METSÄNTUTKIMUSLAITOKSEN TIEDONANTOJA 805, 2001
FINNISH FOREST RESEARCH INSTITUTE, RESEARCH PAPERS 805, 2001

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The Case of Sawnwood Imports and Sawlog Demand

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Hetemäki, Lauri, Hänninen, Riitta and Anne Toppinen. 2001. A System for Short Term Forecasting of the Finnish Forest Sector (MESU): The Case of Sawnwood Imports and Sawlog Demand. Metsäntutkimuslaitoksen tiedonantoja 805. Finnish Forest Research Institute, Research Papers 805. ISBN 951-40-1775-7, ISSN 0358-4283. 64p. + appendices.

ABSTRACT

This paper explains the framework for the System of Short Term Forecasting of the Finnish Forest Sector (MESU) using a case study. The MESU system is a tool used by the Finnish Forest Research Institute in making forecasts for the *Finnish Forest Sector Economic Outlook* (an annual publication). The use of the MESU system enables assessments in which the development of Finnish forest products export markets and the adjustments of Finnish roundwood markets are analyzed consistently. It is a hierarchical, derived-demand-led system consisting of three parts (models). First, the *import demand* for forest products in the major export countries/regions is forecasted. In the second stage, these forecasts are inserted as exogenous information in the next stage, *the export market model*, which determines the Finnish forest products exports. In the third stage, the forecasts from the export market models are, in turn, inserted in to *the roundwood market model*, which determines the forecasts for roundwood demand. The paper demonstrates the MESU system by analyzing how short-term changes in the sawnwood import demand in Germany affect Finnish sawnwood exports and sawlog demand in Finland. The empirical models are estimated using quarterly time series data from 1980:1-1996:4, and the observations for 1997:1 – 1998:4 are used in analyzing the ex post forecast performance of the models. It appears that MESU is a first attempt to build a *short-term* forecasting system that links import demand for forest products to exporting countries' roundwood markets using econometric models. The methodological framework for the MESU system is general, so that a similar modeling approach could be applied to other countries and other forest product categories as well.

Key words: *forest sector, short-term forecasting, sawnwood import demand, sawnwood export supply, sawlog demand*

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Publisher: Finnish Forest Research Institute

Approved by: Kari Mielikäinen, Research Director 4.4.2001

Distribution: Finnish Forest Research Institute, Helsinki Research Unit, Unioninkatu 40 A, 0170 Helsinki, Finland. Telephone + 358 9 857051, Fax: + 358 9 8570 5717

Acknowledgements:

We are grateful to Jari Kuuluvainen at the University of Helsinki for the valuable comments to improve the manuscript and Maarit Kallio at the Helsinki School of Economics for helpful comments at the final stage of the report. The research is part of the forest cluster project *"Short-Term Forecast of Forest Industries Exports and Timber Trade"* in the Finnish Forest Cluster Research Program *"Wood Wisdom"* 1998-2001, co-funded by the National Technology Agency of Finland (Tekes), the Academy of Finland, the Ministry of Agriculture and Forestry and the Ministry of Trade and Industry. We would also like to thank members of the consortium steering group for valuable comments.

Content

1 INTRODUCTION*

The empirical literature on forest product markets and roundwood markets is mainly concerned with long run developments. Typically, the literature provides tools for *long-term projections*, or aims to construct models that could be used for forest policy analysis. From this literature has come the TAMM (Adams and Haynes 1980), GTM (Kallio et. al. 1987) and PELPS (Zhang et. al. 1993) models, as well as a great number of studies on which these models are based (surveys: Solberg and Moiseyev 1997; Buongiorno 1996). Less attention has been paid to the *short-run* behavior of forest products and roundwood markets, and there are even fewer studies that are explicitly concerned with the *short-term forecasting* issues. Important exceptions are studies by Buongiorno et al. (1979, 1984), which construct short-term forecasting models for the US softwood sawnwood import demand. However, due to recent changes, such as liberalization of capital and currency markets, globalization of the forest industry, and developments in information technology and logistics, the world's forest product markets have become more interrelated and they react ever more rapidly to changes in macroeconomic conditions. Therefore, short-term analysis and forecasting of forest products markets has also become more important.

Moreover, an issue that seems not to have been addressed previously is the linkage from import demand for forest products to the exporting country's roundwood markets. Indeed, Baudin (1997) states in his review of forest product market models, that "there is an increasing interest regarding the whole chain from forest to final product" (p. 379). For example, the short term fluctuations in US construction markets determine to a significant degree the import demand for sawnwood from Canada, which in turn determines the fluctuations in Canadian sawlog markets (Jennings et al. 1991). Similarly, the casual empiricism suggests that business cycles in European Union to a large extent determine the import demand for forest products from Sweden and Finland and, in turn, the short-term fluctuations in roundwood markets in these countries. However, we are not aware of studies that link the forecasts of import demand to the forecasts of roundwood demand.

**Hetemäki is responsible for the German sawnwood import demand model; Hänninen for the Finnish sawnwood export model; and Hetemäki and Toppinen for the Finnish sawlog demand model.*

In this study, a short-term forecasting system for the Finnish forest sector (MESU) is demonstrated using a case study of German sawnwood import demand, its impact on Finnish sawnwood exports and, in turn, on the demand for sawlogs in Finland. The MESU system is designed to fit the needs of *the Finnish Forest Sector Economic Outlook*, published annually since 1991 by the Finnish Forest Research Institute (for the most recent version, see FFSEO 2000). *The Outlook* provides forecasts for the whole forest sector, i.e. for both the final forest products (e.g. printing and writing paper and sawnwood) and the roundwood markets (pulpwood and sawlog). The main forecast horizon is the next year (in practice five to six quarters ahead, depending on the particular variable forecasted). Thus, the emphasis in MESU is on the practical short term forecasting quality of the model, rather than on a theoretically well specified model or long term forecasting qualities.

In principle, the MESU system consists of many different forest product categories and market regions, but for simplicity only one case study is used here to illustrate the principles of the system. The case study consists of three interlinked stages. First, the total import demand for sawnwood in one major exporting country, i.e. Germany, is modeled and forecasted. In the second stage, the share of Finnish exports in total German sawnwood imports is modeled and forecasted. Finally, the impact of Finnish sawnwood exports to Germany on the sawlog market in Finland is analyzed.

Despite MESU's specific purpose, the approach and models used could be of a more general interest in constructing similar short-term forecasting models for other countries and other forest product categories as well. In particular, the present approach could be helpful in modeling short-term fluctuations in the forest sector in countries that depend heavily on forest product exports. Moreover, the present study adds to the rather scarce literature on short term forecasting of the demand for forest products. For example, since the pioneering studies of Buongiorno et al. (1979 & 1984), new time-series econometric methods have been developed (e.g., vector-error-correction models and cointegration models), which are also useful for short-term forecasting purposes.

The paper is organized as follows. In Section 2 the MESU system structure and the links between the three different stages are explained; Section 3 discusses the theoretical background of the models; In section 4, the institutional setting, the data and its time series properties are analysed; Section 5 reports the results of the three different stages of the MESU system; and in section 6 some conclusions and general remarks are provided.

2 BACKGROUND: THE MESU SYSTEM

Forecasting Finnish forest product exports and the demand for roundwood in Finland is important for a number of reasons. At the macroeconomic level, the net share of the forest sector in exports of goods and services from Finland was 35 percent in 1998. Thus, the sector plays an important role in the country's foreign trade balance. Moreover, the forest industry generates stumpage earnings for a large number of forest owners. In 1998, the total gross stumpage earnings amounted to FIM 10.4 billion, of which the bulk was paid to non-industrial private forest owners (NIPF). Since there are about one million NIPFs in Finland (about 20 percent of total population), the stumpage earnings are spread to a relatively large sector of the population. Both the economy as a whole, as well as the large number of NIPFs, need an estimate of future demand and prices of forest industry products (which in turn determine the stumpage prices) e.g. for planning the state budget and scheduling stumpage sales.

The model or system that provides these forecasts should be able to incorporate the stylized facts of the Finnish forest sector. One essential feature is that Finland exports around 90 percent of its production of paper and paperboard, and 70 percent of its production of sawnwood. Although the exports are geographically widely distributed, the European Union is the most important market area – typically accounting for around 70 percent of the total value of both sawnwood and paper exports. Therefore, export markets largely determine the forest product demand. Finland's roundwood exports account less than 5 percent of total wood consumption, but due to the derived demand nature of domestic wood consumption, the demand for sawlogs and pulpwood in Finland is to a large extent also determined by the export markets.

The MESU system reflects the derived demand nature of forest products and roundwood consumption. The modeling principles are the same for both the sawnwood and paper and paperboard parts of the MESU system. In the case study of the present paper, only the sawnwood part of the system is considered. Furthermore, for simplicity, only one end product market is considered, namely Germany. The setting of the present study can be illustrated by Figure 2.1, shown below.

<u>Derived-Demand-Led Forecast Model</u>

Stage I: Forecasts for Germany's Import Demand for Sawnwood

↓

Stage II: Forecasts for Finland's Exports of Sawnwood to Germany

↓

Stage III: Forecasts for Sawlog Demand in Finland

Figure 2.1. MESU system Linking Germany's Import Demand for Sawnwood to Finnish Roundwood Market

Sawnwood demand is derived from consumers' demands for housing and other construction, furniture, and all products and services that use sawnwood. Sawlog demand is in turn derived from sawnwood demand. Thus, the end-product demand is the basis of sawlog demand. In the case of Finland, the bulk of sawnwood and sawnwood end product demand originates from the European Union, in particular from Germany and United Kingdom. Therefore, the starting point of the modeling is the import demand model for sawnwood in various export market regions. These models provide the forecasts for import demand for sawnwood, which, in turn, enter as an explanatory variable in Finland's sawnwood export model. Finally, the export forecasts for sawnwood are used, along with other variables, to forecast the demand for sawlogs in Finland. The primary interest is to forecast the short-term quantities traded, rather than the prices of the products. Technically, it is more straightforward to forecast quantities than prices, since one does not have to worry about the impacts of e.g. exchange rates and transport costs. Therefore, as in many econometric forest product trade models, demand is analyzed in isolation from the supply side of the market. However, when system methods are used (VAR and VECEM, see below), the import price equation is estimated simultaneously with the demand equation.

The variables included in the different stages of the system are determined by economic theory, based on the previous literature and statistical criteria, as well as casual empiricism from the markets. For example, the import demand and export model are in accordance with Armington's (1969) two- stage import demand theory. The two-stage optimization implies that the aggregate import demand for sawnwood is determined first, after which the allocation of aggregate imports to sawnwood from different supplier countries is determined. In addition to the theory, previous empirical studies on forest product trade may indicate what types of variables could be helpful in forecasting imports and exports. For example, construction or housing permits is often used in the literature to explain changes in sawnwood demand. Finally, although the theory and existing literature is helpful in determining the variables that could explain the long-run equilibrium behavior of the markets, they may not be very informative about the short-run disequilbrium behavior of the markets. Indeed, it is difficult to derive theoretical short-run models that are also consistent in the long run. Therefore, for the models of the MESU system, it is left to the data (statistical criteria) to determine the short-run dynamics.

In practice, the forecasts are *ex ante conditional forecasts*. That is, the future values of the endogenous and the exogenous variables are not known in the models when the forecasts are computed. Therefore, also the values for the exogenous variables have to be forecasted. This can be achieved either by computing them from a separate forecast models (e.g. using univariate ARIMA models), or by taking the values from publicly available forecasts (e.g. OECD Economic Outlook). However, for brevity here the actual values of the independent variables in the forecast periods are known and they are used instead of forecasted values. Thus, when interpreting the results, one should bear in mind that in practice the forecasting ability of the models would be not as good as in the present experiment.

As concerns the actual method used for forecasting it is difficult, if not impossible, to determine a priori which is best for forecasting sawnwood imports and exports, and sawlog demand. There are many different approaches available for forecasting economic variables, each of which may be suitable for the present purpose (see e.g. Clements and Hendry 1998). In the present study, it was decided to compare a number of commonly used forecasting models: 1) univariate Box-Jenkins (ARIMA) approach, 2) partial multivariate approach, 3) VAR system approach, and 4) vector error correction (VECM) system approach. However, it should be stressed that some of these approaches are in fact special cases of more general approaches, or they can be regarded as complementary tools in the construction of a forecasting model. Thus, for example, an ARIMA specification may be a restricted case of a more general VAR specification.

3 THE MODELS

3.1 German Sawnwood Import Demand Model

The econometric modeling of aggregate or sectoral imports has a long history. The earlier literature is surveyed e.g. in Goldstein and Khan (1985) and some of the more recent studies are Clarida (1994), Urbain (1995), Croix and Urbain (1998) and Senhadji (1998). Croix and Urbain (1998) distinguish two different approaches, *atheoretical* and *theoretical intertemporal optimization models with rational expectations* (TIOM). The first approach is the more common one, and it has dominated the literature up until recent years. The TIOM approach was motivated by the Lucas critique, and the first applications appeared in the mid-1980s. Besides the impact from economic theory, the empirical import demand literature has in the last decade or so been influenced by new developments in time series econometrics, in particular by the unit root and cointegration literature (c.f. Urbain 1995, Croix & Urbain 1998).

The empirical import demand literature has mainly been concerned with finding a long-run import demand equation that could explain the historical data on imports of a particular country or product. In contrast, studies trying to build short term forecasting models for practical purposes are rare. Whether the model is intended primarily as a theoretically justifiable long-run structural model or as a short-term forecasting tool has important implications for the modeling. Indeed, it appears that these different objectives are not necessarily consistent (Greenslade et. al. 1999, Pesaran, Shin, & Smith 1999, Stock 2001). Models that perform well in explaining historical structural relationships and are useful for economic policy analysis do not necessarily perform as well in forecasting. For example, typically the TIOM models include more variables in the import demand equations, such as the opportunity cost of postponing imports (interest rates). Thus, in practice there is a trade-off between estimation efficiency and theoretical consistency. Moreover, each additional variable in VAR or VECM may complicate the forecasting evaluation significantly. In terms of data and resource requirements, tractability and easiness of updating forecasts is also a virtue. Finally, Stock (2001) argues that besides pragmatic considerations, there are also theoretical justifications for having separate models for forecasting and for structural estimation and policy analysis (p. 31).

The starting point for modeling the German sawnwood import demand is a prototypical long-run import demand model formulated as (see e.g. Goldstein and Khan 1985 or Urbain 1995)

$$Q_t = f(Y_t, IP_t / DP_t), \tag{3.1}$$

where Q_t is import volume, Y_t some activity or demand variable (usually GDP), IP_t import prices expressed in domestic currency, and DP_t domestic price of a tradable good. The above specification implicitly assumes that imports are not perfect substitutes for domestically produced goods. For the present study, this assumption appears to be reasonable, since in the case of German sawnwood, two-way trade has been observed during the whole study period. That is, imports, exports and domestic production play significant roles in Germany's sawnwood trade. Thus, in line with the bulk of the sawnwood import demand literature, a perfect substitute model is ruled out for the modeling of import demand (Buongiorno et al. 1979 & 1984, McKillop and Wibe 1987, Solberg and Moiseyev 1997).

Within the framework of an imperfect substitutes model, the exchange rate variable is often included. However, there are two reasons not to include it in the present study. First, it would be difficult to construct, update and forecast a quarterly exchange rate index that would accurately describe changes in exporting country exchange rates. In fact, the German mark has been fixed against some of the important exporting countries currencies, such as the Finnish mark, since 1999, and from 2002 onwards the two national currencies will be abolished, with the launch of the euro. Although exchange rate changes still have an impact, especially changes in the euro vis-a-vis the US dollar, the role of exchange rates within internal European Union trade has diminished and will further diminish in the future.

In the literature, price terms are sometimes included for goods that can be regarded as either substitutes or complements for sawnwood, such as MDF panels, engineered wood products, or aluminium (Buongiorno et al. 1979 & 1984). However, in the short term, substitution is likely to be limited, as customers tend to be commited to particular product designs and production processes. Over the long term, there is greater scope for substitution. Therefore, substitution is likely to be reflected more in the trend movement of sawnwood consumption than by the fluctuations in relative prices (see also *Figure 4.2*). Moreover, considering the small sample size here, it is desirable to restrict the number of variables entering the model to as few as possible.

The relative price ratio variable assumes price homogeneity, which may not hold, especially in short-run import demand models (Urbain 1995). Therefore, a specification in which the price effects enter separately is also possible, i.e.

$$Q_t = f(Y_t, IP_t, DP_t)\,. \tag{3.2}$$

Since the emphasis is on short-term forecasting of imports, there are some practical issues, which suggest further modifications to the above specification. In order to improve the forecasting ability of the model, a number of "leading indicator" variables that posses explanatory power in forecasting sawnwood imports, and are available within a short time lag, where examined (the variables experimented were series from the OECD Main Economic Indicators for Germany). The choice of indicator was based on its ability to predict the volume of imports and its time series properties in relation to the import volume variable. Of the 24 indicators analyzed, the prefered one turned out be the index for the *number of construction permits* (*CPERS*) issued (both residential and non-residential) (Linden 1999). The data on this variable is published monthly, is not usually corrected afterwards, and is available with a lag of about two months. It may be noted that for the construction industry, and thus for the demand for sawnwood, the number of housing permits has been used as a leading indicator in a number of studies (Buongiorno et al. 1979 & 1984, McKillop and Wibe 1987, Jennings et al. 1990, Penm and Terrell 1994). Consequently, equation (2) is modified to include the number of construction permits variable, i.e.

$$Q_t = f(Y_t, IP_t, DP_t, CPERS_t)\,. \tag{3.3}$$

The above static equilibrium structure of the import demand model was formulated on the basis of the economic theory and findings of the previous literature. The short-run dynamics are left to the data to determine. A prior, it is difficult to hypothesize a priori the most suitable dynamic structure of a particular data set. It is only during the estimation process that the appropriate lag and/or difference structure of the dependent and independent variables can be determined.

In empirical estimation, the theoretical variables are approximated by the available empirical data. Moreover, all variables are expressed in logarithms in order to scale the units, and to allow interpretation of estimated coefficients as elasticities. The estimable partial import demand equations corresponding to the above models are

$$lq_t = \alpha_0 + \alpha_1 lip_t / ldp_t + \alpha_2 \, lg\,dp_t + \alpha_3 lcpers_t + \sum_{i=2}^{4} \gamma_i SD_{i,t} + \delta_7 T_{1,t} + \delta_8 T_{2,t} + \varepsilon_t, \tag{3.4a}$$

and

$$lq_t = \beta_0 + \beta_1 lip_t + \beta_2 ldp_t + \beta_3 \, lg\,dp_t + \beta_4 lcpers_t + \sum_{i=2}^{4} \lambda_i SD_{i,t} + \varphi_7 T_{1,t} + \varphi_8 T_{2,t} + \eta_t \tag{3.4b}$$

where *lq* is the quantity of sawnwood imported to Germany, α_0 and β_0 are constant terms; *lip* is the implicit (unit) price for imported sawnwood; *ldp* is the implicit (unit) price for domestic production of sawnwood; *lgdp* is real gross domestic product (in 1991 prices); *lcpers* is an index of total construction permits issued; T_1 and T_2 are local time trends; *SD2*, *SD3*, and *SD4* are centered (orthogonalized) seasonal dummy variables; and ε_t and η_t denote error terms, assumed to be distributed as $\sim NID(o, \Omega^2_{\varepsilon or \eta})$. (For the justification for including local trends and seasonal dummy variables, see sec. 4.3). If the impact of the import and domestic prices are assumed symmetric, equation (3.4a) is used; if they are assumed asymmetric, equation (3.4b) is used.

Considering the expected impacts of the independent variables on sawnwood imports, one would expect α_1 to be negative, since a rise in import price relative to domestic price should, ceteris paribus, lead to a decrease in imports; α_2 should be positive, since sawnwood imports should rise when aggregate economic activity alone increases; and α_3 should also be positive, since the literature suggests that the growth of sawnwood imports is mainly the result of increasing activity in construction. Similarly, one would expect $\beta_1 < 0$, $\beta_2 > 0$, $\beta_3 > 0$, and $\beta_4 > 0$.

Finally, it should be noted that the above single equation model might be biased due to the possible simultaneity of prices and quantities, which may hinder identification of the true demand equation. In the present case, it may be reasonable to assume that the price of sawnwood in the world market is given for a single exporter. However, one should check for possible correlation between the error term and the price of imports.

3.2 Finnish Sawnwood Export Model

The Armington (1969) model was used as a basis for formulating a short-term forecasting model for Finnish sawnwood exports to Germany. The model is based on separability of the consumption function and a two-stage optimization process. Two-stage optimization means here that first the German aggregate import demand for sawnwood is determined and then the allocation of aggregate imports to different supplier countries. The Armington model can be written as

$$X_{f,t} = b_{f,t}^{\pi} X_{o,t} (P_{f,t} / P_{o,t})^{-\pi}, \tag{3.5}$$

where $X_{f,t}$ and $P_{f,t}$ are the quantity and nominal price of Finnish sawnwood exports to Germany, $X_{o,t}$ denotes the total German sawnwood demand or economic activity in the end use sector, $P_{o,t}$ is the competitors' price of sawnwood in the German market, b_f is a constant, and η is the elasticity of substitution, which is assumed to be constant for any pair of suppliers in the market. The Armington equation assumes homogeneity of demand with respect to prices (i.e., the impacts of $P_{f,t}$ and $P_{o,t}$ are symmetric), which does not always hold empirically (Urbain 1995). For example, in the model of export demand for Finnish sawnwood in the UK market, price homogeneity was rejected (Hänninen 1998).

Results from earlier studies indicate that Finnish forest product exports have been sensitive to exchange rate changes. However, the Finnish markka (FIM) has clearly stabilized with respect to the DEM since October 1996, when Finland joined the European Exchange Rate Mechanism (ERM). Consequently, exchange rate impacts are less important than before. Once the euro is introduced in 2002, the national currencies of EMU countries will be totally abolished.[1]

Equation (3.5) assumes that Finland has only one destination market, Germany, and that sawnwood from different origins are imperfect substitutes for each other in the German market. The estimable partial export demand relation based on the variables in Equation (3.5), without the price-homogeneity assumption, can be presented in the following logarithmic form:

$$ldifq_t = a_0 + a_1 lq_t + a_2\, ldifp + a_3\, ldisp_t + \sum_{i=2}^{4} \gamma_i SD_{i,t} + a_4 T_t + \varepsilon_t, \qquad (3.6)$$

where $ldifq_t$ Finland's coniferous sawnwood exports to Germany, lq_t is total German coniferous sawnwood imports, $ldifp_t$ is the price of coniferous sawnwood exported from Finland to Germany, $ldisp_t$ is the price of coniferous sawnwood exported from Sweden to Germany, T_t is the local time trend (see sec. 4.3), the SD_i are seasonal dummy variables, and ε_t is the error term.

[1] Note also that Buongiorno et al. (1988) and Jennings et al. (1991) found that the exchange rate had a negligible effect on the level of lumber production and exports from Canada to the USA.

According to the theory, one would expect the signs of the coefficients to be as follows: $a_1 \geq 0$, indicating that an increase (decrease) in German sawnwood demand causes an increase (decrease) in Finnish exports; Finnish own price elasticity of export demand should be negative, i.e. $a_2 \leq 0$; and $a_3 \geq 0$, i.e. the competitors' sawnwood is expected to be a substitute for Finnish sawnwood.

In order to form forecasting models for Finnish exports to Germany, experiments with several variable specifications were run. The purpose was to find the specifications that would contribute the most to the forecasting ability of equation (3.6). For example, alternative demand variable specifications for $x_{o,t}$ were tested (total imports of sawnwood, construction activity, business confidence indicator and the interest rate). In addition, for the competitors' price variable, experiments with a number of variables representing different competitor's prices were analyzed (Sweden, Austria, Canada, Russia or German domestic sawnwood production).

The results indicated that the variable measuring total German imports of sawnwood, and variables for Finnish and Swedish sawnwood prices, were found to be the best indicators for Finnish exports compared to the other tested variables. Consequently, these three explanatory variables were chosen for inclusion in the forecasting models used to forecast Finnish sawnwood exports to Germany.

3.3 Finnish Sawlog Demand Model

In the forest economics literature, typically roundwood demand is derived from a forest industry production (or profit) function (e.g. Johansson and Löfgren 1985, Hetemäki and Kuuluvainen 1992). In line with this literature, Finnish sawnwood industry output can be described using the production function

$$X_t = f(K_t, L_t, R_t), \tag{3.7}$$

where X is sawnwood output, K is capital input, L is labor input, and R is the sawlog input needed to produce an amount X of final product. In terms of economic significance, sawlog input is the most important component in *the short-run total cost* of sawnwood production, accounting for more than half of the total cost. Capital is more or less fixed in the short run. In order to simplify the model, we assume that the sawlog input is weakly separable from the capital and labor inputs, and leave these out from the model. Furthermore, firms in the sawnwood industry are assumed to sell their final products on the competitive domestic and export markets at given prices (i.e. they are price takers), PX. Ignoring decisions on the holding of sawlog inventories, the profit-maximizing problem for the representative firm and Hotelling's lemma can be used to derive the short-term demand function for sawlogs (Johansson & Löfgren 1985):

$$R_t = f(PX_t, SP_t), \tag{3.8}$$

where *R* is the demand for sawlogs, *PX* is the sawnwood price, and *SP* is the stumpage price. However, for practical short-term forecasting purposes, equation (3.8) is probably not able to provide the best forecasts - it simply contains too little information. In order to improve the forecasting ability of the model, it is useful to experiment with variables that are likely to contain important information about short-term variations in sawlog demand. For example, since sawlog demand is determined to a significant degree by final product demand, one should probably include variable(s) describing the sawnwood demand. In the case of Finland, about 65 percent of total sawnwood production is exported and 35 percent is used in domestic markets. Consequently, the above equation can be modified to include the sawnwood export quantity, *EX*, and the domestic usage of sawnwood, *DX:*

$$R_t = f(\underset{+}{PX_t}, \underset{-}{SP_t}, \underset{+}{EX_t}, \underset{+}{DX_t}). \tag{3.9}$$

The signs under the arguments denote the a prior signs of the partial derivatives. In the present study, we use the information provided by the earlier stages of the MESU system (Stage II) to obtain forecasts of the *EX* variable. That is, in the empirical model, sawnwood exports are approximated by coniferous sawnwood exports to Germany (see sec. 3.2). As concerns the domestic usage of sawnwood, there are no data available at the quarterly level for the study period. However, data exists for the domestic production of the woodworking industry, which can be used as a rough proxy for *DX*. The sawlog quantity variable is approximated by data on spruce sawlog stumpage sales, and the respective price is the spruce sawlog stumpage price. Consequently, the empirical equation corresponding to equation (3.9), after logarithm transformations, can be expressed as

$$lqkut_t = a_0 + a_1 lpkut_t + a_2 ldifp_t + a_3 ldifq_t + a_4 lwoodq_t + \sum_{i=2}^{4} \gamma_i SD_{i,t} + \varepsilon_t, \tag{3.10}$$

where $lqkut_t$ is coniferous spruce sawlog quantity, $lpkut_t$ is spruce sawlog stumpage price, $ldifp_t$ is Finnish coniferous sawnwood price in Germany, $ldifq_t$ is the amount of Finnish coniferous sawnwood exports to Germany, $lwoodq_t$ is production of the woodworking industry in Finland, the SD_t are seasonal dummy variables, and ε_t is the error term. It is assumed that increases in sawnwood price, sawnwood exports and domestic production of the woodworking industry effect positively sawlog demand, while an increase in sawlog stumpage price decreases its demand, which implies that $\alpha_1 \leq 0$, $\alpha_2 \geq 0$, $\alpha_3 \geq 0$ and $\alpha_4 \geq 0$ in equation (3.10).

4 INSTITUTIONAL SETTING, DATA AND TIME SERIES PROPERTIES

4.1 Institutional Setting

Germany is an important sawnwood consumer, producer and importer in Europe. In 1998, about 20 percent (14 mill.m^3) of the sawnwood production in the EU area was produced in Germany (see *Figure 4.1*). During the study period, German coniferous sawnwood imports declined from about 5.8 to about 4.8 million cubic meters and its own production increased from about 10.3 to 13.8 million cubic meters. Indeed, the share of imports in consumption (= production + imports - exports) declined from 37% to 29% during the study period. Germany's sawnwood exports increased from about 0.5 to 1.9 mill. cubic meters during the study period. However, the figures show that exports play a minor role relative to imports and own production.

Figure 4.2 shows indexes of the ratios of sawnwood imports to construction activity (*imp/cpers)* and sawnwood imports to gdp (*imp/gdp*). Over the study period, the *imp/cpers* ratio declined significantly (especially in the last decade), indicating that the importance of construction activity as a determinant of sawnwood imports has probably declined. This appears to be the result of both increasing domestic production and the substitution of other materials for sawnwood (particularly MDF and engineered wood products). In contrast to the *imp/cpers* ratio, the long-term development of *imp/gdp* ratio has been fairly stable over the last decade. Consequently, the *cpers* and *gdp* series appear to incorporate somewhat different economic activity impacts in relation to sawnwood imports.

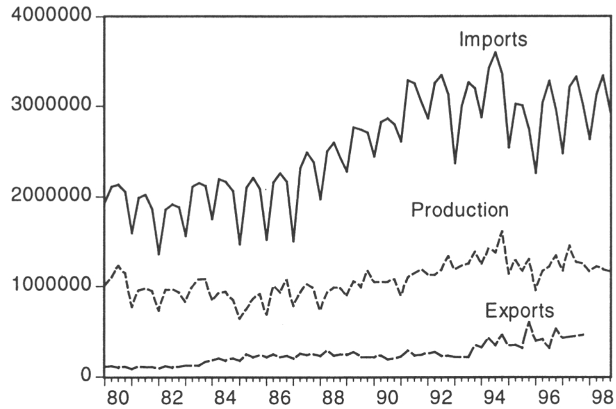

Figure 4.1. German Coniferous Sawnwood Imports, Production and Exports, 1980:1 - 1998:4,in cubic meters (export data for 1998 missing).

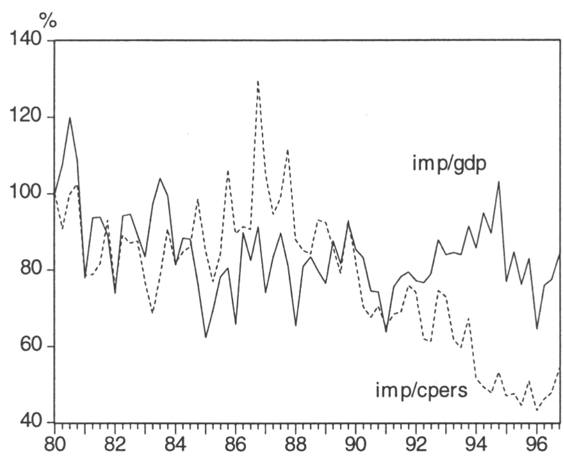

Figure 4.2. Ratios of Sawnwood Imports (IMP) to GDP and to Construction Permits (CPERS)

Germany imports its sawnwood mainly from Europe, Finland and Sweden being the largest exporters. These exporters maintained their market shares fairly well during the study period (*Table 4.1*). Austria, Russia and Canada lost market shares, while the shares of the rest of the countries (especially Czech Republic, Lithuania and Estonia) increased. However, it should be noted that the fluctuations in market shares were quite large. For example, during the forecasting period 1997-1998, the Finnish market share exhibits an increasing trend. Germany (along

Britain) is the single most important market for Finland's sawnwood exports: in 1998, about 18 percent of total Finnish sawnwood exports were exported to Germany.

Table 4.1. Exporters' Market Shares of German Coniferous Sawnwood Imports.

Exporter	**Market share, % of total imports** **1980:1-1989:4**	**1990:1-1998:4**
Finland	17.4	16.8
Sweden	27.2	26.1
Austria	13.6	8.8
Russia	15.7	10.0
Canada	3.1	2.3
Others	23.0	36.0
Total	100.0	100.0

Finnish sawnwood exports to Germany and Germany's *total* sawnwood imports followed similar patterns in the study period (*Figure 4.3*). This points to a positive dependence between the two variables. Note however that during the study's forecasting period, 1997:1-1998:4, the behavior of these series was countercyclical.

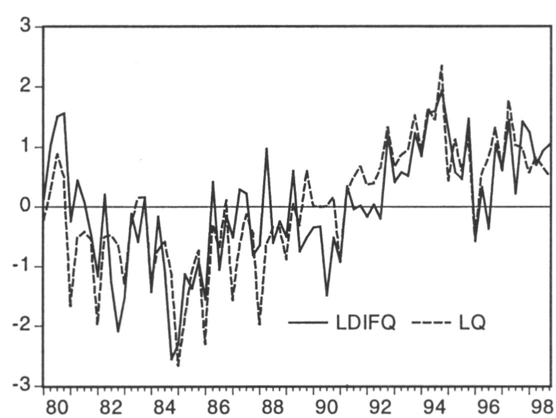

Figure 4.3 German Total Coniferous Sawnwood Imports (LQ) and Imports from Finland (LDIFQ), normalized values.

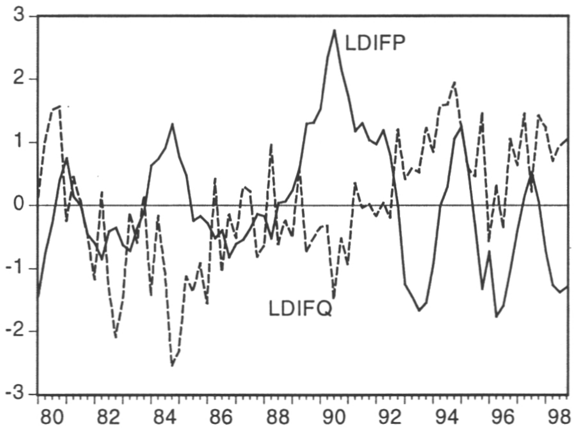

Figure 4.4 Finnish Export Quantity (LDIFQ) and Unit Price of Coniferous Sawnwood to Germany (LDIFP), 1980:1-1998:4, normalized values.

Figure 4.4 shows that movements in Finnish sawnwood exports to Germany and the respective prices were mainly countercyclical during the study period. This also indicates a negative own price elasticity (α_2), as was assumed in equation (3.6).

Figure 4.5 represents Finnish coniferous sawnwood exports to Germany and the quantity of spruce sawlogs traded in Finland. The fluctuations in spruce sawlog quantities traded and Finland's exports of sawnwood to Germany are quite similar. However, during the 1980s the co-movement of the series was weaker than during the 1990s. In addition, the seasonal patterns for the two series seem to be somewhat different.

4.2 Data

The empirical analyses of German sawnwood imports and Finnish sawnwood exports are based on quarterly time series data for the period 1980:1 – 1996:4. However, the data for the Finnish sawlog market is available only from 1986:1 onwards. Observations for the period 1997:1 – 1998:4 are used for post sample forecast evaluation.

The data are seasonally *unadjusted.* Unadjusted data are used also for German total sawnwood imports, unlike Linden (1998), who used seasonally *adjusted* data to study German sawnwood import demand. There are two reasons for not adjusting the data. First, besides forecasting the annual changes, we are also interested in forecasting the seasonal patterns of demand within the year. Secondly, as e.g. Marvall (1995) has stated, a "VAR model should not be used to model a vector of time series some of which have been seasonally adjusted (p.51)". This is because when the underlying model contains components with unit roots, seasonal adjustment procedures will induce noninvertible moving average (MA) components into the seasonally adjusted data. Therefore, VARs fitted to seasonally adjusted data are misspecified, and most of the statistical specification tests for dimensionality, encompassing, unit root and cointegration tests etc., are inappropriate. Due to these considerations, the seasonality is explicitly considered and modeled using dummy variables, which take into account any systematic seasonal variation not captured by other variables.

In the German sawnwood import demand part of the MESU system, five variables were included in the multivariate models – *the volume of imports*, *real GDP,* an *index for total construction permits*, *nominal domestic price for sawnwood*, and *nominal import price for sawnwood* (for details on the data, see *Appendix I*). The import price and the price of domestic production were constructed as implicit unit price indices from the quantity and value data. The Construction industry, which is the sector that uses the bulk of the imported sawnwood, shows seasonal variation, and this pattern is in turn reflected in seasonal variation in sawnwood imports.

In the second stage of the MESU system, Finnish sawnwood exports to Germany are explained using data on *German total sawnwood imports* and *nominal prices of sawnwood from Finland* and *Sweden*. The price variables are implicit unit price indices constructed from the quantity and value data. The seasonal variation in total German sawnwood imports appears to introduce seasonality also to Finnish sawnwood exports to Germany.

In the roundwood market part of the system, the *spruce sawlog demand in Finland* (quantities traded) is explained by *spruce sawlog stumpage price in Finland, Finnish sawnwood exports to Germany* and the respective *unit export price*, and by the *production level of the Finnish woodworking industry* (see *Appendix I*). Stumpage prices for spruce sawlogs bought from private non-industrial forest owners (NIPFs) are used to represent prices for the total sawlog market. This is not necessarily a poor approximation, since sawnwood exported from Finland to German markets consists mainly of spruce (over 80 percent of total sawnwood exports to Germany in 1998). Moreover, NIPFs currently account for about 80 percent of the total supply of sawlogs to industry. Finally, a dummy variable (*redcum*) taking account of two exceptional observations (1991:2 and 1996:2) was introduced (see *Figure 4.7*). The 1991 exceptional observation relates to the so called "roundwood boycott", during which the private forest owners' organization recommended that its members not sell roundwood in order to strengthen their position in price agreement negotiations. The exceptionally low value for 1996:2 is also related to difficulties between forest industry and private forest owner's organization in agreeing on the stumpage price level.

4.3 Time Series Properties

Before the forecasting models are formed and estimated, it is necessary to analyze the time series properties of the data (stationarity, normality, seasonality, etc). *Appendix II* describes some of these basic time series properties. *Figures A1-A14* (in *Appendix II*) show the movements of the logarithmic transformations of the level series and their respective first differences over time, with correlograms up to 20 lags. *Tables A2-A4* show the simple correlation coefficients, *Table A5* provides statistics for Doornik-Hansen normality tests, *and*

Table A6 shows the results for the Augmented Dickey-Fuller (ADF) unit root tests. The latter test indicates whether one should use differenced series or cointegration specifications instead of models in levels.

Before turning to the actual results concerning the data, a few caveats are called for about the stationarity analysis of the data. First, the large theoretical and empirical literature on testing stationarity properties of time series indicates how complicated the actual determination of unit roots and co-integration can be (e.g. Maddala and Kim 1998). Indeed, in finite samples, it is ultimately not possible to draw definite conclusions on whether a series is stationary or non-stationary, since any process with a unit root can be approximated infinitely closely by a stationary process. Moreover, although the econometric time series literature has in recent decades advocated the role of differencing and cointegration methods in constructing models for non-stationary time series, there have recently been studies questioning the superiority of these procedures. For example, Harvey (1997), Pesaran, and Shin (1999) point out that it is often not necessary to difference in order to specify statistically suitable models. Specifying models in levels has the advantage of being more easily interpretable.[2] Also, for short-run forecasting purposes, the stationary or non-stationary of the specification is not as crucial as for long-run forecasting purposes. These caveats suggest that one should experiment with a number of different specifications for stationary tests, and that it may be impossible to draw clear cut conclusions.

Time Series Properties: German Sawnwood Import Model

Figure A1 (*Appendix II*) indicates that the statistical modeling of the sawnwood import series is challenging. First, there appear to be local trends in the series. Imports are decreasing along a trend from 1980:1 to 1988:1, and then there is an increase in the trend up to 1994:4, after which the series does not exhibit any clear trend. The changing patterns of the trends make the forecasting of the series difficult. *Figure A1* also shows, that there is a seasonal pattern in the

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[2] According to Harvey (1997) "Testing unit roots has become almost mandatory in applied economics.This is despite the facts that, much of the time, it is either unnecessary or misleading, or both" (p. 196).

import quantity series (*LQ*). In order to examine this in more detail, a regression was estimated for two sub-periods (1980:1 – 1989:4 and 1990:1 – 1996:4):

$$lq_t - lq_{t-1} = \mu_1 D_{1,t} + \mu_2 D_{2,t} + \mu_3 D_{3,t} + \mu_4 D_{4,t} + u_t\,, \quad t=2,3,\ldots,n, \tag{4.1}$$

where the D_t's are seasonal dummy variables. *Figure 4.8* gives the values of the coefficients for the deterministic seasonal dummies from the two sub-period regressions. The growth rate for sawnwood imports is clearly very low in the first season (reflecting a low activity level in winter), and it is highest at the second or fourth season, depending on the sub-sample. Relative to the first subsample, the second quarter becomes less important and the fourth quarter becomes more important in the second subsample. Thus, the seasonality has changed between the sub-samples. Also, the $\bar{R}^2$ value for the first sub-sample is 0.77 and for the latter sample 0.66, indicating that the seasonal pattern explains less of the changes in import growth rates in the 1990s than in the 1980s.

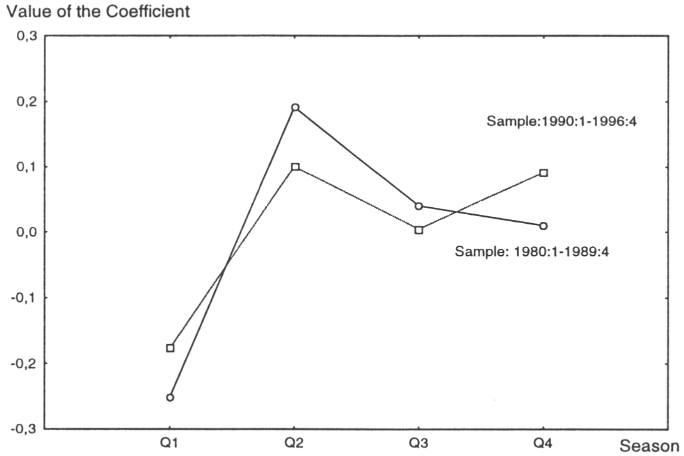

Figure 4.8 Seasonality in German Sawnwood Imports

Figures A1-A6 seem to indicate that all the series in the German sawnwood import model are probably I(1)-series (i.e. stationary after differencing), except for the price ratio variable (*lipdp*). However, there is some ambiguity in determining the properties for the *lq* series (imports). Comparison of the level and difference *lq* series, and the respective correlograms, does not produce a clear-cut conclusion. The autocorrelation function for the level series approaches zero very slowly with the increase of lags, indicating non-stationarity. On the other hand, the correlogram also shows that the first autocorrelation coefficient of the level series is 0.64, which is not close to 1. The unit root tests also pointed to difficulties in determining whether the *lq*-series has a unit root or is a stationary process around local deterministic trends. The ADF test results in *Table A6* (*Appendix II*) show that the series is non-stationary, in specifications both with and without one deterministic trend. However, experiments with ADF tests including two local trends (for periods 1980.1-1988:1 and 1998:2-1994:4), indicated that the test rejects the unit root hypothesis (results not reported in the Table).

Perhaps the most unexpected result concerning the time series properties of the data is that, unlike the sawnwood import series, the *lcpers* series is not trend stationary, even when the two local trends are included. One would expect trend stationarity due to the very similar pattern of the two series (see *Figure 4.9*) and the high correlation coefficient (0.84) between the series (*Appendix II, Table A2*). Indeed, on the basis of the graph it would be tempting to conclude that the two series are cointegrated. As one would expect, the domestic (*ldp*) and import prices (*lip*) for sawnwood have very similar patterns, also indicating a potential cointegration relationship. The nominal and real price series are clearly downward trending, and there appears to be a negative relationship between the price series and import volume.[3]

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[3] It should be noted that when the domestic and import prices were deflated (using the wholesale price index), the real and nominal prices were highly correlated (the correlations were 0.85 and 0.86). Also, the substantial results concerning the time series properties of the data were not sensitive to whether real or nominal price series were used.

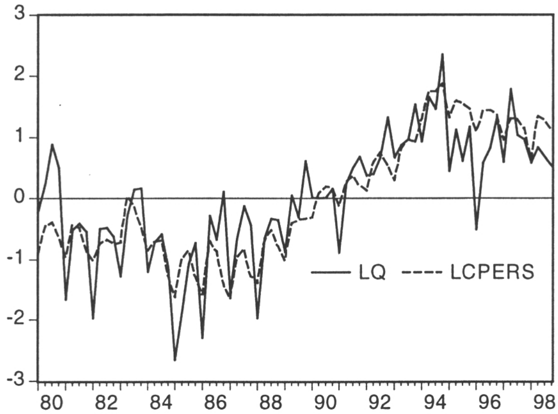

Figure 4.9. Sawnwood Imports (lq) and Construction Permits (lcpers), 1980:1 - 1998:4, normalized values.

All the series, except *lgdp* and *lcpers* appear to be normally distributed (see *Appendix II, Table A5*). Both of the series have "fat" tails, indicating that outliers or extreme values are more common than for the normal distribution. The symmetry (skewness) of the distribution for the series is near zero, therefore resembling the skewness of normal distribution.

Time Series Properties: Finnish Sawnwood Export Model

Moving to the Finnish sawnwood export model, the correlation matrix for variables in logarithmic levels, shown in *Table A3* (*Appendix II*), indicates that the Finnish export quantity (*ldifq*) is highly correlated (0.78) with total German sawnwood imports (*lq*). The *ldifq* series is negatively correlated with the Finnish and Swedish sawnwood prices (-0.28 and -0.18, respectively). This indicates that, for example, a rise in the Finnish price decreases Finland's exports (see also *Figure 4.4*). The high correlation between Finnish and Swedish prices (0.83) indicates similarity in the two price series.

The Finnish sawnwood export series appears to have two local trends. *Figure A7* (*Appendix II*) shows that Finnish exports are decreasing during 1980:1-1984:4, after which there is an increasing trend up to the end of the study period. Finnish exports also show a clear seasonal pattern. The seasonal pattern was analyzed using the coefficients of the deterministic seasonal dummies obtained from the estimation of Equation (4.1) for $ldifq_t - ldifq_{t-1}$. It seems that the seasonality of Finnish exports has changed between the two sub-samples, 1980:1–1989:4 and 1990:1–1996:4 (*Figure 4.10*).

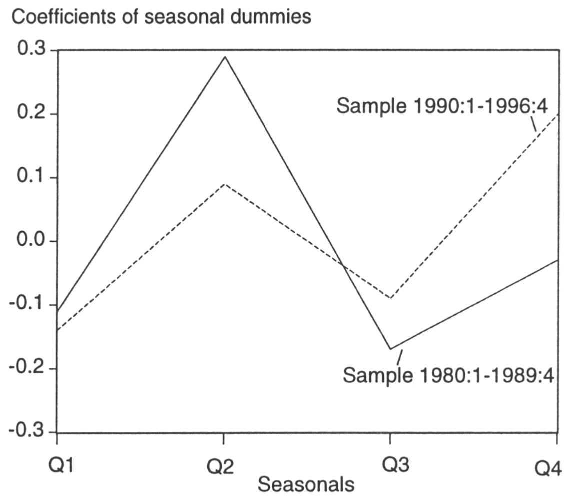

Figure 4.10. Seasonality in Finnish Sawnwood Exports to Germany

Relative to the first subsample, the second quarter becomes less important and the fourth quarter more important in the second sub-sample. Thus, the growth rates of these series have been the highest at the fourth season during the 1990s. The $\bar{R}^2$ values also indicate that the seasonal pattern explains somewhat more of the changes in Finnish export growth rates in the 1990s ($\bar{R}^2$ =0.54) than in the 1980s ($\bar{R}^2$ =0.48). Finally, there is also similarity between the behavior of the seasonals of German total sawnwood imports and Finnish sawnwood exports (c.f. *Figure 4.8*).

Table A6 (*Appendix II*) shows the unit root test results for *ldifq, lq, ldifp* and *ldisp*. The ADF test for the Finnish export series (*ldifq*) indicates that the variable is I(1), but stationary, i.e. I(0), around a linear trend. The first autocorrelation coefficient of the level series *ldifq* is 0.59, indicating that it could be an I(0)-process. On the other hand, the autocorrelation function approaches zero very slowly with the increase of lags, thus pointing to an I(1) process. The correlogram of the difference series seems to be stationary. In the following estimations (see sec. 5.2), *ldifq* is assumed to be an I(1)-series.

In the case of the Finnish unit price series *ldifp*, the ADF test results indicate that the series is I(0) with constant included and I(1) with constant and trend included. On the other hand, the Swedish price series *ldisp* is I(0) in both cases. Also, the first differences of both of the price variables appear to be I(0), with constant or with constant and trend included in the test equation. The correlograms indicate non-stationarity of price levels (*Figures A8* and *A9*, *Appendix II*), but their first differences seem to be stationary. The nonstationarity of some of the data series suggests that dynamic specifications are necessary for the estimation of the forecasting models.

Time Series Properties: Finnish Sawlog Demand Model

The first autocorrelation coefficients of the corelograms for sawlog quantity traded (*lqkut*), sawnwood exports (*ldifq*), and woodworking industry production (*lwoodq*) are clearly less than one, suggesting possible stationarity of these series (*Figures A10* and *A12*, *Appendix II*). In contrast, for sawlog stumpage price (*lpkut*) and sawnwood price (*ldifp*) the first autocorrelation coefficient is close to one and the autocorrelation functions are slowly decaying (*Figures A11 - A13*), indicating possible nonstationarity. *Table A5* (*Appendix II*) gives the results for the Doornik-Hansen normality test for the time series. There are no signs of excess skewness or kurtosis of the data, i.e. the series appear to be normally distributed.

The ADF unit root tests (*Table A6*, *Appendix II*) indicate that the sawlog quantity traded series is stationary in levels, but all the other series of the sawlog demand model are probably I(1). However, due to shortness of the data set, the unit root tests should be interpreted with caution.

There is distinct seasonality present in the quarterly sawlog quantity series, as indicated by the results from estimating regression equation analogues to equation (4.1) for $lqkut_t - lqkut_{t-1}$. The coefficient for the first quarter is well below average, reflecting the low activity in forestry during the winter. In the third quarter, sawlog quantities traded are above average, reflecting traditionally high level of activity in the Finnish roundwood market that occurs especially in September (*Figure 4.11*).

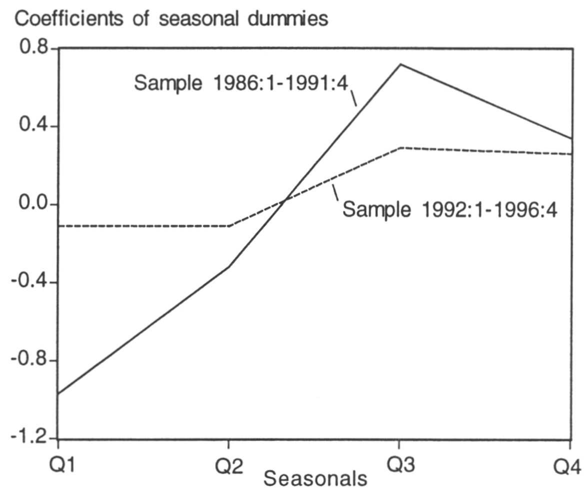

Figure 4.11. Seasonality in Finnish Sawlog Demand.

In the 1990s, the highest level of activity in the Finnish sawlog market occured in the third and fourth quarters. Moreover, the seasonal variation clearly decreased in the 1990s relative to 1980s. Comparing *Figure 4.11* to *Figure 4.10* strengthens the conclusion already drawn above about the different patterns of seasonal variation in the sawlog and sawnwood export markets. The seasonal variation has been stronger in sawlog quantities traded than in sawnwood exports. The differences in the seasonal pattern are also reflected in the low correlation coefficient between the series (0.10) (see *Table A4*). However, the correlation coefficient for annual data (1986-96) is much higher (0.57).[4]

[4] The similarity of the movements in the two series appears to have increased recently, the correlation coefficient for the period 1986-1998 being 0.67.

5 EMPIRICAL RESULTS

5.1 Results for German Sawnwood Import Demand

Autoregressive Model

A univariate time series model, the *Box-Jenkins* ARIMA model (Box and Jenkins 1970), was estimated. This approach provides a method of decomposing the *lq* series into its components, such as autoregressive (AR), moving average (MA), and seasonal (SA) components. The general autoregressive-moving average model of order *p* and *q*, denoted by ARMA(*p*,*q*), is given by

$$y_t = \Phi_1 y_{t-1} + \ldots + \Phi_p y_{t-p} + \xi_t + \theta_1 \xi_{t-1} + \ldots + \theta_q \xi_{t-q}, \qquad \xi_t \sim NID(0, \sigma_\xi^2). \tag{5.1}$$

If y_t is stationary only after differencing, the correct specification is an ARIMA(*p*,*d*,*q*) model, in which *d* refers to the number of differencings required for stationarity. Univariate ARIMA models are often used for forecasting, but the forecasts are naive in the sense that they just extrapolate on the past movements of the series under consideration. However, at a minimum, the forecasts provide a yardstick for assessing the performance of more elaborate multivariate models. The most simple univariate model is the *random walk*, which is just an AR(1) process:

$$y_t = \alpha y_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma^2 I) \tag{5.2}$$

where $\alpha = 1$, and the optimal forecast for the next period is simply the current value, regardless of the forecast horizon. Due to the trends and seasonal patterns of the sawnwood imports series, a random walk with drift and seasonal dummies was chosen as the baseline model for forecast evaluations. The estimated coefficients for this model, called the *Naive model*, are shown below with *t*-values in parentheses (see *Appendix IIIa*):

$$lq_t = \underset{(2.09)}{1.89} + \underset{(13.18)}{0.86}\, lq_{t-1} + \underset{(10.44)}{0.34}\, SD_2 + \underset{(7.86)}{0.24}\, SD_3 + \underset{(8.61)}{0.26}\, SD_4 . \tag{5.3}$$

Considering the simplicity of the model, it has a good fit, since it explains 78 percent of the variance of the sawnwood imports series (i.e., $\bar{R}^2 = 0.78$). The test results, reported in *Appendix IIIa*, indicate that residual serial correlation or heteroskedasticity is not a problem at the 5 percent significance level, and that the residuals are normally distributed (i.e. $\varepsilon_t \sim (0, \sigma^2 I)$). Neither did the other specification tests (Ramsey functional form test and Chow forecast test) indicate problems (see *Appendix IIIa*). If the absolute value of the coefficient for the lagged dependent variable in equation 5.3 is less than one, the underlying process is stationary and the model in levels is a statistically adequate representation of the data. The estimated value of the coefficient is clearly less than one (0.86). Also, a Wald coefficient restriction test for determining whether the difference is statistically significant, indicated that the null hypothesis of a unit coefficient for the lagged dependent variable can be rejected at the 5 percent significance level, indicating that the import series may be stationary. Despite this result, it was thought to be informative to experiment with both levels and with the differenced forms of the data, and with moving average component specifications.

A large number of different ARMA/ARIMA models were estimated. The models varied according to the specification of autoregressive (AR), moving average (MA), seasonal autoregressive (SAR), seasonal moving average (SMA) components, and whether the import series was in levels or first difference form. The final model was chosen on the basis of the residual sum of squares (RSS), Akaike (AIC), and Schwartz (SIC) information criteria. When the AIC and SIC disagreed, the SIC criteria was used, since it favors the more parsimonious specification. According to the above criteria, the preferred specification (ARMASA) is (t-values in parentheses)

$$lq_t = \underset{(26.08)}{14.69} + \underset{(7.58)}{0.69}\, AR(1) + \underset{(45.07)}{0.97}\, SAR(4) - \underset{(21.58)}{0.90}\, MA(4). \qquad (5.4)$$

The model slightly improves the explanatory power of the Naive model; $\bar{R}^2$ is 0.81. Also for this specification, the residual series appears to be well behaved (test results reported in *Appendix IIIa*). However, the functional form test (Ramsey reset test) indicated a non-zero mean vector for the residuals, pointing to possible problems with the specification of the model (e.g. omitted variables, wrong functional form, correlation between the explanatory variables and error term). However, for the purpose of comparison with the Naive model, the forecasts for the ARMASA model are presented.

Figure 5.1 shows the 8-step-ahead dynamic forecasts for the Naive and ARMASA models with the actual post-sample values (in logarithms). According to *Figure 5.1* the pattern of the forecasts from the ARMASA model and Naive model are very similar. The ARMASA model forecasts the first quarter rather well, and also the direction in the second quarter, whereas the level is somewhat underestimated. The forecasts do not capture turning points in the series in the third and fourth quarter, although the forecast for the third quarter and the Naive forecast for the fourth quarter are close to the actual values. ARMA forecasts the fifth quarter accurately. The change in direction in the sixth quarter is correctly anticipated, but the level is overestimated (ARMASA) or underestimated (Naive). For the seventh and eight quarters, the ARMASA forecasts are poor. Naive forecasts are better, although once again for ARMASA the changes in direction of actual values are wrongly anticipated.

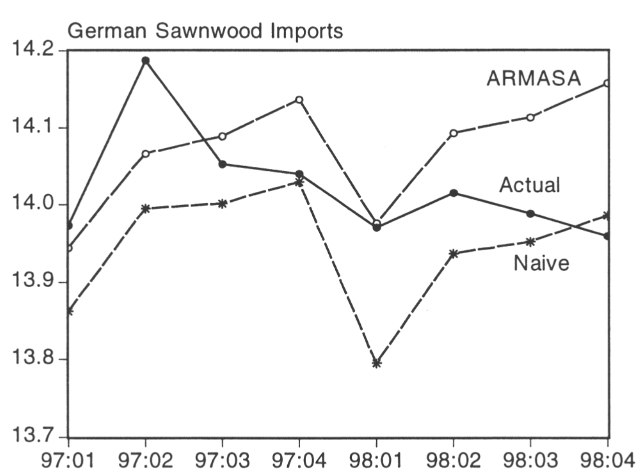

Figure 5.1. Dynamic Forecasts from Naive and ARMASA Models, 1997:1-1998:4.

In general, there are at least two major weaknesses with the ARIMA approach. First, the forecasts are based only on the past information of the series being forecasted. Thus, the information from other available data is ignored even though it may be helpful in forecasting. Secondly, even tough the ARIMA specification is chosen on the basis of the sample autocorrelation function and information criteria, the model selection procedure is *ad hoc*. Indeed, in some cases it may be almost impossible to identify the correct ARIMA specification. This is especially the case when one has to operate with a small sample and possibly a non-stationary series. Thus, the forecasts based on such models may also be seriously inaccurate. Finally, according to Harvey (1997, p. 194) "the problem with the ARIMA class is that there are many models and parameter values which have no sensible interpretation and give forecasts functions which may have undesirable properties".

Partial Multivariate Model

The univariate models tend to lose their forecasting power relative to multivariate models as the the forecasting horizon is lengthened. Indeed, for Germany's sawnwood imports, the Naive and ARMASA models forecasted rather well the first two quarters and the fourth quarter, but after that the ability to track actual values became quite poor. Among other things, this provides justification for considering multivariate models. The starting point of the modeling was a general multivariate single equation model (all variables are in logarithms, except dummies and time trends),

$$lq_t = \alpha_0 + \sum_{i=1}^{N} \beta_i lq_{t-i} + \sum_{j=0}^{N} \phi_j (lip / ldp)_{t-j} + \sum_{j=0}^{N} \varphi_j \, lg\, dp_{t-j} + \sum_{j=0}^{N} \lambda_j lcpers_{t-j} + \sum_{k=2}^{4} \gamma_k SD_{k,t} + \sum_{h=1}^{2} \delta_h T_{h,t} + \varepsilon_t , \tag{5.5}$$

which allows for both distributed lags and contemporaneous variables. Although the above model assumes symmetric price impacts, estimations with separate price terms were also run. A number of different dynamic specifications were estimated. For example, the specifications varied according to whether the variables entered in levels or differences, whether relative price or separate import and domestic price terms were included, and the number of lags that were included. Based on the diagnostic statistics and Schwarz information criteria, the following specification (with t-values in parentheses) was chosen for forecasting:

$$\begin{aligned} lq_t = \underset{(1.20)}{2.99} + \underset{(2.52)}{0.37}\, dlq_{t-4} - \underset{(3.88)}{1.38}\, lgdp_{t-1} + \underset{(5.44)}{2.05}\, lgdp_{t-3} + \underset{(5.92)}{0.46}\, lcpers_{t-1} + \underset{(5.46)}{0.35}\, lcpers_{t-4} \\ - \underset{(2.15)}{0.28}\, lip_{t-3} + \underset{(2.29)}{0.56}\, ldp_t + \underset{(0.18)}{0.01}\, SD2 - \underset{(0.94)}{0.04}\, SD3 + \underset{(3.88)}{0.12}\, SD4\,, \end{aligned} \tag{5.6}$$

where *dlq(-4)* is the difference term for *lq* lagged 4 quarters, and the *SD* variables denote the deterministic centered seasonal dummy variables. In turned out that the domestic and import price variables worked better when they were assumed to be assymmetric and separate, rather than in ratio form. Also, the specification tests indicated that the two local time trends variables could be omitted. The estimation results and the specification tests are shown in detail in *Appendix IIIa*. In general, the model does well in explaining changes in the dependent variable ($\bar{R}^2 = 0.91$), and the analysis indicated that the specification is robust based on conventional specification tests. Moreover, according to the results, one cannot reject at the 5 percent significance level the hypothesis that the observations of the forecast period (8 quarters) are explained by the same model as in the estimation sample.

The coefficients in equation (5.6) represent the short-term, or instantaneous elasticities of sawnwood imports with respect to lagged *lq*, *lgdp*, *lip*, and *lcpers*. The long-run elasticities, which measure the full impacts of changes in variables determining imports, were also computed. The solved static long-run equation (with respective standard errors in parentheses) of the coefficients is

$$lq = \underset{(2.49)}{3.00} + \underset{(0.08)}{0.37}dlq + \underset{(0.13)}{0.67}lgdp + \underset{(0.04)}{0.11}lcpers - \underset{(0.13)}{0.28}lip + \underset{(0.24)}{0.56}ldp. \tag{5.7}$$

The Wald test of the null that all of the long-run coefficients are zero (except the constant term) is rejected at the one percent signifigance level (Wald test $\chi^2(8)$ = 473.99). The signs of the coefficients are as *a priori* expected. Starting from an equilibrium situation, increases in economic (*lgdp*) and construction (*lcpers*) activity of, say, 10 percent would ultimately lead to increases in quarterly sawnwood imports of 6.7 and 1.1 percent, respectively. Also, an increase in domestic price of 10 percent, ceteris paribus, would cause imports to increase by 5.6 percent. However, a 10 percent increase in import price would decrease sawnwood imports by 2.8 percent.

The models dynamic forecasts (denoted as "Partial") with the actual values are shown in *Figure 5.2*. The figure indicates that on the whole, the out-of-sample forecast performance of the Partial model is good. Both the levels and the turning points are forecasted accurately, except the last observation (8th quarter). However, one should bear in mind that in the present case the values for the exogenous variables during the forecast horizon are the actual values. Therefore, in reality, the forecasts of the partial model would not be as good as in this experiment.

Figure 5.2. Dynamic Forecasts from Partial model, 1997:1-1998:4.

VAR Model

The above Partial multivariate model specification may be subject to the simultaneity problem. For example, the single-equation estimates may be biased due to the simultaneity of import prices and quantities, resulting in a lack of identification of the true import demand equation. If that indeed were the case, the estimates of the single-equation specification would be weighted averages of demand and supply elasticities. One way to solve the problem would be to use instrument variable estimation methods. Alternatively, one could estimate a vector autoregression (VAR) model. Moreover, it was considered important to analyze whether the systems approaches, such as VAR and vector error correction (VECM, see next section) methods, could provide better forecasts than the partial approach.[5]

The idea underlying the VAR model is first to summarize the dynamic correlation patterns among observed data series and then use this summary to explain and predict likely future values for each series. Mathematically, a VAR expresses the current value of each of m series as a weighted average of the recent past of all the series plus a term that contains all the other influences on the current values. A VAR representation of order p can be expressed as

$$y_t = \upsilon + A_1 y_{t-1} + ... + A_p y_{t-p} + \mu_t, \tag{5.8}$$

where y_t is the m x 1 vector of variables for quarter t, and μ_t is a vector of innovations. The innovations measure the extent to which y_t cannot be determined exactly as a linear combination of the past values of y_t with weights given by the constant coefficients v and $A_l, l = 1,...., p$. It is assumed that μ_t is a random vector with zero mean and error covariance matrix Σ positive definite, and that μ_t is uncorrelated with lagged values of y_t. The VAR can be rewritten as

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[5] Some early studies using the VAR approach to model forest products imports and exports are Jennings et al. (1991) and Alavalapati et al. (1996).

$$\Delta y_t = \Pi\, y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + Bx_t + \varepsilon_t, \tag{5.9}$$

where $\Pi = \sum_{i=1}^{p} A_i - I$, $\Gamma_i = -\sum_{j=i+1}^{p} A_j$. Because the number of parameters to be estimated increases by n^2 with each additional lag, and by $(2n+1)p$ with each additional variable for a given lag length, such a models quickly use up all the degrees of freedom in the data set. Forecasting with unrestricted VARs that are overfit to the data, can be quite problematic.

In the general VAR system with n variables, if all the variables are stationary, using an unrestricted VAR in levels is appropriate. If these variables are all I(1) but no cointegration relation exists, then application of unrestricted VAR in first differences is appropriate. However, if the variables are cointegrated, then one can model the system as a vector error correction model (VECM) (see next section).

Since the time series properties of the data showed that some of the series are most likely I(1), the VAR systems were estimated both in levels and difference form. However, according to the AIC and SC information criteria and the forecasting ability of the VAR models, the levels specification was preferred one. Moreover, considering the small sample size, it was considered necessary to reduce the VAR system by using one relative price term instead of separate terms for domestic and import prices.[6] The analysis also indicated that the relative price term (*lipdp*) could be treated as an exogenous variable (*Appendix IIIa*). Thus, the final restricted VAR specification had three endogenous variables (*lq*, *lgdp*, and *lcpers*). The order of the VAR system was chosen on the basis of a number of VAR lag order selection criteria (see *Appendix IIIa*). VARs of order 1 through 6 were considered. The results were mixed; the Log-Likelihood Ratio (LR), the Final prediction error (FPE), and the Akaike information criterion (AIC) tests indicate 5 lags, while the Schwarz (SC) and the Hannan-Quinn (HQ) information criteria test indicate 1 lag. Although the results are ambiguous, the 5th order VAR specification was chosen. Moreover, the residual correlation was smaller for the 5th order VAR than for the 1st order VAR.

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[6] It should be noted that experiments with separate price terms showed that the forecasting ability of the VAR system could slightly be improved if separate price terms were used.

The results, shown in *Appendix IIIa*, indicate that the VAR specification provides a good fit for the data. Indeed, with 5 lags for each endogenous variable, this is what one should expect. There appear to be no serious problems with autocorrelation or heteroskedasticity. However, for some of the equations, the residuals are not normally distributed. The forecasts from the VAR model are shown in *Figure 5.3.* We return to these and to the vector-error-correction model forecasts in the next section.

VECM Model

In empirical time series studies, in which some of the series are non-stationary, the presence of cointegration relationships is possible. Often the economic theory may suggest long-run restrictions between the series. For example, in the present case, one would expect that there may be a cointegration relationship between sawnwood imports and construction permits. That is, that there is a long-run relationship between the series by which they tend to move close to each other. If the VAR systems under study include cointegrated variables, one should also experiment with vector-error-correction-models (VECM).

A priori, the simple correlation coefficients would suggest that the most likely cointegration relationship would be between the *lq*, *lcpers*, and *lgdp* series (see *Appendix II, Table A2*). However, in order to analyze in more detail the possibility of cointegration, formal tests were implemented. The literature on cointegration testing shows that the test results are very sensitive to the specification of the test procedure and the particular test type chosen (Maddala and Kim 1998, Sec. 6). Thus, a large number of cointegration tests were carried out. However, in order to keep the test procedure comprehensible and fairly simple, only one test type was used, namely the Johansen (1988) likelihood-ratio cointegration test. The Johansen test is widely applied, and according to Maddala and Kim (1998) should be preferred to a number of other commonly used cointegration tests. However, Johansen's test is not without its weaknesses. The main problems appear to be "sensitivity to misspecification of lag length, and substantial size distortions in the tests for the second and subsequent cointegration vectors when the ratio of data points to the number of parameters is small (of the order of 5 or less)" (Maddala and Kim, p. 220). Consequently, the tests were computed for specifications up to 6 lags.

The various cointegration tests indicate that there is most likely one cointegration relationship in the system (see *Appendix IIIa*), involving the *lq*, *lcpers* and *lgdp* series. Thus, a VECM model with one cointegration relationship imposed was estimated.[7] Note that unlike the VAR specification, which was estimated in the level form, the VECM was specified in differences. The results, shown in *Appendix IIIa*, do not differ very much from the unrestricted VAR results. A variation in the sawnwood import series is explained quite well by the model, and there appear to be no problems with autocorrelation or heteroskedasticity. However, like for the VAR specification, some of the residuals of the VECM system have non-normally distributed residuals.

Figure 5.3 shows the dynamic forecasts from the VAR and VECM models with the actual values. The forecasts from the VAR and VECM models are almost identical. The only difference is that the VAR model does perform slightly better in forecasting the levels of imports. Both models forecast the first three quarters and the fifth quarter fairly accurately. For the other quarters, they fail to forecast actual levels or/and turning points for sawnwood imports. In summary, by imposing the cointegration relationship on the VAR, no gains in forecast accuracy are obtained. Indeed, the literature indicates that the unrestricted VARs may provide better forecasts in the short-run than VECMs, even if cointegration relationships exist in the data (see discussion in Maddala and Kim 1998). The advantages of the VECM specifications over unrestricted VARs appear to be the greater, the longer the forecast horizon.

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[7] Following Johansen (1995, p.84), centered (orthogonalized) seasonal dummy variables were used. Thus, the dummies are transformed in such a way that they will sum to zero over a year. Consequently, the linear trend from the dummies disappears and only the seasonally varying means remain.

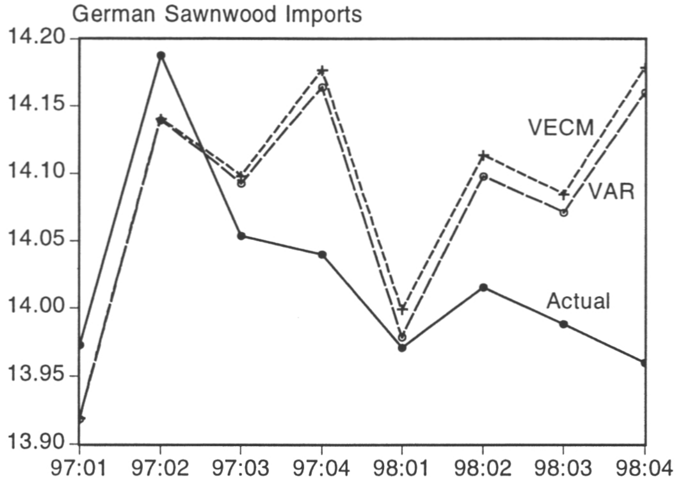

Figure 5.3. Dynamic Forecasts from VAR and VECM Models, 1997:1-1998:4.

Forecasting evaluation

Forecasts of the present study are *ex post dynamic* forecasts from the different specifications. Dynamic forecasts involve multi-step forecasts starting from the first period in the forecast sample (1997:1-1998:4). With dynamic forecasts, quarterly import forecasts do not benefit from knowing the imports in the previous time period or knowing the previous forecast errors. Unlike in *static forecasts*, the previous error is not checked, nor are corrections for errors incorporated in subsequent forecasts.[8] However, these ex post dynamic forecasts differ in one important way from the actual forecasts computed e.g. for the *Finnish Forest Sector Outlook*. Values of the exogenous variables (GDP, construction permits, import and domestic prices) are based on historical data and not on the forecasted values. Thus, they differ from *ex ante forecasts* in which all exogenous variables must be forecasted and hence tend to overestimate the capability of the models in forecasting Germany's sawnwood imports.

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[8] A *Static forecast* produces a sequence of one-step-ahead forecasts, using actual rather than forecasted values for the lagged dependent variables.

There are a number of different measures of forecast accuracy, none of which can be regarded unambiguously as the best (Clements and Hendry 1998). The most widely used measure is probably the root mean squared error (RMSE), given below,

$$RMSE = \sqrt{\frac{1}{h+1}\sum_{t=s}^{s+h}(f_t - a_t)^2}\ , \qquad (5.10)$$

where the forecast sample is $t = s, 1+1, \ldots, s+h$, h being the number of forecast periods, and the actual and forecasted values in period t are denoted as a_t and f_t, respectively. The forecast error statistics depend on the scale of the dependent variable, but since we are comparing forecasts for the same series across different models, this is not a problem.

Table 5.1 shows the RMSEs for the different models for the forecast horizon. The lower the RMSE value, the better the forecasts. The results indicate that one can improve over the Naive forecasts quite easily. Univariate ARMASA provides slightly better forecasts and major improvements are obtained by moving from univariate models to the Partial multivariate model. The Partial model provides clearly the most accurate forecasts. Thus, the RMSE statistics reinforce the conclusions already obtained from comparison of *Figures 5.1-5.3*, which show the 8-step-ahead forecasts and actual values.

Although, on theoretical grounds the system approaches (VAR, VECM) are often favored, from the practical forecasting point of view partial (single equation) models are easier to handle and are more flexible. Indeed, when the exogeneity conditions are satisfied, partial approaches have optimal properties similar to those of full systems based approaches (e.g. Urbain 1995). In the present case, the Partial model should be favored also on the basis of its forecasting ability.

It is perhaps surprising that the forecasting performance of the restricted VAR model is somewhat better than that of the VECM. The latter incorporates more information, and one would expect this information to improve the forecasting. However, as was noted above, empirical studies have pointed out that the comparative advantages of VECM specifications increase with the length of the forecasting horizon. In the present case, it appears that the 8-quarters-ahead horizon may still be too short to realize the advantages of the VECM approach.

The root mean squared forecast error (RMSE) can be decomposed to three components: the bias proportion (BP), variance proportion (VP), and covariance proportion (CP). The BP indicates how far the mean of the forecast is from the mean of the actual series (i.e. the models' tendency to systematically overestimate or underestimate imports), VP indicates how far the variation of the forecast is from the variation of the actual series, and CV measures the remaining unsystematic forecasting errors. The Partial model clearly performs the best and the naive model the worst. For the Partial model, less than one percent of the forecast error consisted of bias during the 8 forecast quarters, while for the Naive model some 54 percent of the forecast error consisted of systematic bias. VP indicates how far the variation of the forecast is from the variation of the actual values. *Table 5.1* shows that the differences in VP values are small and, surprisingly, it is the smallest for the ARMASA model.

Table 5.1. Decomposition of RMSE forecasts for the different models, 1997:1 – 1998:4

Model	RMSE	Bias Proportion (BP)	Variance Proportion (VP)	Covariance Proportion (CP)
Naïve	0.107	0.543	0.002	0.455
ARMASA	0.104	0.217	0.000	0.783
Partial	0.047	0.007	0.013	0.979
VAR	0.097	0.309	0.019	0.672
VECM	0.107	0.363	0.019	0.618

$MSE = \sum_{t=1}^{h}(f_t - a_t)^2 / h$; $BP = (\bar{f} - \bar{a})^2 / MSE$; $VP = (s_f - s_a)^{\wedge 2} / MSE$; $CP = 2(1 - r) s_f s_a / MSE$;

where a_t = actual value in quarter t, f_t = forecasted value in quarter t (the respective means are $\bar{a}, \bar{f}$); s_a and s_f are the standard deviations of a_t and f_t; r is the correlation between a_t and f_t; and h is the sample size from estimation.

Finally, the CP value measures the remaining unsystematic forecasting errors. For example, for the Naive model, only 45 percent of the forecast error is totally random, but for the

Partial model this figure is as high as 0.98 percent. In summary, based on the RMSE and its decomposition, the Partial model clearly provides the best forecasts. The ARMASA and VAR models appear to provide roughly equally good forecasts. Indeed, it is interesting to note that the univariate models can provide as good forecasts as the multivariate system models.

5.2 Results for the Finnish Sawnwood Export Model

Autoregressive Model

Analogues of the German sawnwood import model were estimated, starting with a Naive univariate autoregressive model for Finnish sawnwood exports to Germany. Finnish exports are explained by their own lags, seasonal dummies and a linear trend. The estimation started with six lags, after which statistically insignificant lags were reduced sequentially using the Schwarz information criterion. The resulting equation follows with t-values in parentheses:

$$ldifq_t = \underset{(2.79)}{3.14} + \underset{(5.07)}{0.51}\, ldifq_{t-1} + \underset{(2.47)}{0.24}\, ldifq_{t-3} - \underset{(-2.65)}{0.01}T1 - \underset{(-4.28)}{0.22}D1 + \underset{(1.58)}{0.08}D2 - \underset{(-3.71)}{0.19}D3, \qquad (5.11)$$

where the trend variable *T1* is defined as: 1980:1–1984:4 = 1, 2,…,20 and 1985:1–1998:4 = 0. Detailed results for the estimation are shown in *Appendix IIIb:1*. The model explains about 62 percent of the variation in Finnish sawnwood exports to Germany. The conventional diagnostic tests indicate that the model is robust. Also, the Chow forecast test shows that the forecast period can be explained by model (5.11) as well as the estimation period 1980:1-1996:4. However, as *Figure 5.4* shows, the model's forecasting performance is not very good. The model cannot forecast the turning points, quarters 1998:2 and 1998:3, and it clearly underestimates the levels of the actual values. The results imply that more information is needed than that incorporated by the univariate model in order to forecast satisfactorily Finnish sawnwood exports to Germany.

Partial Multivariate Model

A number of different specifications of a partial multivariate model were estimated. In the preliminary estimations, experiments were run with different combinations of explanatory variables and different lag structures (from zero to six lags). The final lag structure was decided on the basis of the Schwarz information criterion. The specification shown as equation (5.12) was found to have the best forecasting ability for the period 1997:1-1998:4 and to have satisfactory statistical properties in the estimation period:

$$ldifq_t = \underset{(1.82)}{3.22} + \underset{(2.20)}{0.25} ldifq_{t-1} + \underset{(4.63)}{0.65} lq_{t-3} - \underset{(-2.83)}{0.99} ldifp_{t-1} + \underset{(1.72)}{0.51} ldisp - \underset{(-3.47)}{0.01} T1 - \underset{(-5.45)}{0.25} D1 - \underset{(-0.67)}{0.04} D2 - \underset{(-5.51)}{0.28} D3 \qquad (5.12)$$

where *ldifq* denotes Finland's coniferous sawnwood exports to Germany, *lq* total German coniferous sawnwood imports, *ldifp* Finnish sawnwood export price, *ldisp* Swedish sawnwood export price, *T1* is time trend, and *D1*, *D2*, *D3* are seasonal dummy variables. The detailed estimation and specification test results are shown in *Appendix IIIb:3*. The specification tests did not indicate any particular problems with the model specification. The coefficients of the model represent the short-term elasticities of Finnish sawnwood exports. The respective long-run elasticities computed from Equation (5.12) follow with the t -values in parentheses:

$$ldifq_t = \underset{(1.86)}{4.28} + \underset{(6.47)}{0.86} lq - \underset{(-3.33)}{1.32} ldifp + \underset{(1.88)}{0.67} ldisp\,. \qquad (5.13)$$

The Wald-test of the null that all long-run coefficients are zero (except for the constant) is rejected at the one percent significance level. The signs of the long-run coefficients are as expected. The magnitude of the coefficient for German total imports (*lq*) is rather close to one, indicating that a rise in German imports increases Finnish exports to Germany almost proportionately. The own-price elasticity of Finnish exports is (-1.32) and the cross price elasticity (0.67). According to these elasticities, for example, a 10 percent rise in Finnish price decreases Finnish export quantity to Germany by about 13 percent.

The 8-step-ahead dynamic forecasts for the Partial and Naive models, with actual post-sample values in logarithms, are shown in *Figure 5.4*. The Partial model forecasts the first quarter quite well and the direction of the second quarter, but the level is clearly underestimated. The forecast for the third quarter is closer to the actual value. The forecasts from the Partial model, as from the Naive model, capture correctly the turning points of the actual export series up to the first quarter of 1998. After this, the following two quarters are missed and the last quarter again gets the right direction. Therefore, the ability to forecast turning points of the actual export series is quite similar for both models. The Naive model underestimates actual values more than the Partial model, although its forecasts for quarters 1997:3 and 1998:2 are close to actual values.

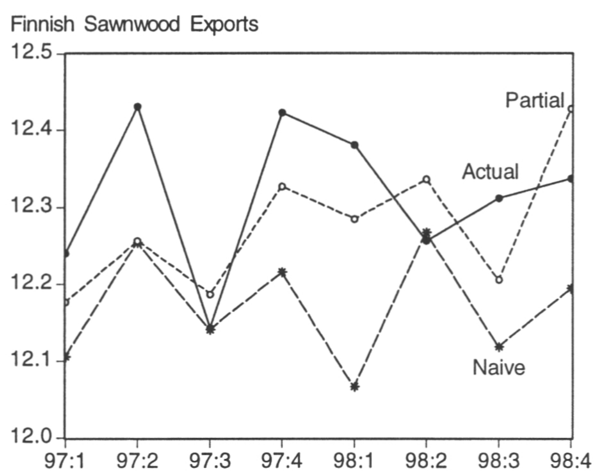

Figure 5.4. Dynamic Forecasts from Naive Model and Partial Multivariate Model, 1997:1-1998:4.

VAR Model

The basic VAR specification includes four endogenous variables (*ldifq*, *lq*, *ldifp*, *ldisp*) and five exogenous variables (*C*, *SD1*, *SD2*, *SD3*, *T1*). VARs of orders 1 to 6 were considered in testing.

The lag length was determined using the lag selection criteria presented in *Appendix IIIb:5*. For the VAR model, the SC information criteria indicated lag 1, but HQ favored lag 2. The results are mixed, and the conclusion concerning the number of lags was based on the three criteria (LR, FPE and AIC) and diagnostic tests. According to the results, the VAR with 4 lags was found the most appropriate approximation of the data generating process. The diagnostic tests indicate no problems of residual autocorrelation or heteroskedasticity in individual equations or in the whole system (*Appendix IIIb:5*). However, normality is rejected in most of the equations and in the system. In the unrestricted VAR the explanatory power of the equation for Finnish exports (*ldifq*) was $\bar{R}^2=0.65$.

One problem with the estimated unrestricted VAR model is its high dimension. Therefore, the VAR model was examined using Granger-causality tests to get some indication of the weak exogeneity of the variables. The tests indicate that Finnish and Swedish prices can be treated as weakly exogenous in the equation for Finnish exports, *ldifq* (*Appendix IIIb:6*). Therefore the unrestricted VAR model was further reduced by assuming Finnish and Swedish prices to be weakly exogenous.

The estimation results for the restricted VAR with exogenous Finnish and Swedish prices are presented in (*Appendix IIIb:7*). Based on the above information criteria, the lag length of 3 was chosen for the endogenous variables. The diagnostic tests for residuals of each equation indicate no autocorrelation, heteroskedasticity or specification problems, but some non-normality is present in the *ldifq* equation. The tests for the whole VAR system indicate that it is an adequate representation of the data. *Figure 5.6* give the forecasts from the VAR model. We discuss these in the next section together with the VECM forecasts.

VECM Model

If the variables in the above VAR system are cointegrated, the system could be specified as a VECM model. Indeed, using Johansen's (1995) trace and maximum eigenvalue tests, one cointegration vector was found (*Appendix IIIb:9*). The estimation and diagnostic test results are presented in (*Appendix IIIb:10)*. The diagnostic tests for the model indicate no problems, except for non-normality in the model.

In the VECM model both short- and long-run variations of data are taken into account in the modeling. The error correction term (the coefficient *CointEq1*) in the *dlifq* equation is statistically significant, negative and rather high (-0.86). Thus, the adjustment of Finnish sawnwood exports to its long-run equilibrium is relatively quick, 86 percent of the adjustment takes place in a quarter.

Figure 5.6 shows that the forecasts obtained from the VECM and the restricted VAR models are very similar. Both models forecast the direction of turning points accurately up to the 1998:1 quarter, after which the turning points at quarters 1998:2 and 1998:3 are missed. Indeed, the ability of the VAR and VECM models to forecast the turning points is not better than those of the Naive and Partial models.

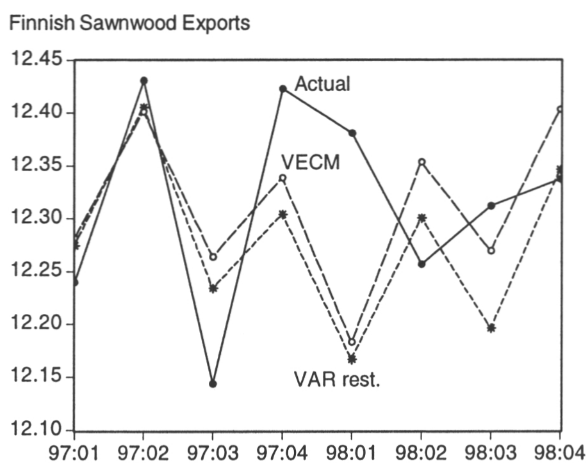

Figure 5.6. Dynamic Forecasts from Restricted VAR and VECM Models, 1997:1-1998:4.

Forecasting evaluation

Of the above models, the VECM has the smallest root mean squared forecast error (RMSE), indicating the best forecasting ability (*Table 5.2*). In addition, the results show that the VECM model clearly has the lowest bias proportion (BP) over the 8 forecast quarters. That is, the VECM forecasts' tendency to systematically under- or overestimate Finnish sawnwood exports is the smallest of the different model forecasts. According to VP statistics, the variation of the forecasts relative to the variations of the actual values, are smallest for the Partial and Naive models. The CV statistics, which measure the remaining unsystematic forecasting errors, are largest for the VECM model, indicating that almost all forecast errors are random (95%). Therefore, the results in *Table 5.2* show that the VECM model provides the best forecasts of the four different model specifications considered.

Table 5.2. ***Decomposition of RMSE for the different models, 1997:1-98:4.***

Model	**RMSE**	**Bias proportion**	**Variance Proportion**	**Covariance Proportion**
Naïve	0.1757	0.6753	0.0183	0.3064
Partial	0.1001	0.1619	0.0128	0.8253
VAR	0.1030	0.1279	0.0389	0.8332
VECM	0.0990	0.0014	0.0530	0.9456

In summary, all the model specifications failed to forecast correctly the turning points of Finnish sawnwood exports to Germany in quarters 1998:2 and 1998:3. More than a half of the variation of Finnish sawnwood exports to Germany could be explained by its own lags and seasonal dummies (Naive model). The more elaborate model specifications did not add much improvement to the explanatory power of the Naive model.

5.3 Results for the Finnish Sawlog Demand Model

Autoregressive Model

The following simple univariate Naive model is a starting point for a forecast model for sawlog demand in Finland (t-values in parentheses):

$$lqkut_t = \underset{(4.91)}{6.01} + \underset{(1.48)}{0.24}\, lqkut_{t-1} - \underset{(2.95)}{0.66}\, SD_1 - \underset{(3.42)}{0.75}\, SD_3 - \underset{(0.77)}{0.18}\, SD_3 \,, \tag{5.14}$$

where t-statistics are in parentheses below the coefficients. The detailed estimation and specification test results are shown in *Appendix IIIc*. According to the results, the Naive model has poor explanatory explanatory power ($\bar{R}^2$ =0.26). However, the diagnostic tests indicate that the model is an adequate statistical representation of the data generation process. The forecasted values from the Naive model and the actual values are shown in *Figure 5.7.* The Naive model is not able to capture the turning points in 1997:2 and 1998:4. In addition, the forecasts consistently underestimate actual levels. Thus, there is clearly room to improve the forecasting ability of the model.

Partial Multivariate Model

A number of different single-equation behavioral models were estimated. The specifications varied on the basis of the dynamic structure and variables included. A partial multivariate model for sawlog demand of the following form was chosen for forecasting analysis (t-values in parentheses):

$$\begin{aligned} lqkut_t = & -\underset{(1.38)}{4.77} + \underset{(4.28)}{6.41}\, dlpkut_{t-1} + \underset{(3.51)}{1.00}\, ldifq_{t-2} - \underset{(2.64)}{2.40}\, dlwoodq_{t-2} - \underset{(4.37)}{1.10}\, recdum_t \\ & + \underset{(1.84)}{0.57}\, SD_2 + + \underset{(3.20)}{0.81}\, SD_3 + \underset{(3.66)}{1.28}\, SD_4 . \end{aligned} \tag{5.5}$$

According to the equation, changes in stumpage prices in the previous period ($dlpkut_{t-1}$), sawnwood exports to Germany a half year earlier ($ldifq_{t-2}$), changes in the woodworking industry's production level in Finland a half earlier ($dlwoodq_{t-2}$), and the dummy variables explain variations in sawlog demand reasonably well ($\bar{R}^2$ =0.71) (the detailed estimation and specification test results are shown in *Appendix IIIc*).[9]

Also, the various specification tests indicate that the model is an adequate representation of the data generation process, and could be used for forecasting purposes. Due to the model structure, coefficients for the static long-run solution for the sawlog demand are not different from those presented in Equation (5.5). As was expected, based on the graphs of the data series (*Figure 4.6*), the *a priori* theoretical assumption of negative own-price elasticity for sawlog stumpage price does not appear to be consistent with the data. None of the different specifications tested

[9] It should be noted that specifications were also estimated in which the sawnwood export price was included (*ldifp*). However, they did not prove to be as good descriptions of the data generation process as equation (5.5).

produced such a result. One plausible explanation is that the sawnwood industry is willing to pay higher prices for sawlogs as long as the demand for sawnwood is increasing and, on the other hand, private forest owners accepted lower stumpage prices during the slump in sawnwood demand. Thus, stumpage prices and sawlog quantities are positively correlated and are to a large extent determined by business cycles and sawnwood demand conditions.[10]

The forecasts from the Partial and Naive models and the actual values, are shown in *Figure 5.7.* Except for the first and fifth quarters (1997:1, 1998:1), the forecasts from the Partial model are clearly better than those from the Naive model. Surprisingly, the forecasts from the Partial and Naive models are better for the last four quarters than for the first four quarters. This indicates that there may still be problems with the dynamic specifications of the models. However, the Partial model provides reasonably good forecasts of Finnish sawlog demand.

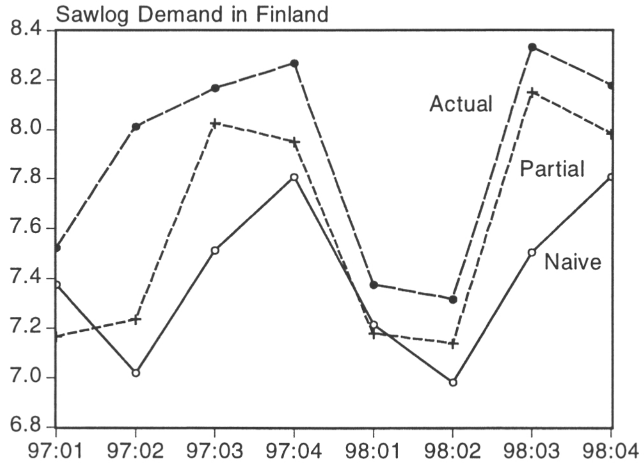

Figure 5.7. Dynamic Forecasts from the Naive and Partial Models, 1997:1-1998:4.

VAR model

A number of different VAR model specifications were analyzed (see *Appendix IIIc* for detailed results). The pairwise Granger causality tests indicated that a system with two endogenous

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[10] The estimations of the model in VAR or VECM form (with endogenous sawlog demand and stumpage price variables) showed that the positive own price elasticity is not due to possible simultaneous equation bias. As shown in Appendix IIIc, the own price elasticity is positive also in the VAR and VECM specifications.

variables, sawlog quantities traded (*lqkut*) and stumpage price (*lpkut*), was most appropriate. Also, the various lag order selection criteria suggested a second order system. Thus, the VAR system consists of two endogenous variables with two lags, and $ldifq_{t-2}$, $dlwood_{t-3}$, a constant term, the recession dummy (*recdum)*, and the centered seasonal dummies as exogenous variables (see Appendix IIIc).

According to the diagnostic tests, fourth order autocorrelation is present in the stumpage price equation, but no autocorrelation was detected in the sawlog quantity equation or in the whole system. The diagnostic tests for heteroskedasticity and normality indicated no problems for the individual equations or for the system as a whole. Actual and forecasted values are presented in *Figure 5.8* along with the VECM forecasts. We discuss these forecasts in the next section.

VECM model

Next, we analyzed whether the above VAR system contains cointegration relationships using Johansen's testing procedure (*Appendix IIIc*). However, it should be borne in mind, that the data period is very short (only 44 observations) for applying cointegration analysis, and the results should therefore be interpreted with caution. The test results indicated that there is one cointegration relationship, between sawlog quantities traded and sawlog stumpage price. On basis of the theory and the data shown in *Figure 4.6*, this result conforms with prior expectations. However, since the unit root tests for the sawlog quantity series indicated that the series is likely to be stationary, the cointegrating relationship could also capture variation of this stationary variable in the model. The specification test results for the VECM were similar to those for the VAR model above.

Turning to the forecasts shown in *Figure 5.8*, the differences between the VAR and VECM models are minor. For six of the eight forecast points do the VAR and VECM models correctly forecast the direction of change. With the exception of the quarter 1998:2, the models tend to underestimate the true level of sawlog demand in Finland.

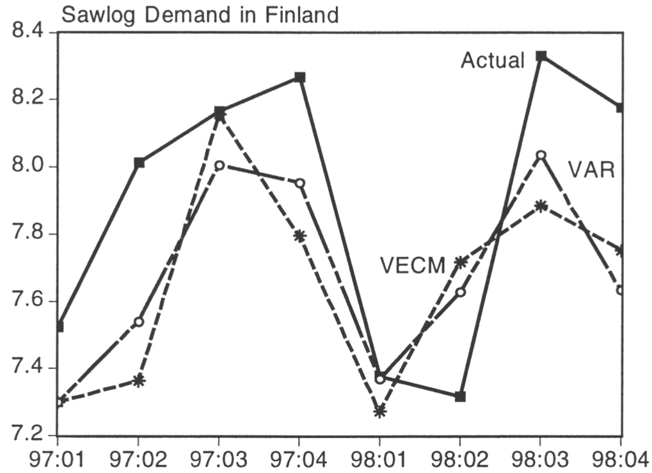


Figure 5.8. Dynamic Forecasts from the VAR and VECM Models, 1997:1-1998:4.

Forecasting evaluation

In *Table 5.3*, the residual mean square errors (RMSE) and its components are shown for the four models. Although the VAR model has the lowest RMSE (0.33), it is very close to that of the Partial model (0.35).

Table 5.3. Decomposition of RMSE for the different models, 1997:1-98:4

Model	RMSE	Bias proportion	Variance proportion	Covariance Proportion
Naïve	0.570	0.747	0.027	0.226
Partial	0.352	0.692	0.009	0.298
VAR	0.331	0.417	0.166	0.417
VECM	0.440	0.299	0.057	0.643

Clearly, the Naive model does worst in terms of RMSE statistics. However, the bias proportion statistics show that systematic forecast errors are much higher for the Partial model than for the VAR model. Indeed, according to the BP and CP statistics, the VECM model proves to be the best model for forecasting. Most of the forecast errors from the VECM model are due to non-systematic random noise. The results show that one can clearly improve forecasting accuracy by moving from the Naive model to multivariate models. In contrast, the gains achieved by moving from the simple single equation Partial model to the more elaborate system approaches (VAR and VECM) are more modest and ambiguous.

6. CONCLUSIONS

A derived-demand-led short-term forecasting system (MESU), which links the Finnish forest industry export markets to the domestic roundwood markets, was demonstrated using a case study. First the total import demand for coniferous sawnwood in Germany was forecasted for eight quarters ahead. In the next stage, these forecasts were used, with other information, to forecast Finland's exports of coniferous sawnwood to Germany. Finally, the latter forecasts were used to forecast spruce sawlog demand in Finland. Thus, the MESU system consists of three different, but hierarchically interlinked, modeling stages. In each of the modeling stages, experiments with four different types of econometric models were applied to provide short-term forecasts. The purpose was to compare the forecasting performance of the different approaches. The MESU system is used in practice to help the Finnish Forest Research Institute to provide the forecasts for the annual publication, *Finnish Forest Sector Economic Outlook.*

The most important results and implications of the study can be summarized as follows. First, the results show that the methodology of the MESU system is useful in the sense that the forecasts of the different stages can be consistently linked and used for making practical forecasts. In particular, forecasts of total sawnwood imports to Germany turned out to be useful in forecasting changes in Finnish sawnwood exports to Germany, which in turn helped to forecast the short-term cyclical demand for sawlogs in Finland. Secondly, the results indicated that one could clearly improve on the simple autoregressive model (Naive model) forecasts by moving to the partial multivariate single equation or systems approaches (VAR and VECM). However, the relative merits of the partial, versus system approaches in forecasting varied between the different stages of the MESU system. For example, for forecasting the German import demand for sawnwood, the partial model turned out to be clearly the preferred specification, whereas for Finnish sawnwood exports to Germany and sawlog demand in Finland, the systems approaches were more useful. However, moving from the single equation framework to VAR or VECM models did not result in large improvements in forecasting accuracy. Considering the fact that systems approaches are more demanding in terms of data and are less tractable compared to the partial model, these gains may not always be large enough to justify their use in practical forecasting.

Since the purpose of the present study was mainly to demonstrate the MESU system and compare a limited number of forecasting models, it is only natural that there is probably still much room for improving the analysis of the present study. One natural improvement would be to use genuine dynamic ex ante forecasts also for all the exogenous variables in the partial multivariate and systems models. This would provide a more realistic comparison in terms of what the actual forecasting situation is in practice. Also, some modeling approaches not used in the present study could be tested. For example, it would be interesting to see how the structural time series (Kalman filter) models, which explicitly allow changing seasonal and trend behavior, would perform in forecasting the different stages of the MESU system (see e.g., Harvey 1989).

REFERENCES

Adams, D. and Haynes, R. (1980). The 1980 softwood timber assessment market model: structure, projections, and policy simulation, *Forest Science Monograph*, 22.

Alavalapati, J.R.R., Luckert, M.K., and Adamowicz, W.L. (1996). Short-term influences on Canadian wood pulp prices and exports: a vector autoregression analysis. *Canadian Journal of Forest Research* 26; 566-572.

Armington, P.S. (1969). A theory of demand for products distinguished by place of production. *Int. Monet. Fund Staff Pap.* 6:159-176.

Baudin, A. (1997). Demand and Supply Analyses of Roundwood and Forest Products Markets in Europe - Sweden, in Solberg and Moiseyev (eds.)

Box, G.E.P. and Jenkins, G.M. (1970). *Time Series Analysis, Forecasting and Control.* San Francisco: Holden-Day.

Buongiorno, J. (1996). Forest sector modeling: a synthesis of econometrics, mathematical programming, and system dynamics methods. *International Journal of Forecasting*, vol. 12; 329-343.

Buongiorno, J., Chou, J-J. and Stone, R.N. (1979). A Monthly Model of the United States Demand for Softwood Lumber Imports, *Forest Science*, vol. 25; 641-655.

Buongiorno, J. Brannman, L. and Bark, T. (1984). Econometric versus Univariate and Bivariate Time-Series Forecasts: The Case of Softwood Lumber Imports. *Forest Science*, Vol. 30, No. 1.; 194-208.

Buongiorno, J., Chavas, J. and Uusivuori, J. (1988). Exchange rates, Canadian lumber imports and U.S. prices: a time series analysis. *Canadian Journal of Forest Research* 18; 1587-1594.

Clarida, R.H. (1994). Cointegration, Aggregate Consumption, and the Demand for Imports: A Structural Econometric Investigation. *American Economic Review* 84: 298-308.

Clements, M.P. and D.F. Hendry (1998). *Forecasting economic time series*. Cambridge University Press,. 368 p.

de la Croix, D. and J.-P. Urbain. (1998). Intertemporal substitution in import demand and habit formation. *Journal of Applied Econometrics* 13: 589-612.

Doornik, J.A. and D.F. Hendry (1997). *PcFiml 9.0 Series PcFiml 9.0* International Thomson Business Pressp.

Engle, R.F. and Yoo, B.S. (1987). Forecasting and testing in co-integrated systems, *Journal of Econometrics*, 35; 143-159.

Fanchon, P. and Wendel, J. (1992). Estimating VAR models under non-stationarity and cointegration: alternative approaches for forecasting cattle prices. *Applied Economics* 24:207-217.

FFSEO (2000). *Finnish Forest Sector Economic Outlook 2000-2001*. Finnish Forest Research Institute, December 2000. pp. 61.

Goldstein, M. and K. Mohsin (1985). Income and price effects in foreign trade. P. 1041-1105 *in Handbook of International Economics*, Jones, R.W. and P.B. Kenen (eds.). Handbook of Economics II, Elsevier Science Publishers.

Granger, C. (1996). Can We Improve the Perceived Quality of Economic Forecasts? *Journal of Applied Econometrics*, vol. 11; 455-473.

Greenslade, J.V., Hall, S.G., and Henry, S.G.B. (1999). On the Identification of Cointegrated Systems in Small Samples: Practical Procedures with an Application to UK Wages and Prices. Discussion Paper No. 07-99, London Business School.

Harvey, A. C. (1989). *Forecasting, Structural Time Series Models and Kalman Filter.* Cambridge University Press.

Harvey, A. C. (1997). Trends, Cycles and Autoregressions, *Economic Journal*, vol. 107; 192-201.

Hendry, D.F and Doornik J.A. (1997) *Empirical Econometric Modelling using PcGive 9.0 for Windows*. International Thomson Business Press, London. p.294.

Hetemäki, L. and Kuuluvainen, L. (1992). Incorporating Data and Theory in Roundwood Supply and Demand Estimation, *American Journal of Agricultural Economics*, November; 1010-1018.

Hänninen, R. (1998). Demand for Finnish exports of forest products: Econometric analyses using time series data. Finnish Forest Research Institute, Research Papers 708. Helsinki. 73+23 p.

Jennings, S., Adamowicz, W. and Constantiono, L. (1991). The Canadian lumber industry and the macroeconomy: a vector autoregression analysis. *Canadian Journal of Forest Research* 21; 288-299.

Johansen, S. (1991). Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models, *Econometrica*, 59; 1551-1580.

Johansen, S. (1995). *Likelihood-based Inference in Cointegrated Vector Autoregressive Models*, Oxford University Press.

Johansson, P-O. and Löfgren, K.G. (1985). *The Economics of Forestry and Natural Resources*, Basil Blackwell, Oxford.

Kallio, M., Dykstra, D.P. and Binkley, C. (eds. 1987). *The Global Forest Sector: An Analytical Perspective*. Wiley, New York.

Linden, M. (1998). Saksan sahatavaran tuonti 1980Q1-1997Q4 ja ennusteindikaattorit: data-analyysi ja ennustemallit. Department of Economics, University of Helsinki, Helsinki. 48 p. (unpublished manuscript). November 1998.

Linden, M. (1999). Saksan sahatavaran tuonti ja rakennusluvat 1980Q1-1997Q4: data-analyysi ja ennustemallit. Department of Economics, University of Helsinki, Helsinki. 7 p. (unpublished mimeo). February 1999.

Linden, M. (1999). Comparing different methods of deriving composite leading indicators: an application to German sawntimber imports and leading indicators Series Comparing different methods of deriving composite leading indicators: an application to German sawntimber imports and leading indicators Department of Economics, University of Helsinki, Helsinki. 12 p.

Maddala, G.S. and Kim, I-M. (1998). *Unit Roots, Cointegration, and Structural Change.* Cambridge University Press.

Marvall, A. (1995). Unobserved Components in Economic Time series. P. 12-72 in *Handbook of Applied Econometrics*, Pesaran, M.H.a.W., M. R. (ed.). I, Blackwell.

McKillop, W. and Wibe, S. (1987). Demand for Sawnwood and Panels, in Kallio, M., Dykstra, D. and Binkley, C. (eds.) *The Global Forest Sector: An Analytical Perspective.* John Wiley & Sons.

Penm, J.H. and Terrell, R. D. (1994). Is Housing Activity a Leading Indicator? *Economic Record* 70: 241-252.

Pesaran, H. and Shin, Y. (1999). An Autoregressive Distributed Lag Modelling Approach to Cointegation Analysis, in (ed) Strom, S., *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium*, 1999, chapter 11. Cambridge University Press, Cambridge.

Pesaran, H., Shin, Y. and Smith, R.J. (1999). Structural Analysis of Vector Error Correction Models with Exogenous I(1) Variables. *Journal of Econometrics* (forthcoming).

Senhadji, A. (1997). Time-Series Estimation of Structural Import Demand Equations: Time-Series Estimation of Structural Import Demand Equations: A Cross-Country Analysis. *IMF Staff Papers*, Vol. 46, No. 3.

Solberg, B. and A. Moiseyev (eds. 1997). Demand and supply analyses of roundwood and forest products markets in Europe - overview of present studies. 1st Workshop of the Concerted Action Project AIR3-CT942288, Helsinki, Finland 3-5 November 1995, Helsinki, 1997. EFI Proceedings No. 17 , European Forest Institute,City. 418 p.

Stock, J.H. (2001). Macro-econometrics, *Journal of Econometrics*, vol 100; 29-32.

Toppinen, A. 1997. Testing for Granger-causality in the Finnish roundwood market. *Silva Fennica*. 31: 225-232.

Toppinen, A. 1998. Incorporating cointegration relations in a short-run model of the Finnish sawlog market. *Canadian Journal of Forest Research*. Vol 28(2): 291–298.

Urbain, J.-P. (1995). Partial versus full system modelling of cointegrated systems: An empirical illustration. *Journal of Econometrics* 69: 177-210.

Zhang, D., Buongiorno, J. and Ince, P. (1993). PELPS III a microcomputer price endogenous linear programming system for economic modeling. Research Paper FPL-RP-526 (USAD Forest Service, Forest Product Laboratory, Madison)

APPENDIX I: Data Sources and Description

Acronym	Variable	Unit	Description	Data Source
			Sawnwood Import Demand Model	
LQ	Sawnwood imports to Germany	Cubic meters	Coniferous sawnwood: CN 44710.	Statistiches Bundesamt, *Aussenhandel nach Waren und Ländern*
LGDP	Gross domestic product, Germany	Real 1991 prices, DEM	GDP by expenditure	OECD *Main Economic Indicators*
LCPERS	Total construction permits issued	Value index	The value of permits is equal to the total value of finished works, all taxes included, estimated at the time of purchase. Permits are for all types of construction above ground level: new constructions, re-constructions, repairs, extensions and conversions. Data refer to unified Germany from 1994 and Western Germany prior to this date. Quarterly data are sum of monthly figures.	OECD *Main Economic Indicators*
LIP	Price for imported sawnwood	Nominal unit price (DEM)	Implicit unit price for imported sawnwood (DEM/cubic meters). Unit values of imports to Germany are used as representative prices of sawnwood. Quarterly data are averages of monthly figures.	Statistisches Bundesamt, *Aussenhandel nach Waren und Ländern*

LDP	Price for domestic production of sawnwood	Nominal unit price (DEM)	Implicit unit price for domestic sawnwood (DEM/cubic meters). Quarterly data are sum of monthly figures.	Statistisches Bundesamt, *Produktion nach Gueterarten*
LIMDP	LIP/LDP			
			Sawnwood Export Supply Model	
LQ	See above			
LDIFQ	Sawnwood exports from Finland to Germany	Cubic meters	Coniferous sawnwood:CN 44710. Quarterly data are averages of monthly figures.	Statistiches Bundesamt, *Aussenhandel nach Waren und Ländern*
LDIFP	Price for sawnwood from Finland	Nominal unit price (DEM)	Implicit unit price for sawnwood from Finland [DEM/cubic meters. Quarterly data are averages of monthly figures.	Statistiches Bundesamt, *Aussenhandel nach Waren und Ländern*
LDISP	Price for sawnwood from Sweden	Nominal unit price DEM/m3	Implicit unit price for sawnwood from Sweden (DEM/cubic meters). Quarterly data are averages of monthly figures.	Statistiches Bundesamt, *Aussenhandel nach Waren und Ländern*
			Sawlog Demand Model	
LQKUT	Sawlog quantity traded in Finland	Cubic meters	Spruce sawlogs traded in Finland. Quarterly data are sum of monthly figures.	Finnish Forest Research Institute, METINFO
LPKUT	Sawlog price in Finland	Nominal FIM/m3	Stumpage price of spruce sawlogs. Quarterly data are averages of monthly figures.	Finnish Forest Research Institute, METINFO

LDIFQ	See above			
LDIFP	Unit price of sawnwood exported from Finland to Germany	Nominal unit price (DEM) as converted to FIM/m3	Implicit unit price for imported sawnwood from Finland. Quarterly data are averages of monthly figures.	*Aussenhandel nach Waren und Ländern*
LWOODQ	Production of Wood Products Industry	Volume index	Based on plant level survey. Base year 1995. Quarterly data are averages of monthly figures.	*Statistics Finland*
T1, T2, T	Time trends			
RECDUM	Dummy variable		Dummy gets value 1 in 1991:2 and 1996:2 and 0 for other observations. See Chapter 4.2 for explanation.	
SD1, SD2, SD3, SD4	Centered (orthogonaliz ed) seasonal dummy variables			

* All variables, whose acronym starts with letter L, are transformed in logarithmic form, and are seasonally unadjusted.

APPENDIX II: Time Series Properties of the Data

Figure A1. LQ and the first difference (DLQ) with the respective correlograms

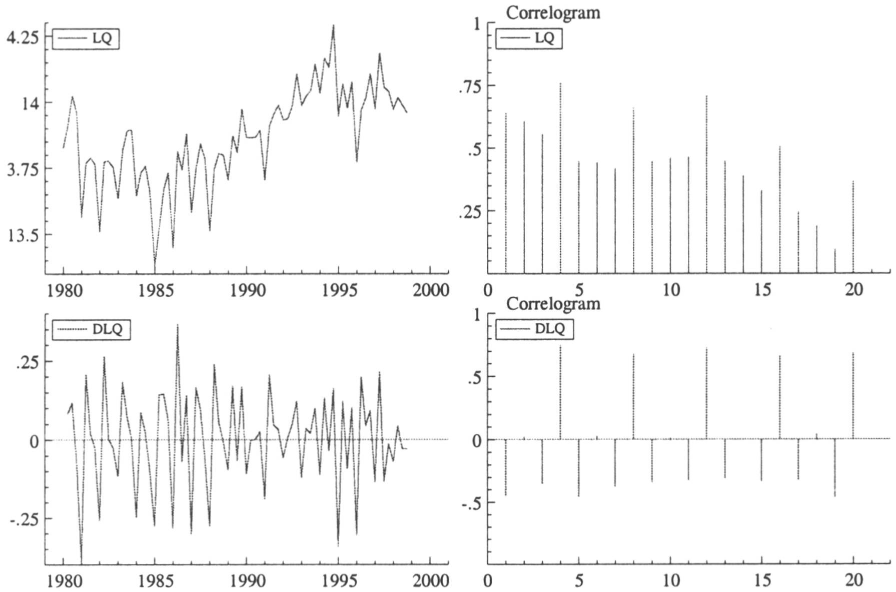


Figure A2. LGDP and the first difference (DLGDP) with the respective correlograms

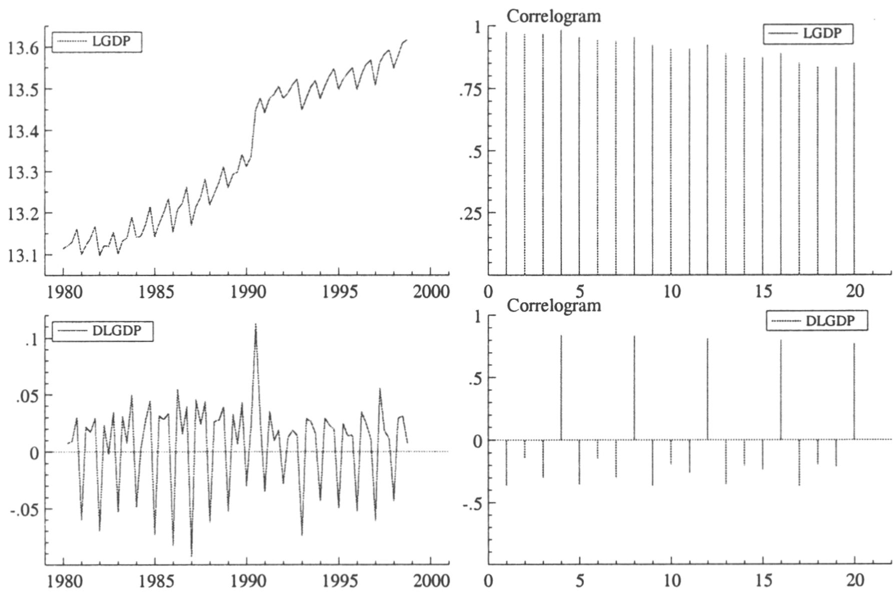


Figure A3. LCPERS and the first difference (DLCPERS) with the respective correlograms

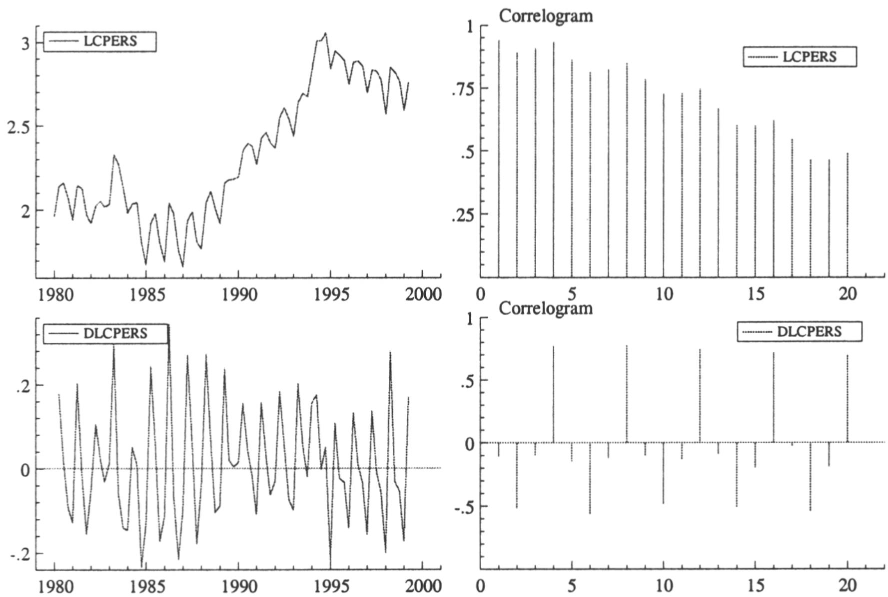
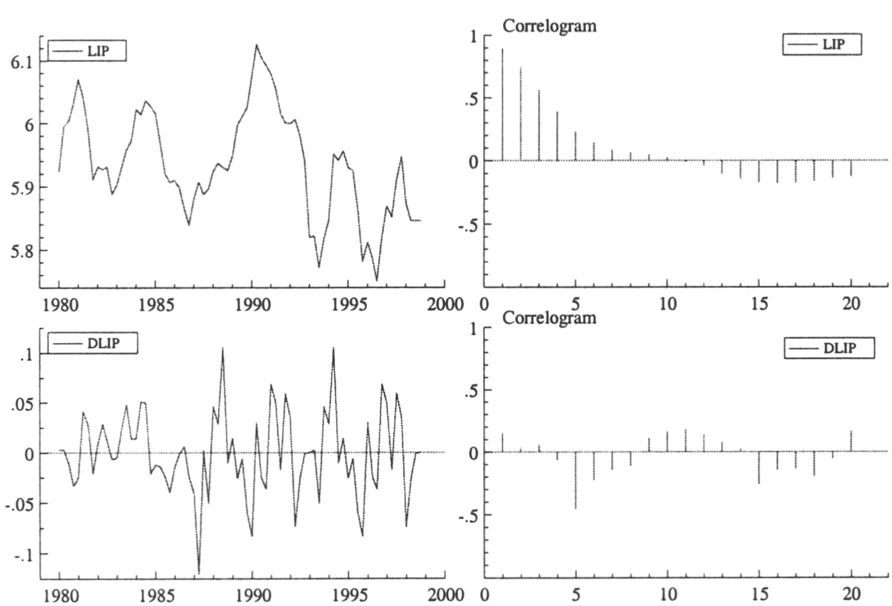


Figure A4. LIP and the first difference (DLIP) with the respective correlograms



Appendix II:3

Figure A5. LDP and the first difference (DLDP) with the respective correlograms

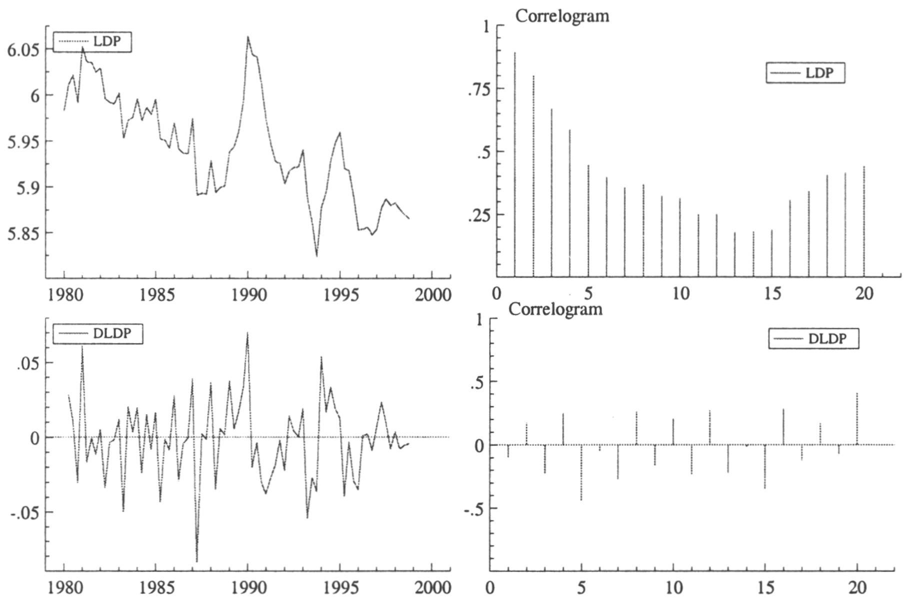


Figure A6. LIPDP and the first difference (DLIPDP) with the respective correlograms

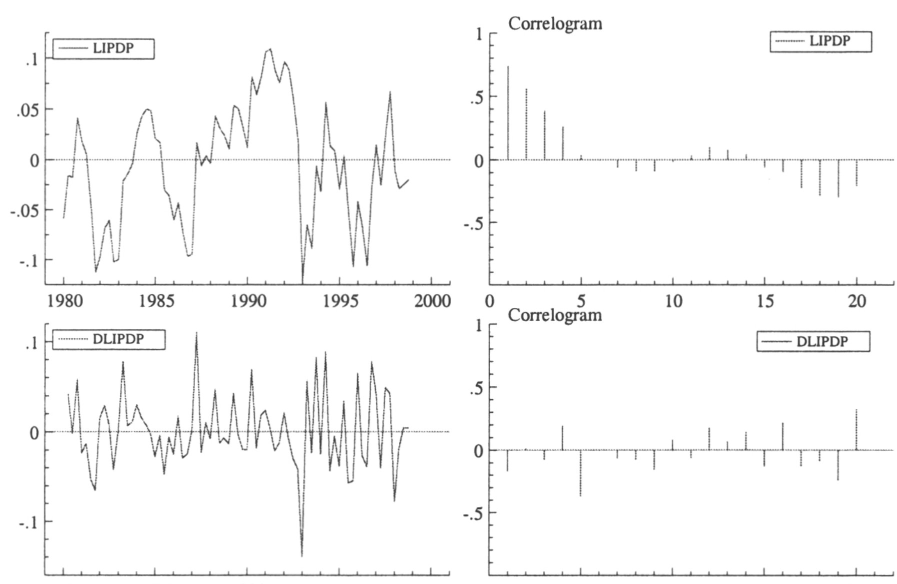


Figure A7. LDIFQ and the first difference (DLDIFQ) with the respective correlograms

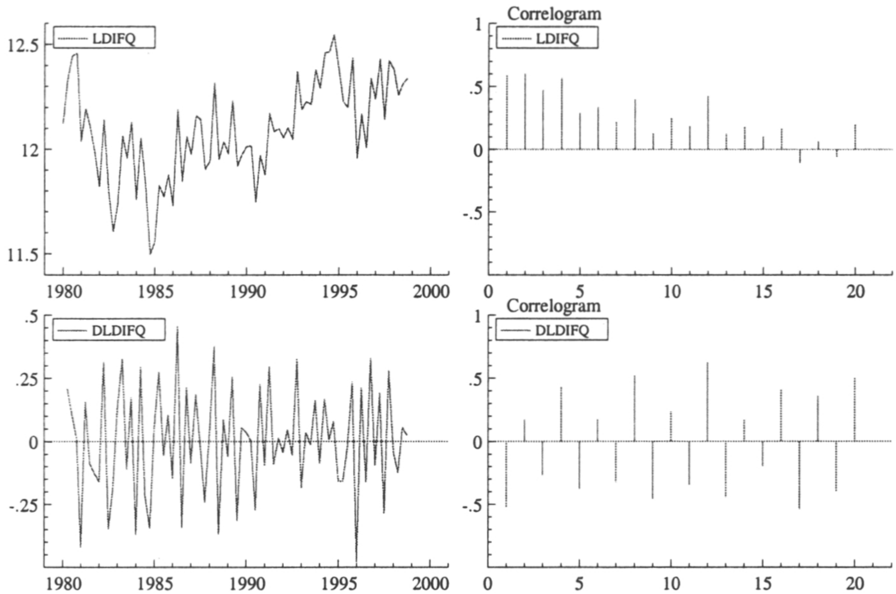
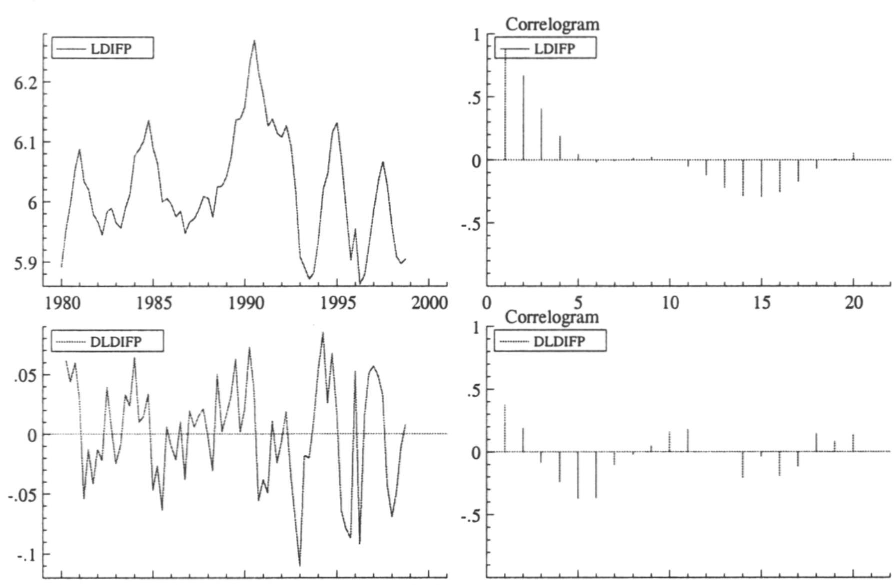


Figure A8. LDIFP and the first difference (DLDIFP) with the respective correlograms



Appendix II:5

Figure A9. LDISP and the first difference (DLDISP) with the respective correlograms

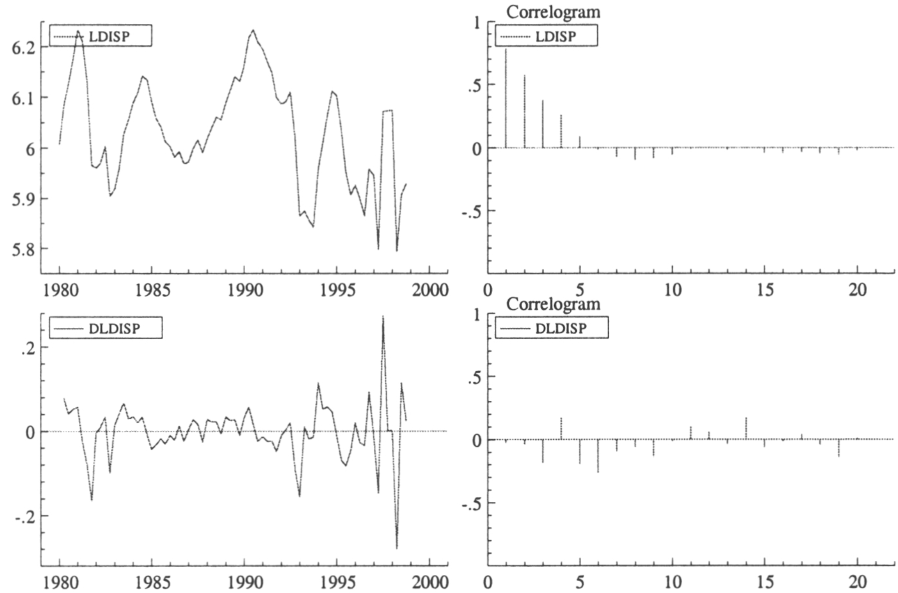


Figure A10. LQKUT and the first difference (DLQKUT) with the respective correlograms

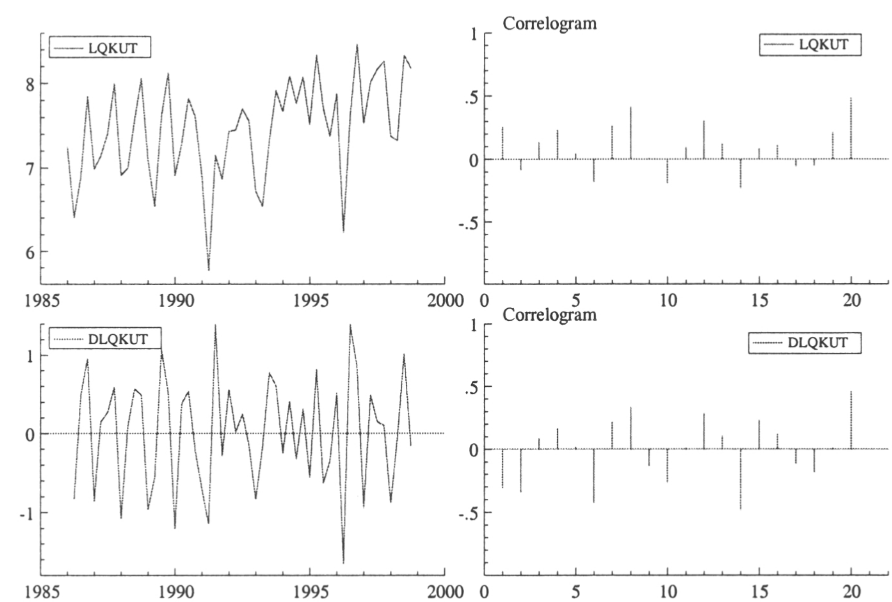


Figure A11. LPKUT and the first difference (DLPKUT) with the respective correlograms

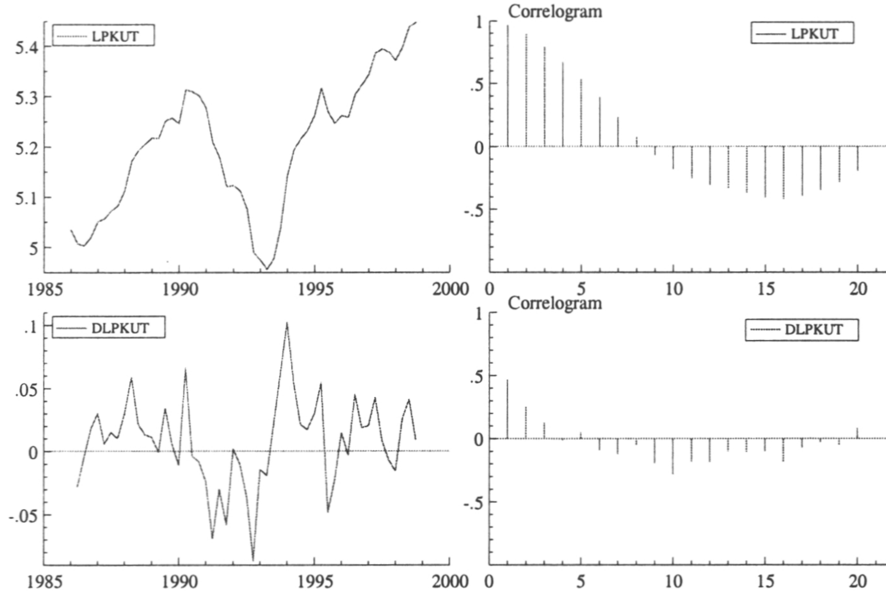
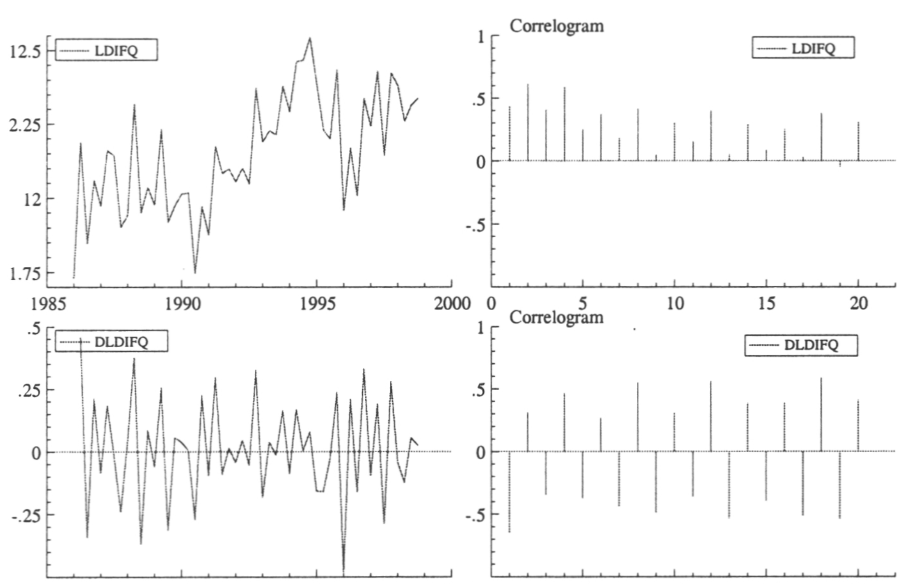


Figure A12. LDIFQ and the first difference (DLDIFQ) with the respective correlograms



Appendix II:7

Figure A13. LDIFP and the first difference (DLDIFP) with the respective correlograms

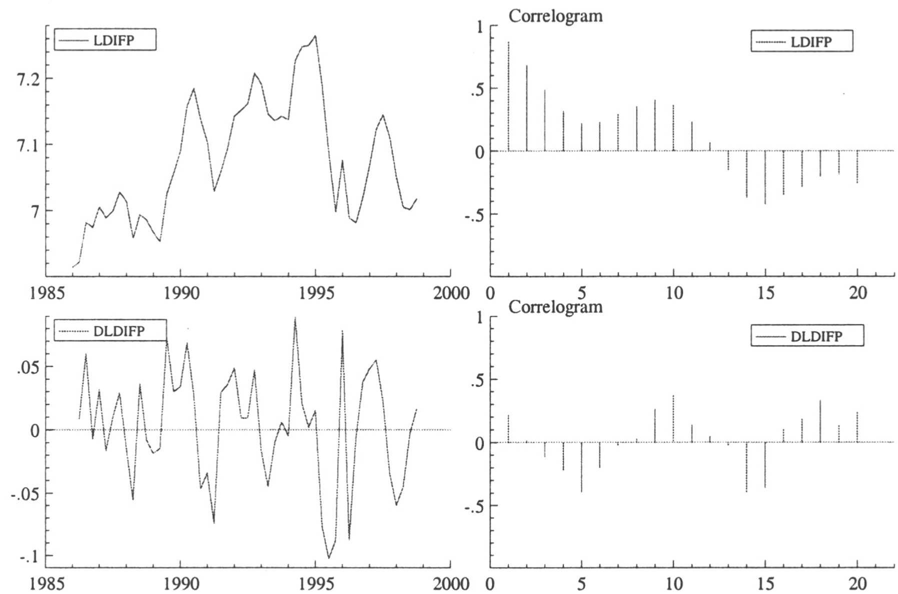


Figure A14. LWOODQ and the first difference (DLWOODQ) with the respective correlograms

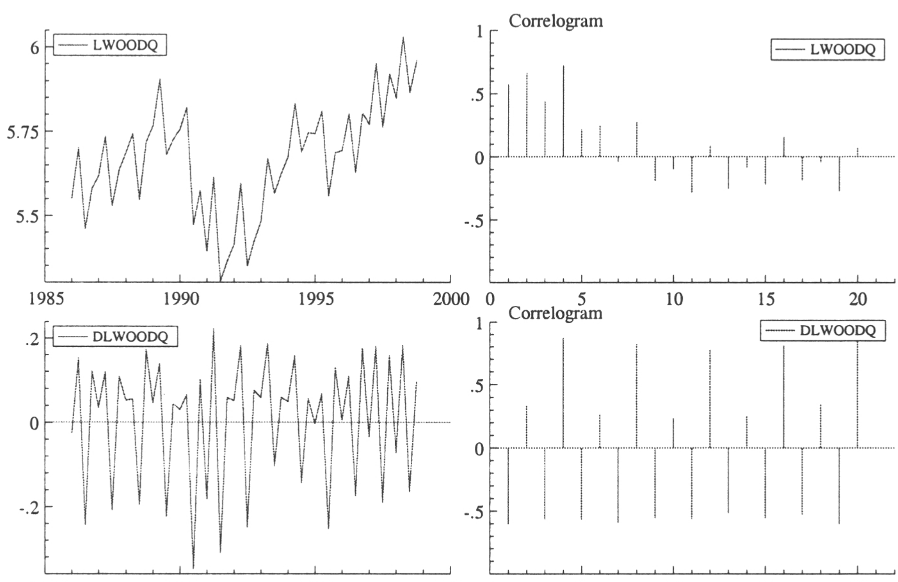


Table A2. Correlation Matrix: German Sawnwood Import Demand Model

	LQ	LGDP	LCPERS	LIP	LDP	LIPDP
LQ, total sawnwood imports to Germany	1.00					
LGDP, real GDP, Germany	0.75	1.00				
LCPERS, construction permits	0.84	0.87	1.00			
LIP, sawnwood import price	-0.27	-0.34	-0.35	1.00		
LDP, domestic price of sawnwood	-0.49	-0.68	-0.56	0.72	1.00	
LIPDP, (=LIP/LDP)	0.08	0.06	0.05	0.73	0.06	1.00

Table A3. Correlation Matrix:Finnish Sawnwood Export Model

	LDIFQ	LQ	LDIFP	LDISP
LDIFQ, Finnish sawnwood exports to Germany	1.00			
LQ, total sawnwood imports to Germany	0.78	1.00		
LDIFP, Finnish sawnwood price	-0.28	-0.12	1.00	
LDISP, Swedish sawnwood price	-0.18	-0.22	0.83	1.00

Table A4. Correlation Matrix:Finnish Sawlog Demand Model

	LQKUT	LPKUT	LDIFP	LDIFQ	LWOODQ
LQKUT, sawlog quantity	1.00				
LPKUT, sawlog price	0.30	1.00			
LDIFP, sawnwood price	0.38	0.19	1.00		
LDIFQ, sawnwood exports	0.10	-0.04	0.45	1.00	
LWOODQ, wood production	0.25	0.60	-0.26	0.47	1.00

Table A5. Normality tests (Doornik-Hansen) for logartihmic transformations of the levels series, 1980:1-1998:4

Variable	Normality	Skewness	Excess Kurtosis
LQ, total sawnwood imports to Germany	1.72 [0.42]	-0.34	-0.03
LGDP, real GDP, Germany	23.90 [0.00]	0.05	-1.62
LCPERS, construction permits	11.47 [0.00]	0.21	1.23
LIP, sawnwood import price	0.41 [0.81]	0.02	-0.53
LDP, domestic price of sawnwood	2.94 [0.22]	0.12	-0.85
LIPDP, (=LIP/LDP)	1.64 [0.43]	-0.09	-0.73
LDIFQ, Finnish sawnwood exports to Germany	1.39 [0.49]	-0.25	-0.39
LDIFP, Finnish sawnwood price	3.22 [0.20]	0.43	-0.19
LDISP, Swedish sawnwood price	0.99 [0.60]	-0.15	-0.53
LQKUT, Finnish sawlog demand	3.08 [0.21]	-0.54	0.04
LPKUT, Finnish sawlog stumpage price	2.47 [0.29]	-0.10	0.04
*LDIFP, Finnish sawnwood price	4.10 [0.12]	-0.10	-0.96
*LDIFQ, Finnish sawnwood exports to Germany	0.89 [0.64]	-0.05	-0.75
LWOODQ, wood production	0.29 [0.87]	-0.14	-0.43

The p-values are in brackets. The normality test indicate that all series are normally distributed. The normality tests indicate that, expect the LGDP and LCPERS series, all the series are normally distributed. The excess kurtosis is too large for LGDP and LCPERS series to be normally distributed. Note. In the sawlog demand model *LDIFP and *LDIFQ differ from sawnwood export model due to the shorter observation period.

Table A6. ADF – tests

	ADF-test statistic		Decision	
Variable	**Constant, C**	**C & trend**	**Constant, C**	**C & trend**
LQ, total sawnwood imports to Germany	ADF(4): -1.69	ADF(4): -3.07	I(1)	I(1)
LGDP, real GDP, Germany	ADF(4): -0.44	ADF(4): -2.38	I(1)	I(2)
LCPERS, construction permits	ADF(4): -1.13	ADF(4): -2.41	I(2)	I(2)
LIP, sawnwood import price	ADF(5): -1.92	ADF(5): -2.24	I(1)	I(1)
LDP, domestic price of sawnwood	ADF(5): -1.72	ADF(4): -4.39*	I(1)	I(0)
LIPDP, (=LIP/LDP)	ADF(4): -3.60*	ADF(4): -3.61*	I(0)	I(0)
LDIFQ, Finnish sawnwood exports to Germany	ADF(1) : - 2.25	ADF(4): -3.81*	I(1)	I(0)
LDISP, Swedish sawnwood price	ADF(4): -3.60*	ADF(4): -3.71*	I(0)	I(0)
LDIFP, Finnish sawnwood price	ADF(1): -3.00*	ADF(1): -3.06	I(0)	I(1)
LQKUT, Finnish sawlog demand	ADF(0): -5.44*	ADF(1): -5.79*	I(0)	I(0)
LPKUT, Finnish sawlog stumpage price	ADF(1): -1.51	ADF(1): -1.97	I(1)	I(1)
*LDIFP, Finnish sawnwood price	ADF(2): -2.12	ADF(1) -2.52	I(1)	I(1)
*LDIFQ, Finnish sawnwood exports to Germany	ADF(2): -2.12	ADF(0): -5.70*	I(1)	I(1)

Appendix II:11

LWOODQ, wood production	ADF(1): -3.33*	ADF(4): -2.12	I(0)	I(1)

Note. i) Critical values for ADF-test are 5%= - 2.90 and 1%=-3.53 with constant, and 5%= -3.47 and 1%=-4.09 with constant and trend; ii) If the ADF-test indicated the series not to be I(0), the test was run for first difference of the variables to anlyse whether the series could be regarded to be either I(1) or I(2). These ADF-results are not reported here, but they are taken into account in determing the order of integration in "Decsion" column. Also, the Table presents only test values of the highest lag with a significant t-value (a method suggested by Hendry & Doornik 1999a, p. 42). *The rejection of the null hypothesis (a unit root) at the 5% significance level is marked using one star.

APPENDIX IIIa: German Sawnwood Import Demand Model

Model I: Autoregressive (Naïve) Model

Dependent Variable: LQ
Method: Least Squares
Sample(adjusted): 1980:2 1996:4
Included observations: 67 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.896897	0.906643	2.092221	0.0405
LQ(-1)	0.863041	0.065488	13.17859	0.0000
D_2	0.343359	0.032899	10.43672	0.0000
D_3	0.236341	0.030085	7.855677	0.0000
D_4	0.257585	0.029921	8.608753	0.0000

R-squared	0.795171	Mean dependent var	13.84653
Adjusted R-squared	0.781957	S.D. dependent var	0.183508
S.E. of regression	0.085689	Akaike info criterion	-2.004486
Sum squared resid	0.455243	Schwarz criterion	-1.839957
Log likelihood	72.15029	F-statistic	60.17305
Durbin-Watson stat	2.337374	Prob(F-statistic)	0.000000

Breusch-Godfrey Serial Correlation LM Test (5th order):

F-statistic	1.732392	Probability	0.141905
Obs*R-squared	8.838471	Probability	0.115683

ARCH Test (1st order):

F-statistic	0.121857	Probability	0.728907
Obs*R-squared	0.127707	Probability	0.720821

Doornik-Hansen Normality-Test:

$\chi^2_{(2)} = 1.81 \quad [0.40]$

Ramsey RESET Test:

Log likelihood ratio	0.141945	Probability	0.706355

Chow Forecast Test: Forecast from 1997:1 to 1998:4

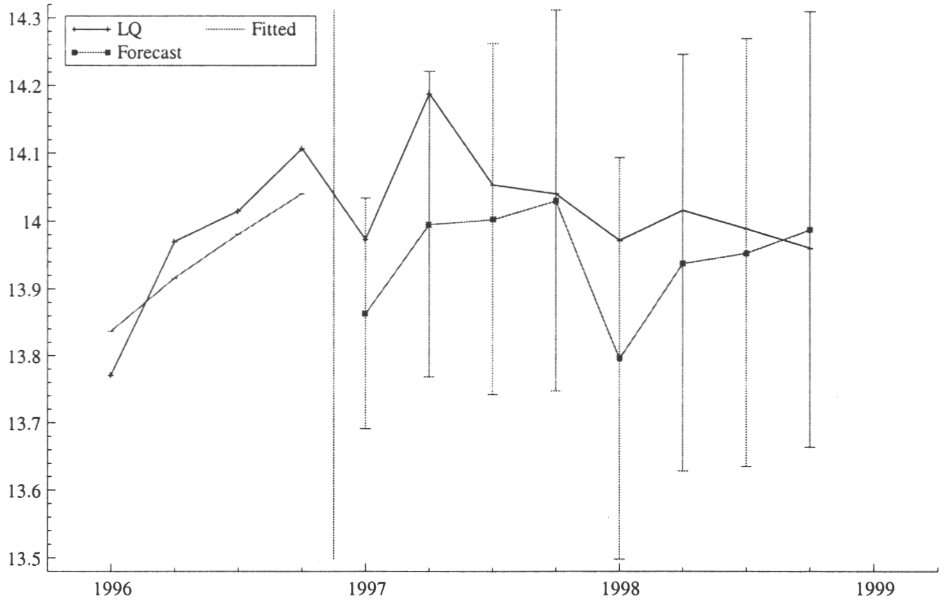
F-statistic	1.152069	Probability	0.342441
Log likelihood ratio	10.39432	Probability	0.238433

Appendix IIIa: 2

Autocorrelation and Partial Autocorrelation Functions for Residuals from the Naïve Model

Sample: 1980:2 1996:4, 67 obs.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.*| . |	.*| . |	1	-0.177	-0.177	2.1898	0.139
. | . |	.*| . |	2	-0.045	-0.079	2.3340	0.311
. |*. |	. |*. |	3	0.158	0.140	4.1310	0.248
. |** |	. |** |	4	0.206	0.272	7.2406	0.124
.*| . |	. | . |	5	-0.145	-0.043	8.8102	0.117
.*| . |	.*| . |	6	-0.082	-0.150	9.3185	0.156
. |*. |	.*| . |	7	0.081	-0.059	9.8232	0.199
. | . |	. | . |	8	0.044	0.040	9.9734	0.267
. |*. |	. |** |	9	0.088	0.237	10.593	0.305
.*| . |	. | . |	10	-0.134	-0.044	12.048	0.282



The Dynamic Forecasts and 2 S.E. Bands for the Naive Model

Model II: ARMASA Model

Dependent Variable: LQ
Method: Least Squares
Sample(adjusted): 1981:2 1996:4
Included observations: 63 after adjusting endpoints
Convergence achieved after 11 iterations
Backcast: 1980:2 1981:1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	14.69172	0.568367	25.84900	0.0000
AR(1)	0.687488	0.090807	7.570879	0.0000
SAR(4)	0.965753	0.021415	45.09715	0.0000
MA(4)	-0.900913	0.041304	-21.81182	0.0000

R-squared	0.822088	Mean dependent var	13.84549
Adjusted R-squared	0.813042	S.D. dependent var	0.183775
S.E. of regression	0.079462	Akaike info criterion	-2.165696
Sum squared resid	0.372536	Schwarz criterion	-2.029624
Log likelihood	72.21943	F-statistic	90.87511
Durbin-Watson stat	2.324704	Prob(F-statistic)	0.000000
Inverted AR Roots	.99	.69	
Inverted MA Roots	.97		

Breusch-Godfrey Serial Correlation LM Test (5th order):

F-statistic	1.585952	Probability	0.179707
Obs*R-squared	8.036118	Probability	0.154256

ARCH Test (1st order):

F-statistic	0.095139	Probability	0.758811
Obs*R-squared	0.098155	Probability	0.754055

Doornik-Hansen Normality-Test:

$\chi^2_{(2)} = 0.79$ [0.67]

Ramsey RESET Test:

F-statistic	6.003254	Probability	0.017318
Log likelihood ratio	6.204927	Probability	0.012740

Chow Forecast Test: Forecast from 1997:1 to 1998:4

F-statistic	0.701651	Probability	0.688720
Log likelihood ratio	6.452581	Probability	0.596672

Appendix IIIa: 4

Autocorrelation and partial autocorrelation functions for residuals from the Autoregressive (ARMASA) Model

Sample: 1981:2 1996:4

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>1</td><td>-0.166</td><td>-0.166</td><td>1.8211</td><td></td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>2</td><td>0.097</td><td>0.071</td><td>2.4482</td><td></td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>3</td><td>0.100</td><td>0.131</td><td>3.1263</td><td></td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>4</td><td>0.149</td><td>0.188</td><td>4.6765</td><td>0.031</td></tr>
<tr><td>**| . |</td><td>.*| . |</td><td>5</td><td>-0.196</td><td>-0.174</td><td>7.3907</td><td>0.025</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>6</td><td>-0.058</td><td>-0.186</td><td>7.6351</td><td>0.054</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>7</td><td>-0.034</td><td>-0.091</td><td>7.7178</td><td>0.102</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>8</td><td>-0.047</td><td>-0.010</td><td>7.8792</td><td>0.163</td></tr>
<tr><td>. | . |</td><td>. |*. |</td><td>9</td><td>0.047</td><td>0.174</td><td>8.0500</td><td>0.234</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>10</td><td>-0.165</td><td>-0.118</td><td>10.151</td><td>0.180</td></tr>
</table>

Model II: Partial Model

Dependent Variable: LQ
Method: Least Squares
Date: 02/26/01 Time: 17:01
Sample(adjusted): 1981:2 1996:4
Included observations: 63 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.999801	2.498974	1.200413	0.2354
D_2	0.008788	0.047846	0.183664	0.8550
D_3	-0.039109	0.041665	-0.938651	0.3522
D_4	0.121247	0.031251	3.879790	0.0003
DLQ(-4)	0.366744	0.083157	4.410245	0.0001
LGDP(-1)	-1.380505	0.355373	-3.884663	0.0003
LGDP(-3)	2.054369	0.377452	5.442734	0.0000
LCPERS(-1)	0.460440	0.077824	5.916394	0.0000
LCPERS(-4)	-0.350665	0.064247	-5.458070	0.0000
LIP(-3)	-0.283295	0.131666	-2.151619	0.0361
LDP	0.558300	0.243257	2.295109	0.0258

R-squared	0.923265	Mean dependent var	13.84549
Adjusted R-squared	0.908509	S.D. dependent var	0.183775
S.E. of regression	0.055587	Akaike info criterion	-2.784408
Sum squared resid	0.160677	Schwarz criterion	-2.410210
Log likelihood	98.70885	F-statistic	62.56603
Durbin-Watson stat	2.153270	Prob(F-statistic)	0.000000

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	1.297638	Probability	0.281074
Obs*R-squared	7.641986	Probability	0.177102

ARCH Test:

F-statistic	0.136841	Probability	0.712745
Obs*R-squared	0.141081	Probability	0.707209

Doornik-Hansen Normality-Test:

$\chi^2_{(2)} = 2.72 \quad [0.26]$

Ramsey RESET Test:

F-statistic	0.918133	Probability	0.342486
Log likelihood ratio	1.124076	Probability	0.289042

Chow Forecast Test: Forecast from 1997:1 to 1998:4

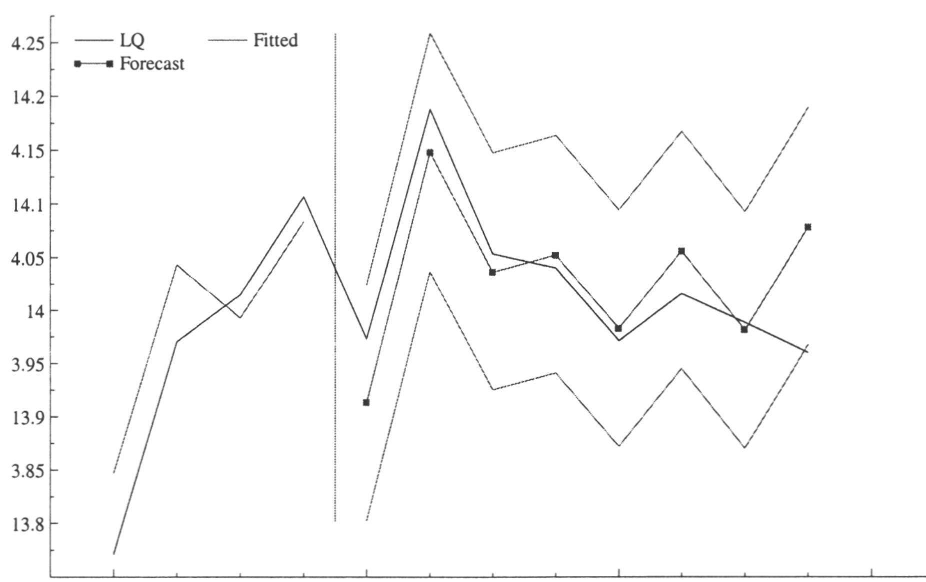
F-statistic	0.784643	Probability	0.618165
Log likelihood ratio	8.091610	Probability	0.424573

Appendix IIIa: 6

Autocorrelation and partial autocorrelation functions for residuals from the Partial Multivariate Model

Sample: 1981:2 1996:4
Included observations: 63

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>1</td><td>-0.087</td><td>-0.087</td><td>0.4972</td><td>0.481</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>2</td><td>0.158</td><td>0.152</td><td>2.1749</td><td>0.337</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>3</td><td>0.087</td><td>0.115</td><td>2.6857</td><td>0.443</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>4</td><td>-0.155</td><td>-0.170</td><td>4.3582</td><td>0.360</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>5</td><td>-0.026</td><td>-0.090</td><td>4.4045</td><td>0.493</td></tr>
<tr><td>**| . |</td><td>.*| . |</td><td>6</td><td>-0.191</td><td>-0.166</td><td>7.0277</td><td>0.318</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>7</td><td>0.035</td><td>0.062</td><td>7.1188</td><td>0.417</td></tr>
<tr><td>. | . |</td><td>. |*. |</td><td>8</td><td>0.034</td><td>0.101</td><td>7.2029</td><td>0.515</td></tr>
<tr><td>. | . |</td><td>. |*. |</td><td>9</td><td>0.063</td><td>0.089</td><td>7.4997</td><td>0.585</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>10</td><td>0.031</td><td>-0.052</td><td>7.5728</td><td>0.670</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>11</td><td>0.052</td><td>-0.005</td><td>7.7853</td><td>0.732</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>12</td><td>-0.038</td><td>-0.066</td><td>7.9032</td><td>0.793</td></tr>
</table>



The Dynamic Forecasts and 2 S.E. Bands for the Partial Multivariate Model

Model III: Restricted VAR Model

Vector Autoregression Estimates
Sample(adjusted): 1981:2 1996:4
Included observations: 63 after adjusting endpoints
Standard errors in ( ) & t-statistics in [ ]

	LQ	LGDP	LCPERS
LQ(-1)	0.007549 [0.05724]	-0.075749 [-1.78736]	-0.409484 [-2.57339]
LQ(-2)	-0.022347 [-0.15395]	0.100977 [2.16453]	0.106746 [0.60943]
LQ(-3)	0.285027 [2.19108]	0.022871 [0.54708]	0.113288 [0.72173]
LQ(-4)	0.241978 [1.78436]	-0.004308 [-0.09886]	0.236856 [1.44747]
LQ(-5)	-0.380937 [-3.11658]	-0.036688 [-0.93398]	-0.198528 [-1.34607]
LGDP(-1)	-1.932849 [-4.26431]	0.741438 [5.08992]	-0.919482 [-1.68118]
LGDP(-2)	0.747296 [1.23088]	0.378629 [1.94054]	0.395578 [0.53998]
LGDP(-3)	2.252757 [3.59727]	0.138176 [0.68656]	1.237241 [1.63732]
LGDP(-4)	-0.135241 [-0.22396]	-0.050506 [-0.26026]	-0.732119 [-1.00478]
LGDP(-5)	-0.453689 [-0.96140]	-0.243091 [-1.60288]	0.535805 [0.94097]
LCPERS(-1)	0.371819 [2.80791]	0.110002 [2.58487]	1.189751 [7.44607]
LCPERS(-2)	0.334909 [1.69409]	-0.066663 [-1.04925]	-0.267769 [-1.12251]
LCPERS(-3)	-0.269519 (0.18221) [-1.47916]	-0.022711 (0.05856) [-0.38784]	0.325315 (0.21986) [1.47962]

Appendix IIIa: 8

LCPERS(-4)	-0.198961	-0.093908	-0.369835
	[-1.05139]	[-1.54414]	[-1.61966]
LCPERS(-5)	-0.135800	0.080784	-0.032101
	[-0.86967]	[1.60977]	[-0.17037]
C	5.427789	0.358700	-4.424112
	[2.31744]	[0.47654]	[-1.56543]
LIPDP(-3)	-0.290958	0.008660	-0.308741
	[-1.94488]	[0.18012]	[-1.71032]
D_2	-0.087476	0.041689	0.103517
	[-1.20881]	[1.79258]	[1.18551]
D_3	-0.034674	0.064968	0.027182
	(0.06662)	(0.02141)	(0.08039)
	[-0.52045]	[3.03431]	[0.33813]
D_4	0.137640	0.072703	0.062695
	[2.27183]	[3.73398]	[0.85761]
R-squared	0.938309	0.991572	0.980260
Adj. R-squared	0.911051	0.987848	0.971538
Sum sq. resids	0.129176	0.013342	0.188080
S.E. equation	0.054810	0.017615	0.066136
F-statistic	34.42249	266.2576	112.3868
Log likelihood	105.5829	177.0968	93.74867
Akaike AIC	-2.716916	-4.987199	-2.341228
Schwarz SC	-2.036556	-4.306839	-1.660867
Mean dependent	13.84549	13.32740	2.282538
S.D. dependent	0.183775	0.159787	0.392017
Determinant Residual Covariance		3.54E-09	
Log Likelihood (d.f. adjusted)		344.7970	
Akaike Information Criteria		-9.041176	
Schwarz Criteria		-7.000095	

VAR Residual Serial Correlation LM Tests
H0: no serial correlation at lag order h
Sample: 1980:1 1996:4
Included observations: 63

Lags	LM-Stat	Prob
1	4.078297	0.9062
2	8.357838	0.4985
3	8.530378	0.4817
4	8.540063	0.4808
5	6.197839	0.7200

Probs from chi-square with 9 df.

Residual Tests for the Restricted VAR Model

Equation	Autocorrelation[a] F_{AR} (5,38)	Heteroskedasticity[b] F_{ARCH} (4,35)	Normality[c] $\chi^2(2)$	Functional Form[d] F(32,10)
ΔLQ	0.52[0.757]	0.86[0.497]	4.63[0.099]	0.54[0.911]
ΔLCPERS	1.93[0.112]	0.61[0.659]	0.64[0.727]	0.49[0.938]
ΔLGDP	0.82[0.538]	0.18[0.950]	19.11[0.000]**	0.17[1.000]
System:	F_{AR} (45,78)= 0.71 [0.890]		$\chi^2(6)$=22.44 [0.001] **	F(192,37)= 0.21[1.000]

Note: Values in square brackets are marginal significance levels and *indicates that the null hypothesis is rejected at the 5 percent level. a) Autocorrelation of the residuals of individual equations and a whole system was examined using the F–form of the Lagrange-Multiplier (LM) test, which is valid for systems with lagged dependent variables. b) Heteroskedasticity was tested using the F-form of the LM test against 4th order autoregressive conditional heteroskedasticity. c) Normality of the residuals of individual equations and the whole system was tested with the Doornik-Hansen test (Doornik and Hansen 1994). For further detail and test references, see Doornik and Hendry (1997). (d Functional form was tested using the Ramsey Reset-test.

VAR Pairwise Granger Causality/Block Exogeneity Wald Tests
Sample: 1980:1 1996:4
Included observations: 63

Dependent variable: **LQ**

Exclude	Chi-sq	df	Prob.
LGDP	39.60532	5	0.0000
LCPERS	36.07210	5	0.0000
All	71.65294	10	0.0000

Dependent variable: **LGDP**

Exclude	Chi-sq	df	Prob.
LQ	8.583373	5	0.1269
LCPERS	11.52539	5	0.0419
All	14.40643	10	0.1552

Dependent variable: **LCPERS**

Exclude	Chi-sq	df	Prob.
LQ	9.794766	5	0.0813
LGDP	17.52427	5	0.0036
All	26.57457	10	0.0030

VAR Pairwise Granger Causality/Block Exogeneity Wald Tests
Sample: 1980:1 1996:4
Included observations: 63

Dependent variable: **LQ**

Exclude	Chi-sq	df	Prob.
LCPERS	32.28548	5	0.0000
LGDP	34.20389	5	0.0000
LIPDP	6.827326	5	0.2338
All	73.74912	15	0.0000

Dependent variable: **LCPERS**

Exclude	Chi-sq	df	Prob.
LQ	11.80362	5	0.0376
LGDP	14.21353	5	0.0143
LIPDP	6.416477	5	0.2678
All	30.38701	15	0.0106

Dependent variable: **LGDP**

Exclude	Chi-sq	df	Prob.
LQ	8.061852	5	0.1529
LCPERS	9.653783	5	0.0857
LIPDP	1.872567	5	0.8665
All	15.53637	15	0.4135

Dependent variable: **LIPDP**

Exclude	Chi-sq	df	Prob.
LQ	11.58827	5	0.0409
LCPERS	12.17016	5	0.0325
LGDP	16.96606	5	0.0046
All	24.14818	15	0.0626

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VAR Lag Order Selection Criteria
Endogenous variables: LQ LCPERS LGDP
Exogenous variables: C LIPDP(-3) D_2 D_3 D_4
Sample: 1980:1 1996:4
Included observations: 62

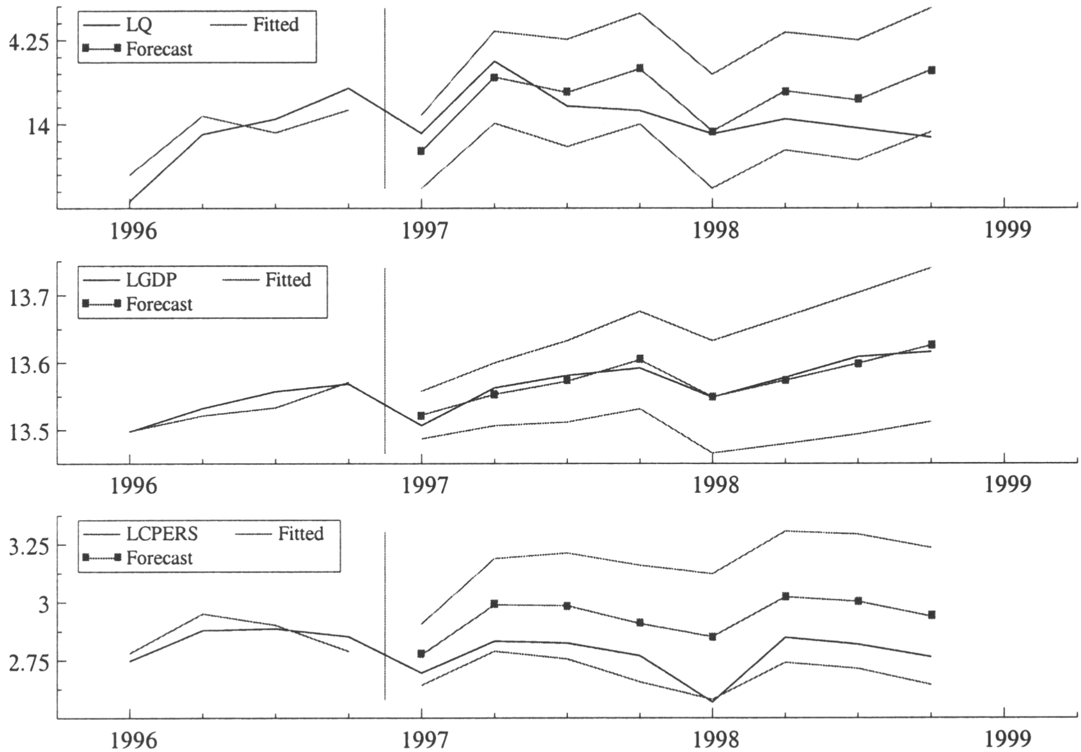
Lag	LogL	LR	FPE	AIC	SC	HQ
0	130.9222	NA	4.78E-06	-3.739425	-3.224796	-3.537369
1	328.5132	344.1909	1.09E-08	-9.823008	-8.999601*	-9.499718*
2	339.2973	17.74153	1.04E-08	-9.880558	-8.748374	-9.436034
3	349.1112	15.19573	1.02E-08	-9.906814	-8.465852	-9.341055
4	356.2526	10.36652	1.11E-08	-9.846858	-8.097118	-9.159866
5	374.2437	24.37510*	8.54E-09*	-10.13690*	-8.078378	-9.328669
6	378.7879	5.716896	1.03E-08	-9.993160	-7.625865	-9.063700

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Johansen's Cointegration Rank-Test for the Restricted VAR Model with 5 Lags for the endogenous Variables, 1980:4-1996:4.

Null hypothesis	Eigenvalues λ_I	λ Max.eigenv. - test statistics	95% critical values	λ Trace-test statistics	95% critical values
$R = 0$	0.47	40.05**	22.0	56.08**	34.90
$R \leq 1$	0.18	12.74	15.7	16.03	20.00
$R \leq 2$	0.05	3.29	9.2	3.29	9.20

Note: ** indicates the rejection of the null-hypothesis at 1 % cent level.



Restricted VAR-Model Dynamic Forecasts and Error Bars for ±2 Standard Errors, 1997:1-1998:4

<u>Model IV. Vector Error Correction (VECM) Model</u>

Vector Error Correction Estimates (VCEM)
Sample(adjusted): 1981:2 1996:4
Included observations: 63 after adjusting endpoints

Cointegrating Eq:	CointEq1		
LQ(-1)	1.000000		
LGDP(-1)	-0.537744		
	[-3.84096]		
LCPERS(-1)	-0.123109		
	[-2.03258]		
C	-6.406049		
	[-3.68644]		
Error Correction:	**D(LQ)**	**D(LGDP)**	**D(LCPERS)**
CointEq1	-0.873529	0.019735	-0.338494
	[-6.38883]	[0.43736]	[-1.87579]
D(LQ(-1))	-0.120078	-0.095647	-0.113817
	[-0.96055]	[-2.31845]	[-0.68985]
D(LQ(-2))	-0.140844	0.007462	0.050176
	[-1.22868]	[0.19726]	[0.33166]
D(LQ(-3))	0.144091	0.030648	0.159799
	[1.26532]	[0.81551]	[1.06323]
D(LQ(-4))	0.384292	0.026760	0.330280
	[3.60015]	[0.75966]	[2.34439]
D(LGDP(-1))	-2.399277	-0.192383	-1.018109
	[-5.52418]	[-1.34222]	[-1.77611]
D(LGDP(-2))	-1.646752	0.208633	-0.444109
	[-3.38976]	[1.30135]	[-0.69266]
D(LGDP(-3))	0.607314	0.346376	0.842067
	[1.29778]	[2.24288]	[1.36340]
D(LGDP(-4))	0.463453	0.289177	-0.205668
	[1.07057]	[2.02415]	[-0.35997]

D(LCPERS(-1))	0.269255	0.107483	0.336510
	[2.31927]	[2.80541]	[2.19622]
D(LCPERS(-2))	0.602593	0.036651	0.013306
	[4.69249]	[0.86484]	[0.07851]
D(LCPERS(-3))	0.332915	0.012317	0.333891
	[2.46699]	[0.27658]	[1.87469]
D(LCPERS(-4))	0.132371	-0.080160	-0.095826
	[0.94262]	[-1.72972]	[-0.51703]
LIPDP(-3)	-0.287834	-0.023852	-0.169516
	[-2.30624]	[-0.57910]	[-1.02912]
D_2	-0.087666	0.042137	0.096116
	[-1.25683]	[1.83053]	[1.04407]
D_3	-0.034910	0.065893	0.017760
	[-0.54260]	[3.10347]	[0.20915]
D_4	0.137688	0.072975	0.064307
	[2.35057]	[3.77503]	[0.83181]
R-squared	0.914534	0.860967	0.804377
Adj. R-squared	0.884807	0.812608	0.736334
Sum sq. resids	0.129203	0.014071	0.225057
S.E. equation	0.052998	0.017490	0.069947
F-statistic	30.76408	17.80354	11.82163
Log likelihood	105.5764	175.4198	88.09478
Akaike AIC	-2.811949	-5.029201	-2.256977
Schwarz SC	-2.233642	-4.450895	-1.678671
Mean dependent	0.008644	0.007435	0.014480
S.D. dependent	0.156150	0.040403	0.136220
Determinant Residual Covariance		3.73E-09	
Log Likelihood		372.8750	
Log Likelihood (d.f. adjusted)		343.1554	
Akaike Information Criteria		-9.147789	
Schwarz Criteria		-7.276799	

VECM Lag Exclusion Wald Tests
Sample: 1980:1 1996:4
Included observations: 63

Chi-squared test statistics for lag exclusion: Numbers in [ ] are p-values

	D(LQ)	D(LGDP)	D(LCPERS)	Joint
DLag 1	35.46710 [9.71E-08]	11.46510 [0.009459]	7.640540 [0.054055]	50.79211 [7.64E-08]
DLag 2	26.63613 [7.02E-06]	4.312551 [0.229632]	0.634623 [0.888463]	33.88874 [9.34E-05]
DLag 3	19.71948 [0.000194]	7.306693 [0.062739]	13.37432 [0.003893]	33.02183 [0.000132]
DLag 4	26.15677 [8.84E-06]	6.070232 [0.108243]	6.144125 [0.104805]	34.75783 [6.57E-05]
df	3	3	3	9

Residual Tests for the VECM Model

Equation	Autocorrelation[a] $F_{AR}(5,40)$	Heteroskedasticity[b] $F_{ARCH}(4,37)$	Normality[c] $\chi^2(2)$	Functional Form[d] F(28,16)
ΔLQ	0.68[0.639]	0.78[0.535]	4.45[0.108]	0.64[0.855]
ΔLCPERS	1.89[0.118]	0.45[0.774]	3.46[0.177]	0.43[0.975]
ΔLGDP	0.80[0.555]	0.22[0.928]	16.36[0.000]**	0.18[1.000]
System:	$F_{AR}(45,83)=0.67$ [0.923]		$\chi^2(6)=22.98$ [0.001] **	F(168,72)= 0.39[1.000]

Note: Values in square brackets are marginal significance levels and *indicates that the null hypothesis is rejected at the 5 percent level. [a)] Autocorrelation of the residuals of individual equations and a whole system was examined using the F–form of the Lagrange-Multiplier (LM) test, which is valid for systems with lagged dependent variables. [b)] Heteroskedasticity was tested using the F-form of the LM test against 4th order autoregressive conditional heteroskedasticity. [c)] Normality of the residuals of individual equations and the whole system was tested with the Doornik-Hansen test (Doornik and Hansen 1994). For further detail and test references, see Doornik and Hendry (1997). [d] Functional form was tested using the Ramsey Reset-test.

VECM Pairwise Granger Causality/Block Exogeneity Wald Tests
Sample: 1980:1 1996:4
Included observations: 63

Dependent variable: **D(LQ)**

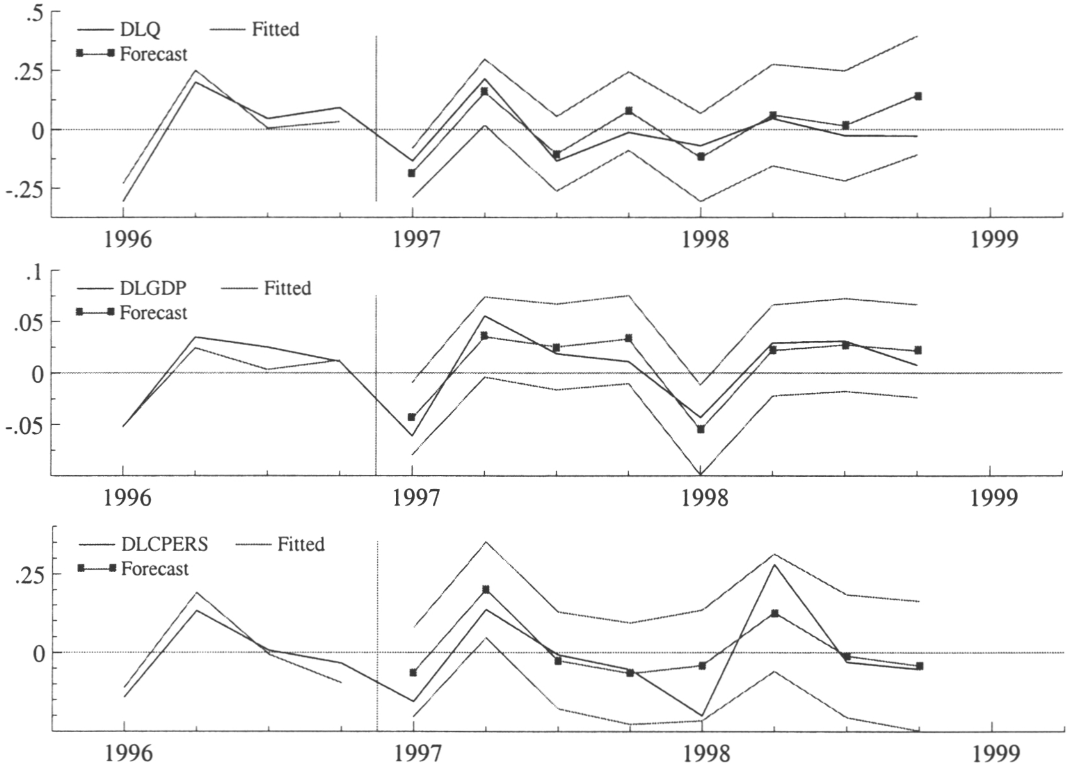
Exclude	Chi-sq	df	Prob.
D(LGDP)	37.51679	4	0.0000
D(LCPERS)	35.37648	4	0.0000
All	51.84820	8	0.0000

Dependent variable: **D(LGDP)**

Exclude	Chi-sq	df	Prob.
D(LQ)	7.899404	4	0.0953
D(LCPERS)	12.37544	4	0.0148
All	15.37017	8	0.0523

Dependent variable: **D(LCPERS)**

Exclude	Chi-sq	df	Prob.
D(LQ)	6.317263	4	0.1767
D(LGDP)	5.922174	4	0.2050
All	11.09322	8	0.1965



VECM-Model Dynamic Forecasts and Error Bars for ±2 Standard Errors, 1997:1-1998:4

APPENDIX IIIb: Finnish Sawnwood Export Model

Model I: Autoregressive (Naïve) Model

Dependent Variable: LDIFQ
Sample(adjusted): 1980:4 1996:4, 65 obs. after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LDIFQ(-1)	0.506938	0.100036	5.067565	0.0000
LDIFQ(-3)	0.241474	0.097683	2.472021	0.0164
D1	-0.223297	0.052161	-4.280932	0.0001
D2	0.080363	0.050736	1.583959	0.1186
D3	-0.187192	0.050405	-3.713773	0.0005
TREND1	-0.008224	0.003106	-2.647557	0.0104
C	3.137805	1.125080	2.788962	0.0071

R-squared	0.655316	Mean dependent var	12.05545
Adjusted R-squared	0.619659	S.D. dependent var	0.228628
S.E. of regression	0.140999	Akaike info criterion	-0.978691
Sum squared resid	1.153077	Schwarz criterion	-0.744527
Log likelihood	38.80747	F-statistic	18.37832
Durbin-Watson stat	1.892753	Prob(F-statistic)	0.000000

Breusch-Godfrey Serial Correlation LM Test (5th order):

F-statistic	0.814250	Probability	0.544876
Obs*R-squared	4.636858	Probability	0.461784

ARCH Test (1st order):

F-statistic	0.771749	Probability	0.383069
Obs*R-squared	0.786849	Probability	0.375054

Doornik-Hansen Normality-Test:

$\chi^2_{(2)} = 2.99 \quad [0.22]$

Ramsey RESET Test:

F-statistic	0.091723	Probability	0.763101
Log likelihood ratio	0.104508	Probability	0.746486

Chow Forecast Test: Forecast from 1997:1 to 1998:4

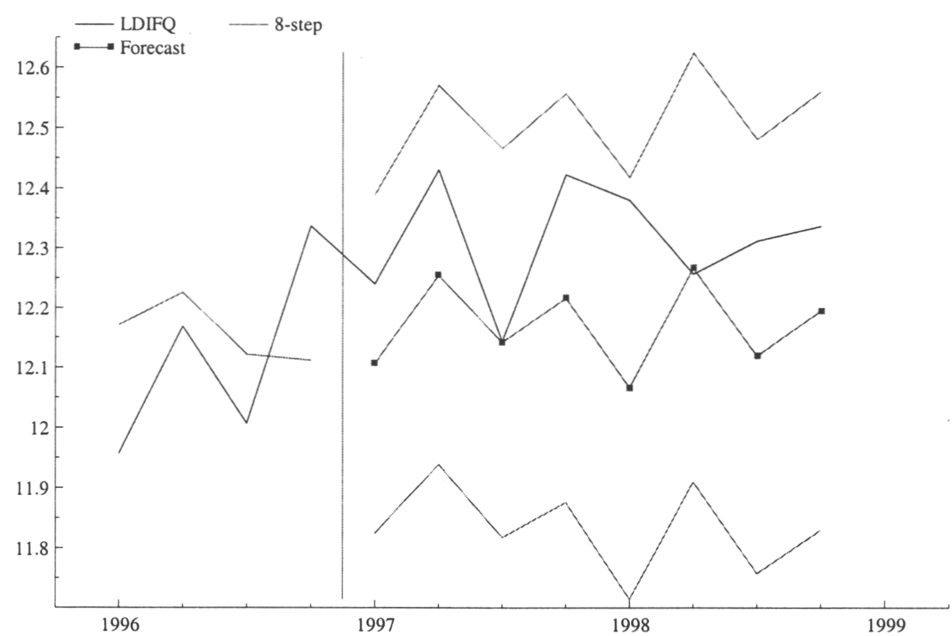
F-statistic	0.870316	Probability	0.546638
Log likelihood ratio	8.275842	Probability	0.406999

Appendix IIIb:2

Residual Auto- and Partial Autocorrelations

Sample: 1980:4 1996:4, 65 obs.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	0.026	0.026	0.0446	0.833
.*| . |	.*| . |	2	-0.074	-0.075	0.4240	0.809
. |*. |	. |*. |	3	0.113	0.118	1.3240	0.723
.*| . |	.*| . |	4	-0.060	-0.075	1.5838	0.812
. | . |	. | . |	5	0.032	0.056	1.6566	0.894
**| . |	***| . |	6	-0.293	-0.330	7.9788	0.240
. | . |	. |*. |	7	0.007	0.077	7.9824	0.334
. |*. |	. | . |	8	0.097	0.014	8.7016	0.368
.*| . |	.*| . |	9	-0.151	-0.066	10.473	0.314
. | . |	.*| . |	10	-0.035	-0.082	10.569	0.392



Naïve Model Dynamic Forecasts and Error Bars for ±2 Standard Errors, 1997:1-1998:4

Model II: Partial Model

Dependent Variable: LDIFQ
Sample (adjusted):1980:4 1996:4, 65 obs. after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.222124	1.768570	1.821881	0.0738
LDIFQ(-1)	0.247883	0.112639	2.200677	0.0319
LQ(-3)	0.647282	0.139703	4.633282	0.0000
LDIFP(-1)	-0.993517	0.351635	-2.825419	0.0065
LDISP	0.505209	0.294166	1.717425	0.0914
TREND1	-0.010137	0.002918	-3.474115	0.0010
D1	-0.258156	0.047339	-5.453320	0.0000
D2	-0.036472	0.054150	-0.673528	0.5034
D3	-0.276572	0.050172	-5.512518	0.0000

R-squared	0.733578	Mean dependent var	12.05545
Adjusted R-squared	0.695518	S.D. dependent var	0.228628
S.E. of regression	0.126157	Akaike info criterion	-1.174695
Sum squared resid	0.891270	Schwarz criterion	-0.873626
Log likelihood	47.17759	F-statistic	19.27411
Durbin-Watson stat	1.951015	Prob(F-statistic)	0.000000

Breusch-Godfrey Serial Correlation LM Test (5^{th} order):

F-statistic	0.636355	Probability	0.672907
Obs*R-squared	3.817065	Probability	0.576043

ARCH Test (1^{st} order):

F-statistic	0.102301	Probability	0.750161
Obs*R-squared	0.105427	Probability	0.745412

Doornik-Hansen Normality-Test:

$\chi^2_{(2)} = 1.02 \quad [0.60]$

Ramsey RESET Test:

F-statistic	0.583891	Probability	0.448057
Log likelihood ratio	0.686416	Probability	0.407386

Chow Forecast Test: Forecast from 1997:1 to 1998:4

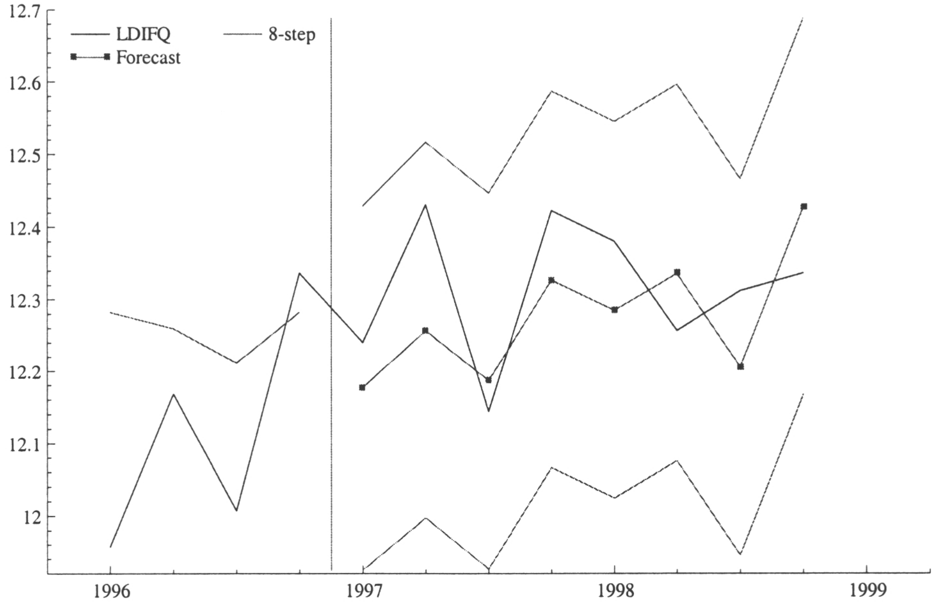
F-statistic	0.710724	Probability	0.680909
Log likelihood ratio	7.059249	Probability	0.530254

Appendix IIIb:4

Residual Auto- and Partial Autocorrelations

Sample: 1980:4 1996:4, 65 obs.

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. | . |	. | . |	1	0.019	0.019	0.0249	0.875
. | . |	. | . |	2	-0.010	-0.010	0.0312	0.985
. | . |	. | . |	3	0.012	0.012	0.0405	0.998
**| . |	**| . |	4	-0.193	-0.194	2.7041	0.608
. | . |	. | . |	5	-0.045	-0.038	2.8486	0.723
**| . |	**| . |	6	-0.240	-0.253	7.1140	0.310
. | . |	. | . |	7	-0.030	-0.024	7.1830	0.410
. |*. |	. | . |	8	0.075	0.024	7.6124	0.472
.*| . |	.*| . |	9	-0.108	-0.132	8.5119	0.483
. | . |	.*| . |	10	0.023	-0.076	8.5550	0.575



Partial Model Dynamic Forecasts and Error Bars for ±2 Standard Errors, 1997:1-1998:4

Lag Order Selection Criteria for the Unrestricted VAR-Model

Endogenous variables: LDIFQ LQ LDIFP LDISP
Exogenous variables: C D1 D2 D3 TREND1
Sample: 1980:1 1996:4, 62 obs.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	280.2782	NA	2.66E-09	-8.396072	-7.709900	-8.126664
1	395.1282	196.3564	1.10E-10	-11.58478	-10.34967*	-11.09985
2	418.5210	36.97572	8.84E-11	-11.82326	-10.03921	-11.12280*
3	440.2802	31.58586	7.58E-11	-12.00904	-9.676052	-11.09305
4	460.7650	27.09285*	6.92E-11*	-12.15371*	-9.271786	-11.02219
5	473.4959	15.19496	8.35E-11	-12.04826	-8.617394	-10.70121
6	490.4163	18.01203	9.16E-11	-12.07795	-8.098146	-10.51538

*indicates lag order selected by the criterion.
LR: sequential modified LR test statistic (each test at 5% level), FPE: Final prediction error, AIC: Akaike information criterion and SC: Schwarz information criterion

Residual Tests for the Unrestricted VAR-Model with 4 lags

Equation	Autocorrelation[a] F_{AR} (4,39)	Heteroskedasticity[b] F_{ARCH} (4,35)	Normality[c] $\chi^2(2)$	Functional Form[d] F(34,8)
ΔLDIFQ	2.54 [0.055]	0.33 [0.853]	9.33 [0.009] **	0.13[1.000]
ΔLQ	2.04 [0.108]	0.38 [0.824]	0.23 [0.892]	0.41[0.966]
ΔLDIFP	0.36 [0.835]	1.19 [0.330]	7.89 [0.019] *	0.34[0.986]
ΔLDISP	0.90 [0.473]	0.61 [0.657]	11.10 [0.004] **	0.49[0.93]
System:	F_{AR} (64,96)=1.34 [0.098]		χ^2(8)=19.51 [0.012]*	F(340,18) = 0.09[1.000]

Note: Values in square brackets are marginal significance levels and *indicates that the null hypothesis is rejected at the 5 percent level. [a)] Autocorrelation of the residuals of individual equations and a whole system was examined using the F–form of the Lagrange-Multiplier (LM) test, which is valid for systems with lagged dependent variables. [b)] Heteroskedasticity was tested using the F-form of the LM test against 4th order autoregressive conditional heteroskedasticity. [c)] Normality of the residuals of individual equations and the whole system was tested with the Doornik-Hansen test (Doornik and Hansen 1994). For further detail and test references, see Doornik and Hendry (1997). [d] Functional form was tested using the Ramsey Reset-test.

Appendix IIIb:6

Pairwise Granger Causality Tests for the Variables of the Unrestricted VAR-Model

VAR Pairwise Granger Causality/Block Exogeneity Wald Tests
Sample: 1980:1 1996:4, 64 obs.

Dependent variable: **LDIFQ**

Exclude	Chi-sq	Df	Prob.
LQ	11.41103	4	0.0223*
LDIFP	5.225109	4	0.2650
LDISP	1.137737	4	0.8882
All	20.61702	12	0.0563

Dependent variable: **LQ**

Exclude	Chi-sq	Df	Prob.
LDIFQ	3.119126	4	0.5381
LDIFP	3.126019	4	0.5370
LDISP	0.934382	4	0.9196
All	12.23422	12	0.4271

Dependent variable: **LDIFP**

Exclude	Chi-sq	Df	Prob.
LDIFQ	15.73919	4	0.0034*
LQ	22.62381	4	0.0002*
LDISP	12.09505	4	0.0167*
All	57.35199	12	0.0000*

Dependent variable: **LDISP**

Exclude	Chi-sq	Df	Prob.
LDIFQ	5.698041	4	0.2229
LQ	2.240416	4	0.6916
LDIFP	5.846296	4	0.2109
All	13.14744	12	0.3584

*indicates rejection of the H0 hypothesis of non-causality at the 5 % level

Model III: Restricted VAR Model

Sample(adjusted): 1980:4 1996:4, 65 obs.t-statistics in [ ]

	LDIFQ	LDIQ
LDIFQ(-1)	0.389305	0.067148
	[2.66262]	[0.74029]
LDIFQ(-2)	-0.243328	-0.177819
	[-1.50579]	[-1.77376]
LDIFQ(-3)	0.041372	-0.082767
	[0.27572]	[-0.88913]
LDIQ(-1)	-0.039499	0.491434
	[-0.15065]	[3.02137]
LDIQ(-2)	0.079288	0.300151
	[0.27462]	[1.67577]
LDIQ(-3)	0.655505	0.279313
	[2.39099]	[1.64226]
C	3.700702	2.872198
	[1.83413]	[2.29460]
DS1	-0.295365	-0.302027
	[-4.98764]	[-8.22110]
DS2	-0.054405	-0.048769
	[-0.64010]	[-0.92491]
DS3	-0.320637	-0.082839
	[-3.66774]	[-1.52744]
LDIFP(-2)	-0.787389	-0.138230
	[-2.88038]	[-0.81510]
LDISP	0.207846	-0.111393
	[0.97108]	[-0.83892]
TREND1	-0.010447	-0.003808
	[-3.45975]	[-2.03257]

R-squared	0.741733	0.847880
Adj. R-squared	0.682133	0.812775
Sum sq. resids	0.863988	0.332517
S.E. equation	0.128900	0.079966
F-statistic	12.44518	24.15286
Log likelihood	48.18796	79.22116
Akaike AIC	-1.082706	-2.037574
Schwarz SC	-0.647829	-1.602697
Mean dependent	12.05545	13.84283
S.D. dependent	0.228628	0.184809
Determinant Residual Covariance		7.33E-05
Log Likelihood (d.f. adjusted)		124.9906
Akaike Information Criteria		-3.045863
Schwarz Criteria		-2.176108

Lag Order Selection Criteria for the Restricted VAR-Model
Endogenous variables: LDIFQ LDIQ
Exogenous variables: C DS1 DS2 DS3 LDIFP(-2) LDISP TREND1
Sample: 1980:1 1996:4, 62 obs.

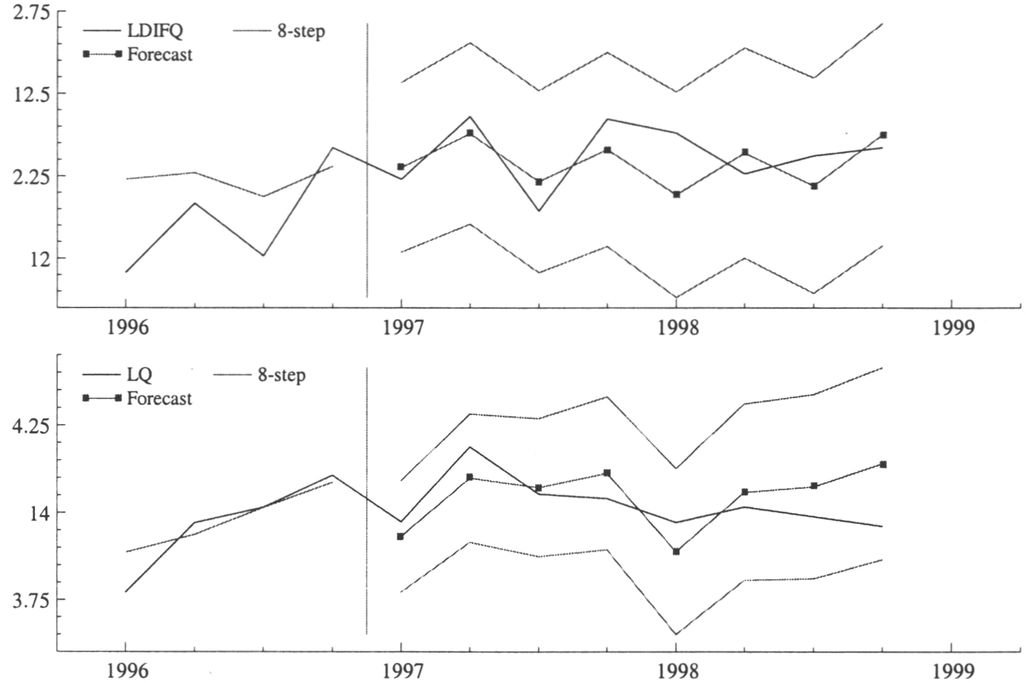
Lag	LogL	LR	FPE	AIC	SC	HQ
0	77.47036	NA	0.000443	-2.047431	-1.567110	-1.858845
1	122.8770	77.63066	0.000117	-3.383128	-2.765573*	-3.140661
2	128.2650	8.864236	0.000112	-3.427905	-2.673115	-3.131555
3	135.3417	11.18573*	0.000102*	-3.527152*	-2.635128	-3.176921*
4	136.0730	1.108699	0.000114	-3.421710	-2.392451	-3.017597
5	138.6649	3.762477	0.000121	-3.376288	-2.209795	-2.918293
6	143.1250	6.186542	0.000120	-3.391129	-2.087401	-2.879252

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Residual Tests for the Restricted VAR-Model with 3 lags for endogenous variables

Equation	Autocorrelation[a] F_{AR} (5,47)	Heteroskedasticity[b] F_{ARCH} (4,44)	Normality[c] $\chi^2(2)$	Functional Form[d] F(18,33)
ΔLDIFQ	1.92 [0.109]	0.20 [0.938]	8.86 [0.012] *	0.80 [0.683]
ΔLQ	0.42 [0.833]	0.49 [0.746]	0.44 [0.801]	0.92 [0.562]
System:	F_{AR} (20,82)= 0.72 [0.793]		$\chi^2(4)$= 8.31 [0.081]	F(36,110)=0.87 [0.715]

Note: Values in square brackets are marginal significance levels and *indicates that the null hypothesis is rejected at the 5 percent level. a) Autocorrelation of the residuals of individual equations and a whole system was examined using the F–form of the Lagrange-Multiplier (LM) test, which is valid for systems with lagged dependent variables. b) Heteroskedasticity was tested using the F-form of the LM test against 4th order autoregressive conditional heteroskedasticity. c) Normality of the residuals of individual equations and the whole system was tested with the Doornik-Hansen test (Doornik and Hansen 1994). For further detail and test references, see Doornik and Hendry (1997).(d Functional form was tested using the Ramsey Reset-test.



Restricted VAR-Model Dynamic Forecasts and Error Bars for ±2 Standard Errors, 1997:1- 1998:4

Johansen's Cointegration Rank-Test for the Restricted VAR Model with 3 Lags for endogenous Variables, 1980:4-1996:4.

Null hypothesis	Eigenvalues λ_I	λ Max.eigenv. - test statistics	95% critical values	λ Trace-test statistics	95% critical values
$r = 0$	0.33	26.04*	15.7	30.01**	20.00
$r \leq 1$	0.06	3.97	9.2	3.60	9.20

Note: ** indicates the rejection of the null-hypothesis at 1 % cent level.

Model IV. Vector Error Correction (VECM) Model

Sample(adjusted):1981:1 1996:4, 64 obs.
t-statistics in [ ]

Cointegrating Eq:	CointEq1	
LDIFQ(-1)	1.000000	
LDIQ(-1)	-0.856607 [-6.62981]	
C	-4.282961 [-1.82272]	

Error Correction:	D(LDIFQ)	D(LDIQ)
CointEq1	-0.856328 [-4.84796]	-0.257413 [-2.29296]
D(LDIFQ(-1))	0.274935 [1.47550]	0.332447 [2.80725]
D(LDIFQ(-2))	0.035075 [0.20382]	0.131012 [1.19783]
D(LDIFQ(-3))	0.120201 [0.79803]	0.059134 [0.61773]
D(LDIQ(-1))	-0.801976 [-2.65365]	-0.685199 [-3.56736]
D(LDIQ(-2))	-0.707101 [-2.23556]	-0.380448 [-1.89256]
D(LDIQ(-3))	0.005604 [0.02088]	-0.039991 [-0.23445]
DS1	-0.324181 [-3.53995]	-0.322756 [-5.54538]
DS2	-0.056078 [-0.59325]	-0.052382 [-0.87192]
DS3	-0.340675 [-3.45296]	-0.109460 [-1.74564]

LDIFP(-2)	-0.716479	-0.140404
	[-2.71963]	[-0.83856]
LDISP	0.141777	-0.031349
	[0.65932]	[-0.22938]
TREND1	-0.010070	-0.003236
	[-3.39044]	[-1.71420]
R-squared	0.727608	0.797372
Adj. R-squared	0.663516	0.749694
Sum sq. resids	0.838264	0.338598
S.E. equation	0.128205	0.081481
F-statistic	11.35253	16.72436
Log likelihood	47.91770	76.92629
Akaike AIC	-1.091178	-1.997696
Schwarz SC	-0.652655	-1.559173
Mean dependent	-0.001902	0.002358
S.D. dependent	0.221016	0.162863
Determinant Residual Covariance		7.43E-05
Log Likelihood		137.1326
Log Likelihood (d.f. adjusted)		122.6009
Akaike Information Criteria		-2.925028
Schwarz Criteria		-1.946784

VECM Residual Serial Correlation LM Tests

H0: no serial correlation at lag order h
Sample: 1980:1 1996, 64 obs.

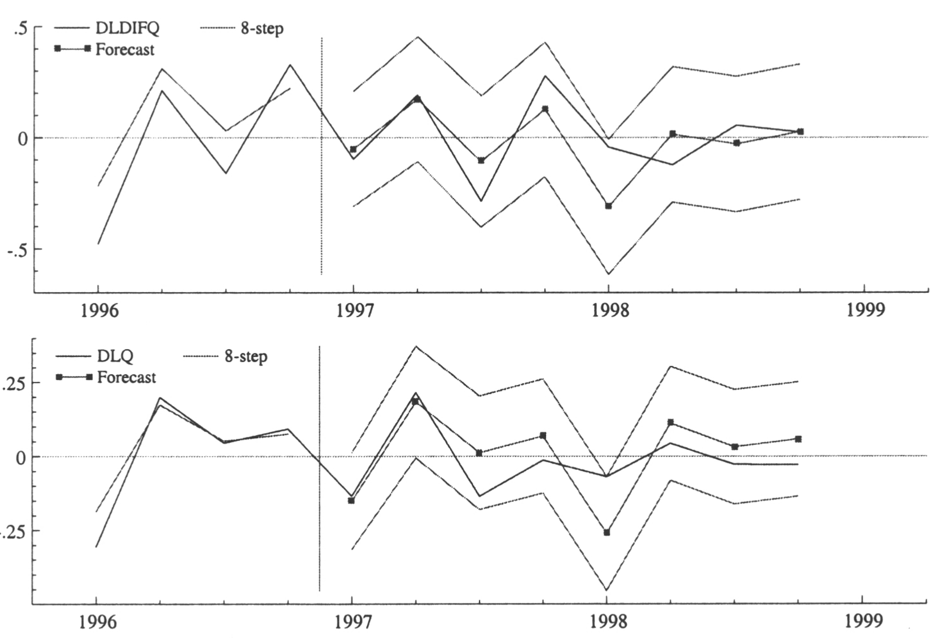
Lags	LM-Stat	Prob
1	5.336335	0.2545
2	1.997770	0.7362
3	1.951359	0.7447
4	8.305226	0.0810
5	2.989144	0.5596

Probs from chi-square with 4 df.

Residual Tests for the VECM Model with 3 lags for endogenous variables

Equation	Autocorrelation[a] $F_{AR}(4,46)$	Heteroskedasticity[b] $F_{ARCH}(4,42)$	Normality[c] $\chi^2(2)$	Functional Form[d] $F(20,29)$
ΔLDIFQ	2.06 [0.102]	0.062568 [0.9925]	9.87[0.007]**	0.63[0.858]
ΔLQ	2.48 [0.057]	0.24435 [0.9115]	1.20[0.550]	0.64[0.846]
System:	$F_{AR}(16,82)$= 1.38 [0.173]		$\chi^2(4)$= 7.85[0.097]	F(60,81)= 0.57 [0.987]

Note: Values in square brackets are marginal significance levels and *indicates that the null hypothesis is rejected at the 5 percent level. a) Autocorrelation of the residuals of individual equations and a whole system was examined using the F–form of the Lagrange-Multiplier (LM) test, which is valid for systems with lagged dependent variables. b) Heteroskedasticity was tested using the F-form of the LM test against 4th order autoregressive conditional heteroskedasticity. c) Normality of the residuals of individual equations and the whole system was tested with the Doornik-Hansen test (Doornik and Hansen 1994). For further detail and test references, see Doornik and Hendry (1997).(d Functional form was tested using the Ramsey Reset-test.



VECM Model Dynamic Forecasts and Error Bars for ±2 Standard Errors, 1997:1-1998:4

APPENDIX IIIc: Finnish Sawlog Demand Model

Model I: Autoregressive (Naïve) Model

Dependent Variable: LQKUT

Sample(adjusted): 1986:2 1996:4, 43 obs. after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.009549	1.221624	4.919312	0.0000
LQKUT(-1)	0.239620	0.161518	1.483545	0.1462
D1	-0.663722	0.224958	-2.950425	0.0054
D2	-0.757808	0.221652	-3.418915	0.0015
D3	-0.177792	0.232390	-0.765058	0.4490

R-squared	0.331222	Mean dependent var	7.376599
Adjusted R-squared	0.260825	S.D. dependent var	0.590073
S.E. of regression	0.507317	Akaike info criterion	1.589582
Sum squared resid	9.780077	Schwarz criterion	1.794373
Log likelihood	-29.17602	F-statistic	4.705022
Durbin-Watson stat	1.947013	Prob(F-statistic)	0.003494

Breusch-Godfrey Serial Correlation LM Test 5th order:

F-statistic	0.569805	Probability	0.722491
Obs*R-squared	3.417331	Probability	0.635932

ARCH 1st Order Test:

F-statistic	0.410730	Probability	0.525254
Obs*R-squared	0.426883	Probability	0.513522

Doornik-Hansen Normality-T

$\chi^2_{(2)} = 2.72 \quad [0.26]$

Ramsey RESET Test:

F-statistic	0.122041	Probability	0.728812
Log likelihood ratio	0.141598	Probability	0.706698

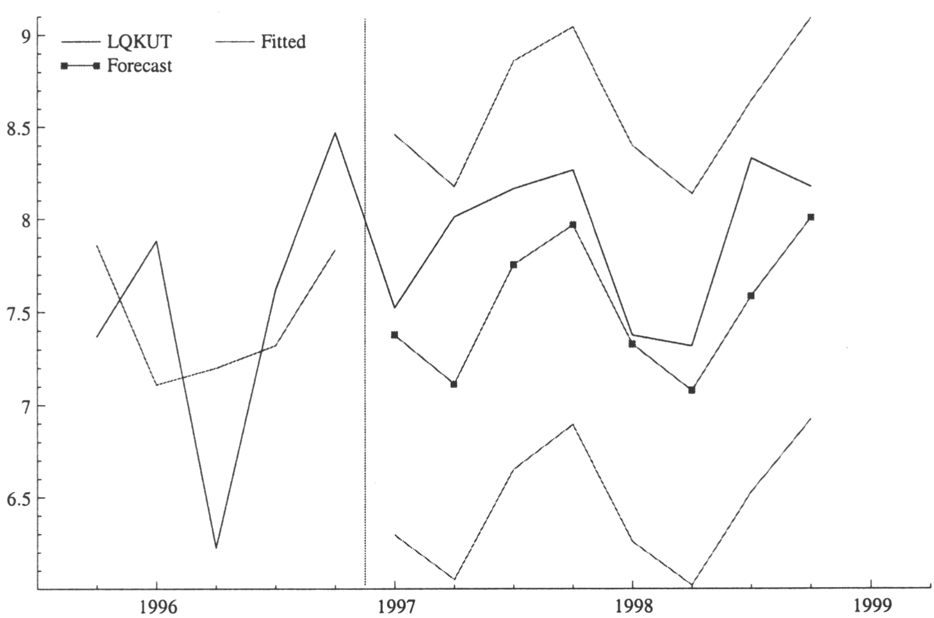
Chow Forecast Test: Forecast from 1997:1 to 1998:4

F-statistic	0.731519	Probability	0.663037
Log likelihood ratio	7.305121	Probability	0.504099

Residual Auto- and Partial Autocorrelations

Sample: 1986:2 1996:4, 43 obs.

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>. | . |</td><td>. | . |</td><td>1</td><td>-0.011</td><td>-0.011</td><td>0.0059</td><td>0.939</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>2</td><td>0.052</td><td>0.052</td><td>0.1319</td><td>0.936</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>3</td><td>0.045</td><td>0.047</td><td>0.2313</td><td>0.972</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>4</td><td>-0.127</td><td>-0.130</td><td>1.0374</td><td>0.904</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>5</td><td>-0.015</td><td>-0.022</td><td>1.0482</td><td>0.959</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>6</td><td>0.009</td><td>0.022</td><td>1.0528</td><td>0.984</td></tr>
<tr><td>. |** |</td><td>. |** |</td><td>7</td><td>0.214</td><td>0.234</td><td>3.5242</td><td>0.833</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>8</td><td>0.030</td><td>0.020</td><td>3.5725</td><td>0.893</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>9</td><td>-0.053</td><td>-0.094</td><td>3.7306</td><td>0.928</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>10</td><td>-0.054</td><td>-0.091</td><td>3.9023</td><td>0.952</td></tr>
</table>



Naive Model Dynamic Forecasts and Eerror Bars for ±2 Standard Errors, 1997:1-1998:4.

Appendix IIIc: 3

Model II: Partial Model

Dependent Variable: LQKUT
Method: Least Squares
Sample(adjusted): 1986:3 1996:4
Included observations: 42 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.773706	3.465415	-1.377528	0.1773
D_2	0.568014	0.308816	1.839325	0.0746
D_3	0.806750	0.252009	3.201269	0.0030
D_4	1.275209	0.347947	3.664948	0.0008
DLPKUT(-1)	6.409921	1.497131	4.281470	0.0001
LDIFQ(-2)	1.004898	0.286186	3.511349	0.0013
DLWOODQ(-2)	-2.401000	0.909131	-2.640983	0.0124
RECDUM	-1.100217	0.251498	-4.374656	0.0001

R-squared	0.760888	Mean dependent var	7.399688
Adjusted R-squared	0.711659	S.D. dependent var	0.577232
S.E. of regression	0.309959	Akaike info criterion	0.664887
Sum squared resid	3.266528	Schwarz criterion	0.995872
Log likelihood	-5.962636	F-statistic	15.45609
Durbin-Watson stat	2.091652	Prob(F-statistic)	0.000000

Breusch-Godfrey Serial Correlation LM Test 5^{th} order:

F-statistic	1.135165	Probability	0.364275
Obs*R-squared	6.874662	Probability	0.230130

ARCH 1^{st} Test:

F-statistic	0.121857	Probability	0.728907
Obs*R-squared	0.127707	Probability	0.720821

Doornik-Hansen Normality-Te

$\chi^2_{(2)} = 1.21 \quad [0.55]$

Ramsey RESET Test:

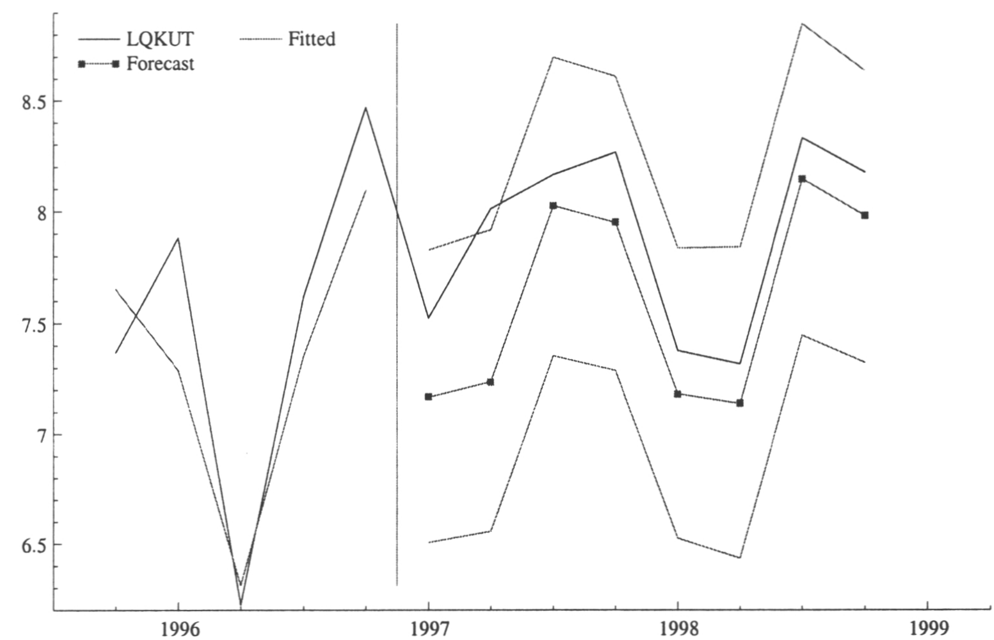
F-statistic	0.002206	Probability	0.962824
Log likelihood ratio	0.002807	Probability	0.957745

Chow Forecast Test: Forecast from 1997:1 to 1998:4

F-statistic	0.993504	Probability	0.458528
Log likelihood ratio	10.50355	Probability	0.231445

Residual Auto- and Partial Autocorrelations
Sample: 1986:3 1996:4; Included observations: 42

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.*| . |	.*| . |	1	-0.071	-0.071	0.2264	0.634
**| . |	**| . |	2	-0.194	-0.200	1.9590	0.375
. | . |	. | . |	3	0.032	0.001	2.0075	0.571
.*| . |	**| . |	4	-0.170	-0.215	3.4128	0.491
. | . |	.*| . |	5	-0.046	-0.078	3.5170	0.621
. | . |	. | . |	6	0.049	-0.049	3.6392	0.725
. |*. |	. |*. |	7	0.084	0.066	4.0131	0.778
.*| . |	**| . |	8	-0.157	-0.198	5.3541	0.719
. |*. |	. |*. |	9	0.099	0.095	5.9075	0.749
. |*. |	. |*. |	10	0.171	0.120	7.5885	0.669



Partial Model Dynamic Forecasts and Eerror Bars for ±2 Standard Errors, 1997:1-1998:4.

Model III: Vector Autoregressive (VAR) Model

VAR Lag Order Selection Criteria
Endogenous variables: LQKUT LPKUT
Exogenous variables: C LDIFQ(-2) DLWOODQ(-3) RECDUM DS2 DS3 DS4
Sample: 1986:3 1996:4
Included observations: 40

Lag	LogL	LR	FPE	AIC	SC	HQ
0	26.79907	NA	0.001821	-0.639954	-0.048846	-0.426228
1	79.09937	81.06545	0.000164	-3.054968	-2.294972	-2.780178
2	91.47061	17.93831*	0.000109*	-3.473531*	-2.544647*	-3.137676*
3	94.14566	3.611313	0.000119	-3.407283	-2.309511	-3.010363
4	98.88284	5.921474	0.000118	-3.444142	-2.177482	-2.986158

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

VAR Pairwise Granger Causality/Block Exogeneity Wald Tests
Sample: 1986:3 1996:4
Included observations: 42

Dependent variable: **LQKUT**

Exclude	Chi-sq	df	Prob.
LPKUT	15.42972	2	0.0004
All	15.42972	2	0.0004

Dependent variable: **LPKUT**

Exclude	Chi-sq	df	Prob.
LQKUT	8.796915	2	0.0123
All	8.796915	2	0.0123

VAR-Model. Sample(adjusted): 1986:3 1996:4
Included observations: 42 after adjusting endpoints; t-statistics in [ ]

	LQKUT	LPKUT
LQKUT(-1)	-0.132537	-0.037988
	[-0.88044]	[-2.92994]
LQKUT(-2)	-0.110287	0.007364
	[-0.88360]	[0.68498]
LPKUT(-1)	5.936678	1.689473
	[3.22011]	[10.6397]
LPKUT(-2)	-4.700851	-0.724646
	[-2.48124]	[-4.44087]
C	-8.857275	0.063971
	[-2.05762]	[0.17254]
D_2	0.639208	0.019365
	[1.38017]	[0.48546]
D_3	0.194254	-0.043995
	[1.01922]	[-2.68009]
D_4	0.609071	-0.013784
	[3.08609]	[-0.81089]
LDIFQ(-2)	0.962844	0.028556
	[3.15693]	[1.08707]
DLWOODQ(-3)	2.345003	0.168076
	[2.34905]	[1.95480]
RECDUM	-1.161383	-0.012770
	[-4.28514]	[-0.54705]
R-squared	0.787701	0.956300
Adj. R-squared	0.719218	0.942203
Sum sq. resids	2.900229	0.021515
S.E. equation	0.305869	0.026344
F-statistic	11.50206	67.83821
Log likelihood	-3.464940	99.51519
Akaike AIC	0.688807	-4.215009
Schwarz SC	1.143911	-3.759905

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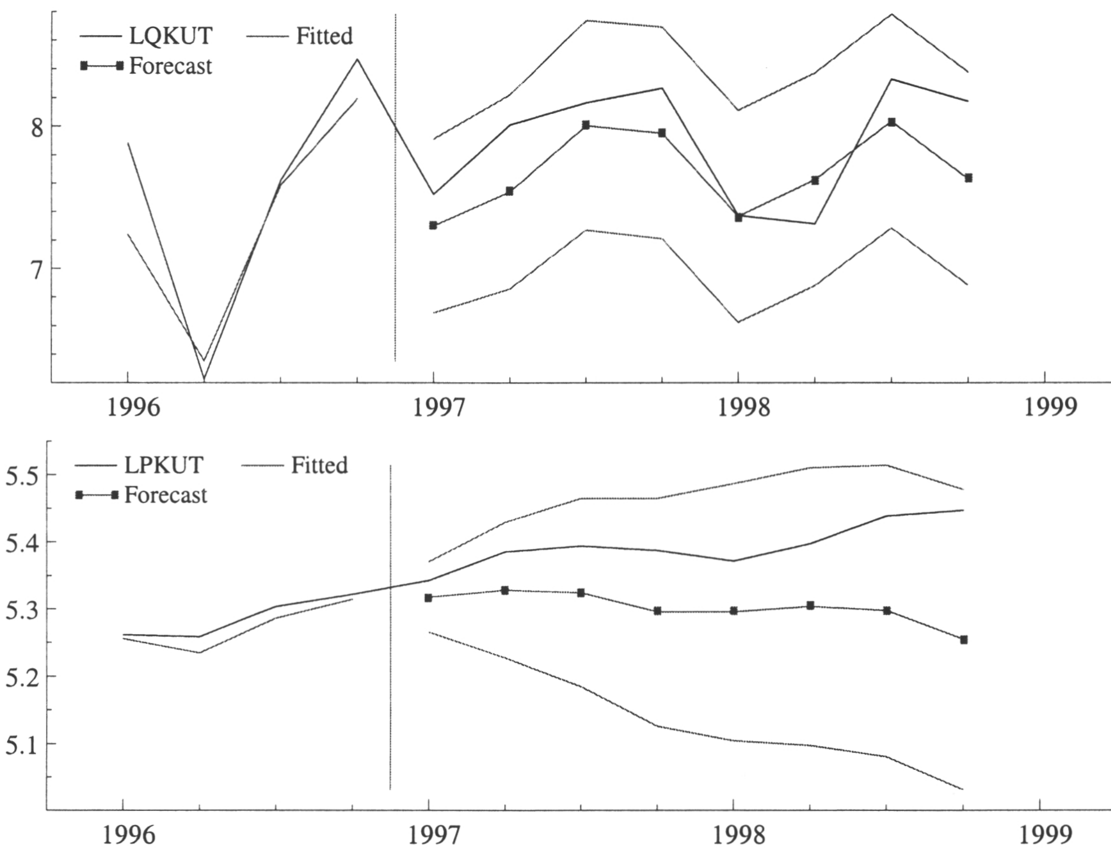
Mean dependent	7.399688	5.169661
S.D. dependent	0.577232	0.109581
Determinant Residual Covariance		6.09E-05
Log Likelihood (d.f. adjusted)		84.62532
Akaike Information Criteria		-2.982158
Schwarz Criteria		-2.071950



VAR Model Dynamic Forecasts and Eerror Bars for ±2 Standard Errors, 1997:1-1998:4.

Residual Tests of the VAR-Model with 2 lags

Equation	Autocorrelation[a] $F_{AR}(5, 26)$	Heteroskedasticity[b] $F_{ARCH}(3, 25)$	Normality[c] $\chi^2(2)$	Functional Form[d] $F(8,22)$
ΔLQKUT	0.97[0.454]	0.57[0.640]	4.57[0.102]	0.469[0.864]
ΔLPKUT	3.23[0.021]*	0.16[0.925]	2.89[0.236]	0.333[0.944]
System:	$F_{AR}(20, 40)$=1.22 [0.286]		$\chi^2(4)$ =7.11 [0.130]	$F_{AR}(24, 58)$= 0.66 [0.86]

Note: Values in square brackets are marginal significance levels. The * indicates that the null hypothesis is rejected at the 5 percent significance level. a) 5th Order autocorrelation of the residuals of individual equations and a whole system was examined using the F–form of the Lagrange-Multiplier (LM) test, which is valid for systems with lagged dependent variables. b) Heteroskedasticity was tested using the F-form of the LM test against 4th order autoregressive conditional heteroskedasticity. c) Normality of the residuals of individual equations and the whole system was tested with the Doornik-Hansen test. For further detail and test references, see Doornik and Hendry (1997). (d Functional form was tested using the Ramsey Reset-test.

Johansen's Cointegration Rank-Test, 1986:3-1996:4

Null hypothesis	Eigenvalues λ_I	λ Max.eigenv. - test statistics	95% critical values	λ Trace-test statistics	95% critical values
$r = 0$	0.67	47.42**	15.7	50.79**	20.00
$r \leq 1$	0.08	3.38	9.2	3.38	9.2

Note: ** indicates the rejection of the null-hypothesis at 1 % cent level;

Model III: Vector Error Correction (VECM) Model

Vector Error Correction Estimates
Sample(adjusted): 1986:4 1996:4
Included observations: 41 after adjusting endpoints. t-statistics in [ ]

Cointegrating Eq:	CointEq1
LQKUT(-1)	1.000000
LPKUT(-1)	-0.570698 [-0.91974]
C	-4.477842 [-1.40025]

Error Correction:	D(LQKUT)	D(LPKUT)
CointEq1	-0.898107 [-4.70834]	-0.037404 [-2.28188]
D(LQKUT(-1))	0.002464 [0.01431]	0.004811 [0.32521]
D(LQKUT(-2))	-0.043041 [-0.34480]	-0.002809 [-0.26184]
D(LPKUT(-1))	4.817222 [2.14065]	0.555070 [2.87032]
D(LPKUT(-2))	-1.053706 [-0.41120]	0.229262 [1.04111]
D_2	1.280883 [2.78841]	0.054306 [1.37570]
D_3	0.422508 [1.81682]	-0.047304 [-2.36703]
D_4	1.150806 [4.93605]	-0.006640 [-0.33141]
DLDIFQ	-0.818002 [-2.07974]	-0.028689 [-0.84880]
DLWOODQ(-3)	3.091534 [3.00762]	0.206611 [2.33902]

RECDUM	-0.921094 [-3.37785]	-0.018590 [-0.79334]
R-squared	0.862387	0.606530
Adj. R-squared	0.816516	0.475373
Sum sq. resids	3.031791	0.022389
S.E. equation	0.317899	0.027319
F-statistic	18.80022	4.624462
Log likelihood	-4.785897	95.83502
Akaike AIC	0.770044	-4.138294
Schwarz SC	1.229783	-3.678555
Mean dependent	0.038524	0.007792
S.D. dependent	0.742146	0.037717
Determinant Residual Covariance		7.08E-05
Log Likelihood		92.33440
Log Likelihood (d.f. adjusted)		79.52703
Akaike Information Criteria		-2.659855
Schwarz Criteria		-1.614994

Residual Tests for the VECM Model with 2 lags for endogenous variables

Equation	**Autocorrelation**[a] $F_{AR}(5,16)$	**Heteroskedasticity**[b] $F_{ARCH}(3,15)$	**Normality**[c] $\chi^2(2)$	**Functional Form**[d]
ΔDLQKUT	0.61[0.691]	0.22[0.882]	3.27[0.195]	F(15,5) 0.14[0.999]
ΔDLPKUT	0.38[0.858]	0.35[0.793]	1.04[0.594]	0.14[0.999]
System:	$VF_{AR}(20,20)$= 0.89 [0.600]		$V\chi^2(4)$=4.59 [0.332]	Vxi^2 F(45,9)= 0.17 [1.000]

Note: Values in square brackets are marginal significance levels and *indicates that the null hypothesis is rejected at the 5 percent level. a) Autocorrelation of the residuals of individual equations and a whole system was examined using the F–form of the Lagrange-Multiplier (LM) test, which is valid for systems with lagged dependent variables. b) Heteroskedasticity was tested using the F-form of the LM test against 4th order autoregressive conditional heteroskedasticity. c) Normality of the residuals of individual equations and the whole system was tested with the Doornik-Hansen test (Doornik and Hansen 1994). For further detail and test references, see Doornik and Hendry (1997). (d Functional form was tested using the Ramsey Reset-test.

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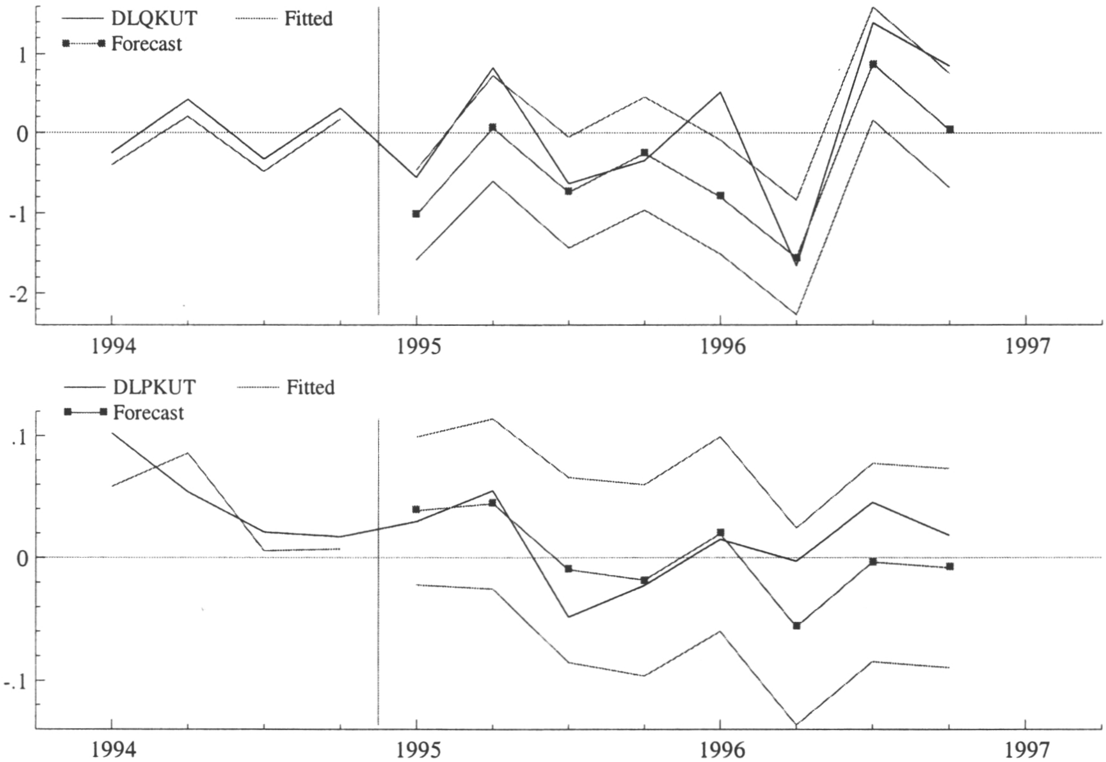

VECM Model Dynamic Forecasts and Error Bars for ±2 Standard Errors, 1997:1-1998:4.

ISBN 951-40-1775-7
ISSN 0358-4283
Hakapaino Oy 2001