1\_1_t, dLinv1\_1_t, dLLC_t, Z1s\_1_t, d1, d11, d12) + \varepsilon_{1st}$$

$$dLSH2_t = f_2(dLP1_t, dLP2_t, dLP3_t, dLP4_t, dLHWM_t, dLDPI_t, Z2d\_1_t, d1, d11, d12) + \varepsilon_{2dt}$$

$$dLSH2_t = f_2(dLP2_t, dLTP2\_1_t, dLinv2\_1_t, dLLC_t, Z2s\_1_t, d1, d11, d12) + \varepsilon_{2st}$$

$$dLY3_t = f_3(dLP1_t, dLP2_t, dLP3_t, dLP4_t, dLHS_t, dLDPI_t, Z3d\_1_t, d1, d11, d12) + \varepsilon_{3dt}$$

$$dLY3_t = f_3(dLP3_t, dLTP3\_1_t, dLLC_t, Z3s\_1_t, d1, d11, d12) + \varepsilon_{3st}$$

$$dLSH1_t = f_4(dLP1_t, dLP2_t, dLP3_t, dLP4_t, dLH_t, dLDPI_t, Z4d\_1_t, d1, d11, d12) + \varepsilon_{4dt}$$

$$dLSH4_t = f_4(dLP4_t, dLinv4\_1_t, Z4s\_1_t, d1, d11, d12) + \varepsilon_{4st}$$

All the variables in the above equations beginning with "d" indicate the first differences of the variables following "d." For example, $dLP1_t$ indicates the first difference of the log-transformed lumber price for region 1 (the West Coast) at period t. The endogenous variables are dLSH1, dLSH2, dLY3, dLSH4, dLP1, dLP2, dLP3, and dLP4. In the above equations the dependent variables of the demand and supply

equations are the first differences of the log-transformed lumber shipments in the West (dLSH1) and the Inland West (dLSH2), lumber production of the South (dLY3), and the lumber import from Canada dLSH4. They are functions of some other endogenous variables (lumber prices), some exogenous variables and the lagged-one-month equilibrium errors from the estimated long-run equations. In these equations, Zis_1 and Zid_1 are the lags of the residuals of the demand and supply equations for region "i." For example, Z3d_1 is the first lag of the residual of the demand equation for region 3. Since in the short-run suppliers will not be able to do anything to deviations of the demand of the previous period, demand equilibrium errors were excluded from the short-run supply equations. For the same reason, supply equilibrium errors were excluded from the short-run demand equations, and equilibrium errors from other regions were also excluded from equations for a specific region. So, only one equilibrium error was included in a short-run equation. The dynamic model was subject to the same constraints for the long-run model. All the equations are identified by both rank conditions and order conditions. The inclusion of the equilibrium errors only add more predetermined variables and does not change the property of identification.

3.3 A U.S.-Canada Model

When the U.S. lumber market is considered as an integrated market, a U.S.-Canada model can be constructed. The U.S.-Canada model includes only U.S. equations and Canadian equations. The U.S. equations can be described as

U.S. demand: $Ly_t = f_1(LP_t, LP4_t, LH_t, LDPI_t, \mathbf{D}_t) + u_{dt}$, (4.1)

U.S. supply: $Ly_t = g_1(LP_t, LTP\_1_t, LLC_t, \mathbf{D}_t, t) + u_{st}$. (4.2)

Ly_t is the log-transformed sum of the monthly lumber shipments for the West Coast and Inland West plus production for the South. Since data for lumber shipment of the South are not available, lumber outputs in the South will be used in place of the lumber shipments. The lumber price LP is the log-transformed value of weighted average lumber prices of all the U.S. regions. LTP_1 is the first lag of the log-transformed weighted average of delivered timber prices in the United States. The lumber inventory for the South is not available, so the lumber inventory for the United States is not available either.

The Canadian equations are:

Demand; $LSH4_t = f_2(LP_t, LP4_t, LH_t, LDPI_t, \mathbf{D}_t) + u_{d4t}$, (4.3)

Supply; $LSH4_t = g_2(LP4_t, LInv4\_1_{t-1}, LTP4\_1_t, \mathbf{D}_t, trend) + u_{s4t}$. (4.4)

Since data for timber prices in Canada will be later found not to be exogenous to the lumber market, LTP4_1 will be excluded in the estimation of the U.S.-Canada model.

The ADF test, PP test, and KPSS will be applied to each of the U.S. national time series to test for unit roots. When there are unit roots, the Error Correction Model will be applied accordingly and regressed by 2SLS using the RATS software.

3.4 Forecasting Models

Both univariate single-equation models and multi-equation model will be estimated for forecasting. The univariate forecasting models use only historical data of a variable to forecast its future values. Different specifications of ARIMA models, spectral models, simple lag models, and simple dummy-variable models will be used. Simple lag models generate forecasts using only observations with a specific lag period. Simple dummy-variable models use only constant and dummy variables as dependent variables.

Multi-equation models used for forecasting in this dissertation include log-transformed VAR model, VAR model, 2SLS model, and ECM model. Estimated multi-equation models will be solved for endogenous variables to forecast their future values. Values of exogenous variables needed for future periods will be forecasted by the univariate forecasting method.

To find the best forecasting models, data were first divided into two subsets, the calibration subset consisting of observations from all but the last few years, and the verification subset consisting of the observations of the last few years. The length of the verification data subset varies depending on the specific forecast. Forecasting models were first estimated with the calibration data subset and then compared against the verification data subset. The goodness of forecasting will be measured by the root of mean square (RMS) and the mean absolute value (MAV) of the forecast errors, which are the absolute values of differences between the forecasts and the actual observed values in forecasting periods. A specific number of month-ahead forecasts with a specific model will be repeated by rolling forecast to get the statistics RMSs and MAVs. Combinations of the best models will be chosen.

Chapter 4 Data and Unit Root Tests

Data were collected for the four supply regions. Geographically, the first region—West Coast includes western Washington, western Oregon, and the northern California coast. The second region—Inland West includes eastern Washington, eastern Oregon, California (excluding the redwood region), Nevada, Idaho, Montana, Wyoming, Utah, Colorado, Arizona, New Mexico, and a portion of South Dakota. The third region—South includes Alabama, Arkansas, Florida, Georgia, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Texas, Virginia, and West Virginia. Canada is the fourth region.

4.1 Lumber Prices

Monthly data for softwood lumber prices Pi (i=1, 2, 3) are from the *Yearbook* published by Random Lengths. The price of one typical type of lumber was picked for each of the regions. They are green Douglas-fir, random length 2×4 Std&B (standard and better) for the West Coast; kiln dried spruce-pine-fir, random length 2×4 Std&B for the Inland West[3]; kiln dried Southern Pine, random length 2×6 #2 for the South. Softwood lumber prices imported into the United States from Canada were from the website of the United States International Trade Commission (http://dataweb.usitc.gov). Figure 4-1 shows the lumber prices of the four regions—P1, P2, P3, and P4 for region 1, 2, 3, and 4 respectively. Although the prices of the lumber from the four regions experienced dramatically changes, these changes followed a very similar pattern over time. From

[3] The published prices before January 2003 for this type of lumber are the base prices, but from January 2003 only the mill prices are available. Both price series are available from January 1995 to December 2002. The regression of the base prices against the mill prices was almost perfect, and the base prices since January 2003 were forecasted with the mill prices.

January 1990 to September 1992, the lumber prices trended upward. After January 1993, the lumber prices reached a higher level and fluctuated significantly around the elevated level. Such changes provide a chance to examine how the lumber market responded to changes in prices. With all four series plotted in one graph (Figure 4-1), relations of the four prices are shown clearly. Generally, when the lumber price of one region went up, the lumber prices of other regions also went up, and vise visa. For example, in March and December 1993, the lumber prices of all the four regions climbed to their peaks; in July 1993 and June 1995, the lumber prices of all the four regions fell to their bottoms or close to them. The pattern of the changes for region 1, 2, and 4 are quite similar. The lumber prices of the South sometimes had directions of changes different from the other regions.

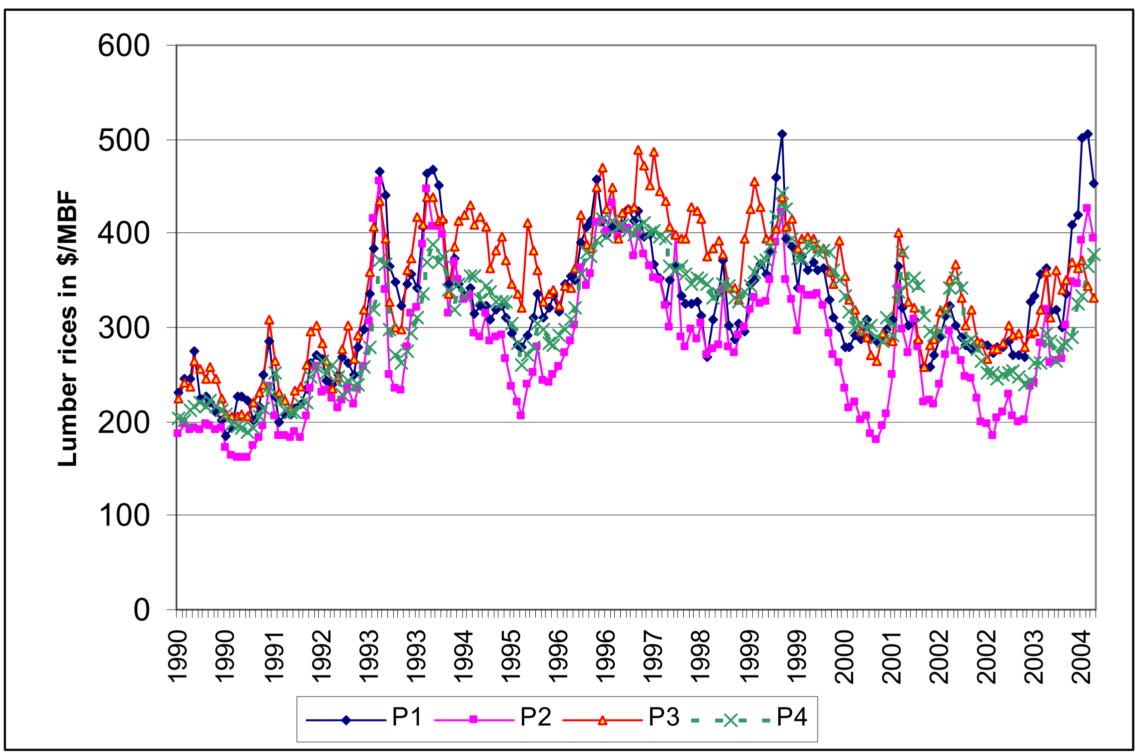


Figure 4-1 Lumber prices of the four regions

4.2 Production and Shipments

Data for monthly productions of region 3 (Y3), shipments for other regions (SH1, SH2, and SH4), and lumber inventories Inv_i (i=1, 2, 4) are available from *Yard Stick* by Random Lengths. Figure 4-3 shows data series of the lumber shipments SH1, SH2, SH4, and production Y3.

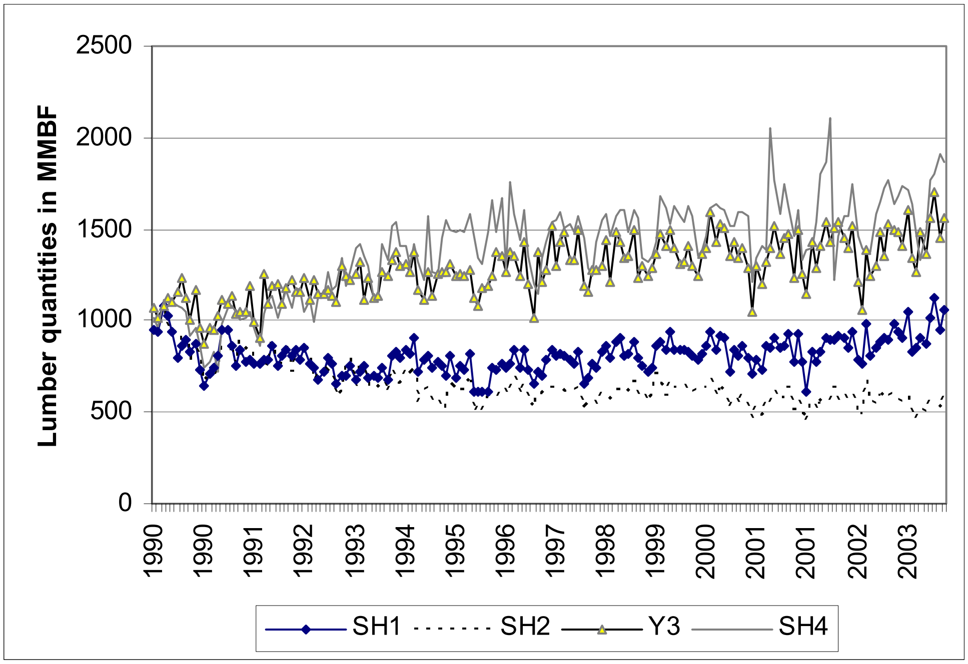


Figure 4-2 Lumber production and shipments

From January 1990 to December 1995, lumber production from the West Coast and Inland West experienced significant reductions right after the spotted owl was listed as a threatened species in 1990. The 6-year adjustment reshuffled market shares. In January 1990, the market shares were 24%, 24%, 27%, and 25% for regions 1, 2, 3, and 4 respectively. These shares were 17%, 15%, 30%, and 38% in December 1995, and they were 23%, 11%, 30%, and 36% in June 2004. By June 2004, the West Coast had almost recovered its lost market share. The Inland West, on the other hand, was still losing its market share and its lost market share was claimed by Canada and the U.S. South. During

the 14.5 years from January 1990 to June 2004, the Inland West lost 13% of its lumber market share while Canada gained 11%. In Figure 4-2, the series show some sign of seasonality. Seasonal changes occur in November, December, and January when the demand and supply for lumber are weak during the Christmas season.

4.3 Housing Starts, DPI, and Labor Costs

Monthly data for the entire U.S. housing starts H and the U.S. regional housing starts were available on the website of the United States Census Bureau (www.Census.gov). Data for Disposable Personal Income (DPI) and the unit manufactural labor cost (LC) were from the website of the Federal Reserve Bank of St. Louis (http://research.stlouisfed.org/fred2/data, accessed in July, 2004). Census regions of the housing starts are the West, the Midwest, the South, and the Northeast (Appendix A). These regions do not coincide with the lumber production regions. However, the Census region West is roughly equal to the total of the West Coast and the Inland West of the lumber production regions. The Census region West includes Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah Wyoming, Alaska, California, Hawaii, Oregon, and Washington. The Census region South includes Alabama, Arkansas, Delaware, District of Columbia, Florida, Georgia, Kentucky, Louisiana, Maryland, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, Texas, Virginia, and West Virginia. This region is roughly equal to the South of the lumber production regions. The Midwest of the Census regions includes Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin. The Northeast of the Census regions includes Connecticut, Maine, Massachusetts, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont. The regional housing starts

are shown in Figure 4-3. The housing starts of the South (HS) were 44% of the U.S. housing starts from 1990 to 2003; the housing starts of the West (HW) and the Midwest (HM) together were 46 % of the U.S. housing starts in the same period. Housing starts of the Northeast (HN) only accounts for 10% of the U.S. housing starts.

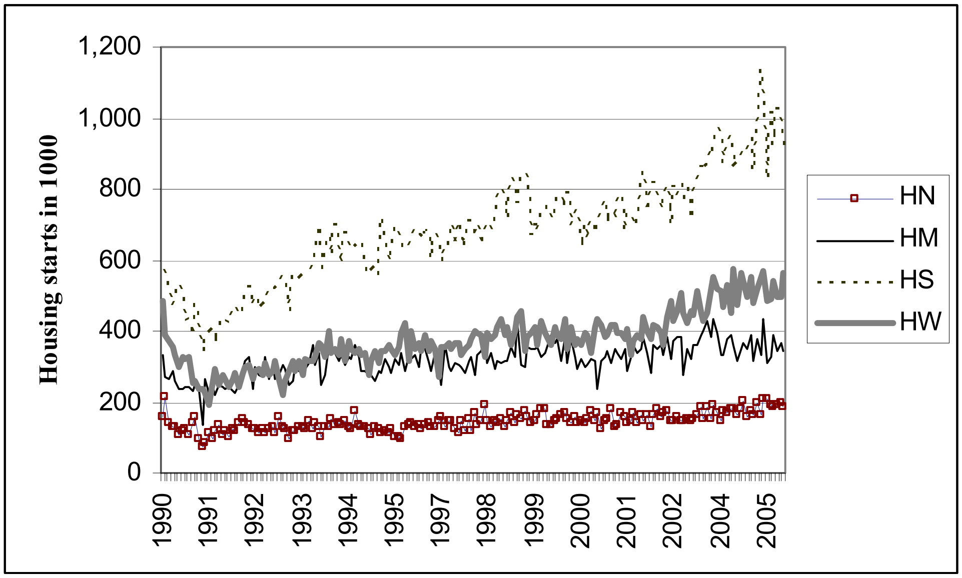


Figure 4-3 Housing starts in different census regions of the United States

Given the huge volume and weight of lumber, it is reasonable to assume that the lumber of a region tends to supply its local market first. Only when it is capable of producing more than the local consumption can its lumber be shipped to its surrounding regions. Since the South and the West (including the West Coast and the Inland West) each supplies about one-third of the U.S. softwood lumber, and the Canadian lumber industry supplies the other one third, it is safe to say that lumber industry in the South supply mainly the South, and that the lumber industry in the West Coast and the Inland West mainly supply the West and the Midwest.

Figure 4-4 shows mortgage rates (in percent) in a light dashed line, disposable personal income (DPI) in a heavy dashed line and housing starts in a solid line at the

bottom of the figure. Obviously, housing starts had little to do with DPI. From April 1971 to April 2004, DPI increased from \$3 trillion to \$8 trillion while the number of housing starts stayed on a stable level between 1 million to 2 million most of the time. Housing starts, however, were negatively correlated with mortgage rate. Although the number of housing starts stayed relatively stable, the consumption of lumber had been increasing most of the time. One suspects that the lumber consumed is related to the growth in DPI.

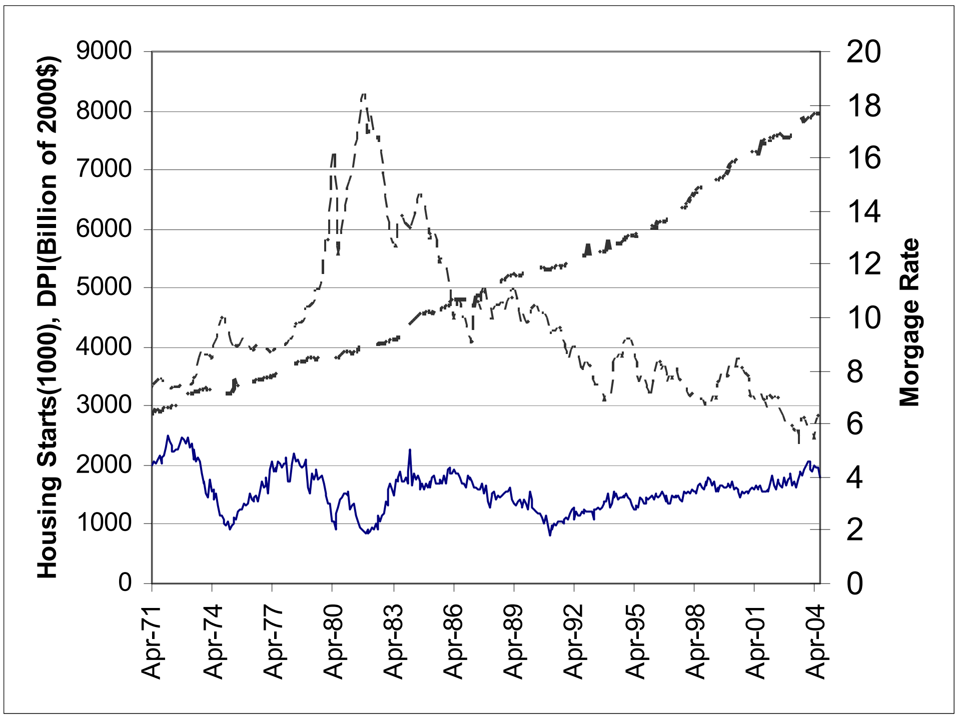


Figure 4-4 Housing starts, DPI, and mortgage rate

The manufactural unit labor cost (Figure 4-5) is a national index with that of 1992 equals 100. They are seasonally adjusted quarterly values. Monthly values were obtained by interpolation.

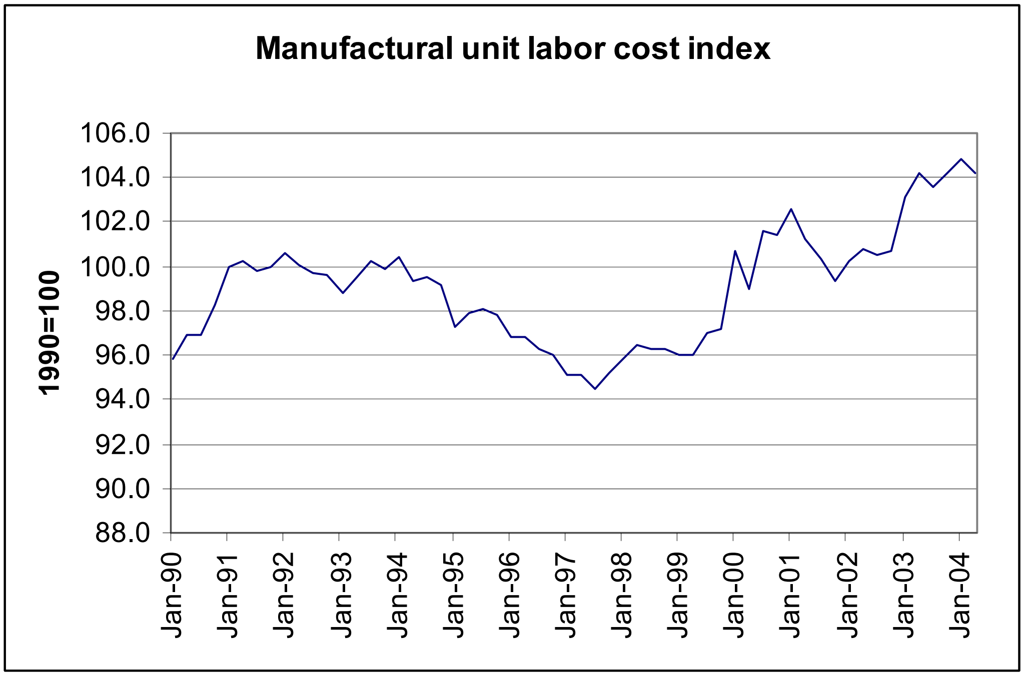


Figure 4-5 Manufactural unit labor cost index LC

4.4 Timber Prices

Pond values of specific species of timbers for different regions within Oregon are available on the state's official website http://oregon.gov/ODF/STATE_FORESTS/TIMBER_SALES/LOGPDEF.shtml (accessed on July 20, 2005). A pond value is the amount that a mill will pay for a log delivered to the mill location. It is what that log is worth floating in the mill's pond. The main species in the Pacific Northwest coastal area is Douglas-fir, and it is mainly used for building houses. No. 2 grade Douglas-fir sawlog is the log suitable for the manufacture of construction-or-better grade lumber. Prices of the No. 2 grade Douglas-fir sawlog of the northwest Oregon and Willamette region can be used as the proxy of the timber prices of the West Coast. The quarterly data were converted into monthly data by interpolation. The lagged Douglas-fir timber prices (TP1_1) is graphed in Figure 4-6.

Stumpage prices of softwood from the national forests on the west side of Washington and Oregon are available from Warren (various years). Some of them are also available at http://www.fs.fed.us/pnw/publications/rbs.shtml. The specific tables including the data are titled "Monthly stumpage volume and average value of timber sold on National Forest lands in Washington and Oregon, ..."

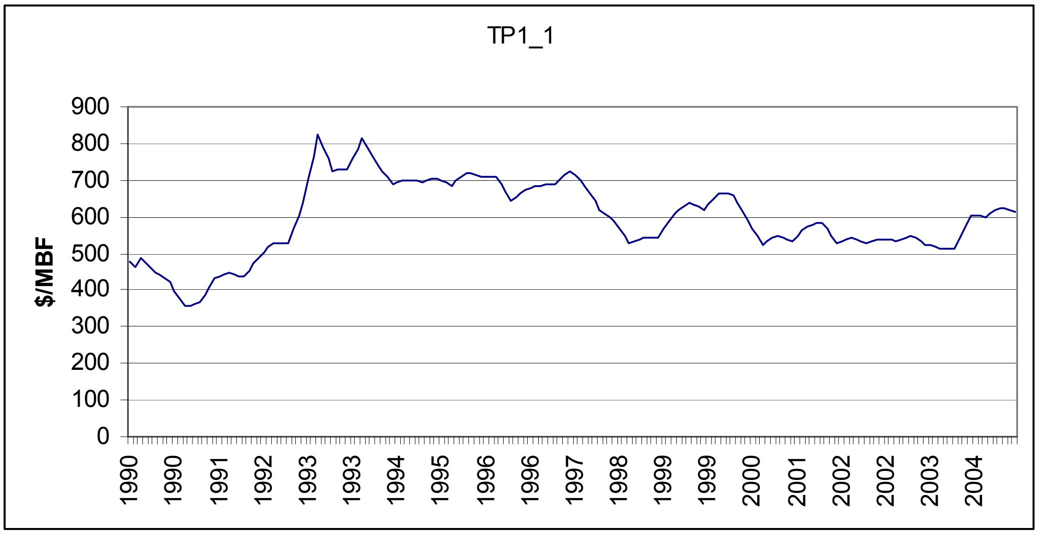


Figure 4-6 The first lags of Douglas-fir timber prices (pond value) in Northwest Oregon and Willamette Valley

Prices of timber sold on National Forest lands on the west side of the two states are listed in the tables. Figure 4-7 is the graph for monthly stumpage prices of timber sold on national forest lands in the West Coast of Washington and Oregon (P_WCN).

Neither of these prices in Figure 4-6 nor those in Figure 4-7 represents timber prices of the entire West Coast, and their values are very different. The No. 2 grade Douglas-fir sawlog prices are prices of a specific grade of Douglas-fir log delivered to sawmills for lumber production. They may reflect the material cost of lumber production better than average stumpage prices of all kinds of timber. Changes of the stumpage prices are very significant; sometimes one price is several times higher than that of the previous month.

This might be the results of differences in the quality or locations of the national forests that produce only a small proportion[4] of the total timber in the West Coast. The random changes may not represent the timber cost for lumber production. On the other hand, prices of the log delivered to the mill are direct costs of the material. So, the pond value is chosen as the timber price index for the West Coastal area.

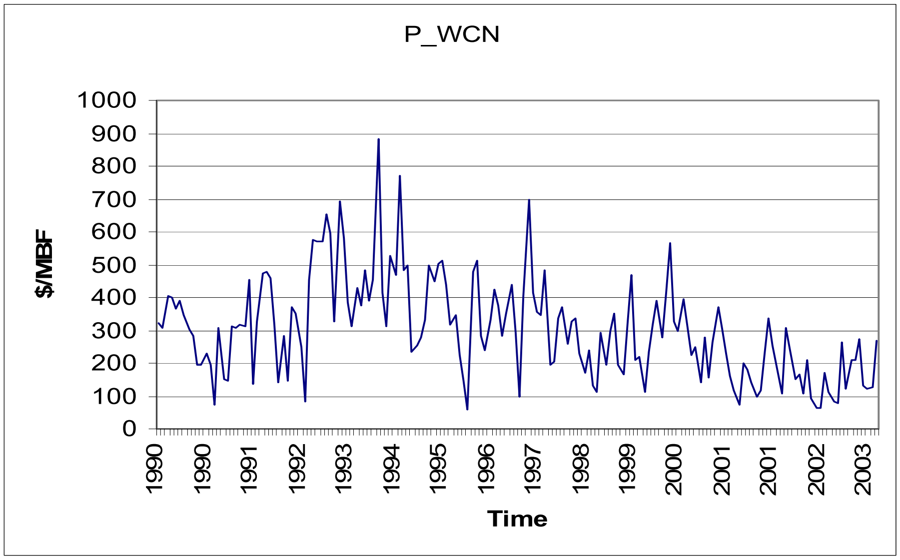


Figure 4-7 Prices of timber sold on national forest lands in western Washington and Oregon

The Inland West includes the forest region Northern Region, a portion of the Rocky Mountain Region, Intermountain Region, Southwestern Region, the east side of Washington and Oregon, and eastern California. As defined by the USDA Forest Service, the Northern Region includes Montana, northeastern Washington, northern Idaho, North Dakota, and northwestern South Dakota; Rocky Mountain Region includes Colorado, Kansas, Nebraska, remainder of South Dakota, and eastern Wyoming; Southwestern

[4] According to endgame.org (http://www.endgame.org/gtt-pnw-publicprivate.html, accessed on 8/15/05), in 1998 the timber produced from private land, national lands, and state land were 3,044, 111, 546 mmbf respectively for Washington state; these number were 2,840, 333, 141 mmbf respectively for Oregon state. The national forest provided only 6% of the timber produced in the two states.

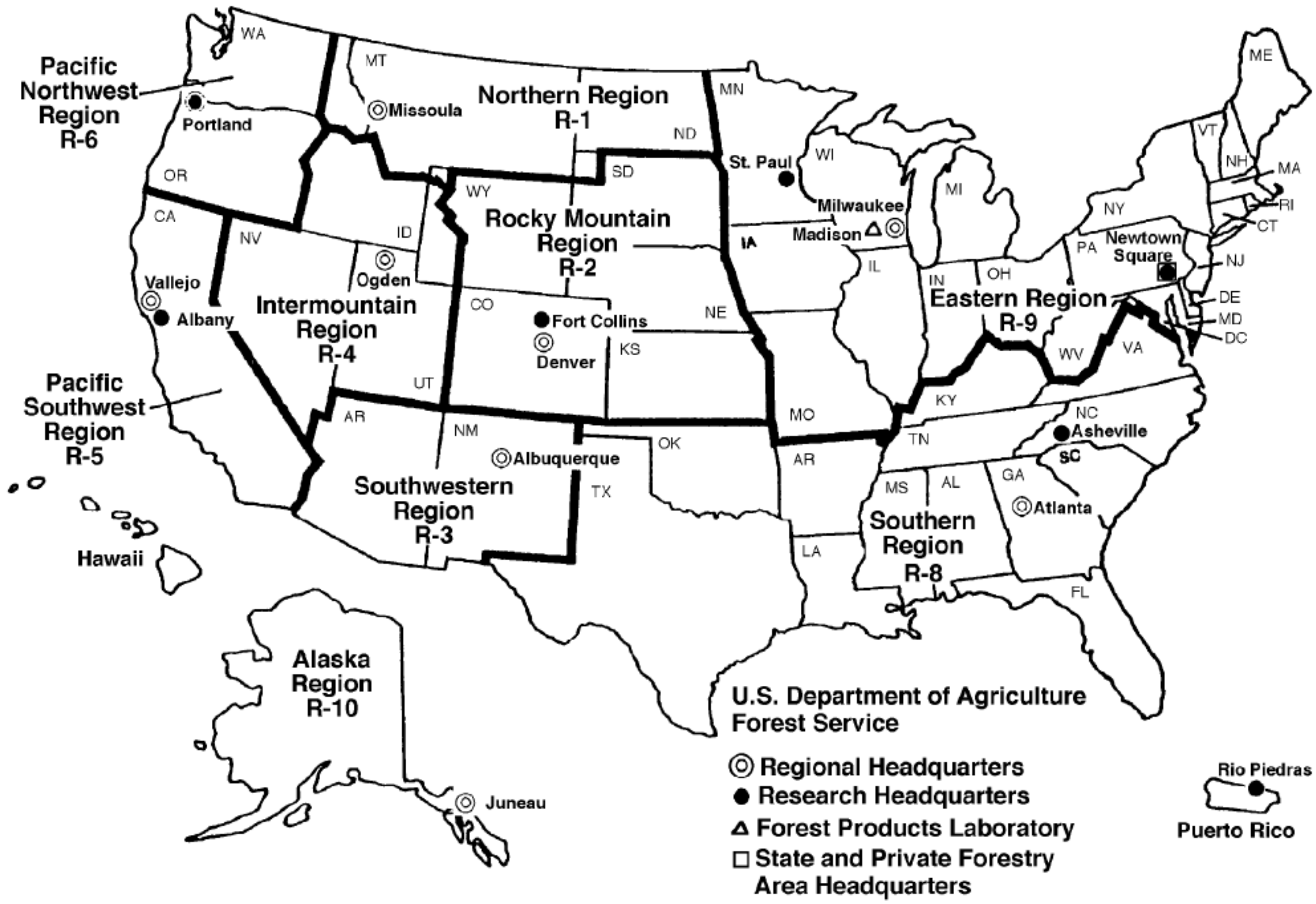


Figure 4-8 A map of the U.S. regions according to the Forest Service

Region includes Arizona and New Mexico; Intermountain Region includes southern Idaho, Nevada, Utah, and western Wyoming (Figure 4-8).

Quarterly stumpage prices of the sawtimber for the Northern Region and the Intermountain Region are available from Warren (various years). Tables including quarterly stumpage prices of the northern region are titled as "*Average stumpage prices for sawtimber sold on National Forests by selected species, Northern Region....*" Species in this region include Douglas-fir, ponderosa pine, western white pine, lodgepole pine, Engelmann spruce, western hemlock, cedars, larch, and true firs. Tables including stumpage prices of the Intermountain Region are titled as "*Average stumpage prices for sawtimber sold on National Forests by selected species, Intermountain Region...*" Softwood stumpage prices of some places in the Inland West were not available. Although stumpage prices are available for Washington and Oregon States, but data are not available for the east side of the two states that are part of Inland West.

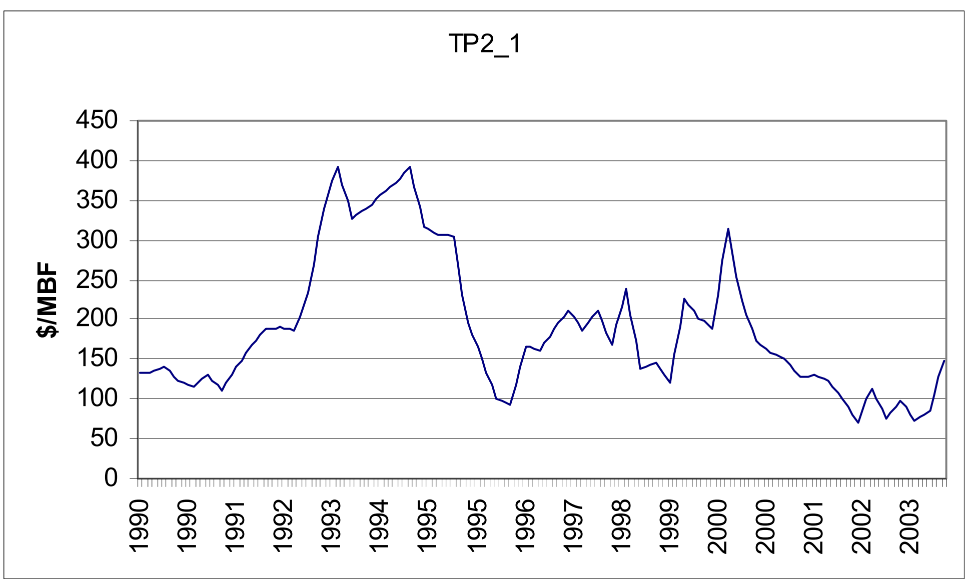


Figure 4-9 The first lags of average stumpage prices of the Inland West

The timber volume produced in the Northern Region and the Intermountain Region is used as weights of the two regions for calculating the average stumpage price. From 1990 to 1993, only yearly volume data are available; after 1994, quarterly timber volume is available. Since these prices are quarterly stumpage prices of sawtimber, they should be positively related to timber prices for lumber production. The average values of these stumpage prices lagged one period (TP2_1) are graphed in Figure 4-9.

Quarterly stumpage prices for the South are the average prices of the 10 southern states from Timber Market South. These states include Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Texas, Virginia. The first lags of monthly stumpage prices for the South (TP3_1) are interpolations of the average quarterly stumpage prices. Figure 4-10 is a graph for this time series.

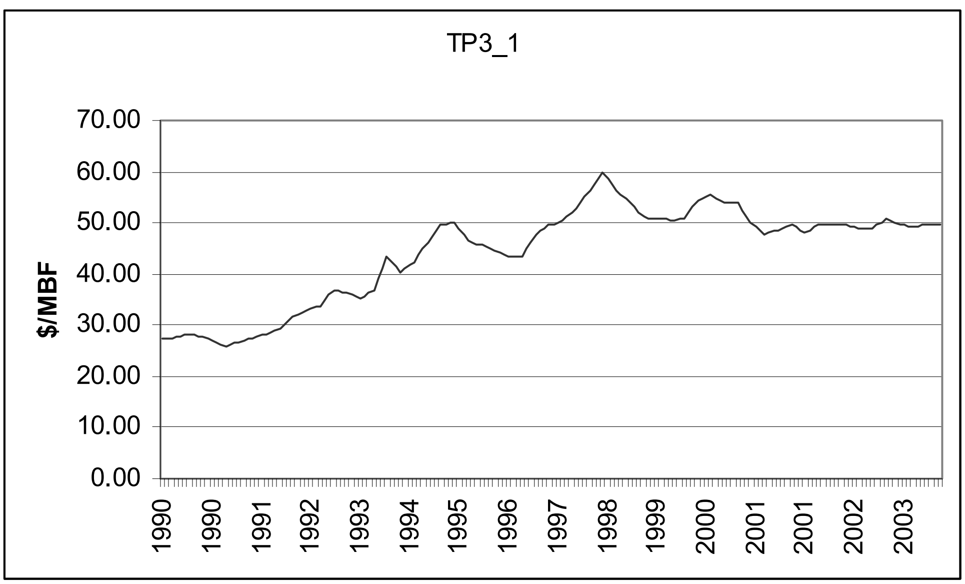


Figure 4-10 The first lags of monthly stumpage prices of the South

Canadian timber price indices were bought from the Statistics Canada (http://www.statcan.ca). This series of timber prices is not true price series but a series of monthly indices with the average timber price in 1997 as 100. Monthly timber price indices are plotted in Figure 4-11.

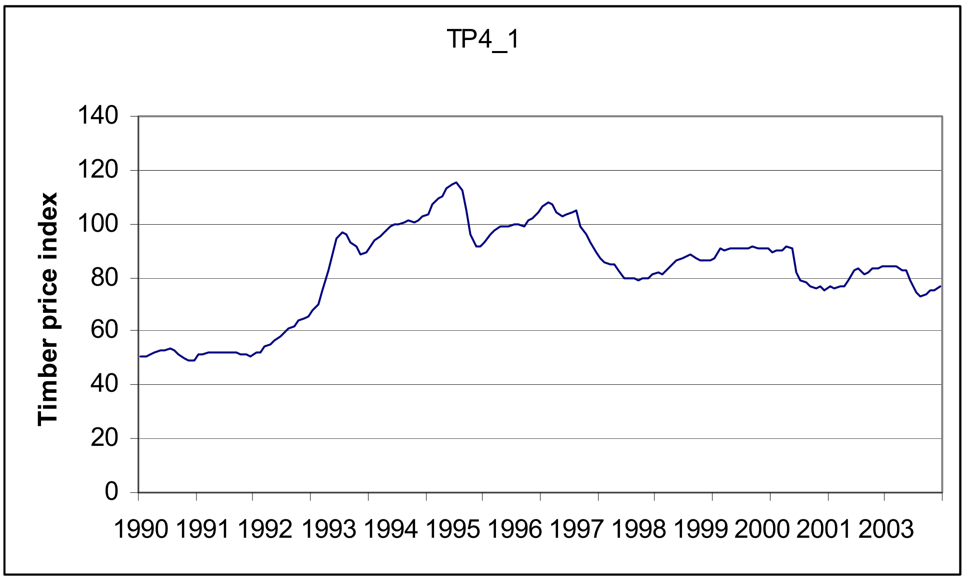


Figure 4-11 The first lags of monthly timber price indices of Canada

4.5 Lumber Inventories

Monthly data for lumber inventories are from the *Yard Stick* published by Random Lengths. Invi_1 (i=1, 2, 4) is the first lag of the inventory for region i. The data for the lumber inventory of the South were not available since 1998, so the Inv3_1 was excluded from the model. The graphed data series for the lumber inventories show that the lumber inventories of the West Coast and Inland West were decreasing, but the lumber inventories of Canada were increasing during the studied period (Figure 4-12).

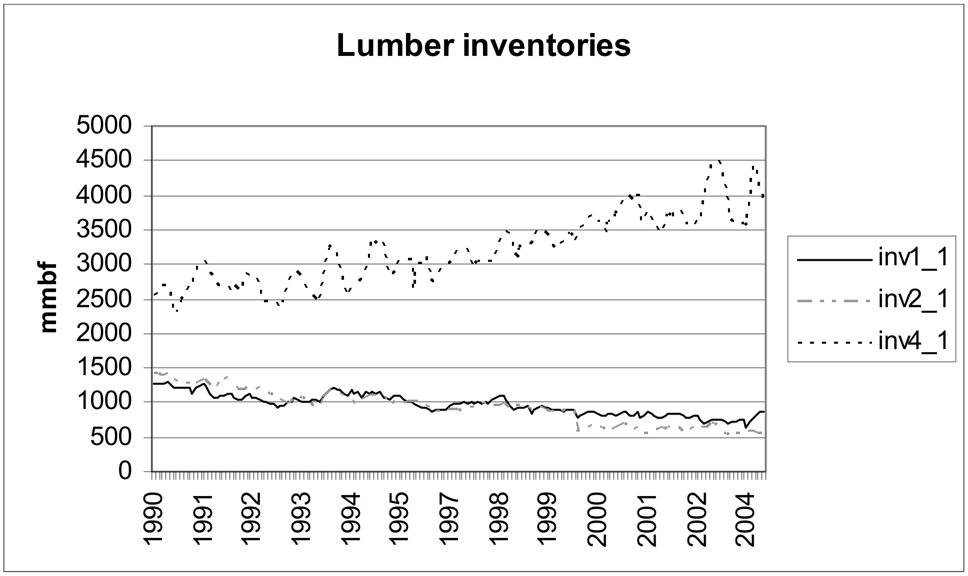


Figure 4-12 The first lags of lumber inventories of regions 1, 2, and 4

4.6 Unit Root Tests

Both the ADF and PP unit root tests were applied to the variables. The numbers of lags for the ADF tests were determined by the Bayesian Information Criterion (BIC). The numbers of lags for the PP tests were 12. If the hypothesis that the level of a time series has unit roots was not rejected and the hypothesis of the unit root tests for differences was rejected; then the time series is nonstationary and integrated of order 1. All time series but Lsh1, Lsh2, and Lsh4 are $I(1)$ either by ADF tests or by PP tests (Table 4-1). The joint null of a joint F test is unit root and zero constant (or no drift). Table 4-1 shows that for LDPI and LLC ADF t-statistics are less than their 5% critical value -2.88, and the F statistics are greater than critical values 4.63. LDPI and LLC have unit roots by t tests, but the joint hypotheses are rejected by F tests. Since a drift implies trending in a level series, it can be concluded that LDPI and LLC are significantly trended. Because the hypotheses are rejected by the t statistics and the F statistics for LSH1, LSH2, and LSH4;

trends of these variables cannot be confirmed by these tests. All other variables are not trended by the 5% critical value; however, the log-transformed lumber prices, timber prices, and two of the three lumber inventories are trended or almost trended by the 10% critical value 2.8.

Table 4-1 Results of ADF and PP unit root tests

	t-test statistic **(ADF)** (lags determined by BIC)					**PP test** (lags=12)		**Stationarity**
Variables	level			difference		level	difference	
5% critical		-2.88	4.63		-2.88		-2.88	
	lags	t	F (joint)	lags	t	t-test statistic		
LSH1	3	-4.17	9.68	11	-5.98	-6.96	-31.36	
LSH2	1	-3.27	5.60	13	-4.48	-4.94	-36.82	
Ly3	13	-1.71	3.69	12	-5.05	-7.1	-42.9	*I*(1)
LSH4	10	-3.75	7.16	0	-9.02	-3.51	-29.42	
LP1	0	-2.54	3.42	0	-11.86	-2.52	-12.06	*I*(1)
LP2	0	-2.70	3.78	0	-11.85	-2.75	-11.99	*I*(1)
LP3	0	-2.99	4.53	0	-13.27	-2.76	-14.69	*I*(1)
LP4	1	-2.67	3.79	0	-9.80	-2.23	-9.55	*I*(1)
LTP1_1	7	-2.63	3.65	6	-3.81	-1.88	-5.56	*I*(1)
LTP2_1	4	-2.38	2.88	3	-4.88	-2.02	-5.99	*I*(1)
LTP3_1	7	-2.00	2.65	6	-3.46	-1.90	-4.70	*I*(1)
LTP4_1	1	-2.17	2.57	0	-6.26	-2.02	-6.03	*I*(1)
LInv1	0	-2.05	2.38	0	-13.57	-1.87	-14.43	*I*(1)
LInv2	0	-0.99	1.77	0	-12.29	-0.75	-12.91	*I*(1)
LInv4	0	-3.20	3.05	0	-17.2	-2.82	-27.92	*I*(1)
LH	1	-1.30	0.93	1	-12.80	-1.94	-19.53	*I*(1)
LHWM	2	-0.98	1.12	1	-14.68	-4.15	-25.23	*I*(1)
LHS	2	-0.61	0.87	1	-14.86	-1.67	-23.49	*I*(1)
LDPI	0	-0.20	31.51	0	-10.58	-0.08	-19.85	*I*(1)
LLC	4	-1.65	7.73	3	-3.92	-1.17	-5.87	*I*(1)

Given that Ly3 and LSH4 are so close together in Figure 4-3, it is hard to believe that one of them is nonstationary while the other is stationary. The low power of the ADF and PP tests are well known, and it is necessary, as suggested by Kwiatkowski et al. (1992), to apply the KPSS test with hypothesis that the particular time series in question does not have a unit root.

Table 4-2 Results of KPSS unit root tests

Variables	KPSS test						Stationarity
	levels			differences			
	lags	ETA(mu)	ETA(tau)	lags	ETA(mu)	ETA(tau)	
5% critical		0.463	0.146		0.463	0.146	
LSH1	3	0.86115	0.4103	11	0.1452	0.07109	*I*(1)
LSH2	1	5.5387	0.69542	13	0.08304	0.0707	*I*(1)
LY3	13	1.13558	0.20721	12	0.08774	0.0462	*I*(1)
LSH4	10	1.2932	0.30679	0	0.01438	0.00681	*I*(1)
LP1	0	3.30655	2.18109	0	0.0611	0.02219	*I*(1)
LP2	0	2.51552	2.15419	0	0.05449	0.02504	*I*(1)
LP3	0	3.92011	2.89464	0	0.06893	0.02135	*I*(1)
LP4	1	2.81244	1.49675	0	0.17725	0.02807	*I*(1)
LTP1_1	7	0.38592	0.37635	6	0.18225	0.05942	*I*(1)
LTP2_1	4	0.89386	0.37427	3	0.09552	0.06532	*I*(1)
LTP3_1	7	1.68328	0.48419	6	0.3403	0.05717	*I*(1)
LInv1_1	0	13.5204	0.7197	0	0.0201	0.02044	*I*(1)
LInv2_1	0	14.79297	1.03276	0	0.02684	0.02472	*I*(1)
LInv4_1	0	13.67872	0.31508	0	0.02363	0.02145	*I*(1)
LH	1	6.61893	0.38372	1	0.14569	0.06326	*I*(1)
LHWM	2	4.06161	0.15794	1	0.12075	0.04687	*I*(1)
LHS	2	4.67203	0.53086	1	0.05496	0.03376	*I*(1)
LDPI	0	16.85454	1.38731	0	0.01717	0.01691	*I*(1)
LLC	4	0.83169	0.60660	3	0.25343	0.18164	*I*(1) *or I*(2)

The procedure for KPSS test, as provided by Estima on its official website (estima.com) may not determine the optimal number of lags. Instead, the procedure provides the test results for all lags less than a number specified. Since models for the ADF and the KPSS tests are the same, the optimal number of lags of the KPSS tests can be determined by the optimal number of lags for the ADF tests. Chosen from the results of the KPSS tests with a maximum 13 lags (Appendix B), the test results are listed in Table 4-2. Based on the ETA(tau) statistics, all stationary null hypotheses were rejected with the level data, and none of the stationary null hypotheses were rejected with the differences except that for LLC. All series were suspected of being nonstationary. This conclusion is a little different from that of the ADF and PP tests. Considering the low

power of all these tests (Maddala and Kim, 1998, Chapter 4), we conclude that all series were suspected of being nonstationary.

4.7 Seasonal Unit Root Tests

Because of the seasonal cycle of forestry is 12 month, $(1\text{-}L^{12})X_t = X_t - X_{t-12} = \Delta_{12}X_t$ is our interest. The purpose of testing seasonal unit root is to find if the difference Δ_{12} is a proper filter for modeling the seasonal effects. For monthly data, integrated of order 1 implies that the frequency $\alpha = 0$ corresponds to a component of the form $(1\text{-}L)x_t = \varepsilon_t$, or a unit root 1 (Engle at el., 1993). Unit roots

$$-1;\ \pm i;\ -(1 \pm \sqrt{3}i)/2;\ (1 \pm \sqrt{3}i)/2;\ -(\sqrt{3} \pm i)/2;\ (\sqrt{3} \pm i)/2$$

are for 6; 3, 9; 8, 4; 2, 10; 7, 5; 1, 11 cycles per year respectively (Beauliu and Miron, 1993). Their corresponding frequencies are π; $\pi/2$; $2\pi/3$; $\pi/3$; $5\pi/6$; $\pi/6$. Estimated statistics for the tests are $\pi_1, \pi_2, \ldots, \pi_{12}.$ It is a little complicated to determine if a unit root exists. For frequencies 0 and π, one simply examines relevant statistics with null $\pi_j = 0$ and alternative $\pi_j < 0$, where j = 1, 2. For other frequencies, the null is that the statistics π_k (with k being an even number) and π_{k-1} are both zero. π_k is tested by a two-side test, but π_{k-1} is tested by a one-side test with an alternative $\pi_{k-1} < 0$. An alternative is an F test with joint null $\pi_k = \pi_{k-1} = 0$. When a null is rejected, there is no unit root at the corresponding frequency. If all $\pi_{i,}$ j = 1, 2, ..., 12 are zero, and none of the hypotheses are rejected, filter Δ_{12} should be applied for modeling.

Statistics of seasonal unit root tests for the time series are listed in Appendix C. Critical values for the tests are from Beaulieu and Miron (1993), and are listed in Appendix D. Results of the tests are listed in Table 4-3. In this table, positions for specific frequencies were marked by “x” when the seasonal unit root null at the

corresponding frequencies were rejected by t-statistic tests; the corresponding positions for specific frequencies were marked by “f” when seasonal unit roots null at these frequencies were rejected by the F-style test. There is at least one rejection for each series. Δ_{12} is not appropriate to be applied as a filter; therefore the 12-month-cycle seasonal changes of the production should be treated as seasonal effects not unit root effects. The relative weak demand and supply during November, December, and January in the following year can then be treated as seasonal effects rather than unit roots. The arrival of the winter season and Christmas apparently reduced the market demand and supply for lumber. Unit roots for other frequencies are empirically not able to be explained and hence ignored.

Table 4-3 Results of seasonal unit root tests

	0	π	π/2	2π/3	π/3	5π/6	π/6
LSH1	x		f			f	
LSH2						f	
Ly3			f			f	
LSH4				f		f	
LP1						f	f
LP2	x			f		f	x f
LP3				f		f	f
LP4	x			f		f	f
LTP1_1	x		f	f		f	f
LTP2_1	x			f	f	f	f
LTP3_1	x			f	f		f
LInv1				f		f	
LInv2				f		f	f
LInv4						f	
LH	x			x f		x f	
LHWM				f			f
LHS	x		f	x f		x f	
LDPI				f			
LLC	x			f	f		f

Chapter 5 Estimations of Structural Models

The structural models estimated in this chapter are the lumber demand and supply models developed in Chapter 3. The long-run and short-run regional models will be estimated and discussed in section 5.1 and 5.3, and the long-run and short-run U.S.-Canadian lumber models will be estimated and discussed in section 5.4. Tests for structural change will be performed in section 5.2. Models will be estimated by 2SLS method based on the results of Hsiao (1997a, 1997b). However, to show the advantage of 2SLS, results of the alternative method of Johansen and Juselius using Maximum Likelihood Method will be estimated and discussed in section 5.5.

5.1 Estimation for the Long-Run Regional Model

With nonstationary time series, sufficient cointegration relations must be confirmed by cointegration tests so that the 2SLS can be used for estimations. With eight endogenous variables, an unrestricted partial VECM (Johansen and Juselius, 1990; Johansen, 1992) with eight equations was estimated by the maximum likelihood method for the cointegration test. Endogenous variables were LSH1, LSH2, Ly3, LSH4, LP1, LP2, LP3, and LP4; exogenous variables were LHWM LHS LH LDPI LTP1_1 LTP2_1 LTP3_1 LTP4_1 Linv1_1 Linv2_1 Linv4_1 LLC. All observations from January 1990 to December 2003 were included in the estimation.

Since cointegration tests are based on the Gaussian distribution of errors, the specification, particularly the number of lags and dummy variables for this model, had to be adjusted to make autocorrelations and correlations between errors of different equations as small as possible (Appendix E). Otherwise the variances may be distorted

and tests may be invalid. The proper specification for this model was determined to include 0 lags, the trend, and three monthly dummy variables D1, D11, and D12 for January, November, and December respectively. Results of the cointegration test are shown in Table 5-1. In this table, the "Eigenvalue" column lists the 8 eigenvalues for the tests. The columns of the "L-max" and "Trace" listed the values of λ_{max} and the "Trace statistic" for the cointegration tests (Johansen, 1988). "L-max90" and "Trace90" are the corresponding 10% level critical values. The hypotheses are listed under the column "H_0". For example, "$r \leq 1$" is for the hypothesis of "at least one cointegration relation." Since all of the hypotheses were rejected, there must be eight cointegration relations.

Table 5-1 Results of the cointegration test

Eigenvalue	L-max	Trace	H_0	L-max90	Trace90
0.5425	129.04	541.87	$r \leq 0$	34.82	176.13
0.4598	101.6	412.84	$r \leq 1$	31.31	141.31
0.3986	83.9	311.24	$r \leq 2$	27.32	110
0.3388	68.27	227.34	$r \leq 3$	23.72	82.68
0.2948	57.62	159.07	$r \leq 4$	19.88	58.96
0.244	46.14	101.45	$r \leq 5$	16.13	39.08
0.1841	33.58	55.31	$r \leq 6$	12.39	22.95
0.1234	21.73	21.73	$r \leq 7$	10.56	10.56

With eight cointegration relations confirmed by the cointegration test, the 2SLS was applied to the eight-equation system. Results of the 2SLS for the long-run demand and supply equations are listed in Table 5-2. Durbin-Watson statistics (DW) for these estimated equations range from 1.19 to 1.99. Small DWs imply the existence of autoregression in the residuals.

Table 5-2 The 2SLS-estimated long-run coefficients of the regional structural model

	LSH1 (demand)	LSH1 (supply)	LSH2 (demand)	LSH2 (supply)	LY3 (demand)	LY3 (supply)	LSH4 (demand)	LSH4 (supply)
Variable								
LP1	-0.69***	0.37*	-0.83***		0.05		0.63***	
LP2	0.52***		1.11***	0.09	-0.05		-0.66***	
LP3	-0.49**		-0.65***		-0.17	0.17***	0.27	
LP4	0.24		-0.12		0.31*		0.25	0.19***
LHWM	0.40***		0.27**					
LHS					0.21**			
LH							0.42***	
LDPI	0.03		-0.51***		0.15		0.21	
LTP1_1		-0.52***						
LTP2_1				-0.09***				
LTP3_1						-0.01		
LTP4_1								0.22***
LInv1_1		0.36**						
LInv2_1				0.15*				
LInv4_1								0.02***
LLC		0.96*		1.5****		-0.06		
trend		0.0013***		-0.0024***		0.0018***		0.0023***
Constant	6.32***	1.01	12.19***	-1.27	3.78***	6.35***	-0.47	4.87***
D1	-0.06**	-0.07***	-0.02	-0.05**	-0.04*	-0.04**	-0.14***	-0.13***
D11	-0.12***	-0.09***	-0.14***	-0.10***	-0.10***	-0.10***	-0.04	-0.04
D12	-0.15***	-0.15***	-0.13***	-0.12***	-0.17***	-0.16***	-0.17***	-0.16***
R^2	0.27	0.39	0.59	0.69	0.70	0.74	0.77	0.81
DW	1.40	1.26	1.32	1.19	1.90	1.99	1.53	1.51

*: significant at10% level; **: significant at 5% level; ***: significant at 1% level

With possible autocorrelations that may cause smaller DWs, robust Newey-West variances with 12 lags were applied to test the significance of these estimated coefficients. Results calculated with robust variances are listed in Table 5-3. With robust variances, some of the estimated coefficients become less significant, but some become more significant. For example, with robust variances, several estimated coefficients of dummy variables become more significant, and estimated coefficients of lumber prices in demand equations are less significant.

The sign of the estimated coefficient of timber price (LTP4_1) in the supply equation of Canada is significant and positive while all other coefficients of timber prices in other supply equations are negative. The positive sign is in conflict with our expectation that cost has negative effects on supply. Most probably the reason is that Canadian stumpage prices (stumpage fee) are determined by a formula that uses final product prices and costs of harvest, transport, processing (Sedjo, 2004). As such, the current timber price is a function of the previous lumber prices. When the lumber prices are autocorrelated, the estimated coefficient of the lagged timber price for Canadian timber is inconsistent since the timber price may be correlated with the error term and is no longer exogenous. So, LTP4_1 should be excluded from the structural model. Although the trend in LDPI, LLC, LInv1_1, and Linv2_1 would tend to distort the regressed coefficients for them, they are nonetheless exogenous variables and are not excluded from the model to help the estimation of other coefficients.

Another problem of the results in Table 5-2 and 3 is that the own-price elasticity in the demand equation for region 2 is significantly positive. This could be caused by the collinearity between the lumber prices. Since the lumber industry in the region 2 is

Table 5-3 The 2SLS-estimated results for the regional model with robust variances

	LSH1 (demand)	LSH1 (supply)	LSH2 (demand)	LSH2 (supply)	LY3 (demand)	LY3 (supply)	LSH4 (demand)	LSH4 (supply)
Variable								
LP1	-0.69***	0.37	-0.83***		0.05		0.63**	
LP2	0.52**		1.11***	0.09	-0.05		-0.66**	
LP3	-0.49		-0.65*		-0.17	0.17***	0.27	
LP4	0.24		-0.12		0.31		0.25	0.19**
LHWM	0.40**		0.27					
LHS					0.21**			
LH							0.42**	
LDPI	0.03		-0.51***		0.15		0.21	
LTP1_1		-0.52**						
LTP2_1				-0.09				
LTP3_1						-0.01		
LTP4_1								0.22***
LInv1_1		0.36						
LInv2_1				0.15				
LInv4_1								0.02
LLC		0.96		1.5****		-0.06		
trend		0.0013***		-0.0024***		0.0018***		0.0023***
Constant	6.32***	1.01	12.19***	-1.27	3.78***	6.35***	-0.47	4.87***
D1	-0.06**	-0.07***	-0.02	-0.05**	-0.04**	-0.04**	-0.14***	-0.13***
D11	-0.12***	-0.09***	-0.14***	-0.10***	-0.10***	-0.10***	-0.04	-0.04**
D12	-0.15***	-0.15***	-0.13***	-0.12***	-0.17***	-0.16***	-0.17***	-0.16***
R^2	0.27	0.39	0.59	0.69	0.70	0.74	0.77	0.81

*: significant at10% level; **: significant at 5% level; ***: significant at 1% level

declining, the long-run response to price changes is weak, and the effects of collinearity are much larger than the own-price effects. To eliminate the collinearity, the lumber prices for the other regions should be excluded from the demand equation of region 2 for a new specification of the model. Without LTP4_1, there are still 8 cointegration relations among the series by the cointegration test with zero lag as well as d1, d11, and d12 (Table 5-4). And the equations are still identified by order and rank conditions.

Table 5-4 Results of the cointegration test without LTP4_1

Eigenvalue	L-max	Trace	H_0	L-max90	Trace90
0.5291	124.26	505.89	$r \leq 0$	34.82	176.13
0.4266	91.77	381.63	$r \leq 1$	31.31	141.31
0.3547	72.27	289.86	$r \leq 2$	27.32	110
0.3229	64.33	217.59	$r \leq 3$	23.72	82.68
0.2924	57.07	153.26	$r \leq 4$	19.88	58.96
0.2428	45.89	96.18	$r \leq 5$	16.13	39.08
0.1791	32.57	50.29	$r \leq 6$	12.39	22.95
0.1019	17.73	17.73	$r \leq 7$	10.56	10.56

The re-estimated results without LTP4_1 are listed in Table 5-5. The estimated long-run own-price elasticities of demand equations are significant and negative 0.73 and 0.17 for the West Coast and Inland West respectively. The corresponding own-price elasticities for the South and Canada are insignificant. The estimated cross-regional lumber price elasticities are mixed. The coefficient for LP2 is significant and positive in the demand equation for the West Coast but significant and negative in the demand equation for Canada, suggesting that the Inland West spruce-pine-fir lumber is a substitute for Douglas-fir lumber but a complement for the imported Canadian lumber. This could be a sign of poor estimated coefficient for LP2 in the demand equation for Canada. It is almost impossible that the spruce-pine-fir from the Inland West is complement with that from Canada. The only reason could be that the LP2 catches the

effects of LP4 since they are highly correlated. LP1 has a significant positive coefficient 0.73 in the demand equation for Canada, suggesting that Douglas-fir lumber is a substitute for the lumber from Canada.

Housing starts have positive effects on the demand for all regions, and the estimated coefficients for housing starts are significant 0.4, 0.23, 0.2, and 0.44 for regions 1 to 4. It implies that housing starts have been driving the consumption of lumber. Dummy variables D1, D11, and D12 have significant estimated coefficients for most of the demand and supply equations, and they are uniformly negative. They reflect weak demand and supply in the Christmas season. Therefore, the estimated monthly effects of Christmas seasons are significant. The dummy variable D11 has obviously smaller estimated coefficient 0.03 and 0.04 for the two equations for Canada, implying that the Christmas season for the lumber import market comes late.

The long-run own-price elasticities of supply equations for all the four regions are positive and less than one and so are inelastic. This is consistent with previous works (e.g. Lewandrowski et al. 1994). Two of these elasticities are significant 0.17 and 0.41 for the South and Canada respectively. The signs of the estimated long-run timber prices (LTP1_1, LTP2_1, and LTP3_1) elasticities are negative for all three American regions. The timber price elasticities are also less than one. Two of them are too small to be significant. Only the timber price in the supply equation of the West Coast has a significant estimated coefficient 0.53.

All of the estimated supply equations have significant trends. Three of them are positive and one is negative. The supply equations of the West Coast, the South, and the Canada have significant monthly trend of 0.0013, 0.0016 and 0.0019 respectively. These

Table 5-5 The 2SLS-estimated long-run coefficients of the regional model without LTP4_1 (robust variances)

	LSH1 (demand)	LSH1 (supply)	LSH2 (demand)	LSH2 (supply)	LY3 (demand)	LY3 (supply)	LSH4 (demand)	LSH4 (supply)
Variable								
LP1	-0.73***	0.38			0.03		0.73**	
LP2	0.58***		-0.17***	0.08	-0.02		-0.79**	
LP3	-0.50				-0.17	0.17***	0.27	
LP4	0.22				-0.30*		0.30	0.41***
LHWM	0.40**		0.23***					
LHS					0.20**			
LH							0.44**	
LDPI	0.05		-0.70***		0.16		0.16	
LTP1_1		-0.53*						
LTP2_1				-0.08				
LTP3_1						-0.01		
LInv1_1		0.36						
LInv2_1				-0.15				
LInv4_1								0.15
LLC		1.00		1.43***		-0.05		
trend		0.0013***		-0.0024***		0.0016***		0.0019***
Constant	6.31***	0.74	12.00***	-0.86	3.76***	6.35***	-0.44	3.53***
D1	-0.05**	-0.07***	-0.05**	-0.06**	-0.03**	-0.04**	-0.15***	-0.12***
D11	-0.12***	-0.09***	-0.11***	-0.10***	-0.10***	-0.10***	-0.04	-0.03
D12	-0.15***	-0.15***	-0.13***	-0.12***	-0.17***	-0.16***	-0.17***	-0.15***
R^2	0.25	0.38	0.63***	0.69	0.70	0.74	0.77	0.77
DW	1.39	1.26	1.14	1.19	1.92	1.99	1.66	1.27

*: significant at10% level; **: significant at 5% level; ***: significant at 1% level

trends are approximately equivalent to yearly trends of 1.6%, 1.9% and 2.3% respectively. The supply equation of the Inland West has a negative trend -0.0024 that is approximately -3% annually.

All coefficients of the lumber inventories Inv1_1, Inv2_1, Inv4_1 are insignificant, suggesting that the lumber inventory has very limited impact on lumber demand and supply in the long run. DPI and labor cost LC have mixed signs of coefficients in the estimated equations. Most of these are insignificant. Since they all have trends and their estimated coefficients are combinations of trends and themselves, it is hard to tell what the effects of these variables are.

5.2 Tests for Structural Changes

The most significant change of the lumber market happened when the U.S. Fish and Wildlife Service (FWS) announced its intention in 1989 to place spotted owl on the 'threatened' list under the Endangered Species Act (the bird was listed as threatened species in 1990). Since then, the West Coast experienced a reduction in its lumber output gradually until April 1996. The reduction in output pushed the lumber price to a higher level accompanied by significant fluctuations. Data show that shipments of lumber from the West Coast gradually adjusted to a lower level around 700 mmbf per month, stayed on that level for several years and then adjusted back to the 1990 level around 1,000 mmbf per month. The transition was very smooth. The lumber output of the Inland West had been trending downward continuously. The trending-down was a factor that kept relatively higher lumber prices even after the lumber output in the West Coast recovered.

Structural changes of the model cannot be determined by simply looking at the data. RATS's official website www.estima.com provides a procedure INCLANTIAO.prg to

test breaking points of time series. The program uses cumulative sums of squares for retrospective detection of changes in variance. According to Estima (http://www.estima.com/Stability.shtml, accessed on March 20, 2006), this is a method of Inclan and Tiao (1994). It is a single series test. The test method was applied to all variables, but the results are not shown in this dissertation since no conclusions were produced from these tests. LSH1 (lumber shipments from the West Coast) that was suspected to have a changing point was not shown to have any breaking points by this test of the program. Results for the other variables are mixed. There was not a common breaking point for them.

CUSUM test was also carried out to detect breaking points in time series. CUSUM test is based on the change of residuals of a model. Scaled recursive residuals are accumulated into a series of statistics and compared with the upper and lower 5% critical values. The code of the test is in the *RATS Reference Manual* (version 5, 2002). This program is a revised version of the CUSUM test. The CUSUM test described by Greene (2002, page 135) uses the estimated forecast variance of the residual Var(e_t), and $e_t = y_t - \mathbf{x}_t'\mathbf{b}_{t-1}$. RATS uses the estimated value of Var(ε_t) that is smaller than the estimated forecast variance of the residual. Therefore,

$$W_t = \sum_{r=K+1}^{r=t} \frac{e_r}{\widehat{\mathrm{Var}}(\varepsilon_r)} > \sum_{r=K+1}^{r=t} \frac{e_r}{\widehat{\mathrm{Var}}(e_r)}.$$

This larger statistics W_t makes the test more likely to reject the hypothesis of no structural changes. It is safe to say that there is no structural change when the hypothesis is not rejected.

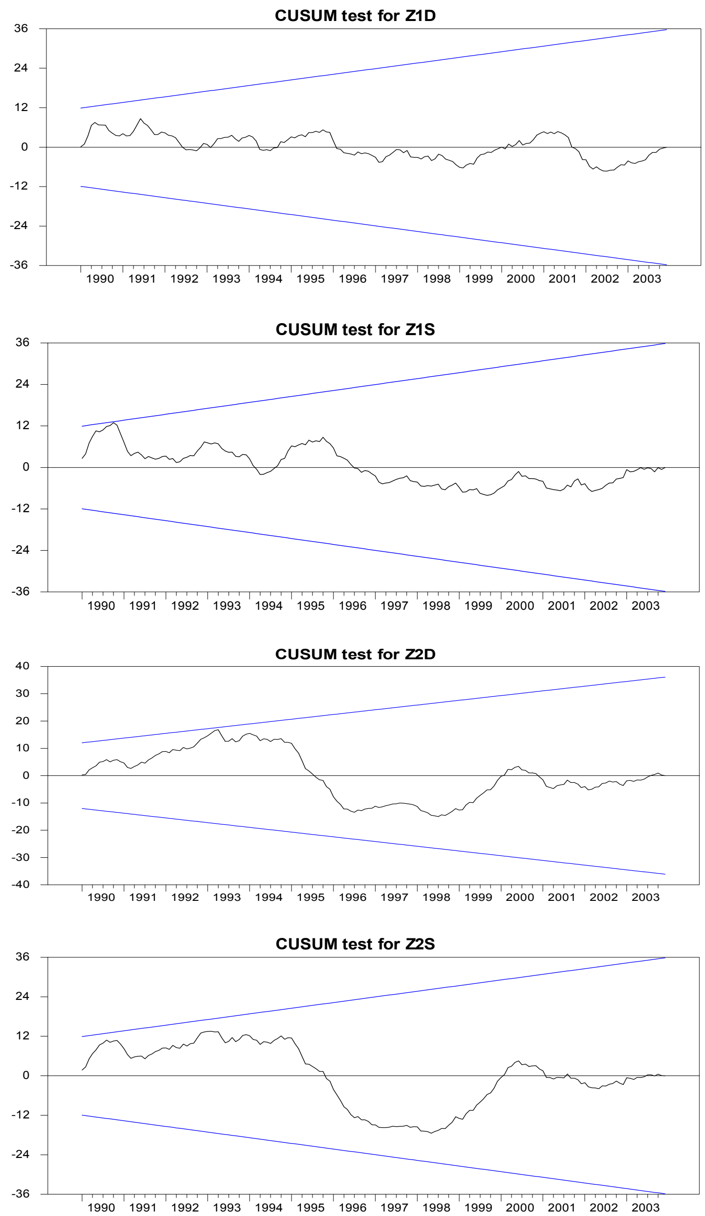


Figure 5-1 Results of CUSUM tests for equations of regions 1 and 2

The test was applied to all eight long-run estimated equations, and test results are graphs of a series of statistics with their upper and lower 5% critical lines (Figure 5-1 and 2). All statistics were within their critical limits, suggesting no structural changes of the model.

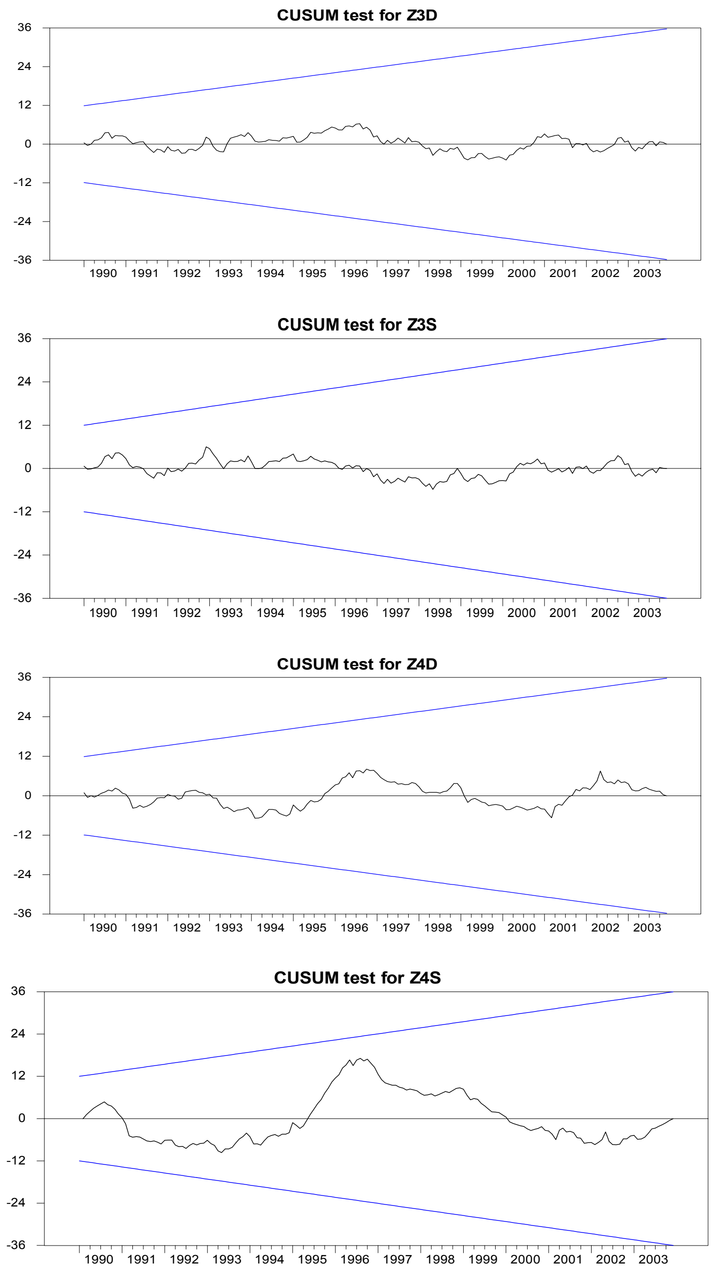


Figure 5-2 Results of CUSUM tests for equations of regions 3 and 4

5.3 Estimation for the Short-Run Regional Model

The short-run model was estimated by 2SLS. Estimated parameters are shown in Table 5-6. The results are very good when compared to the long-run estimation. The DWs range from 1.9 to 2.19, meaning that the autocorrelation of error terms is weak. For estimated equations with DW greater than 2.1, robust variance with 12 lags were applied.

All estimated own-price elasticities of demand are negative as microeconomics would suggest. Those for regions 1 and 2 are significant -0.52 and -0.38 respectively. All estimated lumber price elasticities in the demand equations are less than 1.0, so they are inelastic in the short-run. LP1 has significantly positive coefficients in demand equations of all other regions, suggesting that the lumber from the West Coast is a substitute for the lumber from other regions in the short-run. The significantly positive coefficient 0.63 for LP2 in the demand equation for the West Coast shows that spruce-pine-fir is a substitute for Douglas-fir in the short-run. The significant negative coefficient -0.57 for LP3 in the demand equation for the West Coast shows that southern pines are not competing with Douglas-fir in the West Coast in the short run. The lumber price from Canada does not have significant short-run effect on any of the equations, suggesting that, in the short-run, responses to the Canadian lumber price are slow.

In the estimated demand equations, all regional housing starts and the national housing starts have positive coefficients, and two of them are significant. The housing starts in the West and Midwest Census regions have a significant positive effect 0.20 on the demand for lumber from the West Coast. The U.S. national housing starts have significant positive effects on the demand for the imported lumber from Canada. DPI and LLC have insignificant effects on demand, but all coefficients for DPI in the equations of U.S. regions are positive as expected.

All own-price elasticities of supply are positive and inelastic or slightly elastic. Those for regions 1, 2 and 3 are statistically significant 1.08, 0.36, and 0.40 respectively. None of the estimated short-run timber price elasticities are significant. The lumber inventory of the West Coast has a significant coefficient 0.95. The estimated effects for disposable

Table 5-6 The 2SLS-estimated short-run coefficients of the regional model[5]

	The West Coast (region 1)		The Inland West (region 2)		The South (region 3)		Canada (Region 4)	
	dLSH1 (demand)	dLSH1 (supply)	dLSH2 (demand)	dLSH2 (supply)	dLY3 (demand)	dLY3 (supply)	dLSH4 (demand)	dLSH4 (supply)
Variable								
dLP1	-0.52*	1.08***	0.55***		0.41**		1.47***	
dLP2	0.63***		-0.38**	0.36***	-0.01		-0.33	
dLP3	-0.57**		0.28		-0.24	0.40***	-0.49	
dLP4	0.32		0.22		0.28		-0.09	0.23
dLHWM	0.20**		0.09					
dLHS					0.12			
dLH							0.49***	
dLDPI	1.52		0.84		1.50*		-1.08	
dLTP1_1		-0.43						
dLTP2_1				0.09				
dLTP3_1						-0.28		
dLInv1		0.95***						
dLInv2				0.20				
dLInv4								0.02
dLLC		0.47		3.87**		-1.64		
Z1d_1	-0.66***							
Z1s_1		-0.63***						
Z2d_1			-0.56***					
Z2s_1				-0.61***				
Z3d_1					-0.97***			
Z3s_1						-1.07***		
Z4d_1							-0.66***	
Z4s_1								-0.61***
trend		0.0001		0.00005		0.000		0.00001
Constant	0.002	0.008	0.005	0.002	0.002	0.008	0.03**	0.02
D1	0.09***	0.07**	0.05*	0.04	0.11***	0.11***	-0.01	0.01
D11	-0.14***	-0.16***	-0.15***	-0.15***	-0.13***	-0.11***	-0.12***	-0.06***
D12	-0.05*	-0.08***	-0.06*	-0.03	-0.08***	-0.06***	-0.14***	-0.13***
R^2	0.36	0.16	0.36	0.43	0.64	0.67	0.17	0.42
DW	2.05	1.99	2.11	2.19	1.98	1.91	2.00	2.12

*: significant at10% level; **: significant at 5% level; ***: significant at 1% level

[5]When DW is greater than 2.1, robust covariance with 12 lags were applied.

personal income DPI and labor cost LC are mixed, and these results are similar to the estimated effects of DPI and LC in the long-run model. These effects are hard to explain.

The coefficients for the long-run equilibrium errors reflect the monthly adjustment rates to equilibriums. All estimated adjustment rates are significantly negative, meaning that monthly adjustments to equilibriums are not trivial. For the West Coast, Inland West, and Canada, the estimated adjustment rates are about 60% for the supply and demand equations. The estimated adjustment rates are 100% for the supply and demand in the South. The reason may be that most of timberlands in the South are owned by the private sector and sawmills, therefore, respond quickly to any deviation from equilibriums.

All significant coefficients estimated for the dummy variable of January are positive, meaning that the corresponding demand and supply recover from December. All significant coefficients for dummy variables of November and December are negative, meaning that the corresponding demand and supply in the Christmas period are weakening.

Tests for structural changes with the short-run model were also carried with the CUSUM test. Results were that there were no structural changes. The test results are not shown in this dissertation.

5.4 Estimation for the U.S.-Canada Model

In this section the U.S.-Canada lumber demand and supply model with equation 4.1 to 4.4 discussed in Chapter 3 will be estimated. Values for total lumber quantity Y are the sums of shipments of the West Coast and the Inland West and productions of the U.S. South. Values for U.S. lumber price P are weighted averages of the three regional U.S. lumber prices. Values for the first lag of LTP_1 are weighted averages of the three

regional U.S. timber prices. Figure 5-3 is the plot of values for the total consumption of the lumber produced in the United States. Unit root test results (Table 5-7) showed that LY, LP, and LTP_1 have unit roots and are integrated of order one.

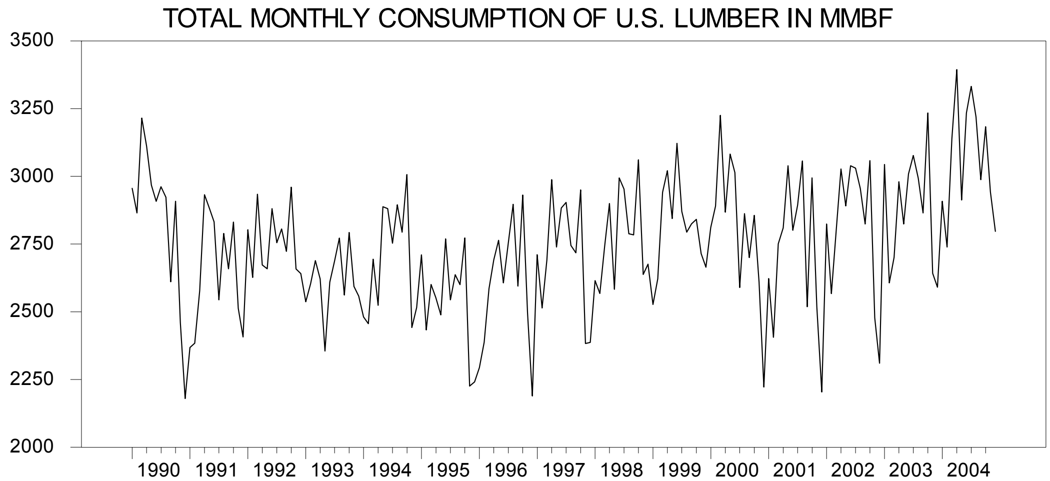


Figure 5-3 Total consumption of U.S. lumber in mmbf

Table 5-7 Results of unit root tests for log-transformed U.S. time series

	t-test statistic **(ADF)** (lags determined by BIC)				**PP test** (lags=12)		**Stationarity**
5% critical	-2.88				-2.88		
Variables	level		difference		t-test statistic		
	lags	t	lags	t	level	difference	
Ly	12	-1.79	11	-6.75	-8.64	-37.44	*I*(1)
LP	0	-2.65	0	-11.92	-2.49	-12.66	*I*(1)
LTP_1	0	-1.41	0	-11.86	-1.78	-12.07	*I*(1)

The cointegration test (Table 5-8) cannot reject the hypothesis of four cointegration relations among the four endogenous variables (LP, LY, LP4, and Lsh4) and the other predetermined variables (LH, LDPI, LTP_1, LInv4, LCC, D1, D11, and D12,). A drift and a trend were included in the test model. All L-max statistics and trace statistics are greater than the critical values.

Table 5-8 Results of the cointegration test for the U.S.-Canada model

Eigenvalue	L-max	Trace	H_0	L-max90	Trace90
0.4308	93.56	169.91	$r \leq 0$	18.03	49.91
0.2410	45.76	76.36	$r \leq 1$	14.09	31.88
0.1111	19.56	30.59	$r \leq 3$	10.29	17.79
0.0643	11.04	11.04	$r \leq 4$	7.50	7.50

Estimated results are very good (Table 5-9). Newey-West variances with 12 lags were applied to the estimation. Most of the signs of the estimated coefficients are as expected. The estimated own-price elasticities of the lumber demand equations are negative, and that for the United States is a significant -0.53. The estimated cross-price elasticities are significant 0.39 and 0.48 for the demand equations for the United States and Canada respectively, suggesting that the lumber from the United States and that from Canada are substitutes. The estimated coefficients of LH are significant 0.46 and 0.23 in the demand equations for the United States and Canada respectively, showing housing starts as the driving force of the lumber market. DPI has a negative effect on the demand for the U.S. lumber but a positive effect for the demand for Canadian lumber implying that when other variables are kept constant, some of the U.S. demand for lumber would shift from the U.S. producers to the Canadian producers with the growth of DPI over time. The estimated price elasticities of the lumber supply equation are positive, and that for the supply from Canada is a significant 0.43. The estimated coefficients for the inventory, timber price, labor cost are insignificant. The supply from Canada has a monthly trend of 0.002, equivalent to about 2% a year, while the supply form the U.S. does not have a significant trend.

Table 5-9 The 2SLS-estimated coefficients of the long-run U.S.-Canada model

	U.S. equations		Canada equations	
	U.S. demand for the U.S.	supply from the U.S.	U.S. demand for Canada	Supply from Canada
LP	-0.53***	0.15	0.48**	
LP4	0.39**		-0.12	0.43***
LH	0.46***		0.23	
LDPI	-0.26***		0.48***	
LInv4_1				0.16
LTP_1		-0.16		
LLC		0.53		
trend		0.00008		0.002***
Constant	7.72***	5.47	0.76**	3.37**
D1	-0.05***	-0.06***	-0.13***	-0.12***
D11	-0.11***	-0.10***	-0.05***	-0.03
D12	-0.16***	-0.15***	-0.16***	-0.15***
R^2	0.27	0.36	0.80	0.76
DW	1.60	1.55	1.56	1.26

*: significant at10% level; **: significant at 5% level; ***: significant at 1% level

The estimation for the Error Correction Model based on the above long-run estimated coefficients resulted in Table 5-10. Zd, Zs, Zd4, and Zs4 are equilibrium errors from the long-run demand and supply equations for the United States, and the long-run demand and supply equations for Canada respectively. All estimated significant coefficients for lumber prices, housing starts, and the equilibrium errors are as expected. The own-lumber-price elasticities in the demand equations are significant -0.29 and -0.58 in the short-run for the United States and Canada respectively. The cross-price elasticities for the lumber demand equations are significant 0.84 and 0.99 in the short-run for the United States and Canada respectively, suggesting that in the short-run the lumber from the United States and that from the Canada are substitutes. The lumber price elasticities in the short-run lumber supply equations are significant 0.84 and 0.38 for United States and Canada respectively.

Table 5-10 The 2SLS-estimated short-run coefficients of the U.S.-Canada model

	U.S. equations		Canada equations	
	demand for the U.S.	supply from the U.S.	U.S. demand for Canada	Supply from Canada
dLP	-0.29**	0.84***	0.99***	
dLP4	0.84***		-0.58***	0.38*
dLH	0.23***		0.20**	
dLDPI	1.61***		-0.29	
dLInv4				0.07
dLTP_1		0.05		
dLLC		1.38		
Zd	-0.88***			
Zs		-0.86***		
Zd4			-0.85***	
Zs4				-0.62***
trend		0.0001		0.0000
Constant	0.00	0.00	0.02***	0.02
D1	0.10***	0.05*	-0.01	0.01
D11	-0.12***	-0.14***	-0.09***	-0.06***
D12	-0.08***	-0.06***	-0.12***	-0.13***
R^2	0.59	0.34	0.40	0.40
DW	1.94	1.80	2.01	2.01

In the short run, housing starts have significant short-run elasticities 0.23 and 0.20 in the demand equations for the United States and Canada respectively. DPI has a significant positive coefficient 1.61 for the demand equation for the United States, suggesting an elastic demand for the U.S. lumber with a one time increments in DPI when housing starts and other variables are held constant, but an insignificant negative one for the demand equation for Canada,. This is contrary to the corresponding estimated effects in the long-run when the differences of DPI no longer carry any trend effects. Apparently, the increase in demand over one month is more likely to be met by domestic suppliers. The short-run effect of the lumber inventory is insignificant.

One interesting result of the estimated regional and U.S.-Canada models is that U.S. lumber supply is more price elastic in the short-run (from 0.36 to 1.08) than it is in the long-run (from 0.08 to 0.38), while the Canadian lumber is less price elastic in the short-

run (0.38, 0.23) than it is in the long-run (0.43, 0.41). This result may implies that the Canadian supply respond slower to the U.S. market changes in the short run.

5.5 MLE for Structural Models with the Method of Johansen and Juselius

The Maximum Likelihood Estimator (MLE) by Johansen and Juselius (1990) is an alternative method to estimate the restricted ECM. Unlike Hsiao (1997a, 1997b) that assumed that "all relevant information is in the structural equation system …" Maddala and Kim (1998) wrote, the Johansen method

> "starts with a VAR model in the *I*(1) variables and first determines the number of CI vectors. ... Cointegration is a purely statistical concept and the CI vectors need not have any economic meaning." (Maddala and Kim, 1998, page 174) "Cointegration relations need not have any economic interpretation. ...whether the cointegration relation has any economic interpretation can never be answered..." (Maddala and Kim, 1998, page 236).

Since the methods of Hsiao (1997a, 1997b) and Johansen and Juselius (1990) are based on different models, Results of the two methods could be different.

The estimated results with method of Johansen and Juselius were listed in Table 5-11. The specification of the estimated ECM in this table is similar to that for the model corresponding to Table 5-3 (LPT4_1 excluded). The Likelihood Ratio (LR) test statistic is 76.28 with 55 degree of freedom. The hypothesis of this test is that all variables excluded from equations of the model have zero coefficients. The p-value for the test is 0.03. The hypothesis is rejected, suggesting the estimation for restricted model is invalid. Many of the estimated coefficients are impossible in the real world. For example, some of the estimated elasticities are as large as several hundred that are empirically impossible.

With restrictions for the model corresponding to Table 5-4, the LR statistic for the MLE by the method of Johansen and Juselius is 100.63, and the p-value is 0.00. The restriction is invalid by the LR test. Short-run parameters cannot be obtained because errors happened while RATS was trying to get variances for estimated long-run parameters. LR test results show that the ECM should not be estimated by the method of Johansen and Juselius, and estimated cointegration vectors show that the estimation for the ECM with their method is very poor.

Table 5-11 The estimated cointegration vectors for the restricted ECM with Johansen and Juselius' method

Regions	1		2		3		4	
	Demand	Supply	Demand	Supply	Demand	Supply	Demand	Supply
LSH1	1	1	0	0	0	0	0	0
LSH2	0	0	1	1	0	0	0	0
LY3	0	0	0	0	1	1	0	0
LSH4	0	0	0	0	0	0	1	1
LP1	-97.037	-0.314	-814.714	0	-0.03	0	0.598	0
LP2	141.193	0	1179.078	-0.228	0.058	0	-0.934	0
LP3	16.4	0	139.779	0	-0.275	-0.163	-0.963	0
LP4	-68.701	0	-574.463	0	0.036	0	0.745	-0.232
LHWM	-88.861	0	-738.761	0	0	0	0	0
LHS	0	0	0	0	0.022	0	0	0
LH	0	0	0	0	0	0	1.135	0
LDPI	76.644	0	640.327	0	-0.366	0	-1.592	0
LTP1_1	0	0.598	0	0	0	0	0	0
LTP2_1	0	0	0	0.068	0	0	0	0
LTP3_1	0	0	0	0	0	-0.061	0	0
LInv1_1	0	-0.428	0	0	0	0	0	0
LInv2_1	0	0	0	-0.397	0	0	0	0
LInv4_1	0	0	0	0	0	0	0	-0.293
LLC	0	-0.754	0	-1.415	0	-0.126	0	0
trend	0	-0.002	0	0.002	0	-0.001	0	-0.003

The LR test result: χ^2_{55} = 76.28 , p-value = 0.03

For the regional model, the results of the method of Johansen and Juselius in Table 5-11 are different from those of the 2SLS (Hsiao's method). However, with the method of Johansen and Juselius the MLE-estimated results of the U.S.-Canada model had long-run coefficients similar to the 2SLS (the results are not included in this dissertation). It is too

early to say which method is better generally. More theory and example are needed to compare the results. What can be concluded from this example is that a set of restriction (excluding some variables in specific equations) for a structural model can sometimes not be accepted by LR tests of the method of Johansen and Juselius when the 2SLS of Hsiao's methods treat the restrictions as truth. Hsiao (1997a, 1997b) suggested that the converging rate of the estimates of 2SLS varies according to restrictions; nonetheless, the 2SLS is valid when there are sufficient cointegration relations. Hsiao's conclusions make the 2SLS valid for more structural models than the method of Johansen and Juselius.

Chapter 6 The Best Forecasting Models

This chapter focuses on forecasting with econometric models. Endogenous variables will be divided into two groups: one on lumber prices, and the other on lumber quantities. Both univariate and multi-equation models will be applied. Section 6.1 will search for the best univariate forecasting models for different number of steps ahead. Section 6.2 will search for the best multi-equation forecasting models for different number of steps ahead. The overall best combinations of models for different numbers of steps ahead and either group of variables will be chosen among the best univariate and multi-equation models. Section 6.3 will examine the validation of the selected best forecasting models with additional observations. All the shaded numbers in tables of this chapter are the smallest statistics for models or groups of models compared.

6.1 The Best Univariate Forecasting Models

Univariate models use only observations of one variable to forecast its own future values. Dummy variables and trend sometimes may be included. Examples of Box-Jenkins and spectral forecasts will be presented in 6.1.1 and 6.1.2. Repeated one-step-ahead forecasts and the calculation of forecasting accuracies will be shown in 6.1.3. In 6.1.4 the best univariate forecasting models will be chosen for multi-step-ahead forecasts by comparing overall accuracies calculated from rolling forecasts.

6.1.1 Box-Jenkins Models and Their Forecasts

The first step of the Box-Jenkins method is to find the numbers of differences needed to make variables stationary. The stationarity of a series or the number of difference of a series can be checked by graphing autocorrelations. The RATS has a procedure called

“bjident.src” that will plot autocorrelations and partial autocorrelations. Autocorrelations were calculated by the direct definition of correlation. The definition for partial autocorrelations can be found in Hamilton (1994, page 111). A partial autocorrelation is the correlation of the current observation and its ith lag net of effects of its previous lags.

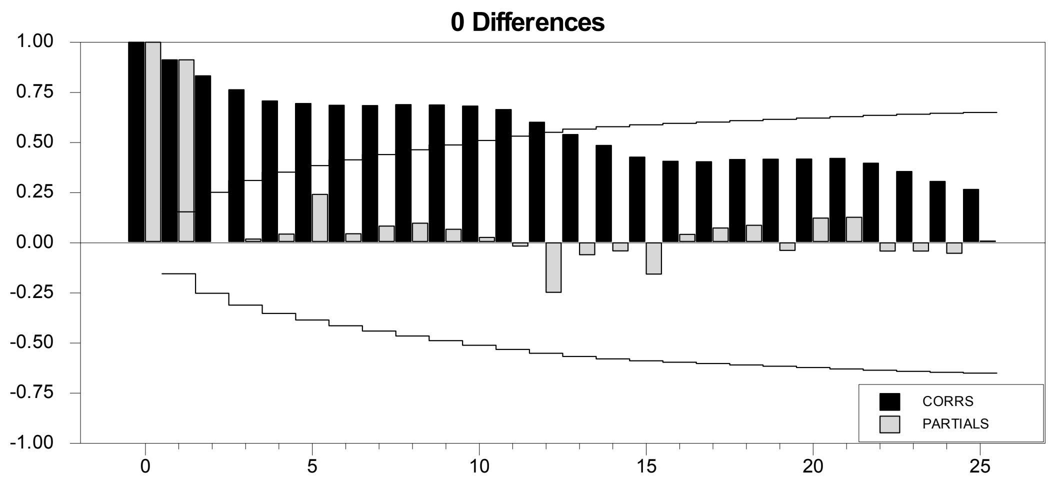


Figure 6-1 Autocorrelations and partial autocorrelations of P3

Figure 6-1 is a graph of autocorrelations and partial autocorrelations of P3. The highest bar is one. Similar graphs were obtained for time series for lumber prices, shipments, and production included in this dissertation. The autocorrelations and partial autocorrelations were similar to Figure 6-1; the first partial autocorrelations are close to 1, and the autocorrelation decays very slowly. Therefore, these time series are nonstationary.

Autocorrelations and partial autocorrelations of the first differences of P3 are shown in Figure 6-2. These correlations are small, and the first difference of the lumber price P3 is stationary. Similar results were obtained for the other endogenous time series.

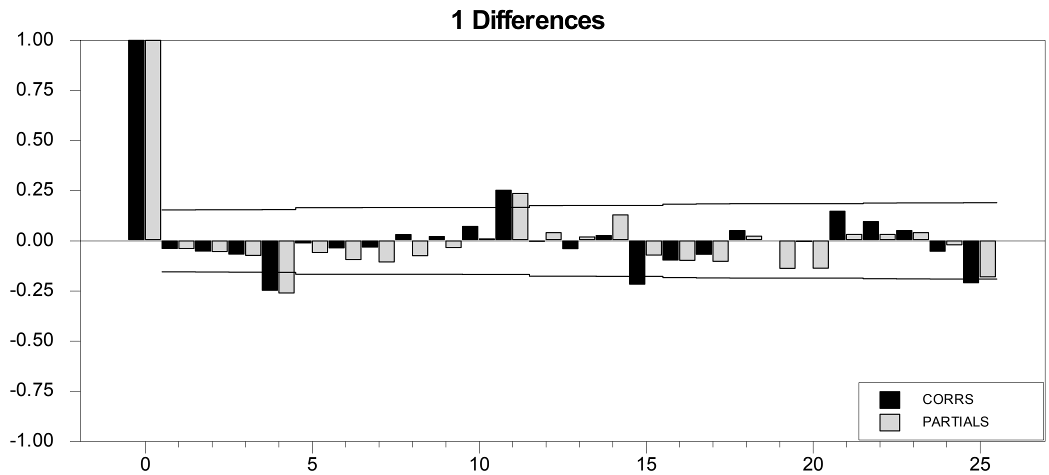


Figure 6-2 Autocorrelations and partial autocorrelations of first differences of P3

A Box-Jenkins model was estimated with data from 1990:1 to 2003:12 and up to 13 lags. Since the data do not show the existence of trend in the short-run, constant was not included in the model. The residual of the autoregressive model is graphed in Figure 6-3.

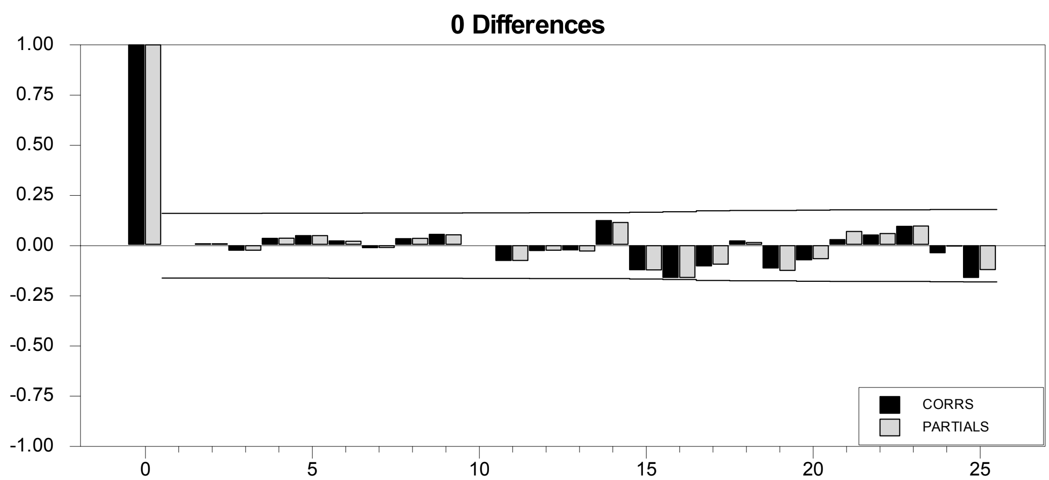


Figure 6-3 Autocorrelations and partial autocorrelations of residuals from the estimated ARIMA model for P3 (diffs=1, ARs=13, MAs=0)

All of the 25 autocorrelations are less than 0.2, suggesting a well behaved disturbance term of this model. Some out-of-sample forecasts of such models are plotted in Figure 6-4. The three graphs in this figure are out-of-sample forecasts beginning from 1999:7, 2002:1, and 2003:1. The dashed lines are for the forecasts, and P3f is the forecast for P3. For the top graph of the figure, data before 1999:7 was used for the first estimation, and forecasts from 1999:7 to 2004:12 were plotted. For the middle graph of this figure, data before 2002:1 were used for the estimation, and out-of-sample forecasts from 2002:1 to 2004:12 were plotted. For the bottom graph of this figure, data before 2003:1 were used for estimation, and out-of-sample forecasts from 2003:1 to 2004:12 were plotted. The first few forecasts are not far from their true values. Forecasts for the later months are usually far from their true values.

Since the means of endogenous variables are different, forecast errors for different variables are not comparable. A relative measure has to be used. A relative forecast error (RFE) is a measure for the relative difference between a forecast and its true value. A RFE measures the accuracy of a forecast, and can be calculated by

$$\text{RFE} = \frac{\text{Forecast value - true value}}{\text{True value}}$$

Table 6-1 and 2 are some relative forecast errors of the eight endogenous variables from eight Box-Jenkins (ARIMA) models. One model was estimated for each of the eight variables. Each of the forecasting models had 13 lags, one difference, no constant, and no moving averages. The estimation period for Table 6-1 is from 1990:1 to 2000:12, and that for Table 6-2 was from 1990:1 to 2002:12. The second-to-the-last columns of Table 6-1 and 2 are for mean absolute values of relative forecast errors (MAV of RFEs) of the eight variables.

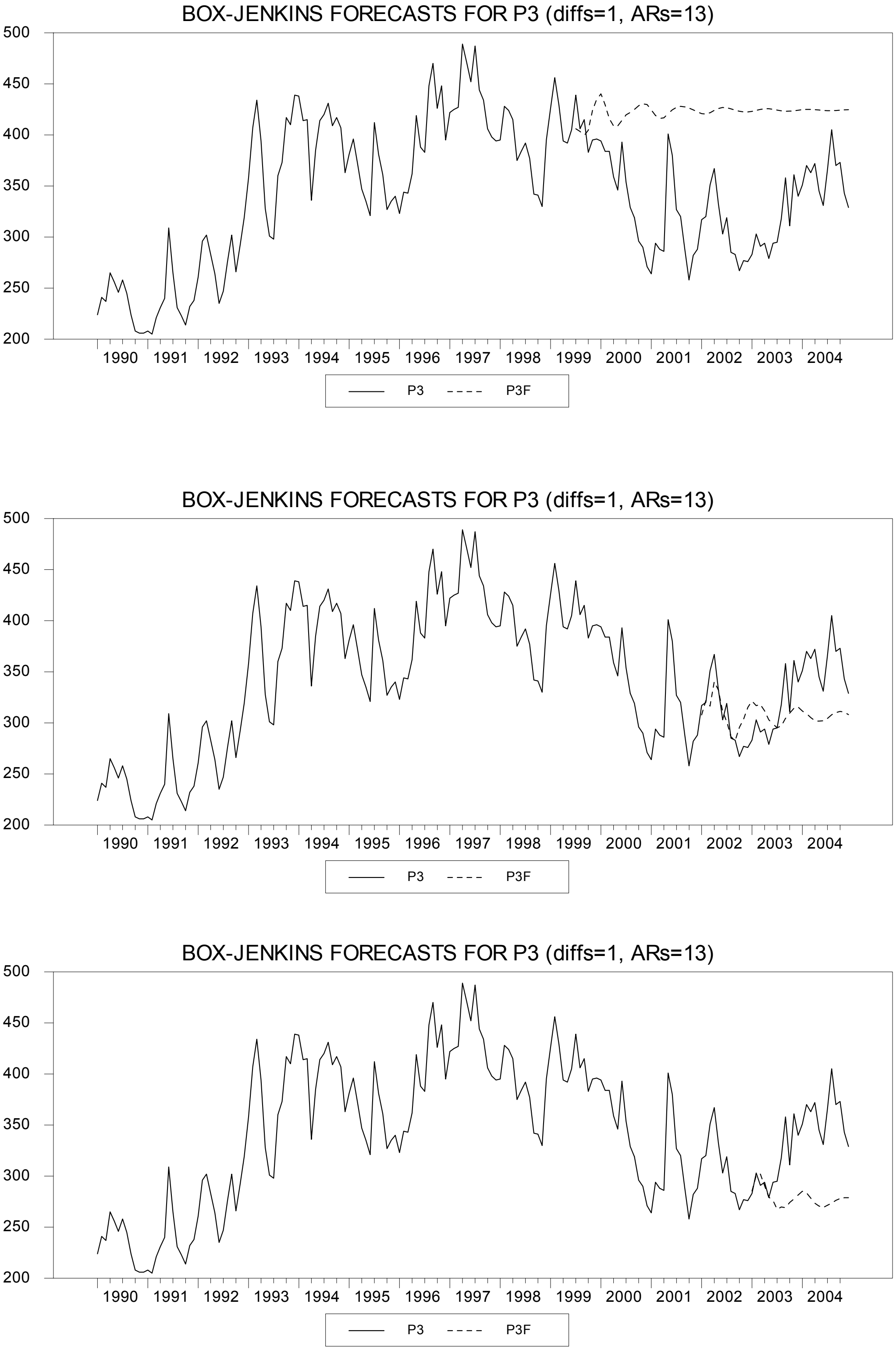


Figure 6-4 Observations of P3 and the forecasted P3 by Box-Jenkins models

Table 6-1 Relative forecast errors of Box-Jenkins models (from 2001)

Month	Relative forecast errors (RFEs)								MAVs of RFEs	RMSs of RFEs
	SH1	P1	SH2	P2	Y3	P3	SH4	P4		
2001:01	0%	0%	7%	0%	4%	4%	-1%	4%	3%	4%
2001:02	9%	-3%	17%	-5%	14%	-4%	1%	4%	7%	9%
2001:03	-2%	-6%	2%	-12%	9%	-1%	8%	-4%	5%	7%
2001:04	-5%	-11%	2%	-29%	3%	-1%	-23%	1%	9%	14%
2001:05	-6%	-24%	-9%	-50%	-8%	-30%	-13%	-15%	19%	24%
2001:06	0%	-15%	1%	-42%	5%	-28%	-3%	-25%	15%	21%
2001:07	-10%	-7%	-2%	-39%	-6%	-19%	-14%	-18%	14%	18%
2001:08	-11%	-8%	-9%	-45%	-8%	-20%	-7%	-19%	16%	20%
2001:09	3%	0%	9%	-40%	10%	-14%	5%	-16%	12%	17%
2001:10	-11%	11%	-2%	-25%	-13%	-3%	-3%	-7%	9%	12%
2001:11	4%	10%	14%	-24%	0%	-12%	13%	-1%	10%	12%
2001:12	27%	2%	22%	-25%	2%	-13%	1%	0%	12%	16%
2002:01	-2%	-3%	1%	-31%	-5%	-20%	-2%	-2%	8%	13%
2002:02	4%	-11%	9%	-39%	10%	-20%	-6%	-8%	13%	17%
2002:03	-1%	-14%	0%	-44%	-1%	-27%	-16%	-15%	15%	21%
2002:04	-11%	-7%	-2%	-41%	-7%	-31%	-18%	-18%	17%	21%
2002:05	-7%	-3%	-1%	-38%	-4%	-26%	-27%	-16%	15%	20%
2002:06	-8%	0%	-10%	-34%	-7%	-20%	23%	2%	13%	17%
2002:07	-13%	3%	-2%	-34%	-9%	-25%	3%	1%	11%	16%
2002:08	-9%	0%	-5%	-27%	-9%	-16%	-5%	5%	9%	12%
2002:09	-6%	-1%	-1%	-18%	-4%	-15%	-3%	10%	7%	10%
2002:10	-13%	0%	-7%	-17%	-14%	-9%	-13%	16%	11%	12%
2002:11	3%	2%	17%	-11%	4%	-12%	2%	15%	8%	10%
2002:12	5%	1%	14%	-20%	19%	-11%	4%	19%	12%	14%
2003:01	-17%	1%	-16%	-22%	-1%	-14%	5%	16%	12%	14%
2003:02	0%	-2%	0%	-28%	14%	-20%	6%	14%	11%	14%
2003:03	-4%	5%	3%	-21%	6%	-17%	-5%	14%	9%	11%
2003:04	-9%	4%	-6%	-18%	-6%	-19%	-8%	17%	11%	12%
2003:05	-9%	5%	-1%	-19%	2%	-15%	-12%	21%	11%	13%
2003:06	-9%	-14%	-4%	-32%	-9%	-19%	-15%	20%	15%	17%
2003:07	-17%	-16%	-7%	-33%	-7%	-19%	-9%	11%	15%	17%
2003:08	-13%	-21%	-1%	-42%	-11%	-25%	-11%	11%	17%	21%
2003:09	-11%	-23%	2%	-49%	-6%	-33%	-13%	-1%	17%	23%
2003:10	-22%	-11%	-4%	-38%	-18%	-23%	-12%	2%	16%	20%
2003:11	-2%	-12%	19%	-38%	-5%	-33%	-9%	10%	16%	20%
2003:12	-5%	-6%	18%	-39%	4%	-29%	0%	3%	13%	19%
Overall									12%	16%

Table 6-2 Relative forecast errors of Box-Jenkins models (from 2003)

Month	Relative forecast errors (RFEs)								MAVs of RFEs	RMSs of RFEs
	SH1	P1	SH2	P2	Y3	P3	SH4	P4		
2003:01	-13%	1%	-19%	3%	0%	1%	7%	1%	6%	9%
2003:02	-3%	-2%	-9%	-4%	-2%	-1%	19%	2%	5%	8%
2003:03	-1%	2%	0%	5%	3%	4%	10%	0%	3%	5%
2003:04	-1%	0%	-9%	6%	1%	-1%	12%	1%	4%	6%
2003:05	-4%	1%	-4%	3%	0%	0%	2%	0%	2%	2%
2003:06	-1%	-16%	-2%	-14%	-2%	-6%	-13%	-4%	7%	9%
2003:07	-9%	-17%	-7%	-16%	2%	-9%	-19%	-8%	11%	12%
2003:08	-7%	-22%	1%	-30%	-6%	-15%	-7%	-8%	12%	15%
2003:09	-5%	-24%	-1%	-37%	2%	-25%	-6%	-18%	15%	19%
2003:10	-15%	-13%	-5%	-21%	-11%	-12%	-5%	-14%	12%	13%
2003:11	-1%	-14%	14%	-22%	-11%	-23%	0%	-7%	11%	14%
2003:12	-3%	-8%	13%	-20%	-6%	-17%	-4%	-12%	10%	12%
2004:01	-5%	-18%	7%	-30%	-8%	-19%	14%	-12%	14%	16%
2004:02	-8%	-33%	8%	-40%	-9%	-23%	10%	-15%	18%	22%
2004:03	-16%	-35%	-2%	-40%	-13%	-23%	-2%	-25%	19%	24%
2004:04	-24%	-45%	0%	-48%	-13%	-27%	-2%	-27%	23%	29%
2004:05	-10%	-45%	7%	-52%	-8%	-22%	-12%	-34%	24%	29%
2004:06	-27%	-39%	-7%	-48%	-3%	-19%	-19%	-35%	25%	29%
overall									12%	17%

$$\text{MAV of RFEs} = \frac{\text{sum of absolute values of RFEs}}{\text{number of forecasts}}.$$

The last column of Table 6-1, 2 is for the Root Mean Square of relative forecast errors (RMS of RFEs).

$$\text{RMS of RFEs} = \sqrt{\frac{\text{sum square of RFEs}}{\text{number of forecasts}}}.$$

Both MAV and RMS of RFEs are statistics measuring the accuracy of a group of forecasts. The MAV of RFEs is the average distance between forecasts and their true values; the RMS of RFEs combines both such distances and the variance of distances. “Larger” errors are given higher weight. Given a variance, a large MAV of RFEs implies a large corresponding RMS of RFEs. When the variance is large, the corresponding RMS

of RFEs is also large; when the variance is zero, RMS equals MAVs. Based on repeated experiments of ARIMA lumber models with different ranges of data, it was concluded that short-run forecasts of ARIMA models are pretty close to their true values, but the long-run forecasts are poor. These results are consistent with the property of dynamic forecasting models.

6.1.2 Spectral Forecasts

Spectral forecasting program of RATS is a frequency domain method for fitting Box-Jenkins models. The explanation can be found in time series textbooks (e.g. Hamilton, 1994). It is tried here as one choice of forecasting method. Since data series are nonstationary, the number of differences of the data is one. Out-of-sample forecasting results are shown in Figure 6-5. The estimation periods are those before forecast periods. The forecasts have the similar pattern as those by the Box-Jenkins model. Only the first few (three by Table 6-3) of forecasts are close to the true values. Longer forecasts are poor.

Table 6-3 and 4 are results of two examples of forecasts from spectral models with first differences and no constant. Table 6-3 is for relative forecast errors from spectral models estimated with an estimation period from 1990:1 to 2000:12, and Table 6-4 is for relative forecast errors from the same spectral model estimated with an estimation period from 1990:1 to 2002:12. MAVs of RFEs and RMSs of RFEs are generally increasing overtime, showing that on the average the farther the forecasts are from estimation periods, the less accurate the forecasts are. The overall MAVs and RMSs of the 288 forecasts included in this table are 11% and 15% respectively.

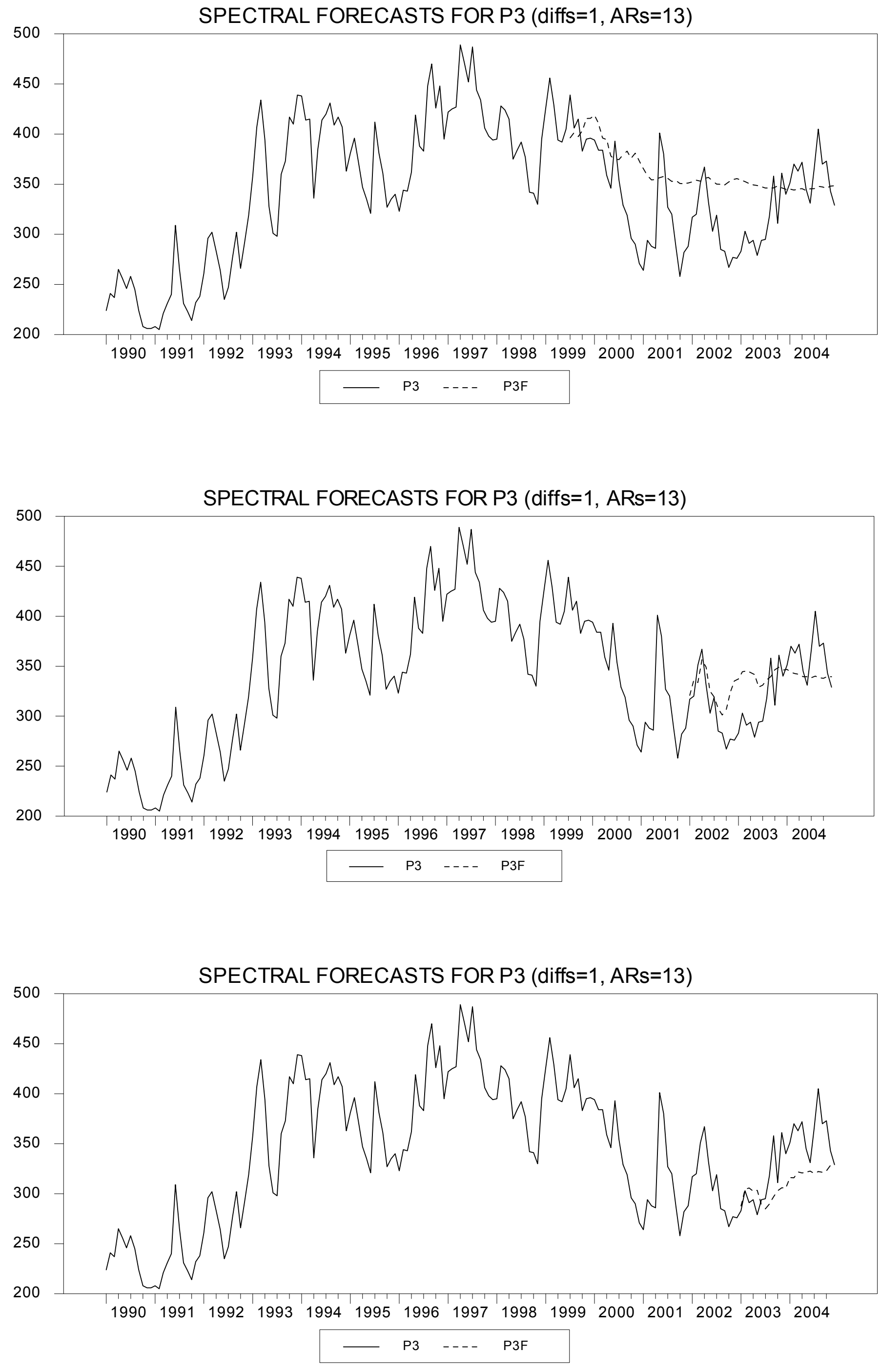


Figure 6-5 Observations of P3 and the forecasted P3 by spectral models

Table 6-3 Relative forecast errors of spectral models from 2001:1

Month	Relative forecast errors								MAVs of RFEs	RMSs of RFEs
	SH1	P1	SH2	P2	Y3	P3	SH4	P4		
2001:1	-4%	0%	1%	0%	-4%	4%	-3%	5%	3%	3%
2001:2	7%	-2%	16%	0%	4%	-3%	-2%	7%	5%	7%
2001:3	-6%	-4%	-4%	-3%	-5%	0%	4%	1%	3%	4%
2001:4	-5%	-4%	-5%	-24%	-8%	2%	-26%	8%	10%	13%
2001:5	-8%	-19%	-14%	-45%	-15%	-26%	-15%	-8%	19%	22%
2001:6	-5%	-4%	-7%	-35%	-3%	-24%	-5%	-18%	12%	17%
2001:7	-12%	4%	-7%	-31%	-11%	-15%	-16%	-9%	13%	15%
2001:8	-13%	3%	-14%	-38%	-12%	-15%	-11%	-11%	15%	17%
2001:9	-1%	14%	3%	-27%	3%	-8%	2%	-7%	8%	12%
2001:10	-12%	29%	-2%	-8%	-15%	1%	-6%	5%	10%	13%
2001:11	3%	28%	11%	-3%	-2%	-6%	10%	11%	9%	12%
2001:12	27%	23%	19%	2%	2%	-2%	0%	17%	12%	16%
2002:1	-1%	15%	-4%	-5%	-12%	-9%	-2%	16%	8%	10%
2002:2	1%	7%	4%	-15%	-1%	-9%	-11%	9%	7%	9%
2002:3	-1%	3%	1%	-20%	-9%	-15%	-20%	1%	9%	12%
2002:4	-10%	10%	-6%	-16%	-16%	-19%	-23%	-2%	13%	14%
2002:5	-8%	14%	-2%	-9%	-9%	-10%	-30%	0%	10%	13%
2002:6	-9%	18%	-15%	-2%	-14%	-4%	19%	21%	13%	14%
2002:7	-15%	20%	-6%	-3%	-16%	-12%	-2%	20%	12%	14%
2002:8	-8%	18%	-5%	7%	-12%	-1%	-6%	23%	10%	12%
2002:9	-6%	17%	-3%	23%	-9%	0%	-7%	29%	12%	15%
2002:10	-13%	18%	-7%	21%	-15%	7%	-16%	35%	17%	19%
2002:11	2%	21%	11%	29%	4%	5%	-2%	34%	14%	18%
2002:12	5%	18%	12%	17%	16%	7%	0%	38%	14%	18%
2003:1	-18%	18%	-17%	13%	-9%	4%	3%	35%	15%	18%
2003:2	-2%	14%	-3%	5%	1%	-2%	3%	33%	8%	13%
2003:3	-5%	20%	1%	15%	-3%	1%	-9%	33%	11%	15%
2003:4	-9%	20%	-9%	17%	-15%	-1%	-14%	36%	15%	18%
2003:5	-10%	21%	-4%	16%	-6%	4%	-18%	41%	15%	19%
2003:6	-10%	-1%	-7%	-1%	-16%	-3%	-19%	39%	12%	17%
2003:7	-18%	-2%	-8%	-3%	-14%	-3%	-13%	29%	11%	14%
2003:8	-14%	-9%	-4%	-18%	-13%	-10%	-15%	29%	14%	16%
2003:9	-11%	-10%	-1%	-27%	-8%	-19%	-17%	15%	14%	15%
2003:10	-23%	3%	-6%	-11%	-20%	-7%	-17%	18%	13%	15%
2003:11	-3%	3%	16%	-11%	-5%	-20%	-13%	27%	12%	15%
2003:12	-5%	9%	16%	-12%	0%	-15%	-3%	20%	10%	12%
overall									11%	15%

Table 6-4 Relative forecast errors of spectral models from 2003:1

Month	Relative forecast errors								MAVs of RFEs	RMSs of RFEs
	SH1	P1	SH2	P2	Y3	P3	SH4	P4		
2003:1	-18%	1%	-24%	1%	-8%	-1%	8%	-2%	8%	11%
2003:2	-6%	2%	-12%	-5%	-9%	-3%	16%	1%	7%	8%
2003:3	0%	9%	1%	10%	-7%	3%	5%	2%	5%	6%
2003:4	-6%	8%	-15%	10%	-11%	-1%	6%	5%	8%	9%
2003:5	-8%	11%	-9%	12%	-5%	5%	-2%	10%	8%	8%
2003:6	-3%	-9%	-7%	-4%	-11%	-6%	-10%	9%	7%	8%
2003:7	-12%	-12%	-11%	-6%	-6%	-9%	-8%	2%	8%	9%
2003:8	-8%	-18%	-1%	-23%	-9%	-14%	-7%	0%	10%	12%
2003:9	-5%	-21%	-6%	-30%	-3%	-22%	-6%	-11%	13%	16%
2003:10	-20%	-8%	-11%	-11%	-15%	-10%	-7%	-9%	11%	12%
2003:11	-2%	-7%	10%	-10%	-7%	-22%	-3%	1%	8%	10%
2003:12	-4%	0%	8%	-9%	-6%	-18%	2%	-4%	6%	8%
2004:1	-11%	-11%	1%	-19%	-13%	-18%	15%	-2%	11%	13%
2004:2	-8%	-26%	5%	-29%	-10%	-23%	9%	-4%	14%	17%
2004:3	-18%	-28%	-5%	-29%	-19%	-21%	-8%	-14%	18%	20%
2004:4	-27%	-39%	-5%	-38%	-24%	-23%	-7%	-16%	22%	25%
2004:5	-11%	-40%	2%	-43%	-11%	-17%	-15%	-24%	21%	25%
2004:6	-30%	-34%	-12%	-39%	-14%	-14%	-16%	-27%	23%	25%
Overall									12%	15%

6.1.3 One-Step-Ahead Forecasts

A forester may be interested in the accuracy of a forecast for a number of months ahead, e.g. a five-step-ahead forecast. To obtain forecasting accuracies, a specific steps-ahead forecasting was repeated with different estimation periods to get a sample of such forecasts. Overall MAVs and RMSs of RFEs were obtained from the sample.

To show how overall MAVs and RMSs are calculated, this section will give some details on evaluating accuracies for one-step-ahead forecasts of different univariate forecasting models. A one-step-ahead forecast is a forecast that is one step ahead of the estimation period. For example if data from 1990:1 to 2000:12 are used for estimation, the one-step-ahead forecast is a forecast for 2001:1; For the next forecast, data from

1990:1 to 2001:1 will be used for estimation, the one-step-ahead forecast is a forecast for 2001:2. Such rolling ahead forecasting will result in a series of forecasts.

Eight models will be used for forecasting. The first Box-Jenkins model is one with the first difference, no constant, and AR(13). The second model is a Box-Jenkins model with the first difference, no constant, and no autocorrelations. The third model is a spectral model with the first difference and no constant. The fourth model is a simple lag model that just takes the nearest available lags as forecasts. For one-step-ahead forecast, the fourth model uses the first lags. The fifth model is a simple 12-lag model that takes the observation in the same month of previous years as the forecast for the current month. The sixth model is a seasonal-dummy-variable model with 11 monthly dummy variables and a constant. This model forecasts with averages of previous observations and dummy variables. The seventh model is a seasonal-dummy-variable model with 12 monthly dummy variables, constant, and AR(1). The eighth model is a model with 3 monthly dummy variables, constant and AR(12). The three monthly dummy variables are for November, December, and January. The other unimportant dummy variables are excluded to save degree of freedom for autocorrelations. The seventh and eighth models are actually ARMA model with different dummy variables and numbers of autocorrelations.

Figure 6-6 shows an example of one-step-ahead Box-Jenkins forecasts of the first model and true values. For each forecast in this figure, the model is re-estimated with one additional period of data. The dashed curve starting from 1999:7 is for forecasts of P3, and the solid curve is for P3. Figure 6-7 shows only the last half of Figure 6-6. The dashed series is for the forecasts. Figure 6-8 is for one-step-ahead spectral forecasts, and

Figure 6-9 shows lags (lagP3) and true values of lumber prices for P3. The one-step-ahead forecasts with ARIMA models are very much like the first lags. It implies that the current value of lumber is important for forecasting the lumber price in the next month.

One-step-ahead forecasts for other lumber prices, outputs and shipments are similar according to further experiments that are not included in this dissertation to avoid redundancy.

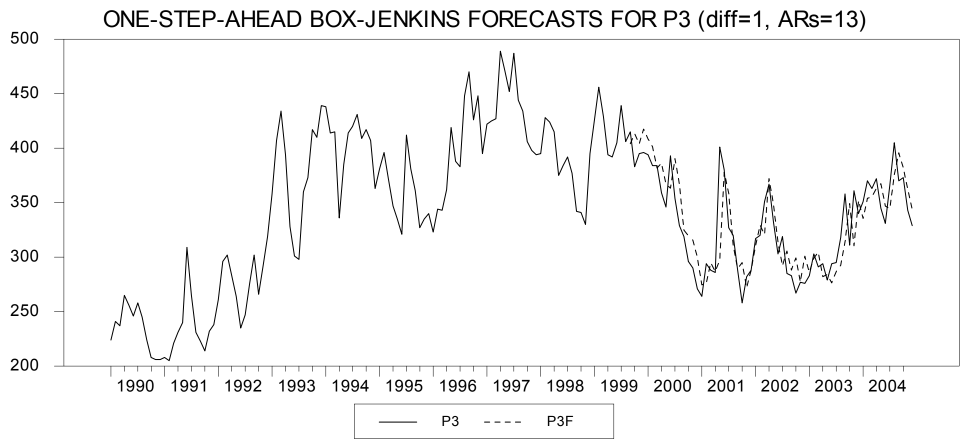


Figure 6-6 Observations of P3 and their one-step-ahead Box-Jenkins forecasts

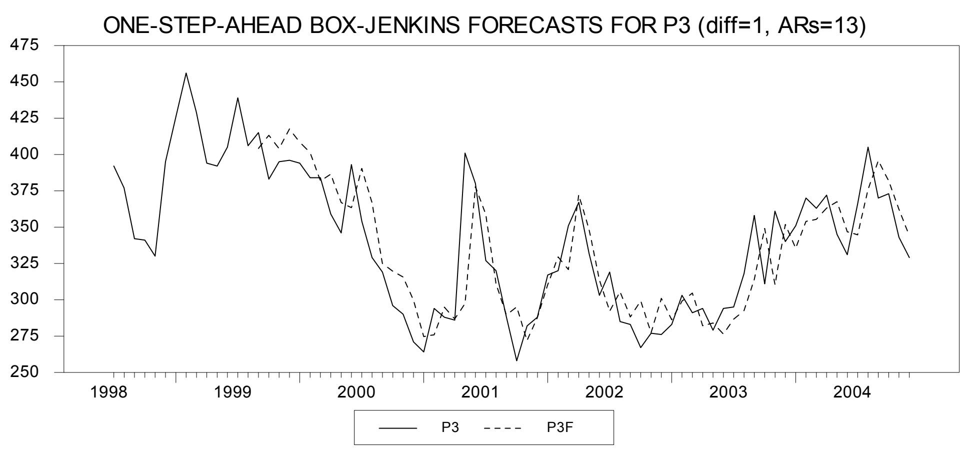


Figure 6-7 One-step-ahead Box-Jenkins forecasts for P3 (a part of Figure 6-7)

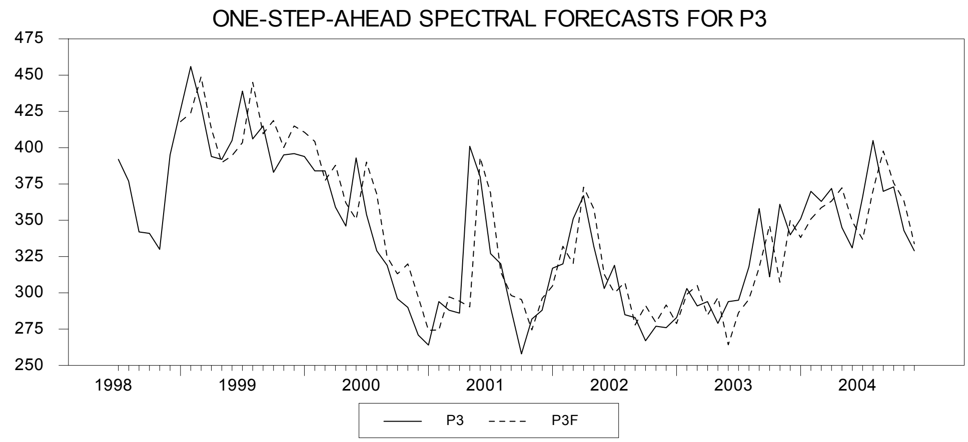


Figure 6-8 Observations of P3 and their one-step-ahead spectral forecasts

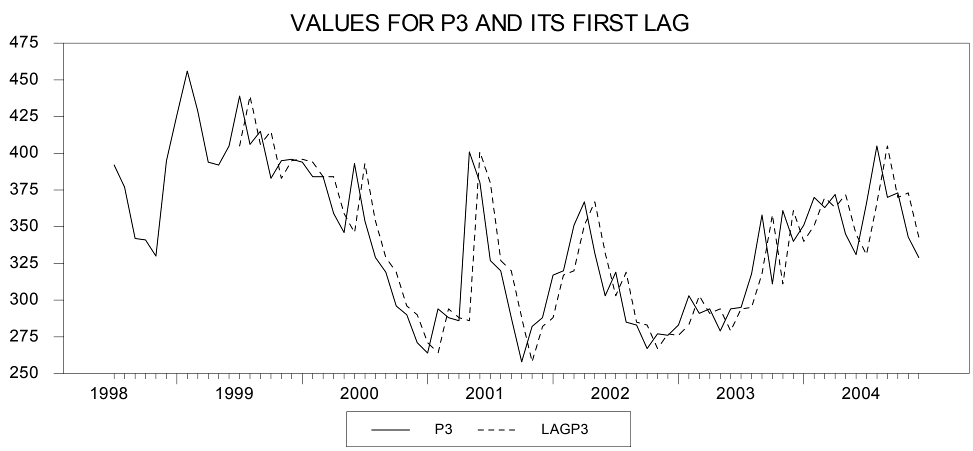


Figure 6-9 Values of P3 and their first lags (the dashed series)

Part of the results was numerically shown in Table 6-5 and 6 as samples for calculating MAVs and RMEs. These two tables list relative forecast errors, MAVs and RMEs of RFEs. Table 6-5 is for forecasts of the first Box-Jenkins model, and Table 6-6 is for forecasts of the Spectral model.

Table 6-5   One-step-ahead relative forecast errors of Box-Jekins AR(13) model

Month	Relative forecast errors								MAVs of RFEs	RMSs of RFEs
	SH1	P1	SH2	P2	Y3	P3	SH4	P4		
2001:1	0%	0%	7%	0%	6%	4%	2%	4%	3%	4%
2001:2	9%	-2%	13%	-5%	16%	-7%	4%	-1%	7%	9%
2001:3	-5%	-3%	-4%	-6%	6%	3%	11%	-7%	6%	6%
2001:4	-5%	-5%	-3%	-19%	-1%	0%	-23%	8%	8%	11%
2001:5	-4%	-15%	-13%	-27%	-11%	-29%	-1%	-17%	15%	17%
2001:6	4%	15%	1%	18%	7%	-1%	7%	-7%	7%	9%
2001:7	-9%	6%	-5%	2%	-4%	12%	-7%	12%	7%	8%
2001:8	-7%	-4%	-9%	-14%	-5%	-4%	-5%	-3%	6%	7%
2001:9	9%	9%	11%	6%	13%	1%	14%	1%	8%	9%
2001:10	-9%	15%	-2%	29%	-9%	17%	1%	8%	11%	14%
2001:11	8%	-2%	10%	0%	3%	-4%	19%	8%	7%	9%
2001:12	29%	-8%	11%	-3%	1%	0%	-3%	-3%	7%	12%
2002:1	-9%	5%	-8%	-2%	-4%	-2%	4%	-1%	4%	5%
2002:2	-5%	-7%	-4%	1%	-2%	4%	-6%	-1%	4%	4%
2002:3	0%	-5%	-4%	-13%	-3%	-10%	-8%	-4%	6%	7%
2002:4	-7%	10%	-9%	11%	-2%	2%	-4%	-2%	6%	7%
2002:5	0%	2%	-1%	6%	2%	6%	-10%	7%	4%	5%
2002:6	-4%	-4%	-10%	-3%	-4%	4%	46%	17%	11%	18%
2002:7	-5%	4%	-1%	-1%	-2%	-9%	5%	-13%	5%	6%
2002:8	1%	-1%	-1%	14%	-1%	8%	1%	7%	4%	6%
2002:9	-4%	-2%	-5%	6%	-1%	2%	-10%	0%	4%	5%
2002:10	-4%	3%	-9%	3%	-3%	13%	-5%	10%	6%	7%
2002:11	6%	7%	17%	16%	9%	0%	7%	1%	8%	10%
2002:12	1%	-1%	2%	-4%	21%	10%	5%	9%	6%	9%
2003:1	-13%	1%	-21%	3%	1%	1%	9%	1%	6%	9%
2003:2	4%	-3%	-4%	-7%	-1%	-1%	19%	1%	5%	7%
2003:3	4%	4%	4%	11%	5%	5%	7%	-1%	5%	6%
2003:4	3%	-2%	-5%	-1%	2%	-4%	10%	1%	4%	4%
2003:5	-7%	2%	-1%	-1%	0%	2%	1%	-1%	2%	3%
2003:6	1%	-17%	1%	-18%	-3%	-6%	-11%	-3%	7%	10%
2003:7	-8%	1%	-7%	1%	4%	-3%	-15%	-4%	5%	7%
2003:8	-1%	-8%	3%	-18%	-5%	-8%	-1%	1%	6%	8%
2003:9	-2%	-4%	-2%	-10%	4%	-13%	-4%	-11%	6%	8%
2003:10	-9%	14%	-4%	20%	-10%	13%	-3%	7%	10%	11%
2003:11	7%	-3%	19%	-3%	-5%	-15%	2%	5%	7%	9%
2003:12	2%	7%	9%	-1%	-1%	4%	3%	-6%	4%	5%
Overall									6%	9%

Table 6-6   **One-step-ahead relative forecast errors of the spectral model**

Month	Relative forecast errors(Spectral Model)								MAVs of RFEs	RMSs of RFEs
	SH1	P1	SH2	P2	Y3	P3	SH4	P4		
2001:1	-5%	0%	0%	0%	-4%	4%	-3%	6%	3%	4%
2001:2	10%	-2%	16%	0%	10%	-7%	1%	0%	6%	8%
2001:3	-9%	-2%	-12%	-3%	-4%	3%	8%	-5%	6%	7%
2001:4	-2%	1%	-6%	-21%	-3%	3%	-26%	10%	9%	13%
2001:5	-5%	-16%	-14%	-26%	-9%	-27%	6%	-17%	15%	17%
2001:6	3%	18%	1%	20%	10%	4%	8%	-7%	9%	11%
2001:7	-8%	7%	-2%	3%	-2%	13%	-8%	11%	7%	8%
2001:8	-6%	-3%	-7%	-15%	-1%	-1%	-3%	-2%	5%	7%
2001:9	9%	13%	14%	11%	13%	4%	13%	2%	10%	11%
2001:10	-8%	18%	1%	31%	-10%	15%	-2%	10%	12%	15%
2001:11	11%	-1%	12%	5%	9%	-3%	19%	8%	8%	10%
2001:12	31%	-4%	9%	1%	5%	3%	-4%	1%	7%	12%
2002:1	-13%	3%	-15%	1%	-6%	-4%	4%	0%	6%	8%
2002:2	-3%	-6%	-4%	-1%	2%	4%	-8%	-1%	4%	4%
2002:3	-1%	-6%	-1%	-8%	-4%	-9%	-9%	-5%	5%	6%
2002:4	-7%	10%	-7%	11%	-3%	2%	-5%	-1%	6%	7%
2002:5	-1%	2%	5%	8%	2%	8%	-11%	6%	5%	6%
2002:6	-5%	-4%	-11%	-1%	-4%	3%	60%	17%	13%	23%
2002:7	-7%	4%	-1%	-1%	-3%	-6%	-6%	-9%	5%	5%
2002:8	4%	-1%	-1%	13%	1%	8%	-3%	5%	4%	6%
2002:9	1%	-2%	-1%	6%	2%	-2%	-8%	1%	3%	4%
2002:10	-6%	2%	-7%	-6%	-1%	9%	-5%	7%	5%	6%
2002:11	8%	8%	13%	14%	12%	1%	11%	-1%	9%	10%
2002:12	1%	-1%	4%	-8%	22%	6%	4%	7%	7%	9%
2003:1	-18%	1%	-25%	1%	-8%	-1%	8%	-2%	8%	12%
2003:2	7%	1%	2%	-5%	0%	-1%	13%	4%	4%	6%
2003:3	5%	7%	12%	16%	0%	5%	-2%	1%	6%	8%
2003:4	-1%	-1%	-7%	-1%	-3%	-3%	4%	2%	3%	3%
2003:5	-7%	5%	-2%	5%	5%	7%	-3%	5%	5%	5%
2003:6	2%	-18%	0%	-15%	-6%	-10%	-8%	-1%	7%	10%
2003:7	-7%	-1%	-5%	0%	4%	-3%	-3%	-6%	4%	4%
2003:8	2%	-8%	3%	-18%	-3%	-7%	-2%	0%	5%	8%
2003:9	-1%	-5%	-2%	-9%	6%	-11%	-4%	-10%	6%	7%
2003:10	-14%	13%	-9%	21%	-12%	12%	-3%	4%	11%	12%
2003:11	14%	-2%	20%	-1%	3%	-15%	1%	8%	8%	11%
2003:12	0%	7%	7%	-1%	3%	3%	5%	-7%	4%	5%
Overall									7%	9%

The MAV and RMS of RFEs over 36-month period from 2001:1 to 2003:12 for the eight variables are 6% and 9% respectively in Table 6-5, and 7% and 9% respectively in Table 6-6. The forecasting accuracy of the first Box-Jenkins and that of Spectral models are quite close.

The overall MAVs and RMSs of RFEs of one-step-ahead forecasts for the eight models are listed in Table 6-7. The forecast period is also from 2001:1 to 2003:12. This table shows that the Box-Jenkins model with differenced data and 13 lags has the smallest MAV and RMS for one-step-ahead forecasts. The first model in Table 6-7 is the most accurate univariate model for forecasting the eight endogenous variables. The shaded MAV and RMS are the smallest ones of their corresponding column.

Table 6-7 The overall MAVs and RMSs of RFEs of one-step-ahead forecasts of univariate models for endogenous variables

Models	Number of forecasts	MAVs of RFEs	RMSs of RFEs
1. Box-Jenkins (1 difference, 13 lags)	36	6%	9%
2. Box-Jenkins (1 difference, No lags)	36	8%	11%
3. Spectral model (1 difference)	36	7%	9%
4. Simple lag model	36	8%	11%
5. Simple 12th lag model	36	12%	17%
6. Seasonal-dummy-variable model	36	15%	18%
7. Seasonal-dummy-variable AR1 model	36	7%	10%
8. Seasonal-dummy-variable AR13 model	36	14%	24%

6.1.4 The Best Multi-Step-Ahead Univariate Forecasting Models

The eight models used for Table 6-7 are applied to different groups of variables for 6, 12, 36, and 60-month-ahead forecasts. The forecasting process is similar to that of section 6.1.3. Since the simple lag model takes the nearest available lags as forecasts, this model uses different lags for different steps ahead forecasts. Results are shown in Table 6-8 to

11. Table 6-8 is for the overall MAVs and RMSs of RFEs for forecasts of shipments or production. In Table 6-8, the first model has the smallest MAVs and RMSs for 1, 6 and 12-step-ahead forecasts. It can be concluded that for 12 or less than 12 months lumber quantity forecasts, the Box-Jenkins model with 13 lags and difference data is the most accurate. The simple lag model has the smallest MAVs and RMSs for the 12, 36, and 60-step-ahead forecasts for lumber quantities in Table 6-8. The 12-step-ahead forecasts of the fourth model have smaller MAVs and RMSs of RFEs than 1 and 6-step-ahead forecasts. Table 6-9 also shows that forecasts of the nearest multiples of 12-month seasonal lags model are more accurate than or as good as forecasts of simple lag models for forecasting lumber quantity. For example, Table 6-9 shows that 24-lag forecasts are better than 13 or 20-lag forecasts, and 36-lag forecasts are better than 26-lag forecasts.

Table 6-8 The overall MAVs and RMSs of RFEs of multi-step-ahead forecasts of univariate models for the four lumber quantities

Models	MAVs of RFEs				
	1 step	6 steps	12 steps	36 steps	60 steps
1.Box-Jenkins (1 difference, 13 lags)	6%	8%	8%	10%	20%
2.Box-Jenkins (1 difference, No lags)	10%	13%	8%	11%	21%
3.Spectral model (1 difference)	7%	8%	8%	10%	22%
4.Simple lag model	10%	13%	8%	9%	9%
5.Simple 12th lag model	8%	8%			
6.Seasonal-dummy-variable model	13%	13%	13%	15%	18%
7.Seasonal-dummy-variable AR1 model	8%	15%	20%	26%	26%
8.Seasonal-dummy-variable AR13 model	8%	14%	17%	27%	32%
	RMSs of RFEs				
	1 step	6 steps	12 steps	36 steps	60 steps
1.Box-Jenkins (1 difference, 13 lags)	9%	10%	10%	13%	23%
2.Box-Jenkins (1 difference, No lags)	13%	16%	11%	14%	25%
3.Spectral model (1 difference)	10%	11%	10%	13%	27%
4.Simple lag model	13%	16%	10%	12%	11%
5.Simple 12th lag model	10%	10%			
6.Seasonal-dummy-variable model	15%	15%	15%	17%	20%
7.Seasonal-dummy-variable AR1 model	12%	21%	27%	32%	30%
8.Seasonal-dummy-variable AR13 model	14%	25%	30%	44%	52%

Table 6-9 The overall MAVs and RMSs of RFEs of multi-step-ahead forecasts of simple lag model for the four lumber quantities

Models	MAVs of RFEs				
	13 step	20 steps	24 steps	26 steps	36 steps
4.Simple lag model	10%	13%	9%	10%	9%
	RMSs of RFEs				
	13 step	20 steps	24 steps	26 steps	36 steps
4.Simple lag model	13%	16%	11%	13%	12%

Table 6-10 The overall MAVs and RMSs of RFEs for multi-step-ahead forecasts of the four lumber prices (univariate model)

Models	MAVs of RFEs				
	1 step	6 steps	12 steps	36 steps	60 steps
1.Box-Jenkins (1 difference, 13 lags)	6%	15%	19%	46%	82%
2.Box-Jenkins (1 difference, No lags)	6%	15%	19%	41%	68%
3.Spectral model (1 difference)	6%	14%	20%	48%	73%
4.Simple lag model	6%	15%	17%	27%	31%
5.Simple 12th lag model	17%	17%			
6.Seasonal-dummy-variable model	16%	16%	16%	16%	14%
7.Seasonal-dummy-variable AR1 model	6%	14%	17%	23%	23%
8.Seasonal-dummy-variable AR13 model	7%	15%	18%	22%	22%
	RMSs of RFEs				
	1 step	6 steps	12 steps	36 steps	60 steps
1.Box-Jenkins (1 difference, 13 lags)	9%	18%	24%	54%	92%
2.Box-Jenkins (1 difference, No lags)	9%	19%	24%	48%	76%
3.Spectral model (1 difference)	9%	18%	26%	55%	78%
4.Simple lag model	9%	19%	22%	33%	37%
5.Simple 12th lag model	22%	22%			
6.Seasonal-dummy-variable model	20%	20%	20%	20%	18%
7.Seasonal-dummy-variable AR1 model	9%	18%	21%	28%	28%
8.Seasonal-dummy-variable AR13 model	9%	19%	23%	27%	27%

Table 6-10 includes the overall MAVs and RMSs of RFEs for forecasts of the four lumber prices. In this table, the spectral model has the smallest MAVs and RMSs for 1 and 6-step-ahead forecasts. The seasonal-dummy-variable model has the smallest MAVs and RMSs for 12, 36, and 60-step-ahead forecasts in Table 6-10. Table 6-11 shows that MAVs or RMSs of forecasts for prices from the seasonal-dummy-variable model 6 are

the same in round-off percent for not only multiples of 12 steps but also any steps greater than 12. These MAVs and RMSs were different in numbers with more digits. MAVs and RMSs with smaller step interval are included in Table F-1 and 2 (Appendix F).

One interesting conclusion of these simulated forecasts is that different groups of variables may be forecasted better by different models, and complicated models sometimes are not necessarily better than simple models. Table 6-12 lists some of the best models with both the smallest MAVs and RMSs for forecasts of lumber quantities and prices.

Table 6-11 The overall MAVs and RMSs of RFEs of multi-step-ahead forecasts of the seasonal-dummy-variable model for the four lumber prices

Models	MAVs of RFEs				
	13 step	20 steps	24 steps	26 steps	36 steps
6.Seasonal-dummy-variable model	16%	16%	16%	16%	16%
	RMS of RFEs				
	13 step	20 steps	24 steps	26 steps	36 steps
6.Seasonal-dummy-variable model	20%	20%	20%	20%	20%

Table 6-12 The best univariate forecast models for endogenous variables

	Up to 12 steps	From 13 to 24 steps	From 25 to 36 steps	From 37 to 48 steps	From 48 to 60 steps
Lumber quantities	model 1	model 4 (lag 24)	model 4 (lag 36)	model 4 (lag 48)	model 4 (lag 60)
Lumber prices	model 3	model 6			

6.2 The Best Multi-Equation Forecasting Models

This section will first find the best combinations of models forecasting exogenous variables. These selected models will be used in multi-equation forecasting to prepare forecasted exogenous variables in the forecast period. VAR model, log-transformed VAR model, simultaneous equations models (estimated by 2SLS), and ECM are models used

as multi-equation forecasting models. Our interest is to find the best multi-equation models for out-of-sample forecasting.

6.2.1 Forecasts for Exogenous Variables

With historical values of exogenous variables their unknown future values can be forecasted by univariate forecasting models. The exogenous variables are divided into housing starts, timber prices, lumber inventories, DPI, and LC five groups. To find the best univariate forecasting models for the exogenous variables, MAVs and RMS of RFEs for each group of the exogenous variables were calculated from 36 repeated forecasts of specific number of steps ahead with specific models. The last of the 36 repeated forecasts is for 2003:12 and the first is for 2001:1.

Table 6-13 MAVs and RMSs of RFEs for the three housing starts

Models	MAVs of RFEs for different number of steps						
	1	6	12	30	36	54	60
1.Box-Jenkins (1 difference, 13 lags)	5%	5%	6%	11%	13%	13%	13%
2.Box-Jenkins (1 difference, No lags)	6%	7%	8%	11%	14%	14%	14%
3.Spectral model (1 difference)	5%	7%	8%	11%	14%	14%	14%
4.Simple lag model	6%	7%	8%	9%	11%	11%	11%
5.Simple 12th lag model	8%	8%					
6.Seasonal-dummy-variable model	16%	15%	14%	17%	19%	19%	19%
7.Seasonal-dummy-variable AR1 model	7%	17%	25%	39%	39%	39%	39%
8.Seasonal-dummy-variable AR13 model	8%	16%	25%	41%	41%	39%	38%
Models	RMSs of RFEs for different number of steps						
	1	6	12	30	36	54	60
1.Box-Jenkins (1 difference, 13 lags)	6%	7%	7%	14%	15%	15%	15%
2.Box-Jenkins (1 difference, No lags)	7%	9%	10%	13%	17%	17%	17%
3.Spectral model (1 difference)	6%	8%	9%	13%	17%	17%	17%
4.Simple lag model	7%	9%	9%	12%	13%	13%	13%
5.Simple 12th lag model	9%	9%					
6.Seasonal-dummy-variable model	17%	17%	17%	19%	22%	22%	22%
7.Seasonal-dummy-variable AR1 model	12%	28%	39%	49%	49%	45%	45%
8.Seasonal-dummy-variable AR13 model	14%	29%	45%	63%	62%	55%	53%

Table 6-13 includes MAVs and RMSs of RFEs for HWH, SH and H; Table 6-14 is for the first lags of timber prices TP1_1, TP2_1, TP3_1, and TP4_1; Table 6-15 is for the first lags of lumber inventories Inv1_1, Inv2_1, and Inv4_1; Table 6-16 is for DPI; Table 6-17 is for LC. Each number for MAV or RMS in these tables was calculated from 36 repeated estimations and forecasts. Each of the 36 repeated estimations used one more observations than its previous one. They were rolling-ahead forecasts that used data as efficient as possible.

Table 6-14 MAVs and RMSs of RFEs for the four timber prices

Models	MAVs of RFEs for different number of steps						
	1	6	12	30	36	54	60
1.Box-Jenkins (1 difference, 13 lags)	2%	10%	19%	45%	52%	69%	129%
2.Box-Jenkins (1 difference, No lags)	3%	9%	18%	38%	44%	53%	60%
3.Spectral model (1 difference)	2%	10%	19%	38%	44%	55%	63%
4.Simple lag model	3%	8%	16%	28%	30%	29%	31%
5.Simple 12th lag model	16%	16%					
6.Seasonal-dummy-variable model	31%	31%	31%	34%	34%	37%	38%
7.Seasonal-dummy-variable AR1 model	5%	16%	27%	56%	59%	66%	70%
8.Seasonal-dummy-variable AR13 model	22%	25%	30%	39%	39%	43%	45%
Models	MAVs of RFEs for different number of steps						
	1	6	12	30	36	54	60
1.Box-Jenkins (1 difference, 13 lags)	4%	14%	32%	76%	93%	99%	306%
2.Box-Jenkins (1 difference, No lags)	5%	14%	29%	64%	74%	70%	81%
3.Spectral model (1 difference)	4%	15%	30%	64%	75%	73%	85%
4.Simple lag model	5%	14%	26%	54%	60%	48%	53%
5.Simple 12th lag model	26%	26%					
6.Seasonal-dummy-variable model	55%	55%	55%	60%	60%	63%	63%
7.Seasonal-dummy-variable AR1 model	10%	28%	40%	87%	80%	81%	86%
8.Seasonal-dummy-variable AR13 model	40%	35%	47%	67%	68%	71%	73%

Thirty and fifty-four-step-ahead forecasts are included in Table 6-13 to 17 to show if the available multiples-of-12-step-ahead forecasts are more accurate. Such was a case in Table 6-9 for lumber prices, but not for exogenous variables as shown in Table 6-13 to 17.

Table 6-15 MAVs and RMSs of RFEs for the three lumber inventories

Models	MAVs of RFEs for different number of steps						
	1	6	12	30	36	54	60
1.Box-Jenkins (1 difference, 13 lags)	3%	7%	8%	13%	15%	15%	18%
2.Box-Jenkins (1 difference, No lags)	3%	8%	7%	13%	12%	11%	11%
3.Spectral model (1 difference)	3%	7%	7%	10%	10%	9%	10%
4.Simple lag model	3%	8%	7%	16%	20%	30%	32%
5.Simple 12th lag model	7%	7%					
6.Seasonal-dummy-variable model	47%	51%	56%	58%	63%	63%	68%
7.Seasonal-dummy-variable AR1 model	10%	41%	66%	114%	118%	116%	116%
8.Seasonal-dummy-variable AR13 model	116%	78%	61%	61%	49%	52%	56%
Models	**RMSs of RFEs for different number of steps**						
	1	6	12	30	36	54	60
1.Box-Jenkins (1 difference, 13 lags)	4%	9%	9%	18%	20%	20%	23%
2.Box-Jenkins (1 difference, No lags)	4%	10%	9%	17%	17%	14%	14%
3.Spectral model (1 difference)	4%	9%	8%	14%	14%	12%	12%
4.Simple lag model	4%	10%	8%	22%	26%	35%	37%
5.Simple 12th lag model	8%	8%					
6.Seasonal-dummy-variable model	54%	59%	65%	66%	72%	72%	77%
7.Seasonal-dummy-variable AR1 model	36%	89%	120%	171%	173%	160%	158%
8.Seasonal-dummy-variable AR13 model	206%	157%	110%	104%	72%	68%	70%

The model that has the smallest MAV and RMS of RFEs will be chosen as the best model for forecasting an exogenous variable for a specific number of steps ahead. When none of the methods has both the smallest MAV and RMS of RFEs for a specific number of steps ahead, the one that has the smallest RMS of RFEs will be chosen as the best forecasting model. When there is more than one model having the smallest MAVs and RMSs for a forecast, only one will be chosen as the best, and the models will be chosen

in a way that the least number of models will be used for a specific group of variables. The best models for each group of exogenous variables are listed in Table 6-18. Differences of MAVs or RMSs of the models in Table 6-18 for a group of variables are usually less than or equal to 2%. For example, for a 30-step-ahead forecast, MAVs for model 1 and 4 are 11% and 9%. Thus either model 4 or model 1 can be chosen for all forecasts. The model chosen from the best models for a group of variables is listed in the last column of Table 6-18. In section 6.2.2 to 5 only the model in the last column will be used for the forecast of each group of exogenous variables for convenience. In section 6.2.6 and 7 the last column of this table is ignored, and combinations of tables in this table will be used for forecasts of exogenous variables.

Table 6-16 MAVs and RMSs of RFEs for DPI

Models	MAVs of RFEs for different number of steps						
	1	6	12	30	36	54	60
1.Box-Jenkins (1 difference, 13 lags)	1%	1%	1%	2%	3%	6%	7%
2.Box-Jenkins (1 difference, No lags)	0%	1%	1%	2%	3%	6%	7%
3.Spectral model (1 difference)	1%	1%	1%	2%	3%	6%	7%
4.Simple lag model	1%	2%	4%	11%	14%	21%	23%
5.Simple 12th lag model	4%	4%					
6.Seasonal-dummy-variable model	27%	27%	27%	31%	31%	35%	35%
7.Seasonal-dummy-variable AR1 model	1%	1%	2%	3%	3%	4%	5%
8.Seasonal-dummy-variable AR13 model	1%	1%	2%	3%	3%	4%	5%
Models	**RMSs of RFEs for different number of steps**						
	1	6	12	30	36	54	60
1.Box-Jenkins (1 difference, 13 lags)	1%	1%	1%	3%	3%	6%	7%
2.Box-Jenkins (1 difference, No lags)	1%	1%	1%	3%	3%	7%	7%
3.Spectral model (1 difference)	1%	1%	1%	3%	3%	6%	7%
4.Simple lag model	1%	2%	4%	11%	14%	21%	23%
5.Simple 12th lag model	4%	4%					
6.Seasonal-dummy-variable model	27%	27%	27%	31%	31%	35%	35%
7.Seasonal-dummy-variable AR1 model	1%	1%	2%	4%	4%	5%	6%
8.Seasonal-dummy-variable AR13 model	1%	2%	2%	4%	4%	5%	5%

Table 6-17 MAVs and RMSs of RFEs for LC

Models	MAVs of RFEs for different number of steps						
	1	6	12	30	36	54	60
1.Box-Jenkins (1 difference, 13 lags)	0%	1%	2%	3%	10%	10%	10%
2.Box-Jenkins (1 difference, No lags)	0%	1%	2%	2%	6%	6%	6%
3.Spectral model (1 difference)	0%	1%	2%	2%	6%	6%	6%
4.Simple lag model	0%	1%	2%	3%	6%	6%	6%
5.Simple 12th lag model	2%	2%					
6.Seasonal-dummy-variable model	3%	3%	3%	4%	3%	3%	3%
7.Seasonal-dummy-variable AR1 model	0%	1%	2%	2%	5%	5%	5%
8.Seasonal-dummy-variable AR13 model	0%	1%	2%	4%	4%	10%	11%
Models	MAVs of RFEs for different number of steps						
	1	6	12	30	36	54	60
1.Box-Jenkins (1 difference, 13 lags)	0%	2%	2%	4%	5%	9%	10%
2.Box-Jenkins (1 difference, No lags)	0%	1%	2%	3%	3%	6%	6%
3.Spectral model (1 difference)	0%	1%	2%	3%	3%	6%	6%
4.Simple lag model	0%	1%	2%	3%	4%	6%	6%
5.Simple 12th lag model	2%	2%					
6.Seasonal-dummy-variable model	4%	4%	4%	4%	4%	4%	4%
7.Seasonal-dummy-variable AR1 model	0%	1%	2%	3%	3%	6%	5%
8.Seasonal-dummy-variable AR13 model	0%	2%	3%	4%	5%	11%	12%

Table 6-18 The best models chosen for forecasting exogenous variables.

Groups of Variables	The best models for different number of steps ahead							
	1	6	12	30	36	54	60	Any steps
Housing starts	1	1	1	4	4	4	4	1
Timber prices	3	4	4	4	4	4	4	4
Inventories	3	5	3	3	3	3	3	3
DPI	3	3	3	3	3	8	8	3
LC	7	7	7	7	7	6	6	7

6.2.2 Forecasts of a Log-Transformed VAR Model

For an out-of-sample forecast, the consistency of estimated parameters is no longer a goal of a forecasting model. The lagged timber price for Canada was also included although it may be improper to be included in structural models. There were eight endogenous variables, twelve exogenous variables, a trend, a constant, and three seasonal dummy variables included in the forecast model. Three lags of each endogenous variable were included. These lags were lag 1, lag 11, and lag 12. This lag specification was based on many different trials. All data were log transformed. Forecasts for endogenous variables were transformed back to MMBF or $/MBF for calculating relative forecast errors.

For the first forecast, data from 1990:1 to 2000:12 were used for estimating with the VAR model. The forecast period started from 2001:1. Values of exogenous variables during the forecast periods were forecasted with models listed in the last column of Table 6-18. Housing starts were forecasted by Box-Jenkins model with 13 lags; timber prices were forecasted by the simple lag model; inventories and DPI were forecasted by the spectral model; LC was forecasted by the seasonal-dummy-variable AR13 model. Forecasts of endogenous variables were calculated from the estimated VAR model with forecasted values for exogenous variables.

Figures 6-10 and 11 are graphs of the forecasted values of endogenous variables. In these examples graphs of forecasts for quantities generally have shapes similar to those of their true values. Forecasts in the first year (12 months) after the estimation period 2000:12 are closer to true values.

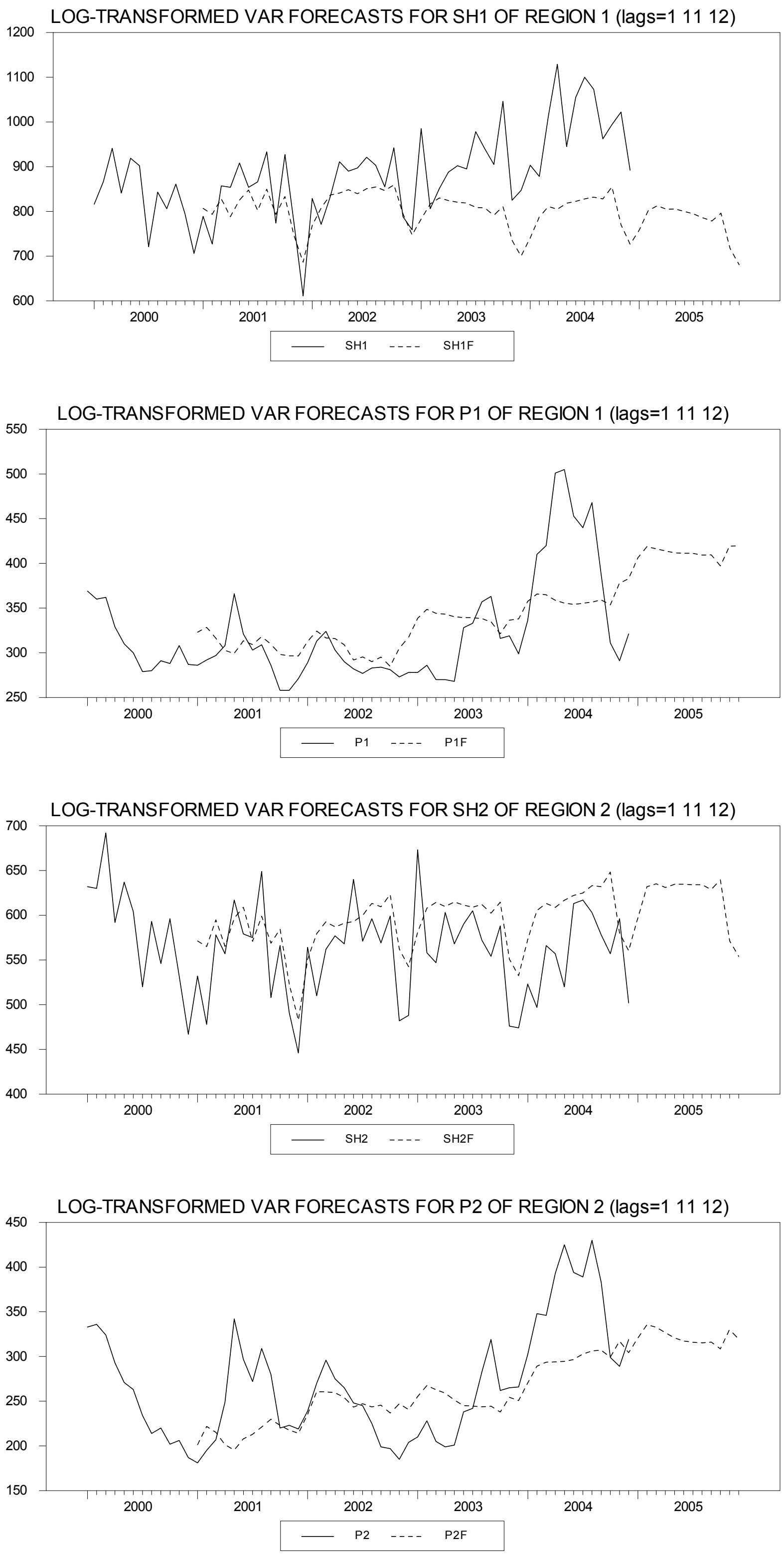


Figure 6-10 Forecasts of the log-transformed VAR model for SH1, P1, SH2 and P2

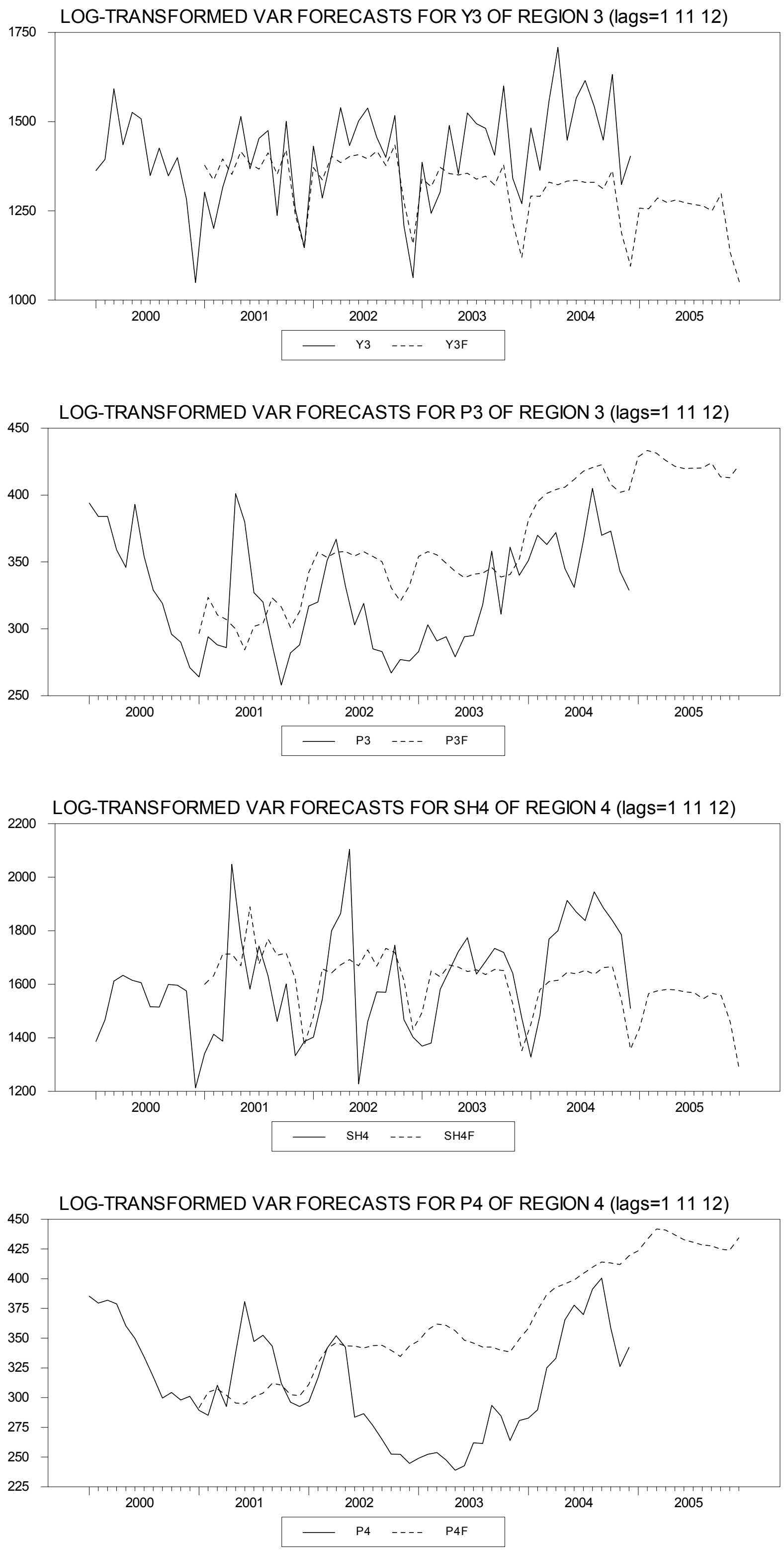


Figure 6-11 Forecasts of the log-transformed VAR model for Y3, P3, SH4, and P4

Table 6-19 Relative Forecast Errors of the log-transformed VAR model

Month	Relative Forecast Errors (RFEs)								MAVs of RFEs	RMSs of RFEs
	SH1	P1	SH2	P2	Y3	P3	SH4	P4		
2001:01	2%	13%	7%	11%	6%	12%	19%	1%	9%	11%
2001:02	9%	12%	18%	14%	11%	10%	16%	7%	12%	13%
2001:03	-3%	6%	3%	4%	6%	8%	23%	-1%	7%	10%
2001:04	-8%	-2%	1%	-19%	-3%	7%	-16%	3%	8%	10%
2001:05	-9%	-18%	-3%	-43%	-6%	-25%	-6%	-13%	15%	20%
2001:06	-1%	-2%	5%	-30%	1%	-25%	19%	-23%	13%	18%
2001:07	-7%	2%	-1%	-22%	-6%	-8%	-4%	-13%	8%	10%
2001:08	-9%	3%	-8%	-28%	-4%	-5%	8%	-14%	10%	13%
2001:09	2%	8%	12%	-18%	9%	12%	17%	-9%	11%	12%
2001:10	-10%	16%	3%	1%	-5%	23%	7%	0%	8%	11%
2001:11	-4%	15%	7%	-2%	-1%	7%	22%	2%	7%	10%
2001:12	12%	9%	8%	-2%	0%	9%	-1%	3%	6%	7%
2002:01	-7%	8%	-2%	-2%	-4%	8%	6%	5%	5%	6%
2002:02	5%	4%	14%	-3%	4%	12%	7%	4%	7%	8%
2002:03	0%	-2%	5%	-12%	0%	1%	-9%	0%	4%	6%
2002:04	-8%	4%	2%	-6%	-10%	-3%	-10%	-2%	5%	6%
2002:05	-5%	7%	4%	-4%	-2%	8%	-20%	0%	6%	8%
2002:06	-6%	4%	-7%	-2%	-6%	17%	36%	21%	12%	16%
2002:07	-8%	7%	5%	1%	-9%	12%	18%	19%	10%	12%
2002:08	-5%	2%	3%	8%	-3%	24%	6%	24%	10%	13%
2002:09	-1%	4%	7%	23%	-2%	24%	10%	30%	13%	17%
2002:10	-9%	1%	4%	20%	-5%	24%	-2%	35%	12%	17%
2002:11	1%	12%	17%	34%	6%	16%	10%	33%	16%	19%
2002:12	-2%	14%	11%	18%	9%	20%	2%	40%	15%	19%
2003:01	-21%	22%	-14%	22%	-3%	25%	9%	40%	19%	22%
2003:02	1%	22%	9%	17%	6%	18%	20%	41%	17%	20%
2003:03	-2%	27%	12%	28%	5%	22%	3%	43%	18%	22%
2003:04	-7%	27%	1%	30%	-9%	19%	1%	46%	18%	23%
2003:05	-9%	27%	8%	25%	0%	23%	-3%	49%	18%	24%
2003:06	-9%	3%	4%	3%	-11%	15%	-7%	44%	12%	17%
2003:07	-17%	2%	1%	1%	-10%	16%	1%	32%	10%	14%
2003:08	-14%	-5%	7%	-14%	-9%	7%	-3%	31%	11%	14%
2003:09	-13%	-8%	9%	-23%	-6%	-3%	-5%	17%	10%	12%
2003:10	-22%	2%	5%	-9%	-14%	9%	-4%	19%	10%	13%
2003:11	-11%	5%	16%	-4%	-9%	-6%	-7%	28%	11%	13%
2003:12	-17%	13%	12%	-6%	-12%	4%	-8%	24%	12%	14%
Overall									11%	15%

Results in Table 6-19 are relative forecast errors of log-transformed VAR models for the eight endogenous variables. Maximums of MAVs a RMSs of RFEs are 18% and 24% respectively, and the overall MAV and RMS for the 288 forecasts in the table are 11% and 15% respectively.

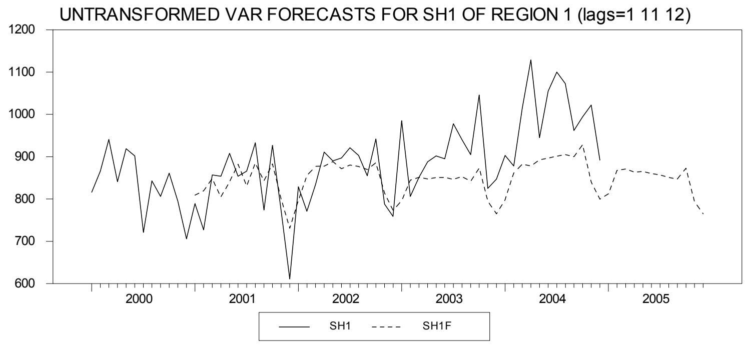
6.2.3 Forecasts of an Untransformed VAR Model

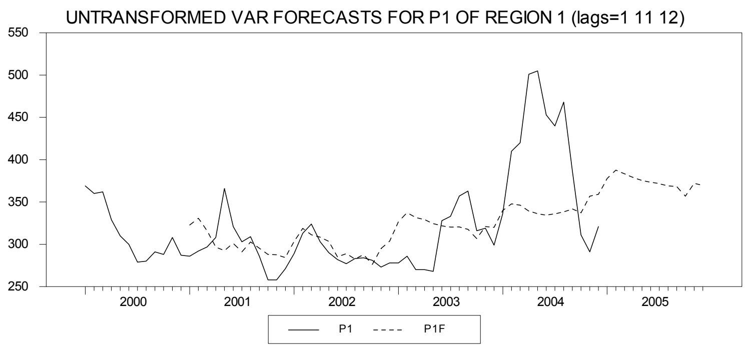
Instead of log transformed data, untransformed data can also be used in VAR models. The biasness is not our concern. The accuracy of forecasts will be obtained by comparing forecasts with their true values.

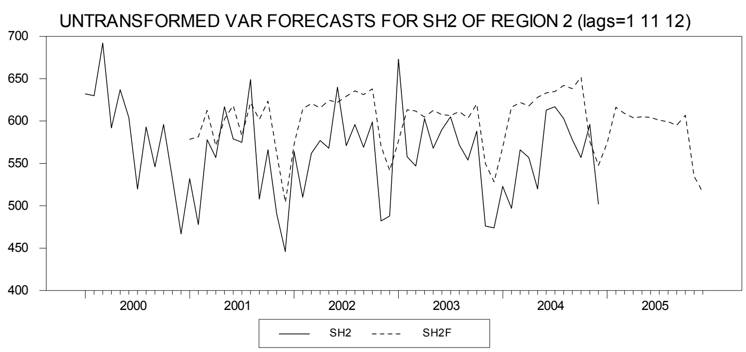
The specification of the VAR was the same as that of the section 6.2.2 except that data were untransformed; lags, dummy variables, and trends were included in the same way for both of the VAR models. The estimation period was from 1990:1 to 2000:12, and the forecast period was from 2001:1 to 2004:12. Forecasts for exogenous variables were calculated by the selected models in the last column of Table 6-18. The forecasted graphs comparing the true observations and their forecasts from the untransformed VAR are shown in Figures 6-12 and 13. The forecasted dashed lines in the graphs of these figures are quite similar to those of Figures 6-10 and 11. MAVs and RMSs of RFEs are listed in Table 6-20. The overall MAV and RMS for the 288 forecasts are 10% and 13% respectively.

6.2.4 Forecasts of a Long-Run Simultaneous Equations Model

The long-run simultaneous equations model represents long-run relations among variables. With forecasts of exogenous variables, estimated long-run equations can be used for forecasting lumber prices and quantities. However, the long-run forecasts of







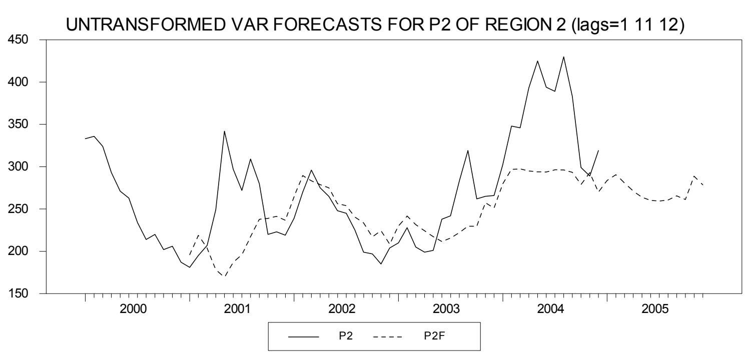
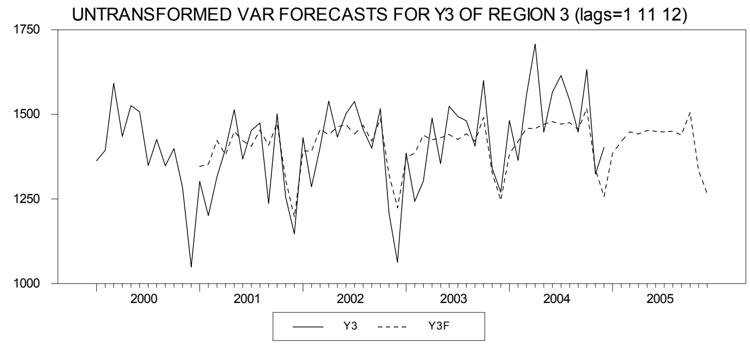
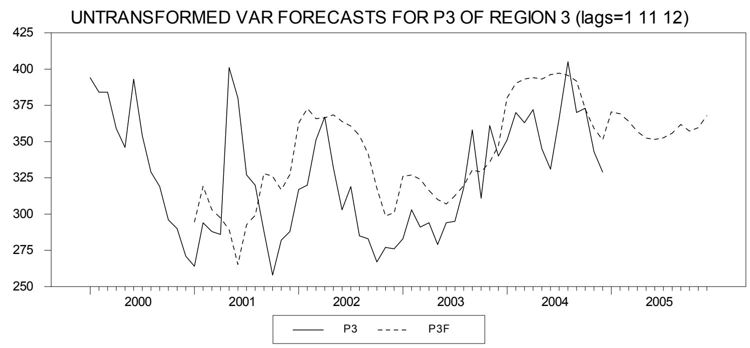
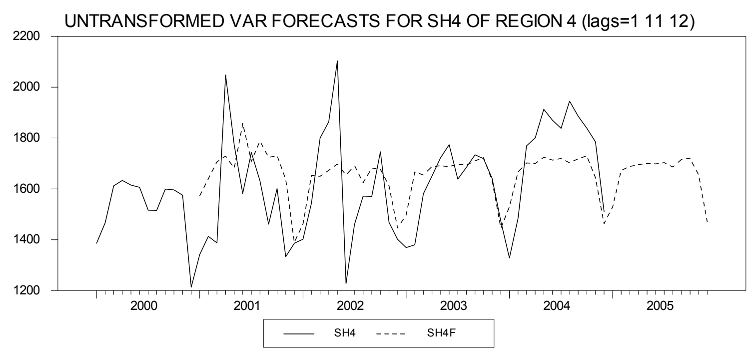


Figure 6-12 Forecasts of the untransformed VAR model for SH1, P1, SH2 and P2







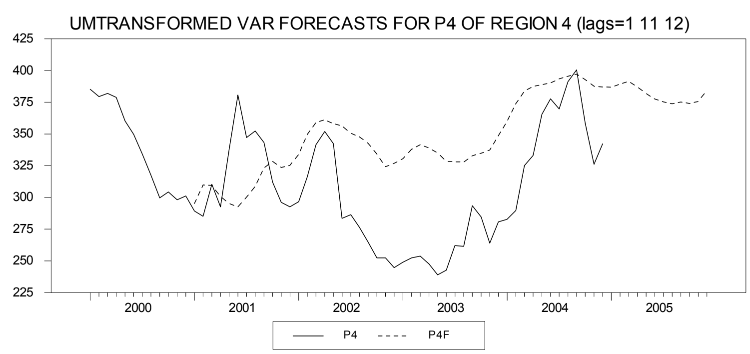


Figure 6-13 Forecasts of the untransformed VAR model for Y3, P3, SH4, and P4

Table 6-20 Relative Forecast Errors of untransformed VAR models

Forecast Periods	Relative forecast errors (RFEs)								MAVs of RFEs	RMSs of RFEs
	SH1	P1	SH2	P2	Y3	P3	SH4	P4		
2001:01	3%	13%	9%	8%	3%	12%	17%	2%	8%	10%
2001:02	13%	13%	22%	12%	13%	9%	16%	9%	13%	14%
2001:03	-1%	6%	6%	-2%	8%	5%	23%	0%	6%	9%
2001:04	-6%	-4%	3%	-28%	-1%	4%	-16%	3%	8%	12%
2001:05	-7%	-20%	-2%	-51%	-4%	-28%	-5%	-13%	16%	22%
2001:06	3%	-6%	7%	-37%	4%	-30%	17%	-23%	16%	20%
2001:07	-4%	-4%	1%	-28%	-3%	-11%	-2%	-14%	8%	12%
2001:08	-5%	-2%	-4%	-30%	-1%	-7%	10%	-12%	9%	12%
2001:09	9%	3%	18%	-15%	14%	14%	18%	-6%	12%	13%
2001:10	-5%	12%	10%	9%	-2%	26%	8%	5%	10%	12%
2001:11	4%	11%	15%	8%	4%	12%	23%	9%	11%	12%
2001:12	20%	5%	13%	8%	4%	14%	0%	11%	9%	11%
2002:01	-4%	5%	1%	11%	-3%	14%	4%	13%	7%	8%
2002:02	11%	2%	20%	7%	8%	17%	7%	11%	10%	12%
2002:03	5%	-4%	10%	-4%	4%	4%	-8%	5%	6%	6%
2002:04	-4%	2%	7%	1%	-6%	0%	-10%	3%	4%	5%
2002:05	0%	5%	10%	4%	2%	11%	-19%	5%	7%	9%
2002:06	-3%	1%	-3%	3%	-2%	20%	35%	26%	12%	17%
2002:07	-4%	4%	10%	4%	-6%	13%	16%	22%	10%	12%
2002:08	-3%	0%	7%	7%	1%	24%	3%	26%	9%	13%
2002:09	2%	1%	11%	17%	1%	21%	7%	29%	11%	15%
2002:10	-6%	-2%	7%	10%	-2%	19%	-4%	32%	10%	14%
2002:11	3%	8%	18%	21%	10%	8%	10%	28%	13%	16%
2002:12	0%	2%	10%	15%	0%	20%	3%	28%	9%	12%
2003:01	-1%	2%	10%	17%	0%	21%	3%	29%	9%	12%
2003:02	-1%	2%	10%	18%	-1%	22%	3%	31%	9%	12%
2003:03	-1%	2%	10%	20%	-1%	23%	2%	33%	9%	12%
2003:04	-1%	2%	10%	21%	-1%	24%	2%	34%	9%	12%
2003:05	-1%	2%	11%	23%	-1%	25%	2%	36%	9%	12%
2003:06	-1%	2%	11%	24%	-1%	26%	2%	38%	9%	12%
2003:07	-1%	2%	11%	26%	-1%	27%	1%	39%	9%	12%
2003:08	-1%	2%	11%	27%	-2%	28%	1%	41%	9%	12%
2003:09	-2%	2%	11%	29%	-2%	29%	1%	43%	9%	12%
2003:10	-2%	2%	11%	30%	-2%	30%	0%	44%	9%	12%
2003:11	-2%	2%	11%	32%	-2%	31%	0%	46%	9%	12%
2003:12	-2%	2%	11%	33%	-2%	32%	0%	48%	9%	12%
Overall									10%	13%

exogenous variables are poor in accuracy; the poor long-run forecasts of exogenous variables may in the end result in poor long-run forecasts from the simultaneous equations model. This section will show an example on calculating accuracies, i.e. MAVs and RMSs, of out-of-sample short-run forecasts of simultaneous equations models.

The inversed demand equations of the model for Table 5-5 of chapter 5 were estimated simultaneously with the supply equations in the same model. The estimated model was solved for endogenous variables so that the endogenous variables were expressed in exogenous variables. Values for the 11 exogenous variables were forecasted by the models in the last column of Table 6-18. Since the purpose of estimations is forecast, the estimated parameters are not shown in this section. The data were all log-transformed. Forecasts of values for exogenous variables were also log-transformed. Expressions for log-transformed endogenous variables were evaluated with forecasted values of log-transformed exogenous variables to obtain out-of-sample forecasts of log-transformed endogenous variables. Then the forecasts of the log-transformed endogenous variables were exponentially transformed to get forecasts for lumber prices and quantities.

Graphs of the forecasts are not shown in this section to save space. Table 6-21 shows relative forecast errors and MAVs and RMSs of RFEs from the simultaneous equations model. The overall MAV and RMS are 21% and 29% respectively. They are larger than the corresponding values for both VAR and the transformed VAR model.

6.2.5 Forecasts of an ECM

Since there are cointegration relations, error correction models should be the data generation functions. Here restricted ECM will be used as a forecasting model. The

Table 6-21 Relative Forecast Errors of the simultaneous-equations model

Month	Relative forecast errors (RFEs)								MAVs of RFEs	RMSs of RFEs
	SH1	P1	SH2	P2	Y3	P3	SH4	P4		
2001:01	1%	32%	5%	87%	8%	57%	16%	40%	31%	41%
2001:02	18%	16%	24%	52%	21%	29%	19%	33%	26%	29%
2001:03	1%	20%	3%	52%	11%	35%	24%	26%	21%	27%
2001:04	1%	12%	6%	23%	5%	40%	-16%	34%	17%	22%
2001:05	-4%	-4%	-4%	-9%	-3%	-4%	-3%	15%	6%	7%
2001:06	2%	11%	2%	7%	8%	5%	10%	4%	6%	7%
2001:07	0%	14%	3%	12%	1%	19%	-2%	12%	8%	11%
2001:08	-7%	16%	-9%	3%	0%	24%	6%	13%	10%	12%
2001:09	12%	22%	16%	10%	19%	37%	18%	15%	19%	20%
2001:10	-6%	40%	4%	46%	-1%	53%	9%	28%	23%	31%
2001:11	2%	32%	9%	37%	6%	31%	26%	27%	21%	25%
2001:12	25%	33%	17%	43%	11%	30%	7%	34%	25%	27%
2002:01	-4%	31%	-4%	42%	0%	28%	13%	37%	20%	25%
2002:02	13%	15%	14%	18%	16%	26%	15%	28%	18%	19%
2002:03	4%	11%	3%	8%	7%	14%	-1%	18%	8%	10%
2002:04	-4%	19%	0%	16%	-3%	9%	-5%	15%	9%	11%
2002:05	-2%	25%	1%	22%	5%	22%	-15%	20%	14%	17%
2002:06	-3%	27%	-10%	28%	0%	32%	45%	43%	24%	29%
2002:07	-5%	32%	1%	33%	-2%	28%	24%	45%	21%	26%
2002:08	-3%	27%	-4%	42%	4%	41%	14%	48%	23%	29%
2002:09	3%	29%	0%	65%	9%	45%	16%	57%	28%	36%
2002:10	-7%	29%	-5%	64%	0%	53%	4%	64%	28%	39%
2002:11	1%	32%	8%	76%	13%	37%	20%	57%	30%	39%
2002:12	1%	31%	3%	55%	23%	40%	10%	66%	29%	36%
2003:01	-18%	41%	-22%	68%	6%	50%	21%	72%	37%	44%
2003:02	9%	30%	0%	45%	24%	36%	33%	67%	31%	36%
2003:03	3%	37%	2%	60%	18%	42%	17%	66%	31%	38%
2003:04	-1%	39%	-8%	68%	4%	42%	12%	72%	31%	41%
2003:05	-3%	39%	-2%	65%	14%	49%	8%	77%	32%	42%
2003:06	-2%	15%	-6%	41%	2%	43%	5%	76%	24%	35%
2003:07	-10%	12%	-9%	38%	4%	41%	14%	63%	24%	31%
2003:08	-6%	6%	-4%	19%	5%	33%	12%	65%	19%	27%
2003:09	-3%	4%	-1%	5%	11%	17%	9%	47%	12%	18%
2003:10	-16%	20%	-7%	29%	-2%	36%	10%	52%	22%	27%
2003:11	-3%	16%	5%	27%	5%	10%	11%	56%	17%	24%
2003:12	-9%	26%	2%	24%	6%	17%	9%	50%	18%	23%
Overall									21%	29%

specification of the supply equations for Table 5-5 was used as the equation for quantities forecasting; the inversed demand equations were used as the forecasting function for lumber prices.

Dependent variables in the demand equations for these tables were lumber prices and expressed in functions of quantities. Part of the data was used for the estimation, and the other part in the forecast period was used for calculating the accuracy of forecasts. Values of exogenous variables during the forecast period were forecasted by the best univariate forecasting models. Since true values in the forecast period were supposed to be unknown, equilibrium errors in this period were supposed to be not available either. Because the expected values of these equilibrium errors were zero they are set to be zero in the forecast period. This means that the errors could not be corrected in the forecast period. Forecasts were performed anyway to examine the performance of the ECM for forecast. Forecasted values for log-transformed endogenous variables were obtained from the last observations in estimation periods and forecasted differences of these variables.

Table 6-22 presents the forecast results from the ECM with estimation period from 1990:1 to 2003:12. The overall MAV and RMS are 15% and 19% respectively. They are larger than those of the VAR models but smaller than those of the long-run model. Since these are only examples of such forecasts, it is too early to make any conclusion at this stage.

6.2.6 The Best Multi-Equation Models for One-Step-Ahead Forecasts

Sections 6.2.2 to 5 have given some examples of one-step-ahead forecasts for 2001:1. The first rows of Table 6-19 and 22 are one-step-ahead forecasts from a VAR and an

Table 6-22   Relative forecast errors of ECM Model

Month	Relative forecast errors (RFEs)								MAVs of RFEs	RMSs of RFEs
	SH1	P1	SH2	P2	Y3	P3	SH4	P4		
2001:01	11%	3%	22%	8%	21%	-2%	7%	9%	12%	12%
2001:02	5%	15%	9%	17%	5%	-6%	7%	9%	10%	10%
2001:03	3%	-2%	2%	8%	7%	-3%	-2%	4%	5%	5%
2001:04	-1%	4%	-14%	4%	11%	-33%	5%	10%	14%	14%
2001:05	-19%	-5%	-40%	-4%	-23%	-21%	-10%	16%	20%	20%
2001:06	-7%	5%	-30%	8%	-18%	-10%	-20%	12%	15%	15%
2001:07	-3%	8%	-25%	3%	-6%	-17%	-13%	9%	12%	12%
2001:08	-7%	-3%	-35%	2%	-5%	-9%	-14%	10%	14%	14%
2001:09	0%	28%	-28%	23%	7%	3%	-12%	15%	18%	18%
2001:10	9%	17%	-11%	2%	17%	-4%	-4%	8%	10%	10%
2001:11	15%	22%	-6%	11%	6%	10%	2%	10%	12%	12%
2001:12	10%	32%	-8%	17%	4%	-7%	5%	15%	18%	18%
2002:01	8%	9%	-11%	7%	0%	-3%	6%	6%	7%	7%
2002:02	0%	25%	-21%	21%	1%	-11%	0%	12%	15%	15%
2002:03	-5%	16%	-29%	12%	-9%	-23%	-8%	13%	16%	16%
2002:04	1%	15%	-24%	3%	-13%	-24%	-11%	11%	14%	14%
2002:05	5%	20%	-21%	13%	-3%	-31%	-8%	13%	16%	16%
2002:06	6%	9%	-18%	8%	5%	20%	11%	10%	12%	12%
2002:07	7%	26%	-17%	7%	0%	3%	9%	10%	12%	12%
2002:08	3%	23%	-11%	14%	10%	-3%	13%	11%	13%	13%
2002:09	2%	33%	0%	20%	12%	-1%	18%	13%	17%	17%
2002:10	2%	30%	0%	13%	18%	-10%	24%	14%	17%	17%
2002:11	9%	45%	11%	28%	11%	2%	24%	19%	23%	23%
2002:12	8%	42%	-3%	40%	13%	-6%	30%	20%	25%	25%
2003:01	14%	8%	0%	23%	17%	2%	30%	12%	16%	16%
2003:02	9%	34%	-9%	38%	9%	3%	28%	19%	23%	23%
2003:03	14%	40%	1%	34%	13%	-9%	28%	20%	23%	23%
2003:04	13%	30%	3%	19%	12%	-11%	31%	17%	19%	19%
2003:05	13%	42%	1%	32%	18%	-14%	35%	21%	25%	25%
2003:06	-9%	41%	-16%	19%	12%	-15%	33%	21%	23%	23%
2003:07	-11%	42%	-18%	23%	11%	-7%	23%	19%	21%	21%
2003:08	-18%	54%	-30%	25%	3%	-8%	23%	23%	27%	27%
2003:09	-20%	63%	-39%	33%	-9%	-9%	10%	27%	32%	32%
2003:10	-9%	58%	-27%	19%	4%	-7%	13%	19%	25%	25%
2003:11	-7%	77%	-24%	29%	-12%	-6%	22%	26%	34%	34%
2003:12	0%	76%	-27%	31%	-6%	-8%	17%	24%	33%	33%
Overall									15%	19%

ECM model. However, forecasts for only one month are not sufficient for measuring the accuracy of them. To find the best forecasting model the accuracies of a series of one-step-ahead forecasts for each of the models are necessary. To find the accuracy of an out-of-sample forecast, a series of one-step-ahead and multi-step-ahead forecasts were repeated from 2001:1 to 2003:12. The overall MAVs and RMSs for the 36 forecasts were calculated. Transformed and untransformed VAR models, long-run simultaneous equations models, and the vector ECM model were candidate models. Their specifications followed exactly those of the models in section 6.2.2 to 5.

Estimation and forecast periods were the same as those for univariate forecasts in 6.2.1. The first estimation period was from 1990:1 to 2000:12, and the rolling forecast period were from 2001:1 to 2003:12. These forecasts simulated the one-step-ahead forecast in the real world. Each of the estimations had one more estimation period. For the last forecasts in 2003:12 the estimation period is from 1990:1 to 2003:11. Values for exogenous variables are forecasted by the method chosen for the one-step-ahead forecast in Table 6-18.

Since forecasted lumber prices and quantities performed differently as shown in Table 6-19 to 22, MAVs and RMSs were calculated for forecasted prices and quantities separately. Results from one-step-ahead forecasts for lumber quantities and prices are listed in column "1-step" of Table 6-23.

6.2.7 The Best Multi-Equation Models for Multi-Step-Ahead Forecasts

Multi-step-ahead out-of-sample forecasts were also repeated in a similar way to the ones in which one-step-ahead forecasts were performed. Values of exogenous variables

ahead of estimation periods were forecasted following the best models in Table 6-18. The flowchart for the forecast programs are shown in Figures 6-14 to 16. Figure 6-14 is the general flowchart. In this flowchart n is the number of steps ahead of the estimation period. nf = 36 is the number of repeated forecasts. nn is the number of values of n. “last” is the last month of forecasts. @initiatingdata is a data input procedure. “en” is the ending month of the estimation period. For every k, the k loop produces n forecasted values of each of exogenous variables from k+1 to k+n and one forecasted value for each of endogenous variables at period k+n. For each n, 36 “k loops” run, and 36 forecasts are made for each of endogenous variables from “last-36” to “last.” The overall MAVs and RMSs of RFEs were calculated from forecasts and observations of endogenous variables that are n month ahead of estimation periods. The n forecasts of exogenous variables for a given k and n are obtained by a segment of program described as the flow chart of Figure 6-15. It follows exactly Table 6-18 that have the best models chosen for different variables and different number of steps ahead of estimation periods. The flowchart in Figure 6-16 demonstrates the process with which endogenous variables were forecasted. In Figure 6-15 and 16, the dashed lines and boxes are for the storage of forecasts and statistics of them. iF1 to iF4 store forecasted values of variable i. and AV is for absolute values of relative forecast errors (RFEs).

MAVs and RMSs for lumber quantities and prices were calculated separately. Table 6-23 presents results of the multi-step-ahead forecasts of multi-equations models for lumber quantities and prices. This table shows that the four models have no difference in accuracy for 1-step forecasting the quantities. All the four MAVs for 1-step forecasts for

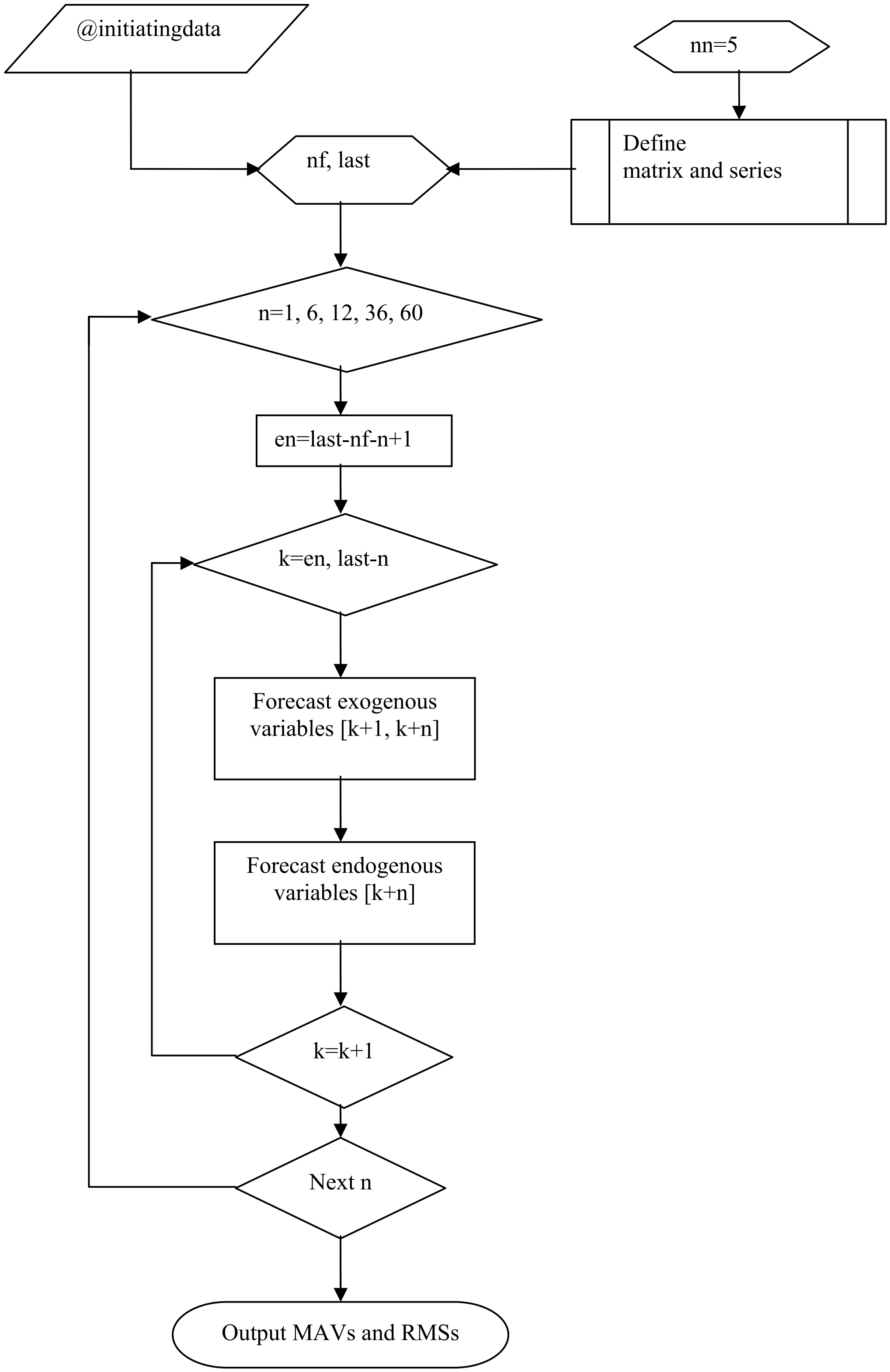


Figure 6-14 Flowchart of the program for choosing the best multi-equation forecasting models

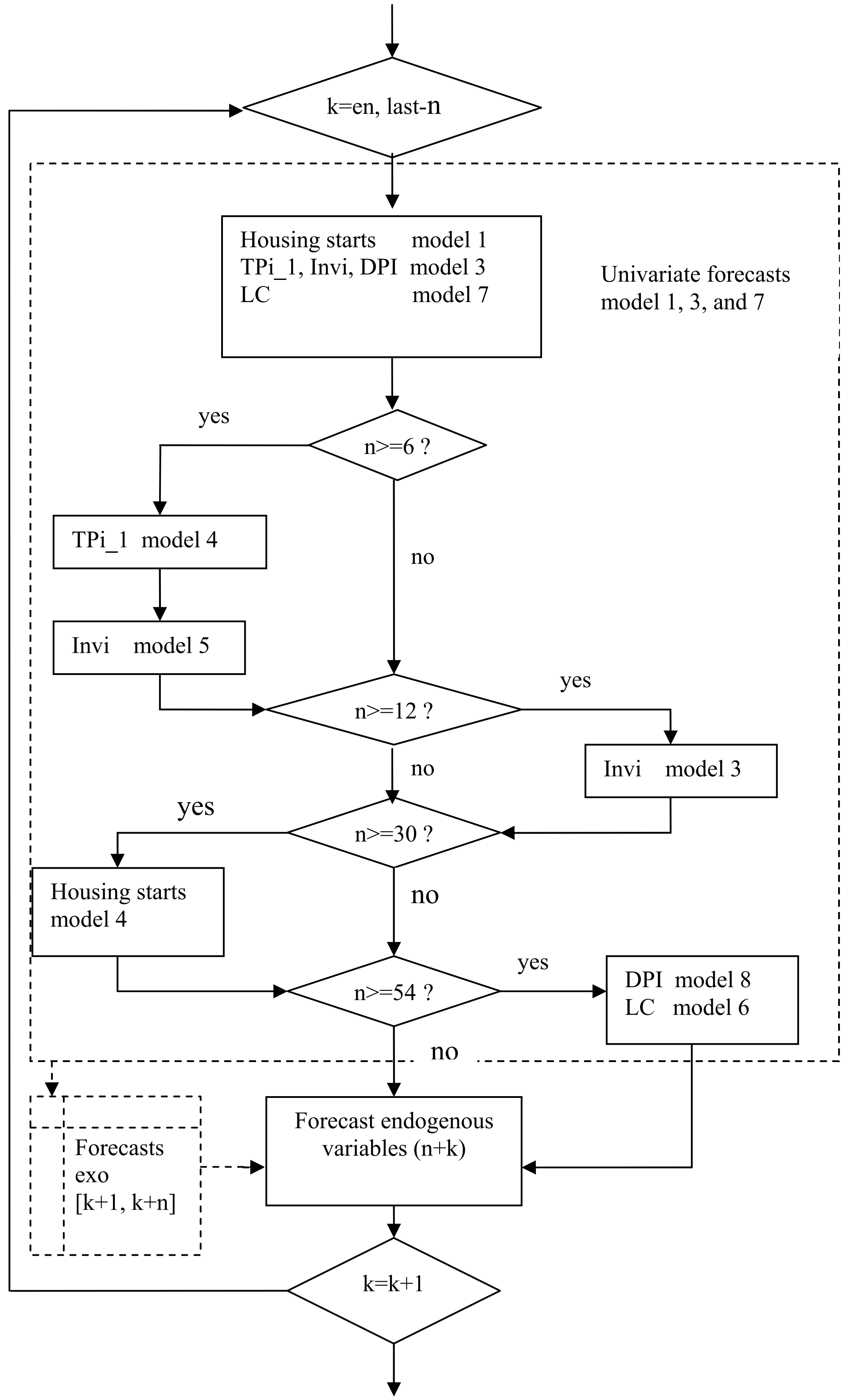


Figure 6-15 Flowchart forecasting the exogenous variables (a part of Figure 6-14 in detail)

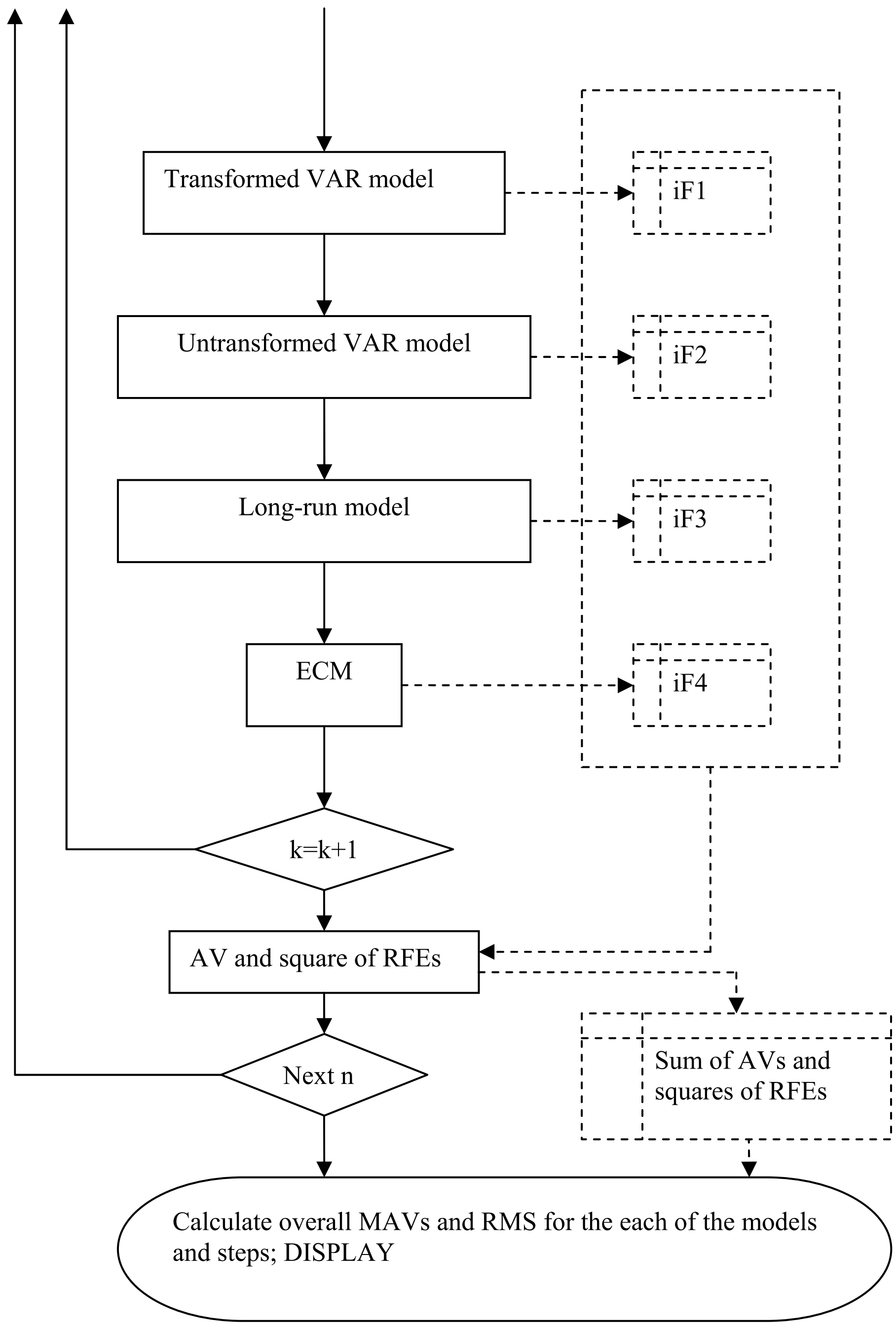


Figure 6-16 Flowchart of forecast process for the Endogenous variables (the last part of Figure 6-14 in detail)

lumber quantities have the same value, and so do the four corresponding RMSs. For 1 to 36 steps forecasts for lumber quantities, the log-transformed VAR model is better than the other models, and the 2SLS model is the best for 60 steps.

Table 6-23 MAVs and RMSs of RFEs of multi-equation forecasts for the four quantities

Models	MAVs of RFEs for quantities				
	1-step	6-steps	12-steps	36-steps	60-steps
I. Log-transformed VAR model	7%	7%	7%	10%	31%
II. Untransformed VAR model	7%	7%	8%	15%	63%
III. 2SLS model	7%	7%	8%	14%	30%
IV. ECM	7%	10%	11%	32%	65%
Models	**RMSs of RFEs for quantities**				
	1-step	6-steps	12-steps	36-steps	60-steps
I. Log-transformed VAR model	10%	9%	10%	13%	41%
II. Untransformed VAR model	10%	10%	11%	19%	75%
III. 2SLS model	10%	10%	10%	18%	34%
IV. ECM	10%	15%	11%	40%	83%
Models	**MAVs of RFEs for prices**				
	1-step	6-steps	12-steps	36-steps	60-steps
I. Log-transformed VAR model	7%	14%	17%	109%	269%
II. Untransformed VAR model	8%	17%	19%	65%	113%
III. 2SLS model	21%	23%	28%	65%	118%
IV. ECM	10%	16%	19%	31%	36%
Models	**RMSs of RFEs for prices**				
	1-step	6-steps	12-steps	36-steps	60-steps
I. Log-transformed VAR model	10%	18%	24%	134%	572%
II. Untransformed VAR model	11%	21%	24%	77%	135%
III. 2SLS model	26%	28%	34%	72%	126%
IV. ECM	13%	22%	24%	51%	109%

Both MAVs and RMSs for prices in Table 6-23 show that the log-transformed VAR model is the best for forecasts of less than or equal to twelve months (or 12-steps) and ECM is the best for forecasts of thirty-six and sixty months ahead.

More experiments on forecasts (Appendix G) show that log-transformed VAR model is the best model for forecasting lumber quantities less than or equal to 48 months ahead, and 2SLS is the best for 60 steps. Log-transformed VAR model is the best for forecasting lumber prices up to 12 steps, for longer forecasts ECM is better. Table 6-24 listed the best multi-equation forecasting models chosen.

Table 6-24 MAVs and RMSs of RFEs of multi-equation forecasting models

<table>
<tr><td rowspan="2">Lumber quantities</td><td colspan="2">Up to 48 steps</td><td>From 49 to 60 steps</td></tr>
<tr><td colspan="2">model I (log-transformed VAR)</td><td>model III (2SLS)</td></tr>
<tr><td rowspan="2">Lumber prices</td><td>Up to 12 steps</td><td colspan="2">From 13 to 60 steps</td></tr>
<tr><td>Model I</td><td colspan="2">Model IV (ECM)</td></tr>
</table>

6.2.8 The Overall Best Combination of Forecasting Models

To compare the accuracy of the univariate models and the multi-equations models, the smallest MAVs and RMSs (Appendix F and G) are listed in Table 6-25. For lumber prices, all the MAVs and RMSs of RFEs of the best univariate forecasts are smaller than those from the multi-equations models. For lumber quantities, the best univariate model forecasts better for 1 and 30 or more steps ahead; for 6 to 24 steps, the best multi-equation models forecast better. The overall best models chosen are listed in Table 6-26. For those steps that are not listed in Table 6-25, the best models for smaller neighboring steps in this table are chosen as the overall best model in Table 6-26.

Table 6-25 The smallest MAVs and RMSs of RFEs of multi-equations and univariate models

Models	MAVs of RFEs for lumber quantities											
	1	6	12	13	20	24	30	36	42	48	54	60
Best univariate models	6%	8%	8%	9%	9%	9%		9%		9%		9%
Best multi-equation models	7%	7%	7%	8%	9%	8%	10%	10%	16%	18%	25%	30%
Models	RMSs of RFEs for lumber quantities											
	1	6	12	13	20	24	30	36	42	48	54	60
Best univariate models	9%	10%	10%	11%		11%		12%		11%		11%
Best multi-equation models	10%	9%	10%	11%	11%	11%	13%	13%	21%	24%	29%	34%
Models	MAVs of RFEs for lumber prices											
	1	6	12	13	20	24	30	36	42	48	54	60
Best univariate models	6%	14%	16%	16%	16%	16%	16%	16%	16%	15%	14%	14%
Best multi-equation models	7%	14%	17%	20%	27%	28%	37%	44%	54%	60%	86%	96%
Models	RMSs of RFEs for lumber prices											
	1	6	12	13	20	24	30	36	42	48	54	60
Best univariate models	9%	18%	20%	20%	20%	20%	20%	20%	19%	19%	18%	18%
Best multi-equation models	10%	18%	24%	27%	37%	35%	45%	51%	64%	68%	95%	109%

Note: The best univariate models are in table 6-12, and the best multi-equation models are in Table 6-24.

Table 6-26 The overall best forecasting models chosen

	Up to 5 steps	From 6 to 29 steps	From 30 to 36 steps	From 37 to 48 steps	From 48 to 60 steps
Lumber quantities	model 1	model I	model 4 (lag 36)	model 4 (lag 48)	model 4 (lag 60)
	Up to 12 steps	From 13 to 60 steps			
Lumber prices	model 3	model 6			

6.3 Validation of the Best Forecasting Models

Near the end of this dissertation research, more data became available. Because these data were not used in finding the best models, they may be used for examining the validation of the best models chosen.

6.3.1 Five-Year Forecasts of the Best Univariate Models

Table 6-27 listed the Relative Forecast Errors of the best models in Table 6-12. The resulted forecasts were plotted in Figure 6-17 and 8. The forecasts started from 2004:1. The first several forecasts are close to the true values although the forecasts of the models could not catch unexpected changes.

Table 6-27 Relative forecast errors by the best univariate models

Month	Relative forecast errors							
	SH1P	SH2P	Y3P	SH4P	P1P	P2P	P3P	P4P
2004:1	5%	8%	-1%	11%	-12%	-14%	-3%	1%
2004:2	-8%	5%	-5%	1%	-25%	-23%	-8%	-2%
2004:3	-12%	-5%	-12%	-10%	-26%	-22%	-8%	-9%
2004:4	-20%	1%	-12%	-6%	-36%	-31%	-9%	-13%
2004:5	-6%	6%	-6%	-11%	-33%	-34%	0%	-20%
2004:6	-15%	-8%	-4%	-9%	-26%	-27%	6%	-21%
2004:7	-14%	-7%	-6%	-9%	-26%	-30%	-3%	-19%
2004:8	-16%	-7%	-8%	-16%	-30%	-35%	-11%	-23%
2004:9	-6%	-6%	1%	-11%	-18%	-30%	-5%	-25%
2004:10	-1%	0%	-7%	-9%	-1%	-13%	-5%	-19%
2004:11	-17%	-10%	2%	-9%	7%	-10%	3%	-11%
2004:12	1%	5%	-4%	3%	-3%	-15%	1%	-11%
2005:1	-1%	19%	-12%	-6%	0%	-19%	-4%	-13%
2005:2	-16%	4%	-15%	-16%	-15%	-24%	-10%	-15%
2005:3	-23%	-10%	-19%	-16%	-16%	-24%	-10%	-17%
2005:4	-19%	8%	-10%	-11%	-12%	-20%	-13%	-15%
2005:5	-16%	3%	-16%	-14%	-12%	-12%	-7%	-2%
2005:6	-23%	3%	-11%	-7%	-12%	-13%	-14%	-9%
2005:7	-3%	15%	-7%	-13%	-7%	-10%	-7%	-5%
2005:8	-18%	-5%	-6%	-4%	-10%	3%	-2%	-2%
2005:9	-16%	-4%	-10%	-5%	-17%	-11%	-14%	0%
AMV	9%				14%			
RMSs	11%				17%			

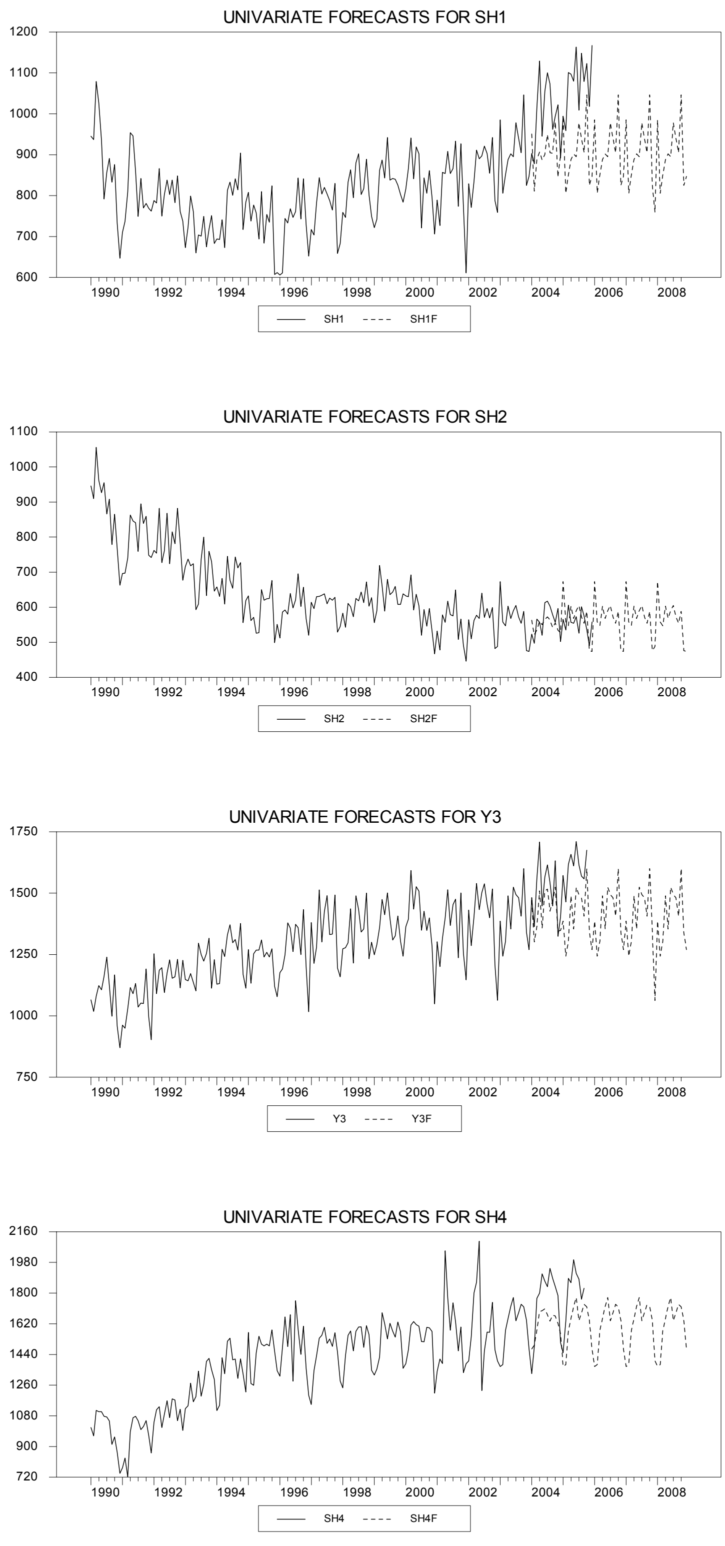


Figure 6-17 Five-year forecasts of the best univariate models for lumber quantities

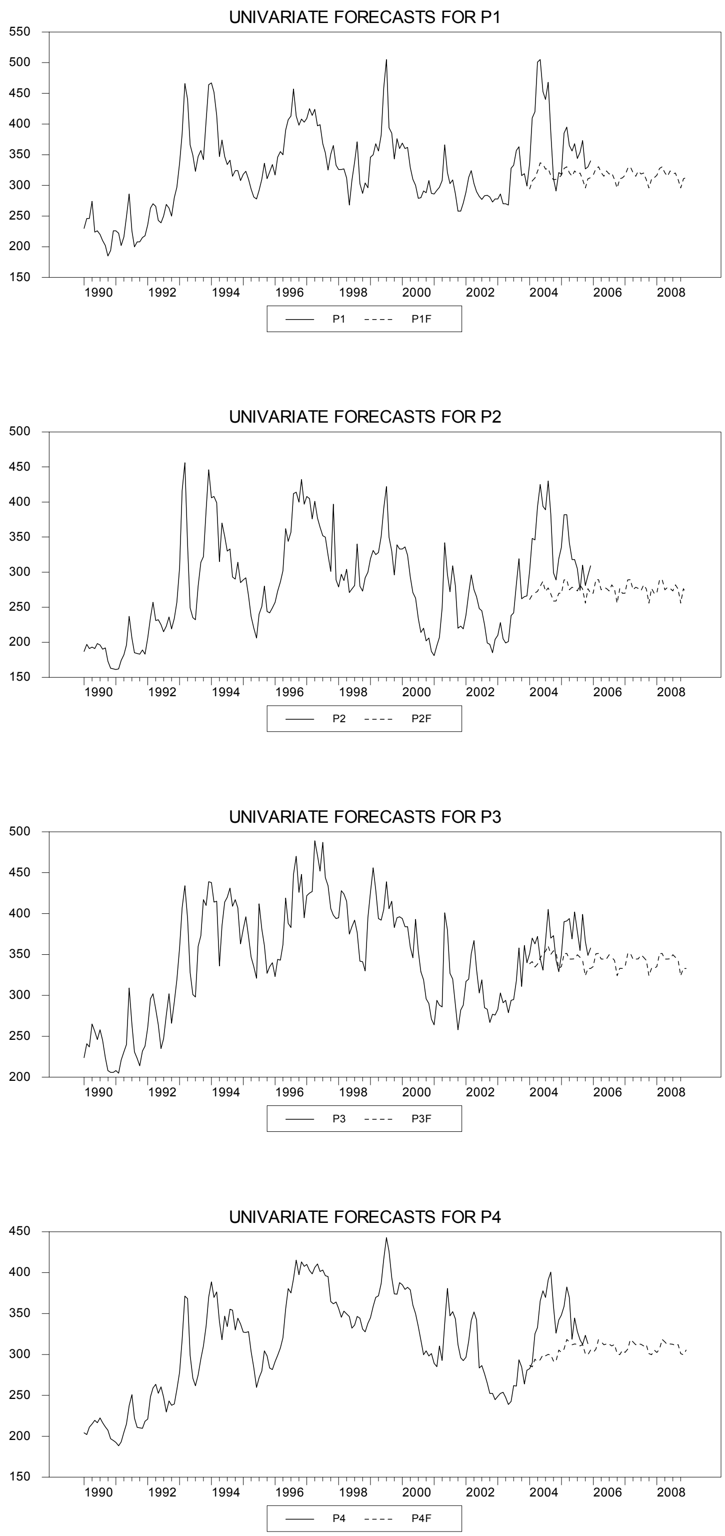


Figure 6-18 Five-year forecasts of the best univariate models for lumber prices

6.3.2 Five-Year Forecasts of the Best Multi-Equation Models

With the best multi-equation models selected in section 6.2 (Table 6-24), lumber quantities and prices were forecasted. Table 6-28 is for the relative forecast errors from 2004:1 to 2005:9 when observations of endogenous variables were available. The overall MAV and RMS for this period are 7% and 8% respectively for lumber quantities. These MAV and RMS are smaller than corresponding values for the same period in Table 6-27. However, the overall MAV and RMS for lumber prices, which are 16% and 19% respectively, are greater than the corresponding 14% and 17% in Table 6-27. The best multi-equation models forecast lumber quantities better than the best univariate models for the 21 month forecast period, but the best univariate models forecast lumber prices better than the best multi-equation models do. The results about the forecasts for lumber prices of this example support the conclusion of section 6.2.8.

The differences of forecasts of the multi-equation models and the univariate models are obvious when the forecasts for the lumber quantities and the observed values of the corresponding variables are plotted in graphs. The rises in lumber quantities of region 1, 3, and 4 during 2004 and 2005 are not captured by univariate models (Figure 6-17). However, the rises are captured by multi-equation models (Figure 6-19). It is hard to tell which kind of models is better for forecasting lumber prices by comparing the graphs in Figure 6-18 and 20.

6.3.3 Five-Year Forecasts of the Overall Best Combination of Forecasting Models

Since the best univariate forecast models are the best models among the univariate and multi-equation models for forecasting the prices, graphs in Figure 6-18 represent the best forecasts based on a combination of model 1 and model 6 of the univariate models

(Table 6-26). The best forecasts for quantities based on a combination of model 1 and model 4 of the univariate models and model I of the multi-equation models (Table 6-26) are shown in Figure 6-21. An obvious improvement is for forecasts for SH2. The overall MAV and RMS for Figure 6-21 are 6% and 8% respectively. The MAV 6% is smaller than the corresponding MAV 7% and 9% in Table 6-27 and 28. Thus, the overall best models chosen in Table 6-26 for the lumber quantities are the best. Therefore, from the results of section 6.3.2 and this section the model combinations chosen in Table 6-26 for lumber quantities and prices are the best. The conclusion in Table 6-26 is upheld.

Table 6-28 Relative forecast errors by the best multi-equation models

Month	Relative forecast errors							
	SH1P	SH2P	Y3P	SH4P	P1P	P2P	P3P	P4P
2004:1	11%	18%	5%	11%	-8%	-10%	-4%	-1%
2004:2	8%	20%	4%	8%	-23%	-20%	-10%	-5%
2004:3	-1%	7%	-2%	-8%	-24%	-18%	-5%	-14%
2004:4	-8%	12%	-7%	-6%	-38%	-30%	-9%	-17%
2004:5	13%	16%	11%	-11%	-38%	-33%	1%	-25%
2004:6	3%	0%	3%	-5%	-31%	-24%	11%	-25%
2004:7	5%	8%	10%	1%	-19%	-9%	12%	-19%
2004:8	3%	9%	8%	-5%	-17%	-7%	11%	-16%
2004:9	11%	7%	12%	2%	3%	7%	16%	-14%
2004:10	18%	20%	13%	7%	31%	33%	10%	-4%
2004:11	-8%	-10%	4%	5%	49%	43%	19%	10%
2004:12	1%	2%	-2%	11%	32%	16%	16%	3%
2005:1	-2%	4%	5%	15%	-3%	-18%	0%	-12%
2005:2	1%	9%	7%	9%	-21%	-29%	-12%	-15%
2005:3	-7%	-1%	2%	-2%	-24%	-30%	-12%	-20%
2005:4	-5%	8%	0%	1%	-19%	-23%	-14%	-17%
2005:5	-3%	8%	2%	-6%	-18%	-17%	-8%	-4%
2005:6	-7%	5%	-3%	-2%	-21%	-17%	-16%	-11%
2005:7	12%	19%	5%	0%	-17%	-15%	-11%	-7%
2005:8	-4%	2%	4%	5%	-20%	-6%	-6%	-4%
2005:9	1%	3%	4%	4%	-25%	-18%	-17%	-2%
MAVs	7%				16%			
RMSs	8%				19%			

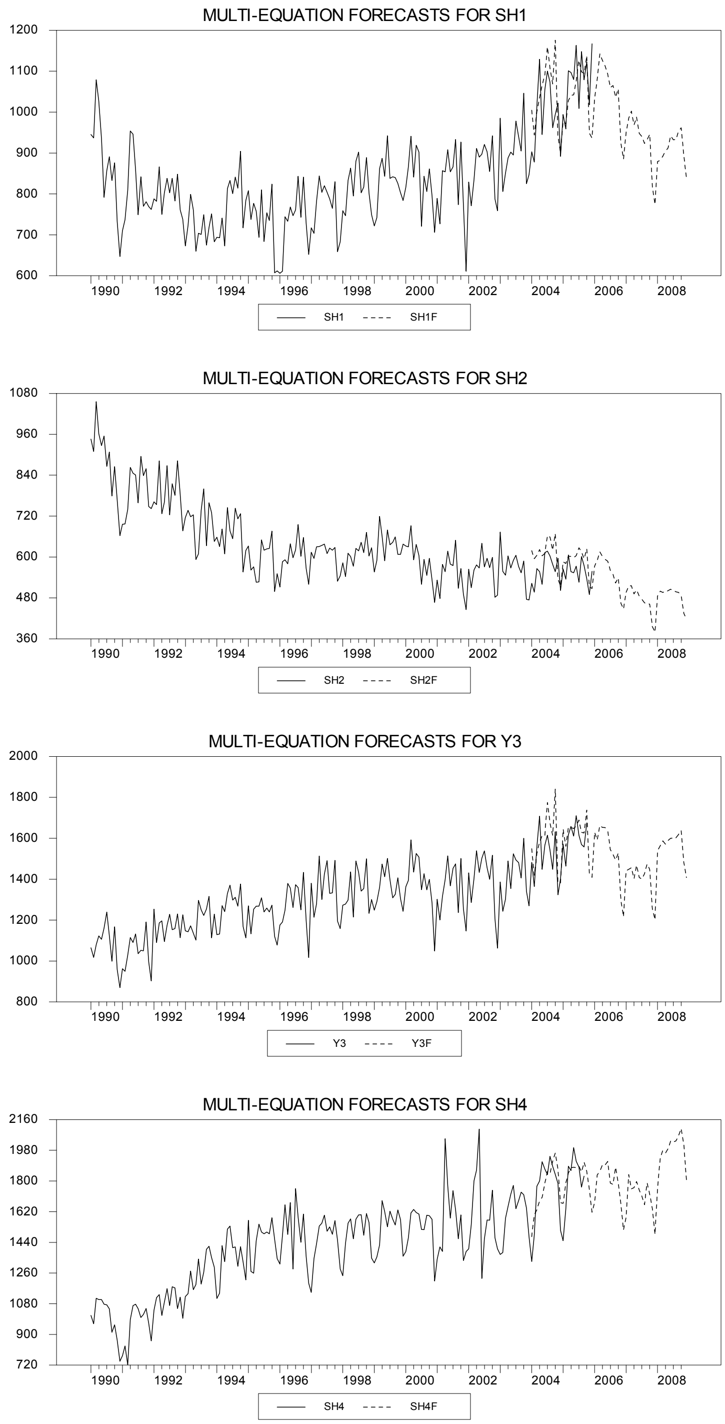


Figure 6-19 Five-year forecasts of the best multi-equation models for lumber quantities

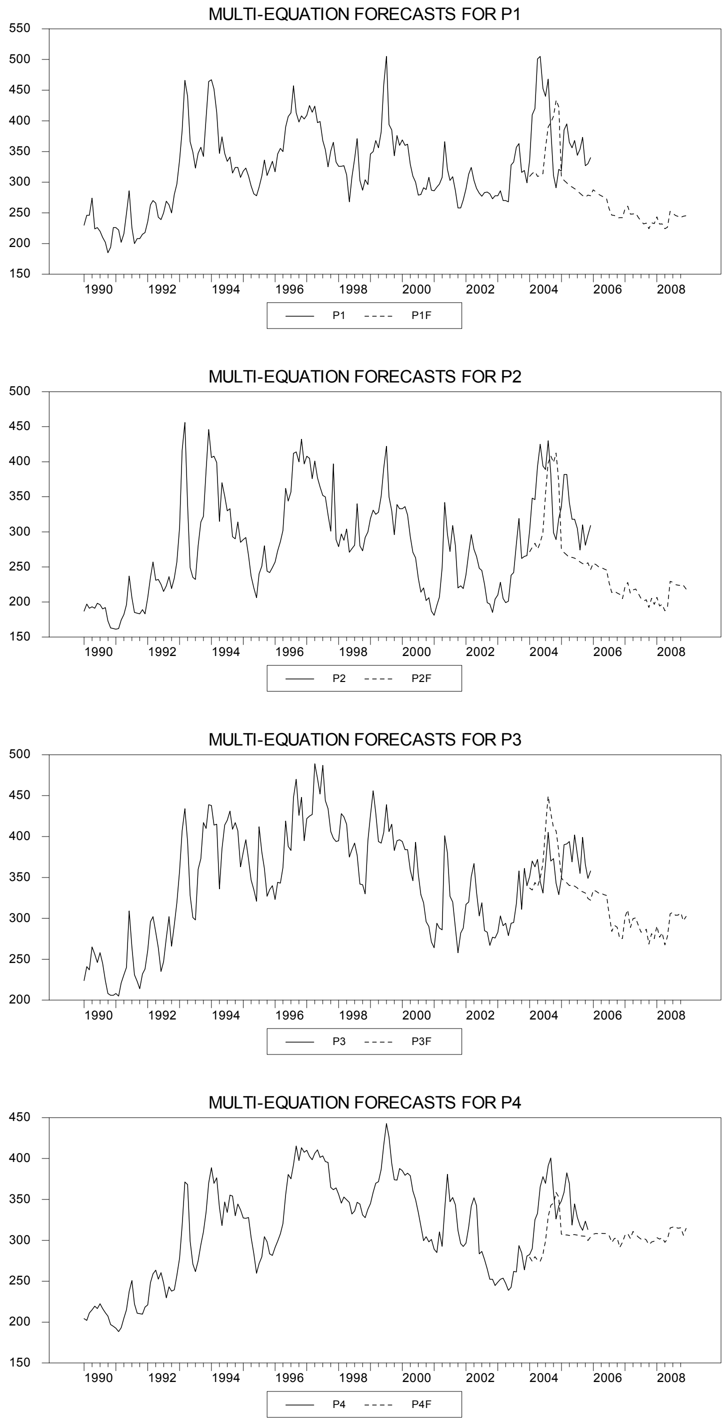


Figure 6-20 Five-year forecasts of the best multi-equation models for lumber prices

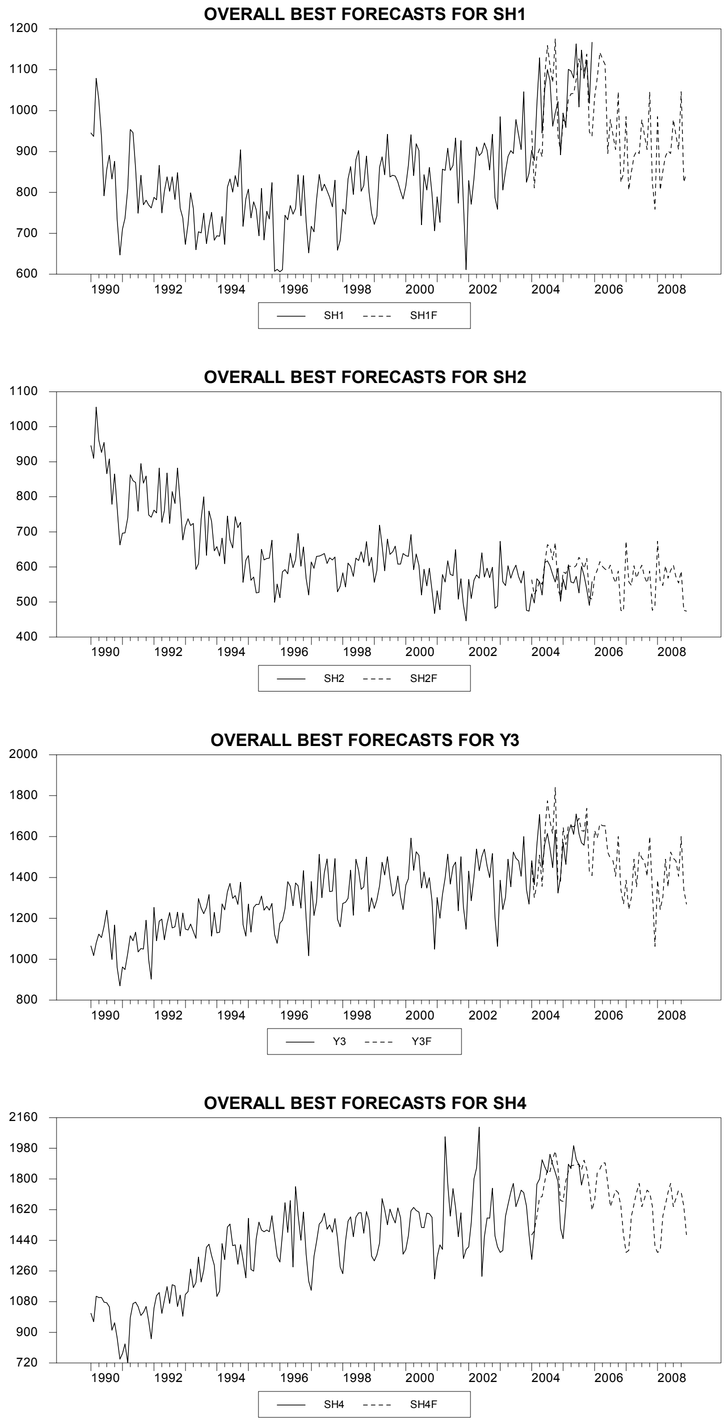


Figure 6-21 Five-year forecasts of the overall best combination of model for lumber quantities

Chapter 7 Discussion and Conclusion

For the first time, Hsiao's results (1997a, 1997b) were applied to forest products modeling. The method of Johansen and Juselius for the ECM did not work in this study for the regional lumber model since the LR test rejected the hypothesis for the restrictions, but the results of 2SLS were reasonable. Most of the major econometric forecasting methods were used for forecasting the lumber quantities and prices. The best combinations of models were selected to forecasting the lumber prices and quantities for different number of months ahead. In sections below, the salient conclusions will be presented.

7.1 Nonstationarity

Various unit root tests indicated that the time series used in developing the supply and demand models for softwood lumber are all suspected to be nonstationary by either nonstationary or stationary-null unit root tests. The stationary-null unit root tests used are ADF and PP tests. By these methods, all but the log-transform shipments of regions 1, 2, and 4 are integrated of order 1. The stationary-null unit root tests used are the KPSS tests. By these tests, the log-transformed shipments of region 1, 2, and 4 are also integrated of order 1. LLC may be integrated of higher order. However, the residuals of the cointegration tests showed that there are stationary linear combinations of the variables involved, and LLC is not a problem. Seasonal unit root tests for the time series showed that the difference of a time series and its 12th lag is not stationary.

7.2 Structural Models

As Granger and Newbold (1974) pointed out, non-stationarity may lead to spurious

regression estimates. However, when there are cointegration relations estimates of ECMs are consistent, and two methods can be used for estimating a restricted ECM. One is the 2SLS suggested by Hsiao (1997a, 1997b), and the other is MLE method developed by Johansen (1988) and Johansen and Juselius (1990, 1992). Both methods were used in estimating the structural lumber models in this study.

A multi-regional structural model and a U.S.-Canada structural model were developed. The long-run and short-run coefficients of these models were estimated. Based on the results of Hsiao (1997a, 1997b), 2SLS can be used when there are enough cointegration relations for the equation system. According to his results, the identification conditions for the long-run and short-run models are the same, and the nonstationarity of the time series can be ignored when using 2SLS method to estimate structural models.

The log-transformed data were used in structural models. The cointegration tests for two different specifications of the long-run model confirmed the cointegration relations. The price of the Canadian timber is excluded from the supply equation for Canada because it may be determined by the autocorrelated previous lumber prices, and thus making this timber price endogenous.

To make sure that the cointegration test was valid, the residuals of the tests were visually examined for unit roots. The reasonably high DWs were signs of valid estimations for both the long-run and the short-run models. Robust variances are applied for determining the significance of the estimates. In the final version of the regional model, only one lumber price was included in the demand equation for the lumber from the Inland West because of the poor estimates of price elasticities of demand for this region. All the estimated long-run demand and supply are price inelastic. These are

consistent with results of Lewandrowski et al. (1994) and Adams et al. (1986). Although Lewandowski et al. argued that their elasticities are short-run elasticities they are actually long-run elasticities by the cointegration theories. The housing starts have positive and significant coefficients estimated in the long-run demand equations. These are also consistent with the results of Lewandrowski et al. (1994). The timber prices and lumber inventories do not have any significant estimated coefficients on the long-run supply of lumber. Lewandrowski et al. had similar results for timber prices, but concluded that inventories had significant effects. The lumber supply equations for the West Coast, the South, and Canada have significant trends of approximately 2% per year. The lumber supply equation for the Inland West has a significant negative trend, and it is approximately -3% yearly. In contrast, Lewandowski had positive trend for all the U.S. regions.

The Christmas season has significant effects on demands and supplies for all the regions. The Christmas season comes earlier for the United States than for Canada since the November dummy variable has significant effects on the U.S. regions but not on Canada.

CUSUM tests were applied to the residuals of the estimated long-run structural model, and the results did not show any structural changes. Consequently, scheme change was not considered to be a problem in the structural models.

The estimated short-run own-price elasticities in the supply equations for the West Coast and the demand equation for Canada are significant and elastic. The estimated short-run inventory has a significant positive effect in the supply equation of the West Coast. The error correction effects are significant. The supply and demand of the West

Coast, Inland West and Canada adjust about 60% of the equilibrium errors while the South will adjust about 100%.

A shortcoming of the regional model is that the correlations among the lumber prices result in distorted estimates of price elasticities since the lumber prices are highly correlated. When the U.S. softwood lumber industry was treated as one supplier of the U.S. market; thus, a U.S.-Canada supply demand model was developed. The unit root tests showed that the aggregate lumber quantities and the average lumber prices are nonstationary time series. The cointegration tests showed that there were four cointegration relations for the four endogenous variables. The 2SLS procedure was used to estimate the long-run and short-run supply and demand equations. In the long-run, the demand and supply for both countries are own-price inelastic. The own-price elasticity for the demand for the U.S. lumber is a significant -0.53; that for the Canadian lumber is an insignificant -0.12. The own-price elasticity for the supply for the U.S. and Canadian lumber are an insignificant 0.15 and a significant 0.43 respectively. The lumber price for Canadian lumber imports has a significant and positive effect of 0.39 on the demand for the U.S. lumber, and the lumber price from the United States has a significant and positive effect of 0.48 on the demand for the Canadian lumber. Therefore, the lumber from Canada and the United States are substitutes. This conclusion confirmed the substitution effects between U.S. lumber and the Canadian lumber (Lewandrowski et al. 1994 and Hseu and Buongiorno, 1993). Rao et al. (2004) showed that the Canadian lumber is a substitute of the untreated southern pine but not other kinds of lumber. This dissertation study cannot tell if this is true. The short-run estimation has similar results to those of the long-run except that the estimated values and significance levels are different.

When the results in Table 5-5 for the long-run regional model and Table 5-9 for the long-run U.S.-Canada model are compared, it is found that the estimated supply equations for Canadian lumber in the two tables are very similar. However the demand equations have different significance and estimated coefficients. Since the regional model was complicated by including 4 linearly correlated lumber prices, the results of the U.S.-Canada model can be explained better.

The MLE suggested by Johansen and Juselius (1990) for the ECM rejected the hypotheses of the restrictions—the exclusion of some variables in equations—on the structural model. The rejection made the MLE unsuitable for estimating the structural model. Consequently, the 2SLS is robust when compared to the MLE method of Johansen and Juselius for estimating the lumber demand and supply models.

7.3 Forecasting Models

Univariate and multi-equation forecasting models were used for out-of-sample forecast for lumber quantities and prices. The values for the exogenous variables during the forecasting periods were forecasted by selected univariate forecasting models. The accuracy of a forecast was measured by the mean absolute values (MAV) and the mean square errors (MSE) of the relative forecast errors (RFE). For comparing the goodness of these forecasting models, the forecasts were repeated 36 times to get the overall MAVs and MSEs for forecasts of a specific number of steps ahead. The model with the smallest MSE and MAV was selected as the best forecasting model for a specific number of steps ahead of the sample. Occasionally, a model with the smallest MAV did not have the smallest MSE. In such a case, a model with the smallest MSE was chosen as the best model.

The results showed that the best models for the quantities and prices are different. Furthermore, forecasts of different numbers of steps have their specific best models. Consequently, combinations of models were selected for the lumber quantities and prices separately. For different numbers of months ahead, different forecasting models were sometimes selected for the best results. Generally, the further ahead a forecast is, the poorer the accuracy is; the lumber quantities can be forecasted better than the prices.

The best univariate model for up to 12 months ahead forecasts of lumber quantities is the Box-Jenkins model with 1 difference and 13 lags; for further ahead forecasts the best univariate model is the simple lag model with the nearest multiples of 12 lags. The best univariate model for up to 12 months ahead forecasts of lumber prices is the spectral model with 1 difference; for further ahead forecasts of lumber prices the best univariate model is the simple lag model with the nearest multiples of 12 lags.

The log-transformed VAR model is the best multi-equation model for forecasting the quantities less than 48 months ahead, while the 2SLS is the best multi-equation model for forecasting the lumber quantities greater than or equal to 49 months and less than or equal to 60 months ahead. For forecasting the lumber prices less than or equal to 12 months ahead, the best multi-equation model is the log-transformed VAR model, but for forecasting the lumber prices from 13 to 60 months ahead the best multi-equation model is ECM.

For lumber quantities, the best univariate forecasts are better than the best multi-equation forecasts for 1 to 5 months ahead or greater than or equal to 36 months ahead. For numbers of months in between, the best multi-equation model is better. A

combination of Box-Jenkins, VAR, and simple lag models are the overall best models for forecasting lumber quantities.

For the lumber prices, the best univariate forecasts for up to 60 months ahead are better than the best multi-equation forecasts. Consequently, for the purpose of forecasting lumber prices, simple univariate models are sufficient. Past studies used only OLS, and OLS is included in the candidate models; therefore, the combinations of models selected by this study should be better than OLS models.

The forecasts for 2004 and 2005 were obtained with the selected best models. The forecasts of the overall best models are the same as or better than those of the best univariate models and the best multi-equation models. Considering only data before 2004 were used for searching the best models, it can be concluded that the searching procedure for the best models is efficient. The results for 2004 and 2005 are very good for the quantities, but the forecasts for the prices are poor.

7.4 Further Studies

This research showed the advantage in applying the 2SLS conditioning on the presence of cointegration with lumber market structural models. However, some of the data, for example, lumber shipments for the South, were not available, and some of the data, such as timber prices for the West Coast, were only observations of proxies. For better structural models, better data always help improve the results of model estimation.

Another problem of the structural models is the collinearity among the variables. This problem makes it hard to explain the estimated results. Since the collinearity cannot be eliminated, more information beyond the model is needed to help explain the relations between these variables.

The production cycle of timber can be as long as 50 year. Even species in the U.S. South have rotations over 20 years for producing sawtimber. The 10 years of data is relative shorts. Further research should collect more data.

It was assumed in this dissertation that the market clears, and the inventory is only an exogenous variable. However, the market actually does not clear with the positive inventory. When data for the inventory of the South are available, it is possible to develop a model with equations of the production, supply, demand, and an identity for the inventory of each of the regions.

Since inventory is involved in the model, future studies may use ECM or non-symmetric ECM with multicointegration approach in lumber market modeling. Multicointegration method was first presented by Granger and Lee (1989, 1990) and then further developed by Engsted et al. (1997) and Haldrup (1998). The basic idea is that the cumulated linear combination of variables may be cointegrated with some of the variables themselves. Granger and Lee (1989) suggested a two-step method involving only $I(1)$ series, but Engsted et al. (1997) developed a one-step method involving the cumulated variables that are $I(2)$. Both of these methods could be used for modeling and forecasting the lumber quantities and prices. Leachman et al. (2005) and Engsted and Haldrup (1999) are examples of applications of this approach.

Econometric forecasting is helpful. However, the random effects on lumber prices that cannot be forecasted by the model are usually large. The model forecasts should be revised as new market information such as new listing of the threatened species, new laws about environmental protection, wars, ect. becomes available.

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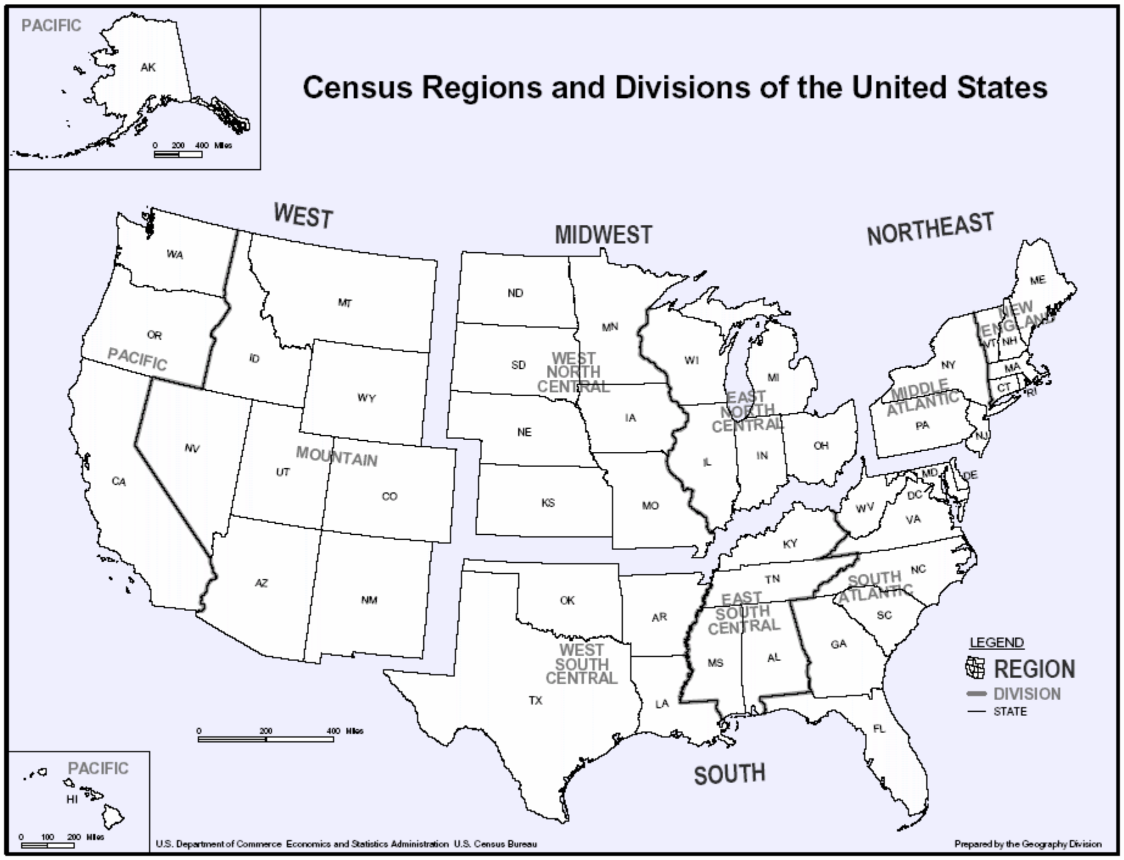
Appendix A Census Regions and Divisions of the United States



Appendix B Results of KPSS Unit Root Tests

	LSH1		dLSH1	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	2.14811	0.97602	0.01569	0.00712
1	1.37305	0.63681	0.02584	0.01173
2	1.04096	0.48975	0.03361	0.01531
3	0.86115	0.4103	0.03444	0.01572
4	0.76192	0.36838	0.04504	0.02065
5	0.69306	0.33997	0.05137	0.02365
6	0.64243	0.31954	0.0602	0.02786
7	0.60236	0.3036	0.06386	0.02967
8	0.57136	0.29185	0.08044	0.03774
9	0.54368	0.28115	0.08833	0.04172
10	0.51897	0.2715	0.1031	0.0492
11	0.49558	0.26195	0.1452	0.07109
12	0.47075	0.25066	0.11542	0.05572
13	0.44826	0.24022	0.12715	0.06191

	LSH2		DLSH2	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	9.76233	1.03457	0.00963	0.00804
1	5.5387	0.69542	0.01771	0.01479
2	3.9093	0.53276	0.02461	0.02058
3	3.04642	0.43819	0.02532	0.02119
4	2.52652	0.38401	0.03344	0.02801
5	2.16925	0.34514	0.03314	0.02778
6	1.91368	0.31932	0.04082	0.03427
7	1.71775	0.29926	0.04372	0.03675
8	1.56349	0.28384	0.05328	0.04489
9	1.43649	0.2702	0.06401	0.0541
10	1.32931	0.25727	0.06533	0.05529
11	1.2382	0.24559	0.08764	0.07459
12	1.15778	0.23348	0.07577	0.06437
13	1.08774	0.22252	0.08304	0.0707

	LY3		DLY3	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	8.39472	0.42085	0.00884	0.00461
1	5.13619	0.32625	0.01588	0.00829
2	3.75535	0.27599	0.02659	0.01389
3	2.94962	0.23434	0.02135	0.01115
4	2.495	0.2217	0.02644	0.01382
5	2.18958	0.21962	0.03419	0.01787
6	1.95808	0.21991	0.03368	0.0176
7	1.78397	0.22722	0.04291	0.02243
8	1.64113	0.23629	0.06336	0.03314
9	1.51406	0.23908	0.0636	0.03327
10	1.40398	0.23932	0.08435	0.04421
11	1.30559	0.2342	0.15187	0.08012
12	1.21408	0.21973	0.08774	0.0462
13	1.13558	0.20721	0.09411	0.04975

	LSH4		DLSH4	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	10.33933	1.34292	0.01438	0.00681
1	5.62795	0.83437	0.01966	0.00931
2	3.94791	0.63923	0.02441	0.01157
3	3.0766	0.53564	0.02679	0.01269
4	2.54644	0.47562	0.03541	0.01679
5	2.17983	0.43161	0.04157	0.01972
6	1.91025	0.39745	0.04828	0.02291
7	1.70301	0.36949	0.05338	0.02534
8	1.53897	0.34632	0.06325	0.03005
9	1.40521	0.32589	0.0777	0.03699
10	1.2932	0.30679	0.097	0.04635
11	1.19753	0.28841	0.12396	0.05963
12	1.11461	0.27051	0.12721	0.06152
13	1.04265	0.25388	0.10166	0.04916

	LP1		DLP1	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	3.30655	2.18109	0.0611	0.02219
1	1.72616	1.14217	0.05673	0.02062
2	1.19418	0.79242	0.05841	0.02126
3	0.92709	0.61688	0.06471	0.02358
4	0.7649	0.51017	0.07319	0.02671
5	0.65532	0.43788	0.07903	0.0289
6	0.57634	0.38566	0.08454	0.03099
7	0.51676	0.34619	0.09454	0.03479
8	0.46996	0.31514	0.10272	0.03798
9	0.43222	0.29006	0.10668	0.03965
10	0.40129	0.26948	0.10666	0.03983
11	0.37571	0.25246	0.10452	0.03919
12	0.35439	0.2383	0.10244	0.03857
13	0.33654	0.22647	0.10423	0.03946

	LP2		DLP2	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	2.51552	2.15419	0.05449	0.02504
1	1.31637	1.1278	0.05014	0.02306
2	0.91341	0.78302	0.05077	0.02338
3	0.71183	0.61057	0.05165	0.02381
4	0.59144	0.50753	0.05691	0.02627
5	0.51079	0.43845	0.06387	0.02955
6	0.45244	0.38846	0.06941	0.03219
7	0.40815	0.3505	0.07642	0.03556
8	0.37321	0.32056	0.08397	0.03923
9	0.34481	0.29623	0.08634	0.04048
10	0.32143	0.27621	0.08813	0.04148
11	0.302	0.25957	0.08707	0.04112
12	0.28581	0.24571	0.08459	0.04007
13	0.27234	0.23419	0.08554	0.0407

	LP3		DLP3	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	3.92011	2.89464	0.06893	0.02135
1	2.04936	1.5159	0.07008	0.02174
2	1.4144	1.04764	0.07297	0.02269
3	1.09508	0.81234	0.0775	0.02415
4	0.9023	0.67029	0.09123	0.02854
5	0.77154	0.57387	0.10693	0.03363
6	0.6762	0.50347	0.12512	0.03963
7	0.60303	0.44938	0.14635	0.04679
8	0.54479	0.40626	0.16642	0.05381
9	0.49728	0.37102	0.18249	0.05975
10	0.45786	0.34173	0.19092	0.06324
11	0.42475	0.3171	0.17796	0.05919
12	0.39689	0.29635	0.16866	0.05637
13	0.37332	0.27881	0.16335	0.05495

	LP4		DLP4	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	5.49901	2.918	0.17725	0.02807
1	2.81244	1.49675	0.14005	0.0223
2	1.91754	1.02424	0.13052	0.02089
3	1.47082	0.78862	0.12838	0.02065
4	1.20322	0.64761	0.13835	0.02243
5	1.02415	0.55332	0.15348	0.02514
6	0.89526	0.48545	0.17065	0.02832
7	0.79763	0.43404	0.19021	0.03209
8	0.72086	0.39361	0.20488	0.03517
9	0.65889	0.36096	0.21104	0.03677
10	0.60793	0.33414	0.20969	0.03698
11	0.56551	0.31184	0.20058	0.03564
12	0.52991	0.29321	0.192	0.03437
13	0.49983	0.27757	0.19003	0.03442

	LTP1_1		DLTP1_1	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	2.85459	2.78249	0.50981	0.16156
1	1.4383	1.40199	0.30728	0.09782
2	0.96787	0.94344	0.23768	0.07589
3	0.73367	0.71521	0.20846	0.06683
4	0.59382	0.57895	0.19315	0.06222
5	0.50106	0.48856	0.18523	0.06
6	0.43513	0.42432	0.18225	0.05942
7	0.38592	0.37635	0.18068	0.05933
8	0.34782	0.33921	0.17848	0.05901
9	0.31751	0.30965	0.17462	0.05811
10	0.29288	0.28562	0.17014	0.05698
11	0.27257	0.26578	0.16613	0.05602
12	0.25559	0.24919	0.16312	0.05541
13	0.24126	0.23516	0.16122	0.05521

	LTP2_1		DLTP2_1	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	4.21791	1.73946	0.18894	0.12857
1	2.13193	0.88273	0.11908	0.08112
2	1.4414	0.59909	0.09873	0.06736
3	1.09869	0.4584	0.09552	0.06532
4	0.89386	0.37427	0.09585	0.06571
5	0.75758	0.31826	0.09617	0.06612
6	0.66043	0.27831	0.09465	0.06525
7	0.58789	0.24848	0.09283	0.06417
8	0.53183	0.22546	0.09137	0.06333
9	0.48737	0.20724	0.09052	0.06291
10	0.45134	0.19255	0.0901	0.0628
11	0.42164	0.1805	0.09	0.06292
12	0.39682	0.17049	0.09009	0.06319
13	0.37584	0.16209	0.09019	0.06346

	LTP3_1		DLTP3_1	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	12.8643	3.61445	1.10125	0.17522
1	6.47734	1.82203	0.63362	0.10152
2	4.34491	1.22507	0.47878	0.07726
3	3.27903	0.9275	0.41018	0.06677
4	2.64	0.74956	0.37258	0.06123
5	2.21442	0.63134	0.35119	0.05831
6	1.91076	0.54716	0.3403	0.05717
7	1.68328	0.48419	0.33371	0.05677
8	1.50656	0.43534	0.32857	0.05663
9	1.36536	0.39637	0.32339	0.05648
10	1.25001	0.36462	0.31812	0.05631
11	1.15407	0.33829	0.31279	0.05612
12	1.07308	0.31613	0.30741	0.05592
13	1.00386	0.29728	0.30324	0.05597

	LINV1_1		DLINV1_1	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	13.5204	0.7197	0.0201	0.02044
1	6.91784	0.39032	0.02124	0.02159
2	4.69444	0.2774	0.02254	0.02292
3	3.5797	0.22077	0.02663	0.02708
4	2.90774	0.186	0.03076	0.03128
5	2.45864	0.16221	0.03417	0.03474
6	2.13698	0.14486	0.03699	0.0376
7	1.89506	0.13166	0.03625	0.03685
8	1.70698	0.12156	0.0355	0.03608
9	1.55685	0.11382	0.03722	0.03783
10	1.43423	0.10775	0.04042	0.04107
11	1.33208	0.10283	0.04317	0.04386
12	1.24564	0.09875	0.04315	0.04383
13	1.1717	0.09542	0.04189	0.04256

	LINV2_1		DLINV2_1	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	14.79297	1.03276	0.02684	0.02472
1	7.51595	0.5492	0.02534	0.02334
2	5.07681	0.38655	0.02532	0.02333
3	3.85498	0.30581	0.02684	0.02473
4	3.12134	0.25767	0.02931	0.02701
5	2.63193	0.22559	0.03274	0.03019
6	2.2816	0.20247	0.03701	0.03413
7	2.01795	0.18476	0.04135	0.03815
8	1.81195	0.1706	0.04542	0.04191
9	1.64627	0.15895	0.04799	0.04428
10	1.51004	0.1492	0.0488	0.04504
11	1.3961	0.14102	0.04887	0.0451
12	1.29946	0.13417	0.04926	0.04547
13	1.2165	0.12842	0.04979	0.04596

	LINV4_1		DLINV4_1	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	13.67872	0.31508	0.02363	0.02145
1	7.01028	0.17537	0.01975	0.01793
2	4.78323	0.13091	0.0178	0.01616
3	3.67497	0.11208	0.01795	0.0163
4	3.01103	0.10399	0.01958	0.01777
5	2.56644	0.10147	0.02207	0.02003
6	2.24669	0.1023	0.02574	0.02337
7	2.00459	0.10512	0.03127	0.02839
8	1.81373	0.10868	0.03916	0.03556
9	1.65827	0.11175	0.05005	0.04542
10	1.5284	0.1132	0.06324	0.05735
11	1.41779	0.11242	0.07025	0.06364
12	1.32254	0.10987	0.06877	0.06224
13	1.23994	0.10657	0.063	0.05698

	LH		DLH	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	12.73115	0.65217	0.09555	0.04107
1	6.61893	0.38372	0.14569	0.06326
2	4.5056	0.28005	0.17995	0.07894
3	3.43201	0.22431	0.18763	0.08286
4	2.78416	0.19023	0.19456	0.08641
5	2.35061	0.16745	0.20361	0.09097
6	2.04005	0.15116	0.21023	0.09441
7	1.80661	0.13901	0.20644	0.09285
8	1.62502	0.12982	0.20167	0.09071
9	1.47982	0.12283	0.20188	0.09084
10	1.3611	0.11739	0.19824	0.08911
11	1.26236	0.11328	0.19144	0.08586
12	1.17928	0.11031	0.19441	0.08709
13	1.10834	0.10802	0.19425	0.08682

	LHWM		DLHWM	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	10.65449	0.30968	0.0666	0.02563
1	5.84945	0.20669	0.12075	0.04687
2	4.06161	0.15794	0.1657	0.065
3	3.12464	0.12927	0.17378	0.06865
4	2.55613	0.11198	0.18674	0.07431
5	2.17391	0.10063	0.2092	0.08397
6	1.89696	0.09217	0.22435	0.09074
7	1.68698	0.08561	0.21146	0.08555
8	1.52415	0.08092	0.22243	0.09053
9	1.39364	0.07745	0.21726	0.08847
10	1.28706	0.07497	0.21842	0.08906
11	1.19832	0.07325	0.20744	0.08438
12	1.12408	0.07238	0.21876	0.08925
13	1.0605	0.07183	0.21454	0.08737

	LHS		DLHS	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	13.11789	1.19987	0.03326	0.02037
1	6.86011	0.72459	0.05496	0.03376
2	4.67203	0.53086	0.08287	0.05115
3	3.55141	0.42044	0.09789	0.06062
4	2.87214	0.34994	0.1028	0.06379
5	2.41786	0.30221	0.10373	0.06448
6	2.09359	0.26879	0.11379	0.07095
7	1.85	0.2438	0.1145	0.07144
8	1.66062	0.2246	0.11216	0.06991
9	1.50935	0.20969	0.12218	0.07618
10	1.38549	0.19741	0.12315	0.07668
11	1.28226	0.18731	0.12036	0.07477
12	1.19519	0.17905	0.12978	0.08049
13	1.12063	0.17191	0.12721	0.07864

	LDPI		DLDPI	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	16.85454	1.38731	0.01717	0.01691
1	8.50269	0.76907	0.0232	0.02286
2	5.70756	0.54543	0.02722	0.02681
3	4.308	0.43018	0.0349	0.03438
4	3.46765	0.358	0.04209	0.04147
5	2.90737	0.30795	0.04462	0.04397
6	2.50723	0.27162	0.04574	0.04508
7	2.20717	0.24443	0.04624	0.04557
8	1.97385	0.22357	0.04597	0.04531
9	1.78727	0.20734	0.04974	0.04903
10	1.63468	0.19427	0.05189	0.05114
11	1.5076	0.18356	0.05971	0.05886
12	1.40015	0.17443	0.05682	0.05601
13	1.30814	0.16676	0.06021	0.05936

	LLC		DLLC	
Critical Level:	0.05	0.05	0.05	0.05
Critical Value:	0.463	0.146	0.463	0.146
Number of lags	ETA(mu)	ETA(tau)	ETA(mu)	ETA(tau)
0	3.91996	2.89217	0.53637	0.38186
1	1.99049	1.46264	0.3304	0.23563
2	1.34625	0.98646	0.26878	0.19208
3	1.02458	0.74896	0.25343	0.18164
4	0.83169	0.6066	0.24528	0.17632
5	0.70318	0.51177	0.23592	0.17004
6	0.61156	0.44415	0.2229	0.16099
7	0.54314	0.39364	0.21118	0.15284
8	0.49026	0.35459	0.20249	0.1469
9	0.44831	0.32358	0.1974	0.14361
10	0.41426	0.2984	0.19345	0.14116
11	0.38612	0.27758	0.18926	0.13853
12	0.36249	0.26009	0.18408	0.13512
13	0.3424	0.24521	0.17917	0.13187

Appendix C   Results of Monthly Seasonal Unit-Root Tests

MHEGY.src is the procedure used for the test. This procedure is downloaded from the official website of the Estima (estima.com). It was written by Ulrich Leuchtmann and revised by Estima. It followed Beaulieu and Miron (1993). Observations were from 1990:01 to 2004:06 for most of the time series. The timber prices of the Inland West and the West Coast (LTP1_1 and LTP2_1) were from 1990:01 to 2003:12. Deterministic components include constant, trend, deterministic seasonal dummy variables. number of lags were selected using the BIC criterion.

Lsh1 (lag 1)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-3.64	-	-
pi	6	-	0.94	-
pi/2	3 and 9	3.66	-1.66	7.5
2pi/3	8 and 4	-3.5	0.48	6.16
pi/3	2 and 10	1.59	1.6	2.8
5pi/6	7 and 5	-2.73	4.16	15
pi/6	1 and 11	0.24	0.72	0.26

Lsh2 (lag 12)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-2.7	-	-
pi	6	-	1.12	-
pi/2	3 and 9	2.3	-0.95	2.84
2pi/3	8 and 4	-2.99	1.04	4.98
pi/3	2 and 10	-1.51	2.13	3.39
5pi/6	7 and 5	-1.19	4.1	10.91
pi/6	1 and 11	-0.18	0.23	0.06

Ly3(lag 4)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-0.9	-	-
pi	6	-	0.59	-
pi/2	3 and 9	4.02	0.1	8.26
2pi/3	8 and 4	-3.3	-0.21	5.61
pi/3	2 and 10	0.89	1.22	1.27
5pi/6	7 and 5	-0.8	4.42	12.89
pi/6	1 and 11	-2.05	-1.72	2.69

Lsh4 (lag 0)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-2.67	-	-
pi	6	-	0.61	-
pi/2	3 and 9	2.9	-0.52	4.21
2pi/3	8 and 4	-2.92	2.3	7.02
pi/3	2 and 10	1.31	1.04	1.59
5pi/6	7 and 5	-1.69	3.89	11.51
pi/6	1 and 11	-1.81	0.75	2.28

LP1 (lag 12)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-2.44	-	-
pi	6	-	1.09	-
pi/2	3 and 9	1.79	0.03	1.61
2pi/3	8 and 4	-0.28	3.93	7.81
pi/3	2 and 10	1.44	0.84	1.51
5pi/6	7 and 5	-0.62	4.88	12.77
pi/6	1 and 11	2.93	-1.45	6.75

LP2 (lag 2)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-3.82	-	-
pi	6	-	-0.22	-
pi/2	3 and 9	1.23	0.26	0.85
2pi/3	8 and 4	-1.2	3.48	7.04
pi/3	2 and 10	2.27	-0.3	2.59
5pi/6	7 and 5	-2.73	4.78	17.02
pi/6	1 and 11	5.82	-2.23	21.86

LP3 (lag 1)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-3.19	-	-
pi	6	-	0.74	-
pi/2	3 and 9	2.75	-0.32	3.78
2pi/3	8 and 4	-2.59	3.38	9.33
pi/3	2 and 10	2.63	-0.36	3.46
5pi/6	7 and 5	-1.43	5.19	17.1
pi/6	1 and 11	4.39	-1.98	13.91

LP4 (lag 12)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-3.3	-	-
pi	6	-	2.82	-
pi/2	3 and 9	1.08	-0.53	0.68
2pi/3	8 and 4	-1.23	3.54	7.43
pi/3	2 and 10	1.57	0.21	1.29
5pi/6	7 and 5	-0.65	4.97	13.51
pi/6	1 and 11	4.75	-1.18	15.04

LTP1_1 (lag 8)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-7.86	-	-
pi	6	-	0.71	-
pi/2	3 and 9	-0.55	-4.06	8.38
2pi/3	8 and 4	0.36	14.08	110.1
pi/3	2 and 10	1.55	-2.1	3.02
5pi/6	7 and 5	-4.69	-0.06	11.17
pi/6	1 and 11	10.48	1.29	57.19

LTP2_1 (lag 5)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-3.71	-	-
pi	6	-	-2.21	-
pi/2	3 and 9	-0.92	0.29	0.45
2pi/3	8 and 4	1.44	9.9	52.26
pi/3	2 and 10	4.76	-1.2	11.34
5pi/6	7 and 5	-2.17	2.82	7.73
pi/6	1 and 11	6.13	-0.68	20.39

LTP3_1 (lag 5)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-4.82	-	-
pi	6	-	-0.74	-
pi/2	3 and 9	-0.03	-0.64	0.21
2pi/3	8 and 4	0.54	12.12	74.71
pi/3	2 and 10	3.96	-2.02	9.02
5pi/6	7 and 5	-2.49	1.67	5.05
pi/6	1 and 11	7.53	-1.28	31.43

LINV1 (lag 1)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-3.2	-	-
pi	6	-	1.07	-
pi/2	3 and 9	3.02	-1.07	4.79
2pi/3	8 and 4	-2.89	4.16	13.38
pi/3	2 and 10	1.53	0.49	1.38
5pi/6	7 and 5	-0.5	3.6	7.03
pi/6	1 and 11	1.93	0.95	2.04

LINV2 (lag 1)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-3.09	-	-
pi	6	-	0.74	-
pi/2	3 and 9	2.19	0.22	2.52
2pi/3	8 and 4	-1.47	4.4	10.89
pi/3	2 and 10	2.8	0.46	4.31
5pi/6	7 and 5	-1.66	3.38	8.16
pi/6	1 and 11	4.94	-1.9	16.56

LINV4 (lag 1)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-1.46	-	-
pi	6	-	3.26	-
pi/2	3 and 9	0.06	0.84	0.36
2pi/3	8 and 4	-0.89	2.35	3.6
pi/3	2 and 10	1.1	3.03	5.82
5pi/6	7 and 5	1.19	4.28	9.19
pi/6	1 and 11	1.13	0.97	0.9

LH (lag 2)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-4.79	-	-
pi	6	-	0.03	-
pi/2	3 and 9	2.72	-1.44	4.22
2pi/3	8 and 4	-3.79	3.96	17.3
pi/3	2 and 10	1.06	0.19	0.6
5pi/6	7 and 5	-3.45	4.15	17.19
pi/6	1 and 11	1.86	0.23	1.73

LHWM (lag 12)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-2.85	-	-
pi	6	-	1.13	-
pi/2	3 and 9	1.6	-0.65	1.36
2pi/3	8 and 4	-2.5	3.15	8.13
pi/3	2 and 10	0.11	1.31	0.9
5pi/6	7 and 5	-2.29	2.03	5.85
pi/6	1 and 11	-3.96	1.62	11.94

LHS (lag 3)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-4.99	-	-
pi	6	-	0.12	-
pi/2	3 and 9	3.5	-1.34	6.66
2pi/3	8 and 4	-4.7	4.65	28.18
pi/3	2 and 10	1.18	-1	1.13
5pi/6	7 and 5	-3.12	3.42	11.29
pi/6	1 and 11	0.09	0.4	0.08

LDPI (lag 1)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-2.57	-	-
pi	6	-	0.77	-
pi/2	3 and 9	2	0.16	2.08
2pi/3	8 and 4	-1.57	3.66	8
pi/3	2 and 10	3.09	-0.62	4.79
5pi/6	7 and 5	-1.18	2.93	5.78
pi/6	1 and 11	1.13	0.92	0.88

LLC (lag 5)

	Cycles	t-Tests		F-Test
Frequency	per Year	pi_odd	pi_even	
0	0	-4.09	-	-
pi	6	-	-1.17	-
pi/2	3 and 9	0.41	-0.58	0.24
2pi/3	8 and 4	1.45	13.89	105.44
pi/3	2 and 10	6.28	-2.28	20.34
5pi/6	7 and 5	-1.8	2.21	4.74
pi/6	1 and 11	6.56	-1.04	23.58

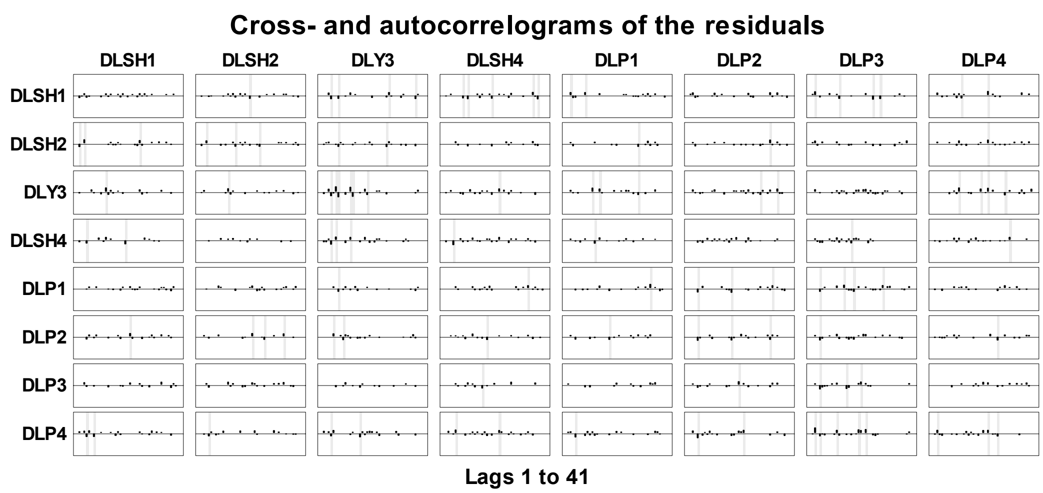
Appendix D Critical Values for the Seasonal Unit Root Tests*

Frequencies	0	π	Odd	Even	'F': $_{odd, even}$
0.01	-3.83	-3.31	-3.79	-2.56	
0.025	-3.54	-3.02	-3.5	-2.18	
0.05	-3.28	-2.75	-3.24	-1.85	
0.10	-2.99	-2.47	-2.95	-1.45	
0.90				1.45	5.25
0.95				1.86	6.23
0.975				2.19	7.14
0.99				2.61	8.33

*: with intercept, seasonal dummy variables, and trend, observations less than 240.

Appendix E Autocorrelograms for the Residual of the Cointegration Test

The graphs below are the autocorrelograms of the cointegration test. They illustrate the partial autocorrelations and cross partial autocorrelation correlations up to 40 lags. DSH1, DSH2, DLY3, DSH4, DLP1, DLP2, DLP3, and DLP4 are the first differences of the endogenous variables for which equations of the model for the cointegration test are normalized. The maximums of the boxes are 1, and the minimums of them are -1. All the autocorrelations and correlations are quite small, so the lags and dummy variables are proper. The cointegration test is valid.



Appendix F MAVs and RMSs of RFEs for the Lumber Quantities and Prices (Univariate Model)

Table F-1 MAVs and RMSs of RFEs for the lumber quantities (Univariate Model)

Models	MAVs of RFEs for the lumber quantities											
	1	6	12	13	20	24	30	36	42	48	54	60
1.Box-Jenkins (1 difference, 13 lags)	6%	8%	8%	9%	9%	9%	10%	10%	11%	13%	16%	20%
2.Box-Jenkins (1 difference, No lags)	10%	13%	8%	11%	14%	10%	14%	11%	15%	14%	20%	21%
3.Spectral model (1 difference)	7%	8%	8%	9%	10%	9%	12%	10%	13%	14%	19%	22%
4.Simple lag model	10%	13%	8%	10%	13%	9%	13%	9%	12%	9%	13%	9%
5.Simple 12th lag model	8%	8%										
6.Seasonal-dummy-variable model	13%	13%	13%	14%	14%	14%	15%	15%	16%	16%	17%	18%
7.Seasonal-dummy-variable AR1 model	8%	15%	20%	21%	24%	24%	25%	26%	26%	26%	26%	26%
8.Seasonal-dummy-variable AR13 model	8%	14%	17%	18%	23%	24%	27%	27%	27%	27%	29%	32%
Models	RMSs of RFEs for the lumber quantities											
	1	6	12	13	20	24	30	36	42	48	54	60
1.Box-Jenkins (1 difference, 13 lags)	9%	10%	10%	11%	12%	11%	13%	13%	15%	16%	19%	23%
2.Box-Jenkins (1 difference, No lags)	13%	16%	11%	14%	18%	13%	18%	14%	18%	17%	24%	25%
3.Spectral model (1 difference)	10%	11%	10%	11%	13%	11%	14%	13%	17%	17%	23%	27%
4.Simple lag model	13%	16%	10%	13%	16%	11%	16%	12%	15%	11%	16%	11%
5.Simple 12th lag model	10%	10%										
6.Seasonal-dummy-variable model	15%	15%	15%	16%	16%	16%	17%	17%	18%	19%	20%	20%
7.Seasonal-dummy-variable AR1 model	12%	21%	27%	28%	30%	31%	32%	32%	31%	31%	30%	30%
8.Seasonal-dummy-variable AR13 model	14%	25%	30%	32%	38%	40%	43%	44%	44%	43%	48%	52%

Table F-2 MAVs and RMSs of RFEs for the Lumber Prices (Univariate Model)

Models	MAVs of RFEs for the lumber prices											
	1	6	12	13	20	24	30	36	42	48	54	60
1.Box-Jenkins (1 difference, 13 lags)	6%	15%	19%	20%	27%	30%	38%	46%	56%	68%	77%	82%
2.Box-Jenkins (1 difference, No lags)	6%	15%	19%	19%	26%	28%	34%	41%	49%	58%	66%	68%
3.Spectral model (1 difference)	6%	14%	20%	21%	30%	34%	40%	48%	57%	65%	71%	73%
4.Simple lag model	6%	15%	17%	18%	21%	21%	24%	27%	29%	32%	33%	31%
5.Simple 12th lag model	17%	17%	17%									
6.Seasonal-dummy-variable model	16%	16%	16%	16%	16%	16%	16%	16%	16%	15%	14%	14%
7.Seasonal-dummy-variable AR1 model	6%	14%	17%	18%	21%	21%	23%	23%	24%	24%	24%	23%
8.Seasonal-dummy-variable AR13 model	7%	15%	18%	19%	21%	21%	22%	22%	23%	23%	23%	22%
Models	RMSs of RFEs for the lumber prices											
	1	6	12	13	20	24	30	36	42	48	54	60
1.Box-Jenkins (1 difference, 13 lags)	9%	18%	24%	26%	36%	37%	44%	54%	65%	76%	85%	92%
2.Box-Jenkins (1 difference, No lags)	9%	19%	24%	25%	35%	35%	41%	48%	58%	66%	73%	76%
3.Spectral model (1 difference)	9%	18%	26%	28%	38%	40%	47%	55%	63%	70%	76%	78%
4.Simple lag model	9%	19%	22%	23%	28%	27%	30%	33%	38%	38%	38%	37%
5.Simple 12th lag model	22%	22%	22%									
6.Seasonal-dummy-variable model	20%	20%	20%	20%	20%	20%	20%	20%	19%	19%	18%	18%
7.Seasonal-dummy-variable AR1 model	9%	18%	21%	22%	25%	25%	27%	28%	30%	29%	28%	28%
8.Seasonal-dummy-variable AR13 model	9%	19%	23%	24%	27%	26%	27%	27%	28%	28%	27%	27%

Appendix G MAVs and RMSs of RFEs for the Lumber Quantities and Prices (Multi-Equation Model)

Models	MAVs of RFEs for the lumber quantities											
	1	6	12	13	20	24	30	36	42	48	54	60
I. Log-transformed VAR model	7%	7%	7%	8%	9%	8%	10%	10%	16%	18%	29%	31%
II. Untransformed VAR model	7%	7%	8%	8%	8%	8%	13%	15%	25%	36%	49%	63%
III. 2SLS model	7%	7%	8%	8%	9%	9%	12%	14%	17%	21%	25%	30%
IV. ECM	7%	10%	11%	12%	17%	20%	27%	32%	37%	42%	58%	65%
Models	RMSs of RFEs for the lumber quantities											
	1	6	12	13	20	24	30	36	42	48	54	60
I. Log-transformed VAR model	10%	9%	10%	11%	12%	11%	13%	13%	21%	24%	38%	41%
II. Untransformed VAR model	10%	10%	11%	11%	11%	11%	17%	19%	32%	44%	59%	75%
III. 2SLS model	10%	10%	10%	11%	12%	13%	15%	18%	21%	24%	29%	34%
IV. ECM	10%	13%	15%	16%	21%	24%	33%	40%	47%	56%	75%	83%
Models	MAVs of RFEs for the lumber prices											
	1	6	12	13	20	24	30	36	42	48	54	60
I. Log-transformed VAR	7%	14%	17%	20%	35%	41%	75%	109%	172%	228%	271%	269%
II. Untransformed VAR model	8%	17%	19%	21%	28%	31%	50%	65%	87%	107%	117%	113%
III. 2SLS model	21%	23%	28%	30%	38%	44%	54%	65%	79%	89%	101%	118%
IV. ECM	10%	17%	19%	20%	27%	28%	37%	44%	54%	60%	86%	96%
Models	RMSs of RFEs for the lumber prices											
	1	6	12	13	20	24	30	36	42	48	54	60
I. Log-transformed VAR model	10%	18%	24%	29%	50%	54%	101%	134%	220%	301%	440%	572%
II. Untransformed VAR model	11%	21%	24%	28%	39%	41%	65%	77%	101%	119%	134%	135%
III. 2SLS model	26%	28%	34%	35%	44%	49%	60%	72%	84%	94%	106%	126%
IV. ECM	13%	22%	25%	27%	37%	35%	45%	51%	64%	68%	95%	109%

Vita

Nianfu Song was born in China in 1965. He received his bachelor's degree in forestry in 1985 and a master's degree in forest economic and management in 1989 from the Northeast Forestry University, China. Before coming to the U.S., he worked for The Forestry Academy of Heilongjiang Province conducting research on forest fire, forest management, forest policy, and forest economics. He led and finished two research projects in China, and was involved in many others. His many publications reported on his research efforts in forest fire, forest management, reform of the forest industry, and the employment of the forest industry in Heilongjiang province, China.

His research interests include modeling the forest products market and forest resource economics. He gave several presentations in three of the SOFEW (Southern Forest Economics Workers) meetings, and had one paper published in a SOFEW proceedings. Two manuscripts of his have been submitted to refereed journals for review. He is expected to receive the degree of Doctor of Philosophy from the School of Renewable Natural Resources, Louisiana State University in the summer of 2006.