Analysis of Lumber Price Transmission in the United States

Zhuo Ning

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Analysis of lumber price transmission in the United States

By

Zhuo Ning

A Thesis
Submitted to the Faculty of
Mississippi State University
in Partial Fulfillment of the Requirements
for the Degree of Master of Science
in Forestry
in the Department of Forestry

Mississippi State, Mississippi
August 2012
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Analysis of lumber price transmission in the United States

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The lumber industry in the South is an important sector, and has connections with many other key industries. The dynamics of the southern lumber market and its linkage with other related markets can be examined by the price transmissions. The first part of this study investigates vertical price transmission traced back to delivered sawlog market and stumpage market, and arrives at the conclusion that the supply chain is generally efficient with positive asymmetric transmission involved in one product. The second part explores the relationship between markets of the South and Pacific Northwest and concludes that the two markets are more balanced with each other after various demand and supply shocks with two regime switching models. This research will benefit market participants and policy makers to update their knowledge and obtain efficient information before decision making.

Key words: market integration, price transmission, regime switching, timber market, time series data
DEDICATION

I would like to dedicate this research to my beloved friend in heaven, Ruizhi Jia.
ACKNOWLEDGEMENTS

The author intends to acknowledge a number of individuals, without whose assistance this thesis could not be accomplished. First of all, sincere gratitude is expressed to Dr. Changyou Sun, the author’s major professor, for his conscientious guidance and full support throughout the master program. The principles learned from him on how to be a good young professional would benefit the author for life.

Appreciations are also due to members of my committee, Dr. Ian Munn and Dr. Randy Campbell. Both of them have been very approachable, helpful, and have provided invaluable assistance during the advising process.

Special thanks are also delivered to Dr. David Jones and Dr. Rubin Shmulsky for their answers on questions about grading and characteristics of lumber products, and Mr. James Howard and Mr. Zoe Abrams for their providing of the most recent data on lumber production.

Finally, the author would like to thank her parents, Kai Li and Weibo Ning, and her fiancé Lei Feng, for their understanding and support during the past two years.
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Lumber production is an important industry sector in the southern United States, with considerable contribution to the regional economy and strong linkage with other sectors such as the housing sector (Lutz, 2012). On one hand, lumber production in the South is vertically connected with upstream timber industries, for example, productions of stumpage and sawlog. On the other hand, it is also spatially linked with lumber industries in other parts of the country, especially another important supplier of lumber products, the Pacific Northwest.

Lumber markets can be studied by price transmission analysis. Because demand and supply behavior is difficult to observe record and analyze, price is often regarded as a sign related to demand and supply, and also a symbol for transaction activity. Therefore, price transmission analysis can be used to assess dynamics of the lumber market vertically and spatially. The analysis can also drop a hint on market structure and market power.

Research on price transmission is important currently, given the stored stumpages that are expected to be harvested earlier postponed by the depression of the housing market. Lumber production decreased one third, compared to recent years, leaving a large proportion of expected harvest still on the mature. Although the economy is on its way to recovery, it will take a few years for housing starts to return to their long term average. Therefore, this surplus will keep prices depressed for an extended period (Lutz, 2012).
Except for the depression, there are also other market shocks in the most recent half century, including harvesting restrictions imposed on federal forests in the Pacific Northwest around 1990, collapse in the Asian housing market around the year 1997, which has greatly reduced export volume, Hurricane Hugo in 1989 and Hurricane Katrina in 2005, and disputes in softwood lumber trade between the US and Canada. Although not all the shocks are directly related to the southern lumber market, they may impact this market through arbitrage activities and price transmissions. To understand market dynamics and mechanisms, vertical and spatial analyses of price transmissions are needed.

The overall objective of this study is to examine the price transmission mechanisms in the southern timber market in United States, and furthermore, to provide an understanding of the efficiency of market information and shifts in welfare distribution after market shocks among timber suppliers, processors and consumers. Under the overall goal, two specific objectives are (1) to examine the dynamics between upstream and downstream prices at three stages in forestry sector in southern United States, and (2) to inspect the influence of western fir prices on southern pine prices especially after harvesting restrictions in 1994.

Thus, two relatively independent papers in journal article style are included. The first one analyzes the price dynamics between prices of standing timber, delivered timber and two representative lumber prices on cointegration and asymmetric price transmission. With the results, impediments against efficient recoveries from market shocks are discussed. A similar objective is expected to be done with the spatial analysis in the second study. Lumber prices of southern yellow pine and Douglas firs are collected to
investigate regime switching behavior in the past 40 years; discriminations among various products are worked on with different performances of their prices.

The thesis is organized as follows. Chapter II contains the first article, entitled “Vertical price linkage between timber and forest products prices in the South”. Four pairs of quarterly data are adopted to testify the hypothesis of symmetric price transmission in southern United States. Chapter III contains the second article, entitled “Spatial price linkage between forest products markets in the South and Northwest”. Three pairs of monthly prices are used to examine market dynamics related to market shocks and recoveries. Finally, Chapter IV summarizes the conclusions for this thesis. It also provided the limitation of this thesis and discussion for future studies.
CHAPTER II

VERTICAL PRICE LINKAGE BETWEEN TIMBER AND FOREST PRODUCTS
IN THE SOUTH

2.1 Introduction

Pine sawtimber production is a traditional and important sector in the South. More than two thirds of softwood in the United States is produced in the South (Howard & Laboratory, 2003). Timber demand and supply has changed a lot with forestland transaction, transmission of timberland ownerships, innovative methods of silviculture, evolution of domestic and international trade, and particularly, market shocks.

Along the supply chain of sawtimber, there are three key stages from upstream to downstream: stumpage is the timber in storage form; sawlog is the raw material of lumber; and lumber is one of the most important ultimate products of stumpage and sawlogs. Market participants, including industrial firms and individuals, are involved in the market at each stage. The logging industry is small and often composed of self-employed loggers. Although historically small sawmills with few workers were the mainstream across the South, technology improvement has altered this situation a lot, and the majority of lumber production is from large sawmills today. Usually, they do not have stable timber source, but search for gatewood, stumpage and other sources within the limit of their woodshed (Anderson & Germain, 2007). The situation of stumpage ownerships is complex: although about 90 percent timberland owners are private, the largest timber suppliers in the South are forest companies (TIMO and RRITS). Power for
pricing can be matched with size of the industries: sawmills are relatively more influential; impacts from loggers and timber transporters are limited; due to the huge potential supply by numerous non-industrial private timberland owners, industrial timberland investors rarely raise or depress price initially, and which can usually be treated as price takers. Consequently, lumber suppliers have stronger initiative on pricing than market participants at the other two stages in the South.

Yin and Caulfield (2002) focus on timber prices and conclude that real prices in the timber market have become more volatile after the early 1990s. The harvesting restrictions in the Pacific Northwest, trade dispute with Canada, damage on forests caused by Hurricane Hugo and Katrina, and the demand shock brought by debt crisis have enhanced this volatility. No matter at which stage a supply or demand shock occurs, it will be vertically transmitted to the other two upward or downward. Traditionally, economic theory has assumed that prices adjust rapidly to equate demand and supply (Brännlund, 1991), which means an upstream price change symmetrically triggers downstream price change, other things being equal. However, symmetric price transmission is not a natural result of market dynamics.

Recent literature provides evidence of asymmetric price transmission (APT) in agriculture, gasoline, and financial markets (Meyer & Cramon-Taubadel, 2004). APT occurs when downstream prices react in a different manner to upstream price changes, depending on the characteristics of upstream prices or changes in those prices. Consequently, a group is not benefiting from a price reduction (buyers), or increase (sellers) that would under conditions of symmetry have taken place sooner and/or have been of greater magnitude than observed (Meyer & Cramon-Taubadel, 2004). In spite of its importance, whether it exists in southern timber market is still unclear. This has
implications for many public policy programs. For example, the cost-share program that intends to reduce costs in an upstream stage may not benefit lumber consumers efficiently. Likewise, monetary policies that keep low interest rate to stimulate the housing market may not benefit loggers or landowners because the profit could be captured by others along the manufacturing process.

Direction of causality along the supply chain is another important issue. According to price determination theory, changes in producer prices determine changes in retail prices. In other words, price transmission flows downward along the supply chain, and the direction of causality runs from upstream to downstream. However, empirical results from studies on different commodities in different countries about this issue are mixed (Saghaian, 2007). For example, Tiffin and Dawson (2000) study the UK lamb market and find that lamb prices are determined in the retail market and then pass upward along the supply chain; the direction of causality is from retail to producer prices. However, Ben-Kaabia, Gill, and Boshnjaku (2002) find both supply and demand shocks are fully passed through the marketing channel, so there is a complete price transmission. In summary, the prior assumption toward the causality direction from upstream to downstream is not necessary, so upstream and downstream prices can both be set as a driving force to the other when estimating the models. Moreover, significance of the causality assumptions can be tested by econometric models.

Depending on the issues and study purposes, APT has been classified and analyzed in several ways. One typical classification is positive versus negative APT. If one price (e.g., price of petrol) reacts more fully or rapidly to an increase in another price (e.g., price of crude oil) than to a decrease, then the price transmission is referred to as positive asymmetry (Meyer & Cramon-Taubadel, 2004). More generally, with positive
APT, price movement that squeezes the profit margin is transmitted more rapidly or completely than the equivalent movement that stretches the profit margin. Conversely, APT is negative when price movements that stretch the margin are transmitted more rapidly or completely. However, it is obvious that this classification of APT will be inverted if the assumed causality between variables changes. According to the conclusion drawn from former research, positive APT is more widespread in natural resource market than the negative one (Meyer & Cramon-Taubadel, 2004). In addition, APT can also be classified as vertical or spatial. A typical example of vertical APT is that consumers often feel increases in farm prices more fully and rapidly transmitted to retail levels than the equivalent decreases (Kinnucan & Forker, 1987). A spatial ATP can be observed when the price of a central market transmits differently to peripheral markets. When this classification is employed in this study, vertical APT among different stages in the southern timber market is the concern.

The objective of this chapter is to examine dynamics between upstream and downstream prices among three stages in the forestry sector in the South, and furthermore, to provide an understanding of market information efficiency and welfare distribution among timber suppliers, processors and consumers. Under the objective, three specific questions are addressed: firstly, is there APT in the forestry sector in the South; secondly, if it exists, what are the magnitude and direction; and finally, the extent to which the deviation can return to equilibrium, and if it can, how long would it take.

To achieve the objective, the remainder of this chapter is organized as follows. In the second section, a literature review is presented. In the third section, the applied methodology is described, including the linear and threshold cointegration approaches.
and the asymmetric error correction model. Following that, the data and the empirical results are given and explained. The final section is the conclusion.

2.2 Literature review

2.2.1 Causes of APT

Various sources of APT have been discussed in the literature (Frey & Manera, 2007). One reason that is widely approved is the market power of traders. Retailers who possess market power try to raise the price immediately to maintain their normal profit, when upstream prices rise. But they will try to capture the expanding profit, at least temporarily, when upstream prices fall (Ben-Kaabia & Gil, 2007). Another cause of spatial APT frequently cited is the asymmetric flow of information between central and peripheral markets (Abdulai, 2000). Prices at a central market, by virtue of its size and network of information, may tend to be less responsive to price changes in individual peripheral market than vice versa. Additionally, if increasing cost is the reason, the farm-retail price transmission elasticity is smaller than if it is expanding demand that has pushed up the price (Kinnucan & Forker, 1987). This suggests that retail competition does not necessarily translate into larger retail price decreases during periods of declining farm price. Other causes of APT include political intervention, inventory management (Meyer & Cramon-Taubadel, 2004) and inflation (Ball & Mankiw, 1994). In spite of potential causes of asymmetric price transmission, empirical analyses on this phenomenon typically do not allow differentiation among the different possible causes (Capps Jr & Sherwell, 2007).
2.2.2 Evolution of models and tests of APT

There are a great number of research articles on market integration and price transmission along the marketing channels. Econometric methods focusing on price transmission with time series data are rooted in the development of cointegration analysis. However, the cointegration technique is used to survey only the speed but not the magnitude of the price transmission (Koutroumanidis, Zafeiriou, & Arabatzis, 2009). Before the 1980s, many economists use linear regressions on nonstationary time series data, which can produce spurious correlation (Clive Granger, 1981). In a study by Perron (1989), tests for unit roots are shown to have low power in the presence of structural breaks that are not taken into account.

Different from traditional methods that treat nonstationary data as normal, models begin to consider the nonstationary property of data and incorporate the cointegration concept into the analysis. The two major cointegration methods are Johansen and Engle-Granger two-step approaches. Both of them assume symmetric relationship between variables. As one of study of this type, Von Cramon-Taubadel (1998) uses cointegration and error correction representation to analyze the transmission between producer and wholesale pork prices in northern Germany. The analysis demonstrates that the price transmission is asymmetric and the margin is corrected more rapidly when it is squeezed relative to its long-term level, than when it is stretched.

Later price transmission studies utilize the error correction model with threshold cointegration. The rationale is that if the true long-term relationship between two prices is asymmetric, a test for cointegration based on a symmetric long-term equilibrium may result in misleading findings. Balke and Fomby (1997) point out that the presence of the fixed costs of adjustment may prevent economic agents from adjusting continuously.
Only when the deviation from the equilibrium exceeds a critical threshold do the benefits of adjustment exceed the costs and, hence economic agents act to move the system back towards the equilibrium. Enders and Granger (1998) and Enders and Siklos (2001) further generalize the standard Dickey-Fuller test by allowing for the possibility of asymmetric movements in time series data. This makes it possible to test for cointegration without maintaining the hypothesis of a symmetric adjustment to a long-term equilibrium.

2.2.3 Achievement of past studies in forestry

Price transmission dynamics has been the subject of several papers in the forest products sector across different areas, but generally speaking, previous studies of linkage between forest product markets are limited (Hänninen, Toppinen, & Toivonen, 2007). Early works emphasize the determinants of southern pine stumpage prices (Guttenberg & Fasick, 1965; Anderson, 1969; Guttenberg, 1970). Among the studies with the issue of price transmission between stumpage price and forest products prices, Haynes (1977) links regional stumpage and national sawnwood markets using the derived demand approach. Regionally, Luppold and Baumgras (1996) and Luppold et al. (1998) analyze how price margins between stumpage and national sawnwood changed in Ohio, conclude that the shrinking market margin is a result of competitive market forces, and short-term deviation is still possible due to insufficient market information. Murray and Wear (1998) analyze alteration of market linkage after harvesting restrictions in the Pacific Northwest in 1989. The Engle-Granger two steps test is employed to do this research. The model with the structure break as dummy variable performs better than the one without it, implying two price series become more interdependent after 1988.
Recently, Zhou and Buongiorno (2005) conduct a research with the issue of price transmission between products at different stages in forest industries in the South from 1977 to 2002. All prices are found to be nonstationary, and there is no evidence of price cointegration. When price transmission is significant, the full adjustment takes about two years. In the latest study, Koutroumanidisa et al (2009) examine asymmetry in the price transmission mechanism between the producer and the consumer prices in the sector of forest products in Greece. The Johansen cointegration and two dynamic models, Error Correction Model and LSE–Henry general to specific model, are estimated. It concludes that the consumer price Granger causes the producer price whereas the reverse is not valid, so the existence of asymmetry in the price transmission mechanism within the roundwood market is confirmed. However, vertical price transmission dynamics between different stages is far from complete, when recent price fluctuation is taken into consideration. Clearly, knowledge gap exists in this field.

2.3 Methodology

In this study, approaches to test linear cointegration and threshold cointegration, as well as an error correction model, are adopted to analyze price dynamics among different stages.

2.3.1 Linear cointegration analysis

Properties of nonstationarity related to upstream and downstream prices, and order of integration can be assessed by the Augmented Dickey-Fuller (ADF) Test (Dickey & Fuller, 1979). The original test is extended by Perron (1989) to address the uncertainty of which deterministic components should be included in the DF test, by allowing for lagged terms of the dependent variable to the test equation. If both the price
series appear to have a unit root, then it is appropriate to conduct cointegration analysis to evaluate their interaction. Following the testing procedure (Pfaff, 2008), the ADF equation is tested without neither constant nor trend. The null hypothesis is that the series are nonstationary in their levels. The nonstationary series are $I(1)$ with the first differences being $I(0)$.

The Johansen approach is a multivariate generalization of the Dickey-Fuller test (Johansen, 1988; Johansen & Juselius, 1990). The test is a procedure for testing cointegration of several $I(1)$ time series. According to Johansen and Juselius, any $p$-dimensional vector autoregression can be written in the following models:

\begin{align}
X_t &= \Pi X_{t-1} + \epsilon_t \tag{2.1} \\
\end{align}

where $X_t$ is a vector of one pair prices with one downstream and the other upstream, $K$ is the number of lags, and $\epsilon_t$ is the error term. The connection between Equation (2.1) and Equation (2.2) is and , and $I$ is an identity matrix.

To implement the cointegration test, two specific models are adopted, one with trend, the other with constant. Johansen (1988) proposes two different likelihood ratio tests of the significance of these canonical correlations and thereby the reduced rank of the coefficient matrix $\Pi$ in each model: the trace test and maximum eigenvalue test. The trace test evaluates the null hypothesis of $r$ cointegrating vectors against the alternative hypothesis of $n$ cointegrating vectors; alternatively, the maximum eigenvalue one tests the null hypothesis of $r$ cointegrating vectors against the alternative hypothesis of $r + 1$ cointegrating vectors. Given that the time series studied are $I(1)$, according to the results
of the ADF test, the Johansen test can be used to examine whether there is a linear relation among the stationary variables.

Another linear cointegration test, the Engle-Granger two-stage approach, practices on the residuals from the long-term equilibrium relationship (Engel & Granger, 1987). In the first stage, long-run relationship between prices series are estimated, and the price of upstream price is chosen to be placed on the right side as the driving force, which can be expressed as:

\[ (2.3) \]

where \( U \) and \( D \) represent upstream prices and downstream prices, separately; \( \alpha \) and \( \beta \) are coefficients; \( \varepsilon \) is error term. In the next step, an augmented Dickey-Fuller test is adopted to check the residuals to see whether the price series of each equation are cointegrated with a unit root test (Engel & Granger, 1987). There should be no serial correlation in the regression residuals with lags involved; Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) can be used as rule for selection. Equation for step 2 is in the form of:

\[ (2.4) \]

where \( \rho \) and \( \lambda \) are coefficients; \( \hat{\varepsilon} \) is the estimated residuals; \( \Delta \) indicates the first difference; \( \varepsilon_n \) is a white noise disturbance term, and \( L \) is the number of lags. Five pairs of prices are analyzed through this model. If the null hypothesis of \( \rho = 0 \) is rejected, then the residual series from the long-term equilibrium is stationary and that pair of upstream price and downstream price is cointegrated with each other.
2.3.2 Threshold cointegration analysis

Linear cointegration analysis potentially implies a symmetric transmission progress; Enders and Granger (1998) argue that the Dickey-Fuller test and its extensions are mis-specified if adjustment is asymmetric. Therefore, Enders and Siklos (2001) propose a two-regime threshold cointegration approach to entail asymmetric adjustment in cointegration analysis, as follows:

\[ I_t = \begin{cases} \rho_1, & \text{if } \tau < 0, \\ 0, & \text{otherwise; or} \\ \rho_2, & \text{if } \tau > 0 \end{cases} \] (2.5)

\[ I_t = \begin{cases} \rho_1, & \text{if } \tau < 0, \\ 0, & \text{otherwise} \end{cases} \] (2.6)

where \( I_t \) is the Heaviside indicator; \( P \) is the number of lags; \( \rho_1, \rho_2 \) and \( \varphi_i \) are the coefficients, and \( \tau \) is the threshold value. The lag \( P \) is specified to account for serial correlation in the residuals, and it can be selected using AIC or BIC values.

The Heaviside indicator \( I_t \) can be specified with two alternative definitions of the threshold variable, either the lagged residual \( \ddot\epsilon_t \) or the change of the lagged residual \( \dot\epsilon_t \). Equations (2.5) and (2.6) together are referred to as the Threshold Autoregression (TAR) model, while Equations (2.5) and (2.7) are named as the Momentum Threshold Autoregression (MTAR) model. The TAR model is designed to capture potential asymmetric deep movements in the residuals (Enders & Granger, 1998; Enders & Siklos, 2001). The MTAR model is useful to take into account steep variations in the residuals; it is especially valuable when the adjustment is believed to exhibit more “momentum” in one direction than the other. Thus, for TAR model if, for example, \(-2 < \tau < 0\), the negative phase of the sequence tends to be more persistent than the
positive phase. For the MTAR model if, for instance, the MTAR model exhibits relatively less decay for positive values of \( \tau \).

The threshold value \( \tau \) can be specified as zero, given the regression deals with the residual series. However, Chan (1993) proposes a search method for obtaining a consistent estimate of the threshold value, which obtains larger test power with an estimated threshold. A total of four models are entertained in this study. They are TAR equation with \( \tau = 0 \); consistent TAR equation with \( \tau \) estimated; MTAR equation with \( \tau = 0 \); and consistent MTAR equation with \( \tau \) estimated. Since there is generally no presumption on which specification is used, it is reasonable to choose the appropriate adjustment mechanism via model selection criteria of AIC and BIC (Enders & Siklos, 2001). A model with the lowest AIC and BIC values will be used for further analysis.

The test statistics for the null hypothesis using the TAR specification and the MTAR specification are called \( \xi \) and \( \xi^* \), respectively. Three factors can determine the distributions of \( \xi \) and \( \xi^* \). These are the number of lags in Equation (2.5), the number of variables, and the type of deterministic elements included in the cointegration relationship. Insights into the asymmetric adjustments in the context of a long-term cointegration relation can be obtained with two tests. First, it is determined whether downstream price and upstream price are cointegrated in the TAR and MTAR models. An \( F \)-test is employed to examine the null hypothesis \( H_0: \alpha = \beta = 0 \) against the alternative of cointegration with either TAR or MTAR threshold adjustment. Secondly, the asymmetric adjustment is tested when the null hypothesis above is rejected. A standard \( F \)-test can be adopted to evaluate the null hypothesis of symmetric adjustment in the long-term equilibrium (\( H_0: \alpha = \beta \)). Rejection of the null hypothesis indicates the existence of an asymmetric adjustment process.
2.3.3 Error correction model with threshold cointegration

The Granger representation theorem (Engel & Granger, 1987) states that an error correction model can be estimated when all the variables have been found to be cointegrated. The specification assumes that the adjustment process due to disequilibrium among the variables is symmetric. Two extensions on the standard specification in the error correction model have been made for analyzing asymmetric price transmission. Granger and Lee (1989) first extend the specification to the case of asymmetric adjustments. Error correction terms and first differences on the variables are decomposed into positive and negative components. This allows detailed examinations on whether positive and negative price differences have asymmetric effects on the dynamic behavior of prices. The second extension follows the development of threshold cointegration (Balke & Fomby, 1997; Engel & Granger, 1987). When the presence of threshold cointegration is validated, the error correction terms are modified further.

The error correction models with threshold employed in this study can be expressed as:

\[
\begin{align*}
\Delta U_t & = \theta \Delta D_{t-1} + \delta E_{t-1} + \alpha \Delta U_{t-1} + \beta \Delta D_{t-2} + \varepsilon_t \\
\Delta D_t & = \theta \Delta U_{t-1} + \delta E_{t-1} + \alpha \Delta U_{t-2} + \beta \Delta D_{t-1} + \varepsilon_t
\end{align*}
\] (2.8)

(2.9)

where \( \Delta U_t \) and \( \Delta D_t \) are the upstream prices and downstream prices in first difference, \( E \) is error correction term, \( \theta, \delta, \alpha \) and \( \beta \) are coefficients, and \( \varepsilon_t \) is error term. The subscript \( U \) and \( D \) differentiate the coefficients by stages, \( t \) denotes time, and \( j \) represents lags. All the lagged price variables in the first difference are split into positive and negative components, as indicated by the superscripts \(^+\) and \(^-\). The maximum lag \( J \) is chosen with the AIC statistic, so the residuals have no serial correlation. The two error correction
terms are defined as \( \text{and} \), which in turn are constructed from the threshold cointegration regressions in Equations (2.5) and (2.7).

Possible presence of asymmetric price behavior can be examined with simple inspection on the coefficients as a first insight. The signs for the driving variables should be positive for either upstream or downstream price, but the signs for price-takers are expected to be negative. Furthermore, three types of several single or joint hypotheses (Frey & Manera, 2007) can be formed as follows. The first type of hypotheses are the Granger causality tests by employing \( F \)-tests: \( H_{01}: = 0 \) and \( H_{02}: = 0 \) for all lags \( i \) at the same time, so that the stage of price driver can be judged. These hypotheses test short run asymmetric transmissions. The second type of hypotheses are the cumulative symmetric effects as \( H_{03}: = \) and \( H_{04}: = \), which are a relatively long run test for asymmetry. And finally, the equilibrium adjustment path asymmetry can be tested with null hypothesis of \( H_{05}: = \), to examine to extent of which it is possible to get back to equilibrium after a shock, and if it is the case, how long it will take.

2.4 Data and variables

In the upstream stage, stumpage and delivered timber prices are collected from Timber-Mart South from 1977 to 2009 by states (Timber-Mart South). Because the reporting frequency has changed from monthly to quarterly since January 1988, the mean of each quarter before 1988 is used as the quarterly observation. Therefore, the upstream prices are quarterly. Prices in 11 southern states are averaged to match data range of downstream prices. The prices of lumber, lumber boards of Southern pine 1×4#3 (LA), and selects of Southern pine1×4 (LB), are selected to be the representatives of lumber
prices. They are collected from yearbook published by Random Lengths from 1977 to 2009 (Random Lengths). Although monthly data is available with Random Lengths Yearbook, only mid-month data of each quarter are reported to gain frequency consistency with stumpage and delivered timber prices. To summarize, the data frequency of this study is quarterly, and the average prices of the 11 southern states are used.

2.5 Empirical results

2.5.1 Descriptive statistics and unit root test

The descriptive statistics of the four variables involved in this study are reported in Table 2.1. When upstream prices are under examination, the delivered timber price is higher than the stumpage price in each quarter, and the gap between them is relatively stable. On the other hand, downstream prices, due to their different sizes and qualities, are not compatible. Price of lumber A, the lumber boards of Southern pine 1×4#3 (LA), varies from $134 to $408 with a mean of $235.4. The mean of lumber selects of Southern pine 1×6 (LB) is $735.6, fluctuating from $342 to $1147. The trend and shift during the period of study can be observed in Figure 2.1. The group of prices seems to change synchronously, with a generally upward tendency and an unstable development in the last 20 years. Furthermore, the correlation coefficient between stumpage price and delivered timber price is as high as 0.99; and correlation coefficient between upstream prices and price of LB are higher than that connecting with LA. Additionally, the correlation coefficient between the two lumbers products is 0.87.

The ADF test is adopted to examine nonstationarity of the four prices. The lag length for ADF test is determined by the AIC statistic and Ljung-Box Q test. The
procedures proposed by Enders (2004) are followed to perform the regression. As reported in Table 2.1, the statistics reveal that unit roots cannot be rejected at the 10% level for all the four prices, but all can be rejected at the 1% level for the first difference form. Thus, it can be concluded that the stumpage price, delivered timber price and the two selected lumber prices in the South are all integrated of order one.

Table 2.1  Descriptive statistics and unit root test results for the prices

<table>
<thead>
<tr>
<th>Name</th>
<th>LA</th>
<th>LB</th>
<th>PD</th>
<th>PS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Definition</td>
<td>Lumber boards of Southern pine 1×4#3</td>
<td>Lumber selects of delivered price of Southern pine 1×6</td>
<td>Average price of Southern pine sawtimber</td>
<td>Average standing price of Southern pine sawtimber</td>
</tr>
<tr>
<td>Observations</td>
<td>132</td>
<td>132</td>
<td>132</td>
<td>132</td>
</tr>
<tr>
<td>Mean</td>
<td>235.4</td>
<td>735.6</td>
<td>273.9</td>
<td>201.4</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>64.1</td>
<td>231.6</td>
<td>94.2</td>
<td>73.1</td>
</tr>
<tr>
<td>Minimum</td>
<td>134</td>
<td>342</td>
<td>120</td>
<td>80</td>
</tr>
<tr>
<td>Maximum</td>
<td>408</td>
<td>1147</td>
<td>439</td>
<td>344</td>
</tr>
</tbody>
</table>

Note: The critical values are 2.58 –1.95 –1.62 for ADF test at the 1%, 5%, and 10% levels, respectively (Enders, 2004). ** and *** denote significance at the 5% and 1% level, respectively. The numbers in the bracket are lags used in the test.
2.5.2 Results of linear cointegration analysis

Cointegration can be investigated for each pair of prices. Delivered timber price is an upstream price when it is matched with lumber prices, but it turns to be a downstream price when it is compared with stumpage price. So finally, five pairs of prices (LA~PD, LB~PD, LA~PS, LB~PS, PD~PS) are under price transmission analysis in this study. To begin with, the linear cointegration between the five pairs of prices can be conducted by both Johansen test and Engle-Granger two-step approach.

Firstly, cointegration between pairs of prices can be determined by the Johansen test. Two specific models with two tests respectively are used to conduct the test. Lag length for all the four test types is three, based on the lowest AIC and BIC values. As reported in Table 2.2, conclusions drawn from each test are different from one another. None of the null hypothesis of one cointegration can be rejected by either maximum eigenvalue or trace statistics. But only one null hypothesis of no cointegration can be
rejected at 10% significance level when there is a trend in the model, implying only stumpage price and delivered timber price out of the five pairs are cointegrated if only this model is taken into consideration. Nevertheless, both null hypotheses can be rejected when the Johansen approach with a constant is applied to pairs of prices including LA. However, pairs of prices with LB cannot be proved to be cointegrated with upstream prices with the constant test, either. This phenomenon may be due to the large price gap between LB and other wood products, and/or to the linear and symmetric transmission assumption rooted in the model per se.

Table 2.2 Results of the Johansen cointegration tests on five pairs of prices

<table>
<thead>
<tr>
<th>Pairs of Prices</th>
<th>Johansen $\lambda_{max}$ Trend</th>
<th>Constant</th>
<th>Johansen $\lambda_{trace}$ Trend</th>
<th>Constant</th>
</tr>
</thead>
<tbody>
<tr>
<td>LA~PD</td>
<td>$r = 1$ 3.52</td>
<td>$r = 1$ 3.32</td>
<td>$r = 1$ 3.52</td>
<td>$r = 1$ 3.32</td>
</tr>
<tr>
<td></td>
<td>$r = 0$ 15.77</td>
<td>$r = 0$ 15.99**</td>
<td>$r = 0$ 19.29</td>
<td>$r = 0$ 19.31*</td>
</tr>
<tr>
<td></td>
<td>$r = 1$ 2.93</td>
<td>$r = 1$ 2.90</td>
<td>$r = 1$ 2.93</td>
<td>$r = 1$ 2.90</td>
</tr>
<tr>
<td></td>
<td>$r = 0$ 10.09</td>
<td>$r = 0$ 9.33</td>
<td>$r = 0$ 13.02</td>
<td>$r = 0$ 12.24</td>
</tr>
<tr>
<td>LA~PS</td>
<td>$r = 1$ 3.10</td>
<td>$r = 1$ 3.09</td>
<td>$r = 1$ 3.10</td>
<td>$r = 1$ 3.09</td>
</tr>
<tr>
<td></td>
<td>$r = 0$ 16.71</td>
<td>$r = 0$ 16.01**</td>
<td>$r = 0$ 19.81</td>
<td>$r = 0$ 19.10*</td>
</tr>
<tr>
<td></td>
<td>$r = 1$ 3.04</td>
<td>$r = 1$ 2.71</td>
<td>$r = 1$ 3.04</td>
<td>$r = 1$ 2.71</td>
</tr>
<tr>
<td></td>
<td>$r = 0$ 10.40</td>
<td>$r = 0$ 10.31</td>
<td>$r = 0$ 13.44</td>
<td>$r = 0$ 13.02</td>
</tr>
<tr>
<td>LB~PS</td>
<td>$r = 1$ 2.83</td>
<td>$r = 1$ 2.98</td>
<td>$r = 1$ 2.83</td>
<td>$r = 1$ 2.98</td>
</tr>
<tr>
<td></td>
<td>$r = 0$ 26.01***</td>
<td>$r = 0$ 9.44</td>
<td>$r = 0$ 28.84**</td>
<td>$r = 0$ 12.43</td>
</tr>
</tbody>
</table>

Note: $r$ is the number of cointegrating vectors. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. The critical values are from Enders (2004).

As the second linear cointegration test, the implement of Engle-Granger approach involves two steps. The first step is a long-term relationship regression between upstream price and downstream price, with specification as Equation (2.3). Without knowing the drive force of market, either upstream or downstream price can be independent variable and placed on the right side of the regression function. The second step would be a unit root test conducted on the residual obtained from step one, as specified in Equation (2.4).
Indicated by AIC value and Ljung-Box Q test, two to seven are proved to be the proper lag lengths, respectively. The statistic results are described in Table 2.3, except the pair of stumpage price and delivered timber price, null hypotheses of no cointegration can all be rejected at least with 5% significance level.

Table 2.3 Results of the Engle-Granger cointegration tests

<table>
<thead>
<tr>
<th>Pairs of Prices</th>
<th>$\rho$ (t-value)</th>
<th>AIC</th>
<th>BIC</th>
<th>QBL (4)</th>
<th>QBL (8)</th>
<th>QBL (12)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LA–PD</td>
<td>$-0.262^{***}$</td>
<td>-4.971</td>
<td>1028.159</td>
<td>1042.419</td>
<td>0.606</td>
<td>0.505</td>
</tr>
<tr>
<td>PD–LA</td>
<td>$-0.182^{***}$</td>
<td>-4.096</td>
<td>1087.792</td>
<td>1102.052</td>
<td>0.996</td>
<td>0.801</td>
</tr>
<tr>
<td>LB–PD</td>
<td>$-0.345^{***}$</td>
<td>-4.861</td>
<td>1199.430</td>
<td>1225.098</td>
<td>0.989</td>
<td>0.999</td>
</tr>
<tr>
<td>PD–LB</td>
<td>$-0.215^{***}$</td>
<td>-3.630</td>
<td>1027.817</td>
<td>1042.077</td>
<td>0.929</td>
<td>0.324</td>
</tr>
<tr>
<td>LA–PS</td>
<td>$-0.262^{***}$</td>
<td>-4.971</td>
<td>1028.159</td>
<td>1042.419</td>
<td>0.606</td>
<td>0.505</td>
</tr>
<tr>
<td>PS–LA</td>
<td>$-0.183^{**}$</td>
<td>-3.276</td>
<td>1034.589</td>
<td>1054.553</td>
<td>0.852</td>
<td>0.793</td>
</tr>
<tr>
<td>LB–PS</td>
<td>$-0.201^{**}$</td>
<td>-3.044</td>
<td>1256.774</td>
<td>1276.738</td>
<td>0.767</td>
<td>0.162</td>
</tr>
<tr>
<td>PS–LB</td>
<td>$-0.192^{**}$</td>
<td>-2.924</td>
<td>978.400</td>
<td>998.364</td>
<td>0.764</td>
<td>0.194</td>
</tr>
<tr>
<td>PD–PS</td>
<td>$-0.089$</td>
<td>-0.924</td>
<td>907.531</td>
<td>930.347</td>
<td>0.968</td>
<td>0.903</td>
</tr>
<tr>
<td>PS–PD</td>
<td>$-0.182^{*}$</td>
<td>-2.327</td>
<td>871.288</td>
<td>882.696</td>
<td>0.765</td>
<td>0.780</td>
</tr>
</tbody>
</table>

Note: $\rho$ refers to $\rho$ in Equation (2.3); *, ** and *** denote significance at the 10%, 5% and 1% level. The critical values are from Enders (2004).

2.5.3 Results of threshold cointegration analysis

Four threshold autoregression models, TAR, MTAR, and their consistent specifications are entailed in the nonlinear cointegration analysis, following the procedure of Chan (1993) to estimate the threshold. When appropriate lag length is chosen to address the serial correction in residual series, rules of AIC, BIC and Ljung-Box $Q$ statistics are adopted. The lag length for two pairs related to LB is seven; the two related to LA are six and three, respectively. Finally, no lag is required for the test between stumpage price and delivered timber price, so the lag length for this pair is zero, implying price is not lagged when it is transmitted within this pair of prices. Under first estimation of the four models, lowest AIC and BIC values can be acquired when the model are consistent, which is a sign of better performance. Therefore, only statistics of
consistent TAR and MTAR are reported in Table 2.4, with threshold $\tau$, estimation of $\rho_1$ and $\rho_2$, and testing results of two null hypotheses. Furthermore, the consistent MTAR has a better performance than consistent TAR.

When cointegrations are investigated with the nonlinear models, all relationships between upstream prices and downstream prices have been proven to be cointegrated at the 1% level regardless of transmission direction, except that no cointegration of one pair can be rejected at the 5% level (PS~LA). Although several pairs of prices are not proven to be cointegrated well with former tests, tests with threshold have shown a high-level of cointegration. It verifies the conclusion that Enders and Granger model with threshold fits the data better, particularly when asymmetric transmission is a potential possibility.

Table 2.4 Results of threshold cointegration tests

<table>
<thead>
<tr>
<th>Method</th>
<th>Threshold</th>
<th>$\rho_1$</th>
<th>$\rho_2$</th>
<th>$\Phi$ (H$_0$: $\rho_1=\rho_2=0$)</th>
<th>$F$ (H$_0$: $\rho_1=\rho_2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LA–PD</td>
<td>TAR</td>
<td>-26.014</td>
<td>-0.191***</td>
<td>-0.387***</td>
<td>15.343***</td>
</tr>
<tr>
<td></td>
<td>MTAR</td>
<td>9</td>
<td>0.023</td>
<td>-0.302***</td>
<td>19.01***</td>
</tr>
<tr>
<td>PD–LA</td>
<td>TAR</td>
<td>32.571</td>
<td>-0.209***</td>
<td>-0.155***</td>
<td>8.600***</td>
</tr>
<tr>
<td></td>
<td>MTAR</td>
<td>-22.908</td>
<td>-0.238***</td>
<td>0.137</td>
<td>16.036***</td>
</tr>
<tr>
<td>LB–PD</td>
<td>TAR</td>
<td>44.164</td>
<td>-0.404***</td>
<td>-0.277***</td>
<td>12.819***</td>
</tr>
<tr>
<td></td>
<td>MTAR</td>
<td>3</td>
<td>-0.254***</td>
<td>0.463***</td>
<td>14.464***</td>
</tr>
<tr>
<td>PD–LB</td>
<td>TAR</td>
<td>-16.655</td>
<td>-0.226***</td>
<td>-0.375***</td>
<td>9.754***</td>
</tr>
<tr>
<td></td>
<td>MTAR</td>
<td>5.885</td>
<td>-0.362***</td>
<td>0.249***</td>
<td>9.120***</td>
</tr>
<tr>
<td>LA–PS</td>
<td>TAR</td>
<td>-25.087</td>
<td>-0.170**</td>
<td>-0.370***</td>
<td>7.415***</td>
</tr>
<tr>
<td></td>
<td>MTAR</td>
<td>10</td>
<td>0.002</td>
<td>-0.331***</td>
<td>13.063***</td>
</tr>
<tr>
<td>PS–LA</td>
<td>TAR</td>
<td>-18.642</td>
<td>-0.174**</td>
<td>-0.111</td>
<td>3.518**</td>
</tr>
<tr>
<td></td>
<td>MTAR</td>
<td>-12.916</td>
<td>-0.199***</td>
<td>0.132</td>
<td>8.783***</td>
</tr>
<tr>
<td>LB–PS</td>
<td>TAR</td>
<td>33.501</td>
<td>-0.273***</td>
<td>-0.242***</td>
<td>7.407***</td>
</tr>
<tr>
<td></td>
<td>MTAR</td>
<td>-31.022</td>
<td>-0.263***</td>
<td>-0.257***</td>
<td>7.347***</td>
</tr>
<tr>
<td>PS–LB</td>
<td>TAR</td>
<td>10.147</td>
<td>-0.185**</td>
<td>-0.268***</td>
<td>5.878***</td>
</tr>
<tr>
<td></td>
<td>MTAR</td>
<td>10.803</td>
<td>-0.069</td>
<td>-0.262***</td>
<td>7.049***</td>
</tr>
<tr>
<td>PD–PS</td>
<td>TAR</td>
<td>6.326</td>
<td>-0.146*</td>
<td>-0.265***</td>
<td>5.795***</td>
</tr>
<tr>
<td></td>
<td>MTAR</td>
<td>2</td>
<td>-0.107</td>
<td>-0.325***</td>
<td>6.917***</td>
</tr>
<tr>
<td>PS–PD</td>
<td>TAR</td>
<td>-5.475</td>
<td>-0.279***</td>
<td>-0.152*</td>
<td>6.303***</td>
</tr>
<tr>
<td></td>
<td>MTAR</td>
<td>-1.7</td>
<td>-0.106</td>
<td>-0.207**</td>
<td>7.426***</td>
</tr>
</tbody>
</table>

Note: *, **, and *** denote significance at the 10%, 5% and 1% level, respectively. The critical values are from Enders (2004).
Moreover, asymmetric price transmission occurs on one lumber price with consistent MTAR model. From the statistics generated by the $F$-test, the most significant asymmetric transmission appears in the two pairs of prices related to LA, especially when upstream prices are set as a driving force. Yet the asymmetry is not quite obvious, when the other three pairs without LA are taken into consideration. Specifically, point estimates have demonstrated that positive deviation converges more slowly from long-term equilibrium than negative deviations, when LA is the dependent variable in the model.

For example, when price transmission is estimated by consistent TAR model from delivered timber price to LA price, positive deviations resulting from increases in the LA price or decreases in the delivered timber price are eliminated at 19.1% per quarter; negative deviations from the long-term equilibrium resulting from decrease in the LA price or increases in the delivered timber price are eliminated at a rate of 38.7% per quarter, twice as fast as that of the positive deviation. In other words, positive deviations take about more than fifteen months ($1/19.1\% = 5.24$ quarters) to be fully digested while negative deviations take less than eight months only. Similarly, when it comes to the dynamics when stumpage price transmits to LA price with consistent TAR model, only eight months are required to digest the shock of negative deviation, while adjustment for shocks on the opposite direction calls for more than one and a half years. Almost all other significant point estimates have shown positive asymmetry on price transmission when lumber prices are set as the dependent variable.

### 2.5.4 Results of error correction model

Given the consistent MTAR model performs best among the four threshold cointegration analyses, the error correction terms are constructed using Equations (2.4)
The asymmetric error correction model with threshold cointegration is estimated, with three to seven selected by AIC, BIC and Ljung-Box $Q$ statistics as number of lags. Key statistics are reported in Table 2.5, including Granger causality tests, cumulative asymmetric effects, and symmetric momentum equilibrium adjustment path.

The hypotheses of Granger causality involved in each pair of prices are assessed with $F$-tests. Generally speaking, causality interactions between stumpage prices, delivered timber prices and lumber prices are not as strong as that between stumpage price and delivered timber price. Specifically, although most prices have a strong impact on their own trend development, only three out of five pairs of prices are found to have brought influence to the paired price. Among the three pairs, causality between delivered timber price and price of LB, and between stumpage price and delivered timber price, are bidirectional. In other words, change of either one price significantly causes change of the other one. On the other hand, influence from stumpage price to delivered timber price appears to be even stronger. But the causality between stumpage price and price of LA exists only when downstream price is transmitted to upstream price. That is to say, the price of LA evolves more independently, or it is driven by factors other than upstream prices. But the price of stumpage price has been dependent on price of LA, or more generally, on the prices of its downstream products.
Table 2.5 Results of the asymmetric error correction model with threshold cointegration

<table>
<thead>
<tr>
<th>Pairs of Prices</th>
<th>δ+</th>
<th>δ‒</th>
<th>H01</th>
<th>H02</th>
<th>H03</th>
<th>H04</th>
<th>H05</th>
</tr>
</thead>
<tbody>
<tr>
<td>From upstream price to downstream price</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 PD</td>
<td>-0.097</td>
<td>0.089*</td>
<td>1.811†</td>
<td>0.641</td>
<td>0.990</td>
<td>0.838</td>
<td>3.268*</td>
</tr>
<tr>
<td>LA</td>
<td>0.085</td>
<td>-0.250***</td>
<td>0.495</td>
<td>13.151***</td>
<td>2.223†</td>
<td>0.269</td>
<td>8.223***</td>
</tr>
<tr>
<td>2 PD</td>
<td>0.007</td>
<td>0.047*</td>
<td>1.442</td>
<td>1.134</td>
<td>0.157</td>
<td>0.043</td>
<td>1.260</td>
</tr>
<tr>
<td>LB</td>
<td>-0.224***</td>
<td>-0.127*</td>
<td>1.977*</td>
<td>14.372***</td>
<td>0.235</td>
<td>1.591</td>
<td>1.345</td>
</tr>
<tr>
<td>PS</td>
<td>-0.023</td>
<td>0.140**</td>
<td>4.363***</td>
<td>0.429</td>
<td>2.745†</td>
<td>0.535</td>
<td>4.728**</td>
</tr>
<tr>
<td>3 LA</td>
<td>-0.059</td>
<td>-0.335***</td>
<td>2.095**</td>
<td>7.505***</td>
<td>0</td>
<td>0.018</td>
<td>8.698***</td>
</tr>
<tr>
<td>PS</td>
<td>0.034</td>
<td>0.013</td>
<td>2.310**</td>
<td>1.071</td>
<td>0.154</td>
<td>1.198</td>
<td>0.414</td>
</tr>
<tr>
<td>4 LB</td>
<td>-0.084†</td>
<td>-0.213***</td>
<td>1.450</td>
<td>12.779***</td>
<td>1.082</td>
<td>4.521**</td>
<td>3.220*</td>
</tr>
<tr>
<td>PS</td>
<td>-0.093</td>
<td>0.070</td>
<td>3.247***</td>
<td>3.653***</td>
<td>2.909*</td>
<td>0.416</td>
<td>0.087</td>
</tr>
<tr>
<td>5 PD</td>
<td>0.006</td>
<td>-0.098</td>
<td>1.792*</td>
<td>1.818**</td>
<td>3.308*</td>
<td>0.926</td>
<td>0.423</td>
</tr>
<tr>
<td>From downstream price to upstream price</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 LA</td>
<td>0.187***</td>
<td>-0.177**</td>
<td>9.034***</td>
<td>1.143</td>
<td>3.990**</td>
<td>1.091</td>
<td>15.726***</td>
</tr>
<tr>
<td>PD</td>
<td>-0.113***</td>
<td>0.014</td>
<td>1.313</td>
<td>2.377**</td>
<td>2.477†</td>
<td>2.897*</td>
<td>2.591†</td>
</tr>
<tr>
<td>LB</td>
<td>0.575***</td>
<td>0.588***</td>
<td>9.835***</td>
<td>1.714*</td>
<td>3.645*</td>
<td>0.342</td>
<td>0.003</td>
</tr>
<tr>
<td>2 PD</td>
<td>-0.097</td>
<td>-0.093</td>
<td>1.981**</td>
<td>1.619*</td>
<td>0.000</td>
<td>0.251</td>
<td>0.001</td>
</tr>
<tr>
<td>LA</td>
<td>0.189***</td>
<td>-0.102</td>
<td>6.200***</td>
<td>1.833*</td>
<td>1.914</td>
<td>1.594</td>
<td>7.607***</td>
</tr>
<tr>
<td>PS</td>
<td>-0.154***</td>
<td>-0.033</td>
<td>0.549</td>
<td>5.072***</td>
<td>2.490†</td>
<td>6.424**</td>
<td>2.302†</td>
</tr>
<tr>
<td>3 LB</td>
<td>0.644**</td>
<td>0.368***</td>
<td>10.048***</td>
<td>1.153</td>
<td>4.451**</td>
<td>0.295</td>
<td>0.987</td>
</tr>
<tr>
<td>PS</td>
<td>0.058</td>
<td>-0.097†</td>
<td>0.898</td>
<td>2.676***</td>
<td>0.049</td>
<td>0.980</td>
<td>1.650</td>
</tr>
<tr>
<td>4 PD</td>
<td>0.117</td>
<td>-0.012</td>
<td>1.823**</td>
<td>1.708*</td>
<td>0.905</td>
<td>3.163*</td>
<td>0.396</td>
</tr>
<tr>
<td>PS</td>
<td>-0.137</td>
<td>0.118</td>
<td>3.659***</td>
<td>3.266***</td>
<td>0.384</td>
<td>3.015*</td>
<td>1.322</td>
</tr>
</tbody>
</table>

Note: §, *, **, and *** denote significance at the 15%, 10%, 5% and 1% level, respectively. H01 and H02, = =0 and = =0 for all lags respectively, which are Granger causality tests. H03 and H04 assess the cumulative asymmetric effect. 

Furthermore, the cumulative asymmetric effects are also examined. Little evidence of asymmetric cumulative effect has been found neither upward nor downward, except that when the transmission is between stumpage price and delivered timber price. Null hypothesis of symmetric cumulative effect can be rejected at the 10% level when delivered timber price is transmitted to stumpage price, but it is not the case if significance level is adjusted to the 5% level or higher.

The final type of asymmetry examined is the momentum equilibrium adjustment path asymmetries. Two pairs with the price of LA have shown this type of asymmetric price transmission with consistent MTAR model, which is a similar conclusion drawn.
from the nonlinear cointegration analysis. For instance, when the transmission from
delivered timber price to LA price is investigated, the point estimates of the coefficients
for the error correction terms are –0.097 for positive error correction term and 0.089 for
the negative one. The first sign is wrong but it is not significantly different from zero; the
second coefficient is only significant at 10% level. It implies that in the short term, the
delivered timber price shows some difference in speed when responding to positive and
negative deviations, but the difference is weak. However, for LA price, coefficient from
negative deviation is –0.25, which is significant at 1% level, with comparison that the
coefficient from positive deviation is not significant at all. It demonstrates that the price
of LA responds to shock with negative deviation much faster, which takes about one year
to fully digest, than the one in opposite direction. On the other hand, when lumber price
is set as the driving force, positive deviation is digested more quickly, which is opposite
to the former results. This is also the similar situation between stumpage price and LA
price. However, generally speaking, momentum equilibrium adjustment path asymmetry
is not a universal phenomenon.

2.6 Conclusion

The pine timber market plays an important role among industries in the South,
and is also an essential component of the national timber market. Therefore, its price
transmission mechanism should be under investigation to make timberland investment
less risky and more attractive. Thus, the present paper aims to study integration and
causality among different products stages and examine possible existence of asymmetry
in vertical price transmission in the southern timber market.
Three main conclusions can be drawn from the analyses among stumpage price, delivered timber price and two lumber prices. Firstly, although the Johansen test shows limited support to cointegration between prices of different stages, the Engle-Granger two-step approach indicates much higher level of market cointegration, particularly when estimating it with a threshold. The conclusion suggests that in general, southern timber market is efficient and can achieve equilibrium among vertical stages in the long term, which is different from that drawn from Zhou and Buongiorno’s paper (2005).

Secondly, when Granger causality tests are employed, causation does not appear to be a prevailing phenomenon among prices of different stages. Unidirectional causation only exists in one out of five pairs of prices, i.e., from LA price upward to stumpage price. Two pairs have shown bidirectional causality. Prices of the left two pairs tend to evolve independently. It partially confirms the previous assumption that lumber prices have stronger influence on the upstream prices. On the other hand, other prices of forest products are independent, or are more liable to be impacted by exogenous variables rather than upstream/downstream prices, such like forestry policy, forestry programs, international trade, etc. This is consistent with another assumption that claims “timber demand is subject to exogenous independent and random shocks”, as discussed by McGough et al. (2004). However, Mohanty et al. (1996) argued that Granger causality focused on short run dynamics rather than long run equilibrium relationships, so when a long period of forest cultivation is added, this conclusion should not be overstated.

Last but not least, both consistent threshold autoregression model and error correction model have confirmed asymmetric price transmission when price of LA is set as the dependent variable: adjustment from positive deviations, i.e., increases in the LA price or decreases in the upstream prices, always requires longer time than that from
negative deviations. That reveals prices of forest products among vertical linkage are more sensitive and act more swiftly when the price margin is squeezed than it is stretched, price of LA being mentioned. But it is not the case when other three transmission relationships are under examination. As a result, the question whether price transmission is symmetric differs by product. But at least, symmetric transmission has been found between the first two stages: from stumpage price to delivered timber price and backward. Once asymmetry comes to existence, lumber manufacturers are profit winners. It is reasonable to deduce the market power across this stage is a possible explanation.

On one hand, with the probable expanding demand on lumber consumption in the long run and the relatively stable supply in timber market, international trade may play a more important role in the future. Vertical market linkage may be altered and lumber prices will be more cointegrated with import prices rather than upstream prices. The conclusions drawn from this study may be a hint of this tendency. On the other hand, large lumber producers overpower the small sawmills and private timberland owners. The power may not only influence the margin between stages, but also the change of margin when shocks occur in timber market, bringing more economic losses to the price takers. This becomes more important when the recent debt crisis has affected the housing market. Therefore, forestry policy and programs are needed to improve the welfare of small-mill and small-tract owners in this intensely competitive market, and moreover, to maintain and attract investors in the forestry sector.
CHAPTER III
SPATIAL PRICE LINKAGE BETWEEN FOREST PRODUCTS MARKETS
IN THE SOUTH AND THE PACIFIC NORTHWEST

3.1 Introduction
Spatial price transmission among separate timber markets is an important issue. This topic has become more relevant as the timber market stays in recession due to the decline of housing starts since 2006. With the background that almost 20 years has passed since execution of harvesting restrictions in federal forests in the Pacific Northwest, price integration between the South and Pacific Northwest lumber markets needs to be redefined and updated.

The concept of equilibrium among separate markets can be summarized into the law of one price (LOP) (Enke, 1951; Samuelson, 1952). LOP implies that arbitrage activities can prevent prices of a homogeneous good in different markets from being disparate when considering transfer costs (including transportation and transaction costs). The process of arbitrage depends on the fact that the price gap is able to exceed transfer cost, efficiency of information, and possibility of spatial trade. Arbitrage activities may enhance market efficiency and cause welfare changing among market participants. With some revision, the LOP can also be applied to the relationship between substitutes, as products made of Douglas fir and southern pine.

Although LOP is developed in the 1950s, economists have not reached consensus on this theory. Isard (1977) found explicit evidence against LOP by using disaggregated
data for traded goods, which is confirmed by Richardson (1978), Thursby, Johnson, and Grennes (1986), Benninga and Protopapadakis (1988) and others with analysis on different markets. A possible drawback of these studies is a general undervaluation of transaction costs and delivery lags. Therefore, models adopting cointegrations have gained popularity and provided compelling evidence for LOP. For example, Buongiorno and Uusivuori’s (1992) examined the LOP for the US pulp and paper exports, Bessler and Fuller’s (1993) for regional wheat markets, and Michael, Nobay and Peel’s (1994) for international wheat prices.

Since then, economists have begun exploring LOP with a variety of non-linear models, but not until recently have they developed tools, most typically in the form of regime switching models, to depict market dynamics between two divided markets. In general, two categories are always mentioned as regime switching models. One category contains a range of Markov-switching (MS) models wherein regimes are supposed to be determined by exogenous variable. Monte Carlo simulation is always applied to estimate MS models. The others are models with the assumption that regime switching is an endogenous process, such as self-exciting threshold autoregression model (SETAR) by Tsay (1989), threshold vector error correction (TVEC) model by Lo and Zivot (2001), Goodwin and Piggott (2001), and smooth transition autoregression model (STAR) by Terasvirta (1994).

Regime switching model is employed as a tool by empirical studies across economic cycle, finance, energy natural resource economics, agricultural economics, and others. For example, Meyer (2004) adopts TVEC model to estimate the integration of European pig market, and concludes that it is a proper method to examine the existence of “band of non-adjustment” when it is difficult to test models with two different
thresholds. Deschamps (2008) adopts both logic smooth transition (LSTAR) model and Markov switching autoregressive (MSAR) model to estimate factors that can impact the US unemployment. This study concludes that although both models provide very similar pictures, Bayes factors and predictive efficiency tests favor LSTAR model. Most recently, Goodwin et al. (2011) models nonlinearity induced by unobservable transaction costs involved in North American oriented strand board markets by estimating time-varying smooth transition autoregressions (TV-STAR). Empirical results suggest that nonlinearity and structural change are important features of these markets. Price parity relationship has also been proved by TV-STAR, which is consistent with economics theory.

However, few studies have investigated price transmission with regime switching between the northwestern and southern lumber markets. Therefore, the objective of this study is to examine history and trend in price transmission between northwestern and southern lumber markets with supply and demand shocks in the past 40 years, particularly before and after harvesting restrictions executed in the early 1990s. To achieve this goal, three specific problems are concerned: (1) to investigate the extent to which prices in two markets are cointegrated under the situations that they are not perfectly substitutes, and also, transaction costs take a considerable part of the lumber’s overall cost; (2) to inspect the deepness and persistence of market shocks and the subsequent recoveries, and the role of arbitrage activity in the process; (3) to further subdivide lumber market by discriminating market dynamics of different lumber products. The results of this research not only provide new information to forest landowners and sawmill owners to reduce asset risks, but also help improving existing policies related to environmental protection and lumber market stabilization.
3.2 Lumber market in the United States

Development of lumber sector in the United States is full of market shocks. The widely-spread shocks have resulted in the fluctuations of lumber price and production volume, and have reshaped the connections between separate markets. To fully develop the issue of spatial price transmission, the lumber market in the US is reviewed with five aspects in this section.

3.2.1 Trends of development

It was not until the early 1990s that West Coast changed the role as a quasi-monopolist in lumber market. Figure 3.1 shows the volume fluctuation related to the production of softwood lumber by regions. The South and West Coast are two most important lumber suppliers domestically, with a proportional increase in production volume from the South. In 1965, West Coast produced 73.05% softwood lumber, compared to only 23.21% produced by the South. But in 2010, production from the West Coast and the South was almost equal, with the aggregate production slightly smaller than 45 years ago.

Although lumber production from southern yellow pine and Douglas fir are comparable, and was able to satisfy most local demand, fir products were more preferred by consumers. In accordance with Forest Research Notes, the nominal price for Douglas-fir sawlog (#2 sawmill grade) had a relatively stronger correlation (0.7024) with the lumber price collected from Random Lengths (Lutz, 2008). On the contrary, the price of southern pine sawlog was poorly correlated with the lumber price (0.1114) (Lutz, 2008). With equivalent volumes of production, it becomes a big issue whether the two markets tend to develop more independently to satisfy local demand, or to be more cointegrated by arbitrage activities.
3.2.2 Supply shocks in the lumber market

Supply shocks in the lumber market were commonly observed either in the form of natural disasters, such as hurricanes or wildfires, or in other forms such as policy alterations. One major shock that significantly alternated lumber market structure was the harvest restrictions imposed to federal forests in the Pacific Northwest, with a primary purpose to protect the spotted owls, which is more generally known as the Northwest Forest Plan (NWFP). The northern spotted owls were proposed as endangered species in the Federal Register on June 23, 1989; the final listing came in the Federal Register on June 22, 1990. After a series of studies and hearings in 1993, NWFP was adopted in 1994 by the Clinton administration, followed by a subsequent federal forest plan. From the volume data of lumber production, when harvesting restrictions became a potential possibility in 1989, lumber production from West Coast still doubled that from the South, but one year after the imposing of the policy in 1995, production in the South exceeded...
that from West Coast. This situation lasted for two years, which were the only two years in American history with larger southern production than that from the West. This shock on lumber production was comparatively gradual; this phenomenon might be due to the higher utilization percentage of western sawlogs. For example, volume of timber sales in 1989 was only one third of that in 1988, but lumber production was still two thirds of the peak volume in 1995. Generally, this plan caused an immediate and sustained impact on lumber market, pushing up lumber prices and the relative prices of fir products in the 1990s.

Other supply shocks were commonly in the form of natural disasters. One among the most influential disasters is hurricane. Hurricanes damaged hundreds of millions of acres forests in the South, especially along Gulf Coast, in 2004 and 2005. Hurricane suddenly increased the supply of pine products when trees blew down, and then pushed up the prices of fir products as pines’ substitutes. However, compared to the influence from harvest restrictions, this shock was digested more quickly and did not disturb the synchronous development of lumber productions in the two regions.

3.2.3 Demand shocks in the lumber market

Compared to supply shocks, causes of demand shocks were more diversified. American housing starts went through a long-lasting and steady growth from 1991 to 2006, with a stable population increasing and a steady economy development. However, lumber prices did not show a similar trend as the estate market. On the contrary, lumber prices fluctuated around the average prices with an actual decrease on real price, which could be attributed to some demand shocks. For instance, during economic crisis in Southeast Asia starting in 1997, prices of lumber declined due to the surplus supply
brought by the volume that was originally expected to export. Moreover, the period from 1982 to 1995 saw a number of disputes in softwood lumber trade between the US and Canada: the largest lumber exporter of the States. The agreement signed between two governments on tariff and quota weakened the market power of Canadian lumber, and also increased the demand of domestic lumber products.

The largest shock in the last 20 years was the steep decline in housing starts with a beginning in the middle of 2006. The decline turned into a depression with the number of housing starts as only 40% of the past 50 years’ average, dragging down the lumber prices 50% when compared to the price in the middle of 2005. During the same period, lumber production dropped around 30%, which was much moderate compared to what happened to estate markets. Pine gained relatively higher prices during the crisis.

3.2.4 **Lumber price, lumber production and housing market**

According to Forest Research Note, the lumber production is highly, but not perfectly, correlated ($\rho = 0.7838$) with the number of housing starts (Lutz, 2008). That is also to say, housing starts do not represent all of the demand for softwood lumber in the US (Lutz, 2008). Actually, housing only accounts for less than half of the consumption on softwood lumber in the US, with the remaining have gone to repairing and renovating existing house, non-residential construction and packaging (Lutz, 2012).

Lumber prices have not shown high correlation with lumber production, but with higher correlation with housing starts (Lutz, 2008). These results are also consistent with the relatively stable real stumpage and sawlog prices in the past 50 years, and can be counted into the low risk of timberland when it is treated as an asset. Nevertheless, sawmill owners with shorter production period than timberland rotation usually enhance
more on cash flow and short-term profit, so they are the people who care more about the
shocks and the subsequent recoveries. For their considerations, a bulky product as lumber
requires relatively longer time for transportation, so lagged terms should be taken into
analysis for further study rather than only the correlation.

3.2.5 Timber market cointegration

Empirical studies on integration of forest products market rarely support the LOP, especially primary products are concerned. Through market shock price imprint tests and bivariate cointegration tests, Prestemon and Holmes (2000) conclude that southern stumpage price does not support LOP. A study on integration of hardwood sumpage markets in the southcentral United States concludes that LOP is not applicable, and the hypothesis of integrated southcentral market is rejected; hardwood sawtimber markets are more integrated than hardwood pulpwood markets (Nagubadi, Munn, & Tahai, 2001). After analyzing data from 13 sawtimber and 11 pulpwood markets, Yin et al. (2002) suggest dealing with the southern region as a few contiguous market segments instead of a fully integrated market, with the probable reason that timber is a bulky commodity with low price. Another study illustrates that multivariate meta-analytic regressions offer limited support for LOP in both southern sawlog and pulpwood markets, but sawlog shows cointegration when a proxy for transfer cost is added (Bingham, Prestemon, MacNair, & Abt, 2003).

Markets tend to be more cointegrated when products are on higher and more standard stage. Buongiorno and Uusivuori (1992) use bivariate Dickey-Fuller test to examine cointegration in pulp and paper export markets in the US and cannot reject the hypothesis of LOP for most pairs of the data. Murray and Wear (1998) predict an
intensifying integration between the Pacific Northwest and Southern lumber markets, after harvest restrictions being imposed to the forests in the Northwest. Most recently, Shahi and Kant (2009) estimate the reaction time for prices to return back to the steady-state equilibrium with three categories of softwood lumber products, and summarize that the markets of softwood lumber products with low prices, homogeneity, and high substitutability have a higher degree of market integration than other products.

3.3 Regime switching models

Nonlinear time series models are more usually applied to the problem of price transmission compared to linear models. Traditionally, the concept of cointegration is always adopted by economists to describe problem of price transmission. However, there is no unified approach to evaluate market integration, because those studies are generally criticized for their ignorance of transaction cost and efficiency of information (Barrett, 2001; Barrett & Li, 2002), which are actually difficult to be included into econometric models. Therefore, nonlinear time series models, which respect transaction cost as threshold parameter, can be adopted in this study. Specifically, price transmission between timber markets in the South and Pacific Northwest is analyzed by threshold vector error correction (TVEC) model and smooth transition autoregressive (STAR) model.

3.3.1 Threshold vector error correction model

The vector error correction (VEC) model is suitably applied to price transmission of integrated markets where the causality relationship is unidentified. A specification of a VEC model is given in the form of following equation:
\[ [ECT_{t-1}] + \] (3.1)

with \( \Delta p_t = p_t - p_{t-1} \), \( \alpha_i \) are constants; \( \Delta p_{t-i} \) are lagged terms; \( ECTs \) are deviations; \( \beta s \) and \( \phi s \) are coefficients; \( \varepsilon s \) are residuals. With this equation, price fluctuation of lumber products can be described by constants, lagged terms, and deviations from the long equilibrium.

However, this model is continuous and linear without the assumption of transaction cost, which implies that adjustment rate is constant regardless of the levels and directions of the deviation. This assumption is inconsistent with real reaction in lumber market, so may lead to biased results because of two reasons. On one hand, there is a probable “band of non-adjustment”, when the transfer cost is greater than the possible arbitrage profit. On the other hand, price adjustment may occur in only one direction when the powers of the competitors are not balanced, so this equation may not be applicable when price goes beyond certain interval. Thus, error correction model has been developed by simulating transaction cost with thresholds, to estimate the dynamics in different regimes.

According to the two concerns, research on price transmission always assumes model with one threshold, as \( c_0 \), when the direction of trade is clearly identified (Balke & Fomby, 1997; Enders & Granger, 1998), or with two thresholds, as \( c_1 \) and \( c_2 \), when trade might occur toward either direction (Goodwin & Piggott, 2001; Obstfeld & Taylor, 1997). The former one is more preferable when transaction usually occurs in only one direction; the latter one is more preferable when the transactions are bidirectional. Error correction model with one or two thresholds (Hansen & Seo, 2002) is in the form of:
regime 1 = + × + [ECTt‒1]+ , if ECTt‒1 ≤ c0 (ECTt‒1 ≤ c1 for three regimes)

regime 2 = + × + [ECTt‒1]+ , if ECTt‒1 > c0 (c1<ECTt‒1 ≤ c2 for three regimes) (3.2)

(regime 3 = + × + [ECTt‒1]+ , if ECTt‒1 >c1, for three regimes only)

For the two-regime model, unidirectional transacton is assumed, with the direction per se examined by the sign of the threshold. For the three-regime model, it is assumed that regime 2 is the “band of non-adjustment”. When deviation is between c1 and c2, no matter it is positive or negative, prices will respond weakly until deviation goes beyond the band and switches to regime 1 or regime 3. The latter model can also be employed to analyze asymmetric price transmission by examing different thresholds values and other coefficients. Selection between the two models can be done by applying some statistical criterion, i.e., the AIC value when the number of lags keeps constant.

Three steps are followed to estimate a TVEC model. Firstly, given that non-stationary is an important property of time series data, the augmented Dickey-Fuller (ADF) unit root test is applied to confirm this property of the data. Once proven non-stationary, the Johansen method is used to test cointegration between pairs of prices. However, data’s nonlinearity may reduce the power of these tests. As the second step, ECM without threshold is estimated by the Johansen method. The number of lags, k, is chosen by minimizing AIC value. Finally, TVEC model is estimated by adopting proper threshold c. The search follows the procedure of Hansen and Seo (2002), and relies on the log determinant of the estimated error covariance matrix to maximize the likelihood.
After $c$ is fixed, statistical significance is calculated with Lagrange Multiplier (sup-LM) test or bootstrap method proposed by Hansen and Seo (2002). When sup-LM test is used, the cointegrating value is estimated from the linear VEC model. Then, conditional on this value, the LM test is run for a range of different threshold values. The maximum of those LM values will be reported. However, sup-LM test can be misleading because the standard cointegration tests can run into considerable power loss, when the alternative is threshold cointegration (as TVEC model), as demonstrated by previous studies (Pippenger & Goering, 2000; Taylor, 2001; Seo, 2006). Therefore, a sup-Wald type test has been developed by Seo (2006) to test the null of no cointegration against threshold cointegration. The power of Seo test is significantly greater than the sup-LM test, with a residual-based bootstrap proposed, and the first-order consistency of the bootstrap established.

### 3.3.2 Smooth transition autoregressive model

For some processes, it may be inappropriate to assume that the threshold is sharp; so Teräsvirta (1994) introduces smooth transition autoregressive (STAR) models which allow the autoregressive parameters to change slowly. Following his method, a basic STAR model of order $m$ for $U_t$ is specified as

$$U_t = \alpha + \beta F(\bullet) + \rho_t,$$

where $U_t$ is the log-level of pine-fir price ratio; $U_{t-i}$ is $U_t$’s $i$th lagged term; $\alpha$ and $\beta$ are coefficients. $F(\bullet)$ denotes the transition function; by it is bounded between 0 and 1, the structure of the model can be changed in a smooth manner. With $c$ as the threshold, the model’s structure varies depending on whether the ratio is in a peak, (i.e., $U_{t-d} > c$) or a trough (i.e., $U_{t-d} < c$) regime, when $d$ is the delay lag parameter.
In practice, two forms of the transition functions are commonly considered: the exponential specification and the logistic specification, respectively, written as:

\begin{align}
\gamma \text{ and } c \\
\text{Equation (3.4)} \\
- \\
\text{Equation (3.5)}
\end{align}

where $\gamma$ is slope, and $c$ is threshold, or, location parameter. Equation (3.4), which is the exponential transition function, has symmetrically bell-shaped distribution around equilibrium level, with $c$ bounded between 0 and 1. The logistic function, which is Equation (3.5), is asymmetric about $c$, so local dynamics are not the same for low and high values of involved $\gamma$. The parameter $\gamma$ measures the speed of transition between two regimes. Equation (3.3) and (3.4) form the exponential STAR (ESTAR) model; and Equation (3.3) and (3.5) form the logistic STAR (LSTAR) model.

On one hand, the ESTAR model is slight generalization of the exponential autoregressive (EAR) model of Haggan and Ozaki (1981). It may also be treated as a generalization of a special case of a double-threshold TAR model (Teräsvirta, 1994). On the other hand, both two regime autoregressive model with abrupt transition and linear AR($m$) model are nested in LSTAR model (Akram, 2005). The LSTAR model is reduced to a self-exciting threshold autoregressive model with threshold value $c$, if $\gamma$ is tremendously large: $F(\bullet) = 0$ for $\leq c$ but $F(\bullet) = 1$ for $> c$. Then, the regime switching becomes instantaneous. The LSTAR model is reduced to an AR($m$) model if $\gamma = 0$, i.e., $F(\bullet) = 1/2$ for all values of $\gamma$.

When model fit between the two is considered, ESTAR model is selected when observations are symmetrically distributed on threshold. The reason is that the transition function of the LSTAR model is monotonically increasing, whereas the range of the
observation stretches out on both tails of the transition function of the ESTAR model. Otherwise, ESTAR and LSTAR models are close substitutes for each other. Furthermore, an LSTAR model cannot be approximated by an ESTAR model when threshold is \( c \) is large. To testify which one is more suitable for existing data, Teräsvirta (1994) suggests a sequence of tests to evaluate the null hypothesis of an AR model against a STAR model, and altogether LSTAR model against ESTAR model. The tests are conducted based on the auxiliary regression for a chosen value of \( d \):

\[
(3.6)
\]

where \( \varepsilon \) is the error term. The test of an AR\((m)\) model against a STAR model is equivalent to conducting a joint test of:

The value of \( d \) can be determined by conducting this test for different values of \( d \) in the range \( 1 \leq d \leq m \). If linearity is rejected for more than one value of \( d \), then the value which brings the smallest \( P \)-value of STAR model is chosen. If AR\((m)\) is rejected, appropriateness of logistic transmission function can be tested against exponential transmission function with a sequence of tests related to the auxiliary regression:

The null hypothesis is tested against the alternative hypothesis by the \( F \)-test. The following decision rules are useful in the determination of LSTAR- or ESTAR-type nonlinearity. After rejecting the \( H_0 \), carry out the three \( F \)-tests above. If the \( P \)-value of \( F \)-
test of \( H_{02} \) is the smallest among the three, select an ESTAR model; otherwise, choose a LSTAR model.

Both ESTAR and LSTAR data can be estimated by conditional least squares following the steps given by Teräsvirta (1994). Considering joint estimation of \( \{\gamma, c, \alpha, \beta\} \) is difficult when estimating an ESTAR model (Haggan & Ozaki, 1981), \( F(\cdot) \) can be standardized by dividing it with the sample variance of \( U_t \), which makes it easier to select a reasonable starting value of \( \gamma \). Then a starting value of \( \gamma (\gamma = 1 \) is often adopted) is selected, and the whole set of parameters is estimated by nonlinear least squares. If the algorithm does not converge, estimation can also be carried out by a grid for \( \gamma \) until a satisfactory specification has been found. Similar methodology can also be applied to the estimation of LSTAR model: diving \( F(\cdot) \) by the sample variance of \( U_t \), fixing \( \gamma \) and finding the specification of the model.

3.4 Data sources

Three pairs of monthly lumber prices are collected from the Rand Lengths Yearbook (Rand Lengths), including two pairs of dimensions, and one pair of stress made of southern pine and Douglas fir, separately. All variables and their names can be found in Table 3.1. Two pairs of prices start in January 1973, except that of 2×4 random dimension starts two years earlier. As a result of change of statistical criterion, price of 2×4 random dimension terminated at the end of 2010. The remaining two have been updated to the end of 2011. So the final sample sizes for the three pairs of prices are 480, 468, and 468, respectively.
<table>
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<th>Skewness</th>
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<th>ADF test</th>
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<td>SDIM1</td>
<td>480</td>
<td>274.846</td>
<td>94.638</td>
<td>0.529</td>
<td>-0.407</td>
<td>0.61</td>
<td>-5.19*</td>
</tr>
<tr>
<td>WDIM2</td>
<td>468</td>
<td>327.282</td>
<td>95.454</td>
<td>0.596</td>
<td>-0.262</td>
<td>0.72</td>
<td>-4.87*</td>
</tr>
<tr>
<td>SDIM2</td>
<td>468</td>
<td>313.479</td>
<td>98.788</td>
<td>0.546</td>
<td>-0.295</td>
<td>0.32</td>
<td>-6.4*</td>
</tr>
<tr>
<td>WSTR</td>
<td>468</td>
<td>282.882</td>
<td>91.913</td>
<td>0.389</td>
<td>-0.717</td>
<td>0.19</td>
<td>-4.99*</td>
</tr>
<tr>
<td>SSTR</td>
<td>468</td>
<td>312.271</td>
<td>98.837</td>
<td>0.671</td>
<td>-0.353</td>
<td>0.81</td>
<td>-4.79*</td>
</tr>
</tbody>
</table>

Note: * indicates that ADF test is significant on 1% degree. Items starting with W and S are prices of Douglas fir and southern pine. DIM1 represents kiln dried 2×4 #2 or #2 & btr. random dimension; DIM2 represents kiln dried 2×10 #2 random dimension; STR is 2×4 #1 random 10/20 stress.

Among the three selected products, kiln dried 2×4 #2 or #2 & btr. random dimension (DIM1) is one of the most commonly used lumber products. Kiln dried 2×10 #2&better random dimension (DIM2) can be regarded as a high-end lumber product. 2×4 #1 random 10/20 stress (STR) is better qualified than dimension 2×4, but is of lower price than dimension 2×10. Furthermore, stress made of fir is green since it can be dried in transportation, but stress of pine should be kiln dried before selling. Products in the same category made of southern yellow pine and Douglas fir are reasonable to be regarded as high-level substitutes when they meet indentical requirements of the same grade. This rule can be slightly violated when particular product is more preferable due to lower percentage of moisture during certain seasons of a year. However, the preference is limit when it is transferred to willingness to pay. So when considering the grades only, dimension 2×4 made of fir is more favored because this category may contain higher qualified products (standard and better) than pine products (#2). Finally, because the process of kiln drying costs time and money, stress made of pine is generally more expensive than the green stress made of fir.
3.5 Empirical results

3.5.1 Descriptive statistics

Descriptive statistics for the three pairs of prices are reported in Table 3.1. Among the three, average price of the fir product is higher than that of pine product when DIM2 is mentioned. Two average prices of DIM1 are almost at the same level, with consideration that average grade for fir product is higher than that of pine product. For stress, average pine price is higher than that of fir; but that is probably because of different techniques of treatment. Furthermore, all six prices are positively skewed and fat-tailed. DIM2 can be regarded as the most standard product among the three categories with kurtosis close to zero. Correspondingly, given that rules for grading are relaxed, prices of DIM1 and WSTR are more extensively distributed.

Price fluctuations in the study period are shown in Figure 3.2. All three pairs of prices appear to be cointegrated, particularly the two dimension products. Moreover, all prices have gone through a dramatic soaring period around 1993 and began to descend around 2007. The harvest restrictions and the economic recession can be assumed as reasonable explanations for the phenomenon.

3.5.2 Results of unit root test and Johansen test

The ADF test is applied to examine nonstationarity of the prices. The lag length for ADF test is determined by choosing the lowest AIC value. The procedures proposed by Enders (2004) are followed to perform the regression. As illustrated in Table 3.1, the statistics reveal that unit roots cannot be rejected at the 10% level for all six prices, but all can be rejected at the 1% level for their first difference form. Thus, it can be concluded that all lumber prices are integrated of order one.
Figure 3.2 Three pairs of monthly prices of forest products selected from Random Length Yearbook.

Linear cointegration between pairs of prices is examined by using the Johansen test. Results of the Johansen test are shown in Table 3.2. Six specific tests with trace or eigenvalue, modeling without intercept, with a constant or with a trend variable
respectively, are conducted to each pair of prices. The lag length is selected based on the lowest AIC and BIC values. Results have shown that all the three prices of pine products are cointegrated well with those of fir. Thus, unlike conclusions drawn from Yin et al.’s study (2002), results of the Johansen test in this study support Law of One Price instead of geographically separated lumber markets.

Table 3.2 Results of the Johansen cointegration tests on lumber prices

<table>
<thead>
<tr>
<th>Pairs of Prices</th>
<th>Johansen $\lambda_{\text{max}}$</th>
<th>Johansen $\lambda_{\text{trace}}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>DIM1</td>
<td>Trend 56.803***</td>
<td>Constant 55.9***</td>
</tr>
<tr>
<td>DIM2</td>
<td>Trend 41.943***</td>
<td>Constant 40.04***</td>
</tr>
<tr>
<td>STR</td>
<td>Trend 25.916***</td>
<td>Constant 22.477***</td>
</tr>
</tbody>
</table>

Note: Null hypothesis is the rank equals to zero. *** denotes significance at the 1% level. The critical values are from Enders (2004).

3.5.3 Results of TVEC model

TVEC models are estimated series of pine and fir prices. Lag length for each pair of prices is selected by choosing the lowest AIC value of the VEC model, which is one for DIM1 and DIM2, and two for STR. As all the estimations with one threshold produce lower AIC values than those with two thresholds, TVEC model with one threshold is selected, implying that transactions for the three selected products are uni-directional.

The Seo and Sup-LM tests are applied synchronously to examine the model fit. Although all three pairs reject null hypotheses of non-cointegration by the Seo test, null hypothesis of AR model cannot be rejected against TVEC model with Sup-LM test when fitting DIM1 and DIM2. However, sup-LM test can be quite misleading because the standard cointegration tests can run into considerable power loss when the alternative is threshold cointegration. Therefore, all three pairs of prices are estimated with TVEC model finally. Results of tests and estimated coefficients are reported in Table 3.3.
Estimated results vary by product. The threshold value is positive when estimating the model with DIM1. But it is negative when the model is estimated with the other two pairs of prices. The signs of the threshold can partially explain that lower regime of DIM1 and higher regime of DIM2 and STR, which can be treated as the “typical regimes”, contain more observations than the corresponding regime, which are the “extreme regimes”. All the three typical regimes contain the value zero, implying that price of pine product does not differ much from the price of fir product. It can be regarded as a signal that one product is the substitute of the other when one pair is concerned.

The price of pine product has more influence in DIM1 market. Regime 1 for DIM1 is defined as an aggregation of prices with absolute deviation smaller than 13.3% from long-term equilibrium. When $273 is taken as the average price, this percentage is roughly $36. Instead of “non-adjustment band”, prices are also adjusted in this regime, but much less responsively, implying that transaction from South to the Northwest is rare in this market. The typical regime contains 79.3% observations, with the remaining 20.7% observations in the extreme regime, where deviation from equilibrium is digested more quickly. Importantly, only are ECT coefficients of southern pine significant for both regimes. It implies that when there is a deviation, it is the pine price that shows reaction and brings market back to equilibrium. Furthermore, taking the significant coefficient from lagged term into account, pine price affects fir price in both short and long terms respectively, implying that adjustment in the extreme regime are two times as fast as that in the typical regime.
Table 3.3 Results from fitting the TVEC model on lumber prices and involved tests

<table>
<thead>
<tr>
<th>Item</th>
<th>Regime</th>
<th>DIM1</th>
<th>DIM2</th>
<th>STR</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Low</td>
<td>High</td>
<td>Low</td>
</tr>
<tr>
<td>Lags</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>Tests</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sup-LM</td>
<td>15.241</td>
<td>12.619</td>
<td>25.682*</td>
<td></td>
</tr>
<tr>
<td>Seo Test</td>
<td>68.501***</td>
<td>49.955***</td>
<td>43.852***</td>
<td></td>
</tr>
<tr>
<td>Model fit</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>AIC</td>
<td>-5391.308</td>
<td>-5034.854</td>
<td>-5373.974</td>
<td></td>
</tr>
<tr>
<td>BIC</td>
<td>-5320.425</td>
<td>-4964.402</td>
<td>-5270.423</td>
<td></td>
</tr>
<tr>
<td>Coefficients</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\varphi^s$</td>
<td>0.144***</td>
<td>0.26**</td>
<td>0.407***</td>
<td>0.077*</td>
</tr>
<tr>
<td>$\varphi^W$</td>
<td>-0.01</td>
<td>0.144</td>
<td>0.108</td>
<td>-0.07*</td>
</tr>
<tr>
<td>$\nu$</td>
<td>0.002</td>
<td>-0.04</td>
<td>0.068**</td>
<td>0.001</td>
</tr>
<tr>
<td>$\omega$</td>
<td>0.007**</td>
<td>-0.055**</td>
<td>0.035</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>0.238***</td>
<td>0.243*</td>
<td>-0.045</td>
<td>0.214***</td>
</tr>
<tr>
<td></td>
<td>-0.019</td>
<td>-0.021</td>
<td>0.228</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>-0.032</td>
<td>-0.33***</td>
<td>-0.021</td>
<td>0.023</td>
</tr>
<tr>
<td></td>
<td>0.201***</td>
<td>0.538***</td>
<td>0.036</td>
<td>0.288***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.044</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>-0.317**</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.056</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.32*</td>
</tr>
<tr>
<td>$c_0$</td>
<td>0.133</td>
<td>-0.119</td>
<td></td>
<td>-0.186</td>
</tr>
<tr>
<td>Percentage</td>
<td>79.3%</td>
<td>20.7%</td>
<td>21.5%</td>
<td>78.5%</td>
</tr>
</tbody>
</table>

Note: *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Transactions in the other two markets are commonly from the South to the Pacific Northwest. There are some other common points shared by DIM2 and STR markets: only the $ECT$ coefficients of pine products are significant in the extreme regime. Adjustment rate in the extreme regime is about five and nine times, for DIM2 and STR, respectively, as large as that in the typical regime. These results imply that the adjustment of pine price is the propulsion bringing market back to equilibrium in the long term. The difference between the two markets is that in the short term, prices of DIM2 tend to be self-evolving, as none of lagged terms from one price to the other are significant in this market. All four lagged terms from fir prices to pine prices are significant when STR...
market is concerned. As coefficients of terms with one lag and two lags are of equivalent values but opposite signs in typical regime, influence from lagged term in this regime can be ignored. However, fir price reacts more severely in the short term when difference between two prices switches into the extreme regime, implying a more responsive behavior of fir product in STR market. Finally, the threshold for DIM2 is about $39 ($320 \times 11.9\%$), and $55$ for STR. So thresholds are similar across the two dimension products with different directions, but it is higher in STR market, suggesting that arbitrage activity in this market is of less propulsion.

3.5.4 Results of STAR model

In this section, regime switching of price transmission between southern and western markets is analyzed with the STAR model. Log form of the pine-by-fir price ratio is regarded as the variable adopted in the STAR model. The AR models are estimated firstly to determine proper number of lagged terms. Lags of 11, 10 and 7 are selected for DIM1, DIM2 and STR, respectively, by minimizing the AIC values. Once number of lags is set, number of delays can be estimated by choosing the smallest $P$-value of $H_0$ estimated by Equation (3.6). $P$-values with different delays from 1 to 10 are reported in Table 3.4. Delay numbers for the three ratios are 4, 9 and 3. Since auxiliary regressions have been set up, LSTAR and ESTAR specifications can be discriminated as the next step. Results of the group of $F$ tests rooted in the auxiliary regression are shown in Table 3.5. None of $H_{02}$ is rejected; instead, $H_{03}$ is rejected by DIM1, and $H_{01}$ is rejected by DIM1 and STR, indicating logistic transaction is more suitable when fitting the data of lumber prices. Final estimation of the STAR model is reported in Table 3.6.
Table 3.4  P-values of different values of the delay parameter for model fit

<table>
<thead>
<tr>
<th>Price Ratio</th>
<th>P-value of the delay parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1</td>
</tr>
<tr>
<td>DIM1</td>
<td>0.6226</td>
</tr>
<tr>
<td>DIM2</td>
<td>0.4319</td>
</tr>
<tr>
<td>STR</td>
<td>0.192</td>
</tr>
</tbody>
</table>

Note: Bold numbers imply that this is the smallest P-value for selection of delay parameter.

Table 3.5  Sequential tests for type of nonlinearity on lumber prices

<table>
<thead>
<tr>
<th>Pairs of prices</th>
<th>F-statistic [p value]</th>
<th>Type of nonlinearity</th>
</tr>
</thead>
<tbody>
<tr>
<td>DIM1</td>
<td>1.307 [0.218]</td>
<td>LSTAR</td>
</tr>
<tr>
<td>DIM2</td>
<td><strong>2.173 [0.019]</strong></td>
<td>LSTAR</td>
</tr>
<tr>
<td>STR</td>
<td>1.864 [0.074]</td>
<td>LSTAR</td>
</tr>
</tbody>
</table>

Note: Bold numbers imply that this is the smallest P-value for selection of model type.

Furthermore, model dynamics can be analyzed with estimated parameters. LSTAR model is appropriate where F = 0 corresponds to the lower regime, and F = 1 corresponds to the higher regime. Briefly, the roots of LSTAR model of autoregressive order m can be calculated by

\[ \hat{\rho}_1 = \sum_{i=1}^{m} \hat{\beta}_i \]  

\[ \hat{\rho}_2 = \sum_{i=1}^{m} (\hat{\beta}_i + \bar{\beta}_i) \]

Threshold values are of identical signs compared to those estimated by TVEC model, confirming the transportation directions illustrated before. Threshold estimated from the ratio of DIM1 is 0.07. Moreover, coefficients in the lower regime are of comparatively smaller absolute values than those in higher regime, indicating that prices react more responsively in the higher regime. Root in the lower regime is 0.084, comparing to that in the higher regime as 0.254. Therefore, price equilibrium in the lower regime is more stable, or more attractive, than that in the higher regime. This result indicates that when pine price exceeds a certain degree of fir price in this market, adjustment is two times faster. Given that the average of the ratio is only 0.013, threshold value is large. However, 0.254 as a
root is not high. Combining the two signs, relatively higher pine price can be tolerated in the dimension 2×4 market.

Table 3.6 Results from fitting the LSTAR model on lumber prices

<table>
<thead>
<tr>
<th>Ratio of Prices</th>
<th>DIM1</th>
<th>DIM2</th>
<th>STR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Item</td>
<td>Estimate</td>
<td>Item</td>
<td>Estimate</td>
</tr>
<tr>
<td>( \alpha_0 )</td>
<td>-0.023**</td>
<td>( \alpha_0 )</td>
<td>0.348**</td>
</tr>
<tr>
<td>( \alpha_3 )</td>
<td>0.298***</td>
<td>( \alpha_1 )</td>
<td>1.91***</td>
</tr>
<tr>
<td>( \alpha_4 )</td>
<td>-0.197***</td>
<td>( \alpha_4 )</td>
<td>-0.624**</td>
</tr>
<tr>
<td>( \alpha_7 )</td>
<td>0.104*</td>
<td>( \alpha_6 )</td>
<td>-0.697***</td>
</tr>
<tr>
<td>( \alpha_{10} )</td>
<td>-0.098*</td>
<td>( \alpha_7 )</td>
<td>0.302*</td>
</tr>
<tr>
<td>( \beta_0 )</td>
<td>0.092**</td>
<td>( \beta_0 )</td>
<td>-0.442**</td>
</tr>
<tr>
<td>( \beta_2 )</td>
<td>0.405***</td>
<td>( \beta_1 )</td>
<td>-1.364***</td>
</tr>
<tr>
<td>( \beta_4 )</td>
<td>0.357***</td>
<td>( \beta_3 )</td>
<td>-0.531**</td>
</tr>
<tr>
<td>( \beta_5 )</td>
<td>-0.23**</td>
<td>( \beta_4 )</td>
<td>1.137***</td>
</tr>
<tr>
<td>( \beta_{11} )</td>
<td>-0.246**</td>
<td>( \beta_7 )</td>
<td>-0.549**</td>
</tr>
<tr>
<td>( \gamma )</td>
<td>52.262**</td>
<td>( \gamma )</td>
<td>14***</td>
</tr>
<tr>
<td>( c )</td>
<td>0.07***</td>
<td>( c )</td>
<td>-0.165***</td>
</tr>
<tr>
<td>( \rho_1 )</td>
<td>0.084</td>
<td>( \rho_1 )</td>
<td>2.108</td>
</tr>
<tr>
<td>( \rho_2 )</td>
<td>0.254</td>
<td>( \rho_2 )</td>
<td>-0.057</td>
</tr>
<tr>
<td>AIC</td>
<td>-2136</td>
<td>AIC</td>
<td>-2136</td>
</tr>
</tbody>
</table>

Note: *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

Situations are slightly different when they come to the markets of DIM2 and STR. Thresholds are negative for the two groups: –0.165 for DIM2 and –0.124 for STR. When threshold values are negative, lower regime is regarded as the extreme regime; in other words, when pine prices are lower than fir prices to certain extent, regime switching occurs. Also because threshold values are negative, coefficients of lagged terms are unstable in either regime. Thresholds can be revised to be positive if estimation adopts the ratios with fir price divided by pine price, but it is not necessary because values of roots and further conclusions will not be altered by the negative thresholds. Roots in the
extreme regime are around 2 for the two products, indicating an explosive behavior when ratios go beyond the typical regime. Root of DIM2 in the typical regime is close to zero, indicating that it is only when fir price exceeds pine price by 16.5% or more that the market tends to adjust toward equilibrium. The results have confirmed that the two markets cannot accept high prices of fir products. However, the much higher threshold and also the reluctance of adjustment in STR market drawn by TVEC model is not supported by the results of LSTAR model.

Figure 3.3 shows trends in three price ratios and the regime switchings estimated by the LSTAR model. Trends in three ratios are not similar. Firstly, all three ratios go through a peak period from 1980 to the execution of harvesting restrictions around 1994. Secondly, there is a rebounding of pine prices in DIM1 and DIM2 markets, which begins in the middle 1990s and lasts for about six or seven years, but this trend is not clearly expressed in STR market. Finally, after 2007, pine prices go beyond fir prices in the DIM1 and STR markets, which is not obviously observed in the DIM2 market.

Considering the lower regime of DIM1 and the higher regimes of the other two are the more stable regimes, stable regime is generally a mainstream under the study period for all the three products, similar to the percentages of lower regimes estimated by TVEC model. When harvesting restrictions are imposed on forests in the West, prices are all in the lower regimes. Therefore, this shock has a deeper and more enduring impact on DIM1 market. Similar explanation can also be extended to the apparent dent in the figure of DIM1 market around 2005, when several hurricanes destroyed hundreds of thousands acres of forests in the South. Last but not the least, when declining of housing starts begins in 2007, only STR market is in the typical regime, so this shock brings more severe and longer feedback in STR market than in the other two.
3.6 Discussion

The major objective of this study is to examine history and trend in price transmission between northwestern and southern lumber markets after demand and supply shocks, particularly before and after harvesting restrictions imposed in the forests of Pacific Northwest in the early 1990s. Estimated results have shown three major findings. First, non-linear models fit the data better than linear time series models. Second, prices of pine and fir products are showed to be cointegrated, indicating that lumber market is efficient. Third, pine products have gained some market power from fir products.

Potential nonlinear features of the lumber prices have been explicitly modeled with structural change. Results have shown that the nonlinear models fit the data better than linear models, when estimating spatial price linkage between the South and Pacific Northwest lumber markets. Both TVEC and STAR models indicate that transaction cost should be incorporated into the analysis. This conclusion is also consistent with the considerable portion of transfer cost in lumber price. Moreover, threshold value of one product is positive, but negative for the other two, when conducting estimations with both models. It implies that directions of arbitrage activities are not uniform among the three products, suggesting that transaction cost alone cannot fully explain market dynamics after supply and demand shocks.
Johansen test confirms the spatial market cointegration. On one hand, it is consistent with the assumption that cointegration can be found among more standard and...
more homogeneous goods (Shahi & Kant, 2009). On the other hand, it confirms the hypothesis that the two markets will be more cointegrated after imposing of harvest restrictions (Murray & Wear, 1998).

Empirical results of the two models are not perfectly consistent, but generally, pine products have gained some market power from the traditional market leader. In the long term, prices of pine products are responsible for bringing the market back into equilibrium after supply or demand shocks across all the three markets. When DIM1 is investigated, market can tolerate relatively higher pine price, but the direction of transactions is commonly from the Pacific Northwest to the South. Moreover, DIM2 requires sawlogs of larger diameters as primary material, and STR calls for timber of higher ductility. When these two products are mentioned, pine prices possess larger market power when there is a deviation from equilibrium, and both markets have shown explosive behaviors when fir prices are too high. But fir products still have some impact in the short run. Combining the situations of all the three products, it can be concluded that various shocks have positively impacted southern lumber industry during the last 40 years, especially after the harvest restrictions. But fir products still have some market power and balance is maintained between the two separate markets.

There are some justifications implied by the results of this study. From the analysis of regime switching within a variety of lumber markets, diversity among different lumber products is as important as it among different assets. Lumber products with distinct characteristics can stay in either typical or extreme regime during shocks. Analysis on shocks and recoveries implies that markets with more influence from pine products have shown faster recovery from harvesting restrictions, where prices happen to be in their faster-adjustment regime during the period. But product with more influence
from fir performs better through some other events. Considering it is almost impossible to predict shocks will happen during either regime in the future, diversification on lumber products for sawmills may reduce risks brought by market shocks. For local sawmills, diverse products may ensure that there are some markets of products recovering sooner than others through market shocks. This justification also enhances the concept of economy of scale in the lumber production sector.

Results of this study have shown that Northwest Forest Plan has reshaped the national lumber market. On one hand, the population of spotted owls has not significantly increased. On the other hand, the shock on lumber price following the policy was fully digested, accompanying the loss of West’s leadership. Currently, the major problem facing lumber market is deficient demand instead of inadequate supply. This situation implies that when both markets are self-sufficient, modification of the existing restrictions is not the first concern of either lumber supplies or consumers.

Future studies can be conducted through a simulation to make a choice between sudden transition and smooth transition. Similar research can be extended to hardwood products, to convey more information on market diversification. Shocks are better to be included into the models as variables, to explain market dynamics more thoroughly and precisely. One rotation has been finished in partial southern timberland since imposing of harvest restrictions in Pacific Northwest. Moreover, there is not a schedule on the recovery of American housing market. Therefore, future development of lumber prices should be continuously paid close attention, to update existing results, to reduce market risks and to benefit investors in lumber production sector.
CHAPTER IV
CONCLUSIONS

Lumber production in the South plays an important role in the local economy, and is also an essential component of the national timber industry. This project investigates the efficiency and dynamics of lumber market in the South, and connects it to upstream market vertically and northwestern market spatially. In general, lumber market shows a high level of integration and efficiency with both points of view when compared to previous studies. This phenomenon may be evolved from the process of market development. Supply and demand shocks, particular the shocks that occur in limited regions, usually require higher frequency of information transmission, and may incur more arbitrage activities. So shocks in timber market of the last 40 years have probably enhanced the cointegration among markets.

In the first study with concern to vertical price transmission, price transmission asymmetry has been examined in three-stage level: price of stumpage, price of delivered sawlog, and two prices of lumber products. Cointegration tests confirm the integration and efficiency of timber market vertically in the South. Results of error correction model reveal that the asymmetric price transmission exists only when price of the lumber board is linked with upstream prices. But cumulative effects are generally symmetric. Moreover, once adjustment path is proven to be asymmetric, adjustment from positive deviations always requires longer time than that of negative deviations, when lumber
price is set as the driving force. But asymmetric transmission is not a prevalent phenomenon in southern timber market.

A couple of points of view have been developed from the analysis. This study predicts that stumpage and sawlog prices are not the only factors that will affect lumber prices in the future: international supply should also be considered. Results of this study also imply that lumber producers have obtained some market power over small mills, small companies and timberland owners along the supply chain.

In the second study on spatial price transmission between lumber markets of the South and the Pacific Northwest, degree of the spatial price linkage is examined with threshold vector error correction model and smooth transition autoregressive model. Estimated results reveal that two markets are cointegrated with each other, but the degree and direction of spatial price transmission vary by product. Some lumber products made of southern pine have gained market leadership over equivalent products from the Northwest. But fir products are still influential. One of the most important products is still mainly transported from the Pacific Northwest to the South, but the direction of transportation is inverse when the other two products are under study.

This study is justifiable when it is related to the welfare of landowners and sawmill-owners, and the decision-making of policy makers. Because different products perform differently through market shocks, product diversification is a rational choice for sawmill-owners. Advice for the policy makers is that modification of the existing restrictions is not the first concern when lumber market stays self-sufficient, particularly when Northwest Forest Plan has already reshaped national lumber market.

There is also some limitation with this thesis. Firstly, only a small number of lumber products among hundreds are selected as representatives of the market. According
to the results that market dynamics are closely related to characteristics of products, it may be difficult to decipher the whole supply chain with several lumber products.

Secondly, price per se is only a signal of market. Thus, results can be more comprehensive if volume data are included in the study, with explanation on real behavior of market participants. And finally, given market powers and market shocks are adopted as potential explanations for the conclusions, this thesis can be enriched if these factors can be incorporated into the models. All the three aspects can also be regarded as development directions for studies in the future.
REFERENCES


APPENDIX A

R CODE FOR CHAPTER II
library(RODBC); library(urca); library(vars)
library(strucchange); library(car); library(TSA); library(fUnitRoots);
library(erer); library(apt)
options(width=160)

1. Import Data
---------------
getwd(); setwd("K:/Sun/10.File Zhuo Ning/Vertical"); getwd()
wood <- odbcConnectExcel2007('wood data.xlsx')
sheet <- sqlTables(wood); sheet$TABLE_NAME
tim <- sqlFetch(wood, "data"); note <- sqlFetch(wood, "note"); odbcClose(wood)
dim(tim); names(tim); head(tim); tail(tim); note

# select sample 1977 to 2008 = 31 yrs = 128 obs; time series; take log

HH <- tim[1:128, c("diw", "stw", "avedw", "avesw",
               "boa", "sle", "aved11", "aves11")]
colnames(HH) <- c("WLB", "WLA", "WPD", "WPS", "LA", "LB", "PD", "PS");
head(HH)
tHH <- ts(HH, start=c(1977,1), freq=4); tHH[1:5,]

hh <- log(HH); head(hh); thh <- ts(hh, start=c(1977,1), freq=4)
colnames(thh) <- tolower(c("WLB", "WLA", "WPD", "WPS", "LA", "LB", "PD", "PS"))

2. Unit Root
--------------
ff <- data.frame(matrix(0, nrow=8, ncol=7))
colnames(ff) <- c("ADF.level", "ADF.dif",
                "PP.level", "PP.dif", "KPSS.level", "KPSS.dif", "lag")
gg <- c(6,5,11,8,6,9,11,11); digit <- 2

for (i in 1:length(gg)) {
  x <- ts(tHH[, i], start=c(1977,1), freq=4)
y <- diff(x);
adf.x <- ur.df(x, type="none", lags=gg[i])
adf.y <- ur.df(y, type="none", lags=gg[i])
pp.x  <- pp.test(x, type = "Z(t_alpha)")
pp.y  <- pp.test(y, type = "Z(t_alpha)")
kpss.x <- kpss.test(x)
kpss.y <- kpss.test(y)
ff[i,1] <- round(adf.x@teststat[1,1], digit)
ff[i,2] <- round(adf.y@teststat[1,1], digit)
ff[i,3] <- round(data.frame(pp.x$statistic)[1,1], digit)
ff[i,4] <- round(data.frame(pp.y$statistic)[1,1], digit)
ff[i,5] <- round(data.frame(kpss.x$statistic)[1,1], digit)
ff[i,6] <- round(data.frame(kpss.y$statistic)[1,1], digit)
ff[i,7] <- gg[i]
rownames(ff)[i] <- colnames(tHH)[i]

(tab2 <- ff)

# Smallest one in diff: significant type=none
# Biggest one in original: unsignificant
summary(adf.xa  <- ur.df(PS, type=c("none"), lags=11)); plot(adf.xa)
summary(adf.dxb <- ur.df(diff(LB), type=c("none"), lags=11))

######## 3. Cointegration ###################################

VARselect(tHH, lag.max=12, type="const") #lag=3
VARselect(tHH, lag.max=12, type="trend") #lag=3
VARselect(tHH, lag.max=12, type="both")  #lag=5
VARselect(tHH, lag.max=12, type="none")  #lag=3
summary(VAR(tHH, type="const", p=1))

# 3A JJ cointegration test (max & trend)
summary( jj1 <- ca.jo(cbind(PS,LA), type='eigen', ecdet="trend", K=3 ))
summary( jj2 <- ca.jo(cbind(PD,LA), type='eigen', ecdet="trend", K=3 ))
summary( jj3 <- ca.jo(cbind(PS,LB), type='eigen', ecdet="trend", K=3 ))
summary( jj4 <- ca.jo(cbind(PD,LB), type='eigen', ecdet="trend", K=3 ))
summary( jj5 <- ca.jo(cbind(PD,PS), type='eigen', ecdet="trend", K=3 ))

# 3B JJ cointegration test (max & constant)
summary( jj11 <- ca.jo(cbind(PS,LA), type='eigen', ecdet="const", K=3 ))
summary( jj12 <- ca.jo(cbind(PD,LA), type='eigen', ecdet="const", K=3 ))
summary( jj13 <- ca.jo(cbind(PS,LB), type='eigen', ecdet="const", K=3 ))
summary( jj14 <- ca.jo(cbind(PD,LB), type='eigen', ecdet="const", K=3 ))
summary( jj15 <- ca.jo(cbind(PD,PS), type='eigen', ecdet="const", K=3 ))

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# 3C JJ cointegration test (trace & trend)
summary( jj21 <- ca.jo(cbind(PS,LA), type='trace', ecdet="trend", K=3 ))
summary( jj22 <- ca.jo(cbind(PD,LA), type='trace', ecdet="trend", K=3 ))
summary( jj23 <- ca.jo(cbind(PS,LB), type='trace', ecdet="trend", K=3 ))
summary( jj24 <- ca.jo(cbind(PD,LB), type='trace', ecdet="trend", K=3 ))
summary( jj25 <- ca.jo(cbind(PD,PS), type='trace', ecdet="trend", K=3 ))

# 3D JJ cointegration test (trace & constant)
summary( jj31 <- ca.jo(cbind(PS,LA), type='trace', ecdet="const", K=3 ))
summary( jj32 <- ca.jo(cbind(PD,LA), type='trace', ecdet="const", K=3 ))
summary( jj33 <- ca.jo(cbind(PS,LB), type='trace', ecdet="const", K=3 ))
summary( jj34 <- ca.jo(cbind(PD,LB), type='trace', ecdet="const", K=3 ))
summary( jj35 <- ca.jo(cbind(PD,PS), type='trace', ecdet="const", K=3 ))

K=3
slotNames(jj1)
out11 <- cbind("LA~PD","eigen", "trend", K, round(jj2@teststat, 2), jj2@cval)
out12 <- cbind("LA~PD","eigen", "const", K, round(jj12@teststat, 2), jj12@cval)
out13 <- cbind("LA~PD","trace", "trend", K, round(jj22@teststat, 2), jj22@cval)
out14 <- cbind("LA~PD","trace", "const", K, round(jj32@teststat, 2), jj32@cval)
out21 <- cbind("LB~PD","eigen", "trend", K, round(jj4@teststat, 2), jj4@cval)
out22 <- cbind("LB~PD","eigen", "const", K, round(jj14@teststat, 2), jj14@cval)
out23 <- cbind("LB~PD","trace", "trend", K, round(jj24@teststat, 2), jj24@cval)
out24 <- cbind("LB~PD","trace", "const", K, round(jj34@teststat, 2), jj34@cval)
out31 <- cbind("LA~PS","eigen", "trend", K, round(jj1@teststat, 2), jj1@cval)
out32 <- cbind("LA~PS","eigen", "const", K, round(jj11@teststat, 2), jj11@cval)
out33 <- cbind("LA~PS","trace", "trend", K, round(jj21@teststat, 2), jj21@cval)
out34 <- cbind("LA~PS","trace", "const", K, round(jj31@teststat, 2), jj31@cval)
out41 <- cbind("LB~PS","eigen", "trend", K, round(jj3@teststat, 2), jj3@cval)
out42 <- cbind("LB~PS","eigen", "const", K, round(jj13@teststat, 2), jj13@cval)
out43 <- cbind("LB~PS","trace", "trend", K, round(jj23@teststat, 2), jj23@cval)
out44 <- cbind("LB~PS","trace", "const", K, round(jj33@teststat, 2), jj33@cval)
out51 <- cbind("PD~PS","eigen", "trend", K, round(jj5@teststat, 2), jj5@cval)
out52 <- cbind("PD~PS","eigen", "const", K, round(jj15@teststat, 2), jj15@cval)
out53 <- cbind("PD~PS","trace", "trend", K, round(jj25@teststat, 2), jj25@cval)
out54 <- cbind("PD~PS","trace", "const", K, round(jj35@teststat, 2), jj35@cval)
jjci <- rbind(out11, out12, out13, out14, out21, out22, out23, out24, out31, out32, out33, out34, out41, out42, out43, out44, out51, out52, out53, out54)
colnames(jjci) <- c("Pair_of_Prices", "test 1", "test 2", "lag", "statistic", 71
# 3B EG cointegration
# 3Ba LA–PS
summary(ba1 <- lm(LA~PS))
(ry1 <- ts(residuals(ba1), start=c(1977,1), freq=4))
summary(eg1 <- ur.df(ry1, type=c("none"), lags=3))
plot(eg1)

(ry1_4  <- Box.test(eg1@res, lag = 4, type="Ljung") )
(ry1_8  <- Box.test(eg1@res, lag = 8, type="Ljung") )
(ry1_12 <- Box.test(eg1@res, lag = 12, type="Ljung") )

source("ur.df.edwin.r")
ry1_2 <- ur.df.edwin(ry1, type=c("none"), lags=3, selectlags="Fixed")
EG1.coef  <- coefficients(eg1@testreg)[1,1]
EG1.tval  <- coefficients(eg1@testreg)[1,3]
EG1.aic  <- ry1_2$aic
EG1.bic  <- ry1_2$bic
EG1.pLB4  <- ry1_4$p.value
EG1.pLB8  <- ry1_8$p.value
EG1.pLB12 <- ry1_12$p.value

OUT1  <- cbind("LA~PS",round(data.frame(EG1.coef, EG1.tval, EG1.aic, EG1.bic,
   EG1.pLB4, EG1.pLB8, EG1.pLB12), 3))
colnames(OUT1) <- c("Pair_of_Prices", "EG_Value", "EG_TValue", "AIC",
   "BIC", "BL4", "BL8", "BL12")

# 3Bb LA–PD
summary(ba2 <- lm(LA~PD))
(ry2 <- ts(residuals(ba2), start=c(1977,1), freq=4))
summary(eg2 <- ur.df(ry2, type=c("none"), lags=3))
plot(eg2)

(ry2_4  <- Box.test(eg2@res, lag = 4, type="Ljung") )
(ry2_8  <- Box.test(eg2@res, lag = 8, type="Ljung") )
(ry2_12 <- Box.test(eg2@res, lag = 12, type="Ljung") )

source("ur.df.edwin.r")
ry2_2 <- ur.df.edwin(ry2, type=c("none"), lags=3, selectlags="Fixed")
EG2.coef  <- coefficients(eg2@testreg)[1,1]
EG2.tval <- coefficients(eg2@testreg)[1,3]
EG2.aic  <- ry2_2$aic
EG2.bic  <- ry2_2$bic
EG2.pLB4  <- ry2_4$p.value
EG2.pLB8  <- ry2_8$p.value
EG2.pLB12 <- ry2_12$p.value

OUT2  <- cbind("LA~PD",round(data.frame(EG1.coef, EG1.tval, EG1.aic, EG1.bic,
EG1.pLB4, EG1.pLB8, EG1.pLB12), 3))
colnames(OUT2) <- c("Pair_of_Prices", "EG_Value", "EG_TValue", "AIC",
"BIC", "BL4", "BL8", "BL12")

#3Bc LB~PS
summary(ba3 <- lm(LB~PS))
(ry3  <- ts(residuals(ba3), start=c(1977,1), freq=4))
summary(eg3 <- ur.df(ry3, type="none", lags=5))
plot(eg3)

(ry3_4  <- Box.test(eg3@res, lag = 4, type="Ljung") )
(ry3_8  <- Box.test(eg3@res, lag = 8, type="Ljung") )
(ry3_12 <- Box.test(eg3@res, lag = 12, type="Ljung") )

source("ur.df.edwin.r")
ry3_2  <- ur.df.edwin(ry3, type="none", lags=5, selectlags="Fixed")

EG3.coef  <- coefficients(eg3@testreg)[1,1]
EG3.tval  <- coefficients(eg3@testreg)[1,3]
EG3.aic  <- ry3_2$aic
EG3.bic  <- ry3_2$bic
EG3.pLB4  <- ry3_4$p.value
EG3.pLB8  <- ry3_8$p.value
EG3.pLB12 <- ry3_12$p.value

OUT3  <- cbind("LB~PS",round(data.frame(EG3.coef, EG3.tval, EG3.aic, EG3.bic,
colnames(OUT3) <- c("Pair_of_Prices", "EG_Value", "EG_TValue", "AIC",
"BIC", "BL4", "BL8", "BL12")

#3Bd LB~PD
summary(ba4 <- lm(LB~PD))
(ry4  <- ts(residuals(ba4), start=c(1977,1), freq=4))
summary(eg4 <- ur.df(ry4, type="none", lags=7))
plot(eg4)

(ry4_4  <- Box.test(eg4@res, lag = 4, type="Ljung") )

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(ry4_8 <- Box.test(eg4@res, lag = 8, type="Ljung") )  
(ry4_12 <- Box.test(eg4@res, lag = 12, type="Ljung") )  

source("ur.df.edwin.r")  
ry4_2 <- ur.df.edwin(ry4, type="c("none"), lags=7, selectlags="Fixed")  

EG4.coef  <- coefficients(eg4@testreg)[1,1]  
EG4.tval  <- coefficients(eg4@testreg)[1,3]  
EG4.aic  <- ry4_2$aic  
EG4.bic  <- ry4_2$bic  
EG4.pLB4  <- ry4_4$p.value  
EG4.pLB8  <- ry4_8$p.value  
EG4.pLB12 <- ry4_12$p.value  

OUT4  <- cbind("LB~PD",round(data.frame(EG4.coef, EG4.tval, EG4.aic, EG4.bic,  
colnames(OUT4) <- c("Pair_of_Prices", "EG_Value", "EG_TValue", "AIC",  
"BIC", "BL4", "BL8", "BL12")  

#3Be PD~PS  
summary(ba5 <- lm(PD~PS))  
(ry5 <- ts(residuals(ba5), start=c(1977,1), freq=4))  
summary(eg5 <- ur.df(ry5, type="c("none"), lags=6))  
plot(eg5)  

(ry5_4 <- Box.test(eg5@res, lag = 4, type="Ljung") )  
(ry5_8 <- Box.test(eg5@res, lag = 8, type="Ljung") )  
(ry5_12 <- Box.test(eg5@res, lag = 12, type="Ljung") )  

source("ur.df.edwin.r")  
ry5_2 <- ur.df.edwin(ry5, type="c("none"), lags=6, selectlags="Fixed")  

EG5.coef  <- coefficients(eg5@testreg)[1,1]  
EG5.tval  <- coefficients(eg5@testreg)[1,3]  
EG5.aic  <- ry5_2$aic  
EG5.bic  <- ry5_2$bic  
EG5.pLB4  <- ry5_4$p.value  
EG5.pLB8  <- ry5_8$p.value  
EG5.pLB12 <- ry5_12$p.value  

OUT5  <- cbind("PD~PS",round(data.frame(EG5.coef, EG5.tval, EG5.aic, EG5.bic,  
EG5.pLB4, EG5.pLB8, EG5.pLB12), 3))  
colnames(OUT5) <- c("Pair_of_Prices", "EG_Value", "EG_TValue", "AIC",  
"BIC", "BL4", "BL8", "BL12")  

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# 3Bf PS~LA
summary(ba6 <- lm(PS~LA))
(ry6 <- ts(residuals(ba6), start=c(1977,1), freq=4))
summary(eg6 <- ur.df(ry6, type="none", lags=5))
plot(eg6)

(ry6_4  <- Box.test(eg6@res, lag = 4, type="Ljung") )
(ry6_8  <- Box.test(eg6@res, lag = 8, type="Ljung") )
(ry6_12 <- Box.test(eg6@res, lag = 12, type="Ljung") )

source("ur.df.edwin.r")
ry6_2 <- ur.df.edwin(ry6, type=c("none"), lags=5, selectlags="Fixed")

EG6.coef <- coefficients(eg6@testreg)[1,1]
EG6.tval <- coefficients(eg6@testreg)[1,3]
EG6.aic  <- ry6_2$aic
EG6.bic  <- ry6_2$bic
EG6.pLB4  <- ry6_4$p.value
EG6.pLB8  <- ry6_8$p.value
EG6.pLB12 <- ry6_12$p.value

OUT6  <- cbind("PS~LA",round(data.frame(EG6.coef, EG6.tval, EG6.aic, EG6.bic,
EG6.pLB4, EG6.pLB8, EG6.pLB12, 3)))
colnames(OUT6) <- c("Pair_of_Prices", "EG_Value", "EG_TValue", "AIC",
"BIC", "BL4", "BL8", "BL12")

# 3Bg LA~PD
summary(ba7 <- lm(PD~LA))
(ry7 <- ts(residuals(ba7), start=c(1977,1), freq=4))
summary(eg7 <- ur.df(ry7, type="none", lags=3))
plot(eg7)

(ry7_4  <- Box.test(eg7@res, lag = 4, type="Ljung") )
(ry7_8  <- Box.test(eg7@res, lag = 8, type="Ljung") )
(ry7_12 <- Box.test(eg7@res, lag = 12, type="Ljung") )

source("ur.df.edwin.r")
ry7_2 <- ur.df.edwin(ry7, type=c("none"), lags=3, selectlags="Fixed")

EG7.coef <- coefficients(eg7@testreg)[1,1]
EG7.tval <- coefficients(eg7@testreg)[1,3]
EG7.aic  <- ry7_2$aic
EG7.bic  <- ry7_2$bic
EG7.pLB4  <- ry7_4$p.value
EG7.pLB8  <- ry7_8$p.value
EG7.pLB12 <- ry7_12$p.value

OUT7 <- cbind("PD~LA", round(data.frame(EG7.coef, EG7.tval, EG7.aic, EG7.bic,
EG7.pLB4, EG7.pLB8, EG7.pLB12), 3))
colnames(OUT7) <- c("Pair_of_Prices", "EG_Value", "EG_TValue", "AIC",
"BIC", "BL4", "BL8", "BL12")

#3Bh LB~PS
summary(ba8 <- lm(PS~LB))
(ry8 <- ts(residuals(ba8), start=c(1977,1), freq=4))
summary(eg8 <- ur.df(ry8, type="none", lags=5))
plot(eg8)

(ry8_4 <- Box.test(eg8@res, lag = 4, type="Ljung") )
(ry8_8 <- Box.test(eg8@res, lag = 8, type="Ljung") )
(ry8_12 <- Box.test(eg8@res, lag = 12, type="Ljung") )

source("ur.df.edwin.r")
ry8_2 <- ur.df.edwin(ry8, type="none", lags=5, selectlags="Fixed")

EG8.coef <- coefficients(eg8@testreg)[1,1]
EG8.tval <- coefficients(eg8@testreg)[1,3]
EG8.aic <- ry8_2$aic
EG8.bic <- ry8_2$bic
EG8.pLB4 <- ry8_4$p.value
EG8.pLB8 <- ry8_8$p.value
EG8.pLB12 <- ry8_12$p.value

OUT8 <- cbind("PS~LB", round(data.frame(EG8.coef, EG8.tval, EG8.aic, EG8.bic,
EG8.pLB4, EG8.pLB8, EG8.pLB12), 3))
colnames(OUT8) <- c("Pair_of_Prices", "EG_Value", "EG_TValue", "AIC",
"BIC", "BL4", "BL8", "BL12")

#3Bi LB~PD
summary(ba9 <- lm(PD~LB))
(ry9 <- ts(residuals(ba9), start=c(1977,1), freq=4))
summary(eg9 <- ur.df(ry9, type="none", lags=3))
plot(eg9)

(ry9_4 <- Box.test(eg9@res, lag = 4, type="Ljung") )
(ry9_8 <- Box.test(eg9@res, lag = 8, type="Ljung") )
(ry9_12 <- Box.test(eg9@res, lag = 12, type="Ljung") )

source("ur.df.edwin.r")
ry9_2 <- ur.df.edwin(ry9, type="none", lags=3, selectlags="Fixed")
EG9.coef  <- coefficients(eg9@testreg)[1,1]
EG9.tval  <- coefficients(eg9@testreg)[1,3]
EG9.aic  <- ry9_2$aic
EG9.bic  <- ry9_2$bic
EG9.pLB4  <- ry9_4$p.value
EG9.pLB8  <- ry9_8$p.value
EG9.pLB12 <- ry9_12$p.value

OUT9  <- cbind("PD~LB",round(data.frame(EG9.coef, EG9.tval, EG9.aic, EG9.bic,
colnames(OUT9) <- c("Pair_of_Prices", "EG_Value", "EG_TValue", "AIC",
"BIC", "BL4", "BL8", "BL12")

#3Bj PD~PS
summary(ba10 <- lm(PS~PD))
(ry10 <- ts(residuals(ba10), start=c(1977,1), freq=4))
summary(eg10 <- ur.df(ry10, type="none", lags=2))
plot(eg10)

(ry10_4  <- Box.test(eg10@res, lag = 4, type="Ljung") )
(ry10_8  <- Box.test(eg10@res, lag = 8, type="Ljung") )
(ry10_12 <- Box.test(eg10@res, lag = 12, type="Ljung") )

source("ur.df.edwin.r")
ry10_2 <- ur.df.edwin(ry10, type="none", lags=2, selectlags="Fixed")

EG10.coef  <- coefficients(eg10@testreg)[1,1]
EG10.tval  <- coefficients(eg10@testreg)[1,3]
EG10.aic  <- ry10_2$aic
EG10.bic  <- ry10_2$bic
EG10.pLB4  <- ry10_4$p.value
EG10.pLB8  <- ry10_8$p.value
EG10.pLB12 <- ry10_12$p.value

OUT10  <- cbind("PS~PD",round(data.frame(EG10.coef, EG10.tval, EG10.aic, EG10.bic,
colnames(OUT10) <- c("Pair_of_Prices", "EG_Value", "EG_TValue", "AIC",
"BIC", "BL4", "BL8", "BL12")

EGTest <- rbind(OUT2, OUT7, OUT4, OUT9, OUT1, OUT6, OUT3, OUT8, OUT5,
OUT10)
(tab3b <- data.frame(EGTest))
### 4a. TAR + Cointegration

```r
# TAR best threshold ====================
t3 <- ciTarThd(y=dpd, x=idp, model="tar", lag=0); t3$basic; plot(t3)
th.tar <- t3$basic
for (i in 1:12) {
t3a <- ciTarThd(y=dpd, x=idp, model="tar", lag=i)
    th.tar[i+2] <- t3a$basic[,2]
}
th.tar

# MTAR best threshold ====================
t4 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=0); plot(t4)
th.mtar <- t4$basic
for (i in 1:12) {
t4a <- ciTarThd(y=dpd, x=idp, model="mtar", lag=i)
    th.mtar[i+2] <- t4a$basic[,2]
}
th.mtar

t.tar <- 44.164; t.mtar <- 3

# lag selection ====================
(g1 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12, adjust=T, thresh= 0)); plot(g1)
(g2 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12, adjust=T, thresh= 0)); plot(g2)
(g3 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12, adjust=T, thresh= t.tar)); plot(g3)
(g4 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12, adjust=T, thresh= t.mtar)); plot(g4)

# Figure of threshold value selection
(t5 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=7)); plot(t5)

win.graph(width=5.1,height=3.3,pointsize=9); bringToTop(stay=T)
par(mai=c(0.7,0.7,0.1,0.1),family="serif")
plot(path.sse~path.thr, data=t5$path, type="l",
```
```
ylab="Sum of Squared Errors", xlab="Threshold value")

fig3 <- ggplot(data=t5$path) +
  geom_line(aes(x=path.thr, y=path.sse)  ) +
  labs(x="Threshold value", y="Sum of squared errors") +
  # scale_y_continuous(limits=c(5100,5650)) +
  # scale_x_continuous(breaks=c(-10:10)) +
  opts( axis.text.x =theme_text(size=8,family="serif", vjust=0.8) )+
  opts( axis.text.y =theme_text(size=8,family="serif", hjust=0.8) )+
  opts( axis.title.x=theme_text(size=9,family="serif" ) )+
  opts( axis.title.y=theme_text(size=9,family="serif", angle=90 ) )

win.graph(width=4.5,height=3,pointsize=9); bringToTop(stay=T); fig3

#### final esitmation ====================

G <- 7
(f1 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=0))
(f2 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=t.tar))
(f3 <- ciTarFit(y=dpd, x=idp, model="mtar",lag=G, thresh=0))
(f4 <- ciTarFit(y=dpd, x=idp, model="mtar",lag=G, thresh=t.mtar))

r0 <- cbind(summary(f1)$dia, summary(f2)$dia, summary(f3)$dia, summary(f4)$dia)
(r1 <- r0[, c(1,2,4,6,8)])
col.name <- c("item","tar","c.tar","mtar","c.mtar")
diag <- r1[c(2, 6:7, 12:14, 8, 9, 11), col.name]
rownames(diag) <- 1:nrow(diag); diag
e1 <- summary(f1)$out; e2 <- summary(f2)$out
e3 <- summary(f3)$out; e4 <- summary(f4)$out
(r2 <- rbind(e1, e2, e3, e4))

ee <- list(e1, e2, e3, e4); vect <- NULL
for (i in 1:4)
  {ef <- data.frame(ee[i]); ef
   vect2 <- c(paste(ef[3, "estimate"], ef[3, "sign"], sep=""),
             paste("", ef[3, "t.value"], ","), sep=""),
             paste(ef[4, "estimate"], ef[4, "sign"], sep=""),
             paste("", ef[4, "t.value"], ","), sep=""))
   vect <- cbind(vect, vect2)
  }
item <- c("pos.coeff","pos.t.value", "neg.coeff","neg.t.value")
ve <- data.frame(cbind(item, vect)); colnames(ve) <- col.name

ThCo01 <- rbind(diag, ve)[c(1,10:13, 7:9),]
ThCo1 <- cbind("LB~PD", t(ThCo01[,c(3,5)]))
colnames(ThCo1) <- cbind("Pairs of Prices", t(ThCo01[,1]))

##### 4Ab LB + PS
dpd <- LB # y
idp <- PS # x

# TAR best threshold ====================
t3 <- ciTarThd(y=dpd, x=idp, model="tar", lag=0); t3$basic; plot(t3)

th.tar <- t3$basic
for (i in 1:12) {
  t3a <- ciTarThd(y=dpd, x=idp, model="tar", lag=i)
  th.tar[i+2] <- t3a$basic[,2]
}
th.tar

# MTAR best threshold ====================
t4 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=0); plot(t4)

th.mtar <- t4$basic
for (i in 1:12) {
  t4a <- ciTarThd(y=dpd, x=idp, model="mtar", lag=i)
  th.mtar[i+2] <- t4a$basic[,2]
}
th.mtar

t.tar <- 33.501; t.mtar <- -31.022

##### lag selection ====================
(g1 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12, adjust=T, thresh= 0)); plot(g1)
(g2 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12, adjust=T, thresh= 0)); plot(g2)
(g3 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12, adjust=T, thresh= t.tar)); plot(g3)
(g4 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12, adjust=T, thresh= t.mtar)); plot(g4)

# Figure of threshold value selection
(t5 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=7)); plot(t5)

win.graph(width=5.1,height=3.3,pointsize=9); bringToTop(stay=T)
par(mai=c(0.7,0.7,0.1,0.1),family="serif")
plot(path.sse~path.thr, data=t5$path, type="l",
     ylab="Sum of Squared Errors", xlab="Threshold value")
fig3 <- ggplot(data=t5$path) +
  geom_line(aes(x=path.thr, y=path.sse)  ) +
  labs(x="Threshold value", y="Sum of squared errors") +
  scale_y_continuous(limits=c(5100,5650)) +
  scale_x_continuous(breaks=c(-10:10)) +
  opts( axis.text.x =theme_text(size=8,family="serif", vjust=0.8) ) +
  opts( axis.text.y =theme_text(size=8,family="serif", hjust=0.8) ) +
  opts( axis.title.x=theme_text(size=9,family="serif" ) )+
  opts( axis.title.y=theme_text(size=9,family="serif", angle=90 ) )
#win.graph(width=4.5,height=3,pointsize=9); bringToTop(stay=T); fig3

#### final estimation ====================

G <- 7
(f1 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=0))
(f2 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=t.tar))
(f3 <- ciTarFit(y=dpd, x=idp, model="mtar",lag=G, thresh=0))
(f4 <- ciTarFit(y=dpd, x=idp, model="mtar",lag=G, thresh=t.mtar))

deeply<- cbind(summary(f1)$dia, summary(f2)$dia, summary(f3)$dia, summary(f4)$dia)
(deep <- r0[, c(1,2,4,6,8)])
col.name <- c("item","tar","c.tar","mtar","c.mtar")
diag <- r1[c(2, 6:7, 12:14, 8, 9, 11), col.name]
rownames(diag) <- 1:nrow(diag); diag
e1 <- summary(f1)$out; e2 <- summary(f2)$out
e3 <- summary(f3)$out; e4 <- summary(f4)$out
(r2 <- rbind(e1, e2, e3, e4))

ee <- list(e1, e2, e3, e4); vect <- NULL
for (i in 1:4) {
  ef <- data.frame(ee[i]); ef
  vect2 <- c(paste(ef[3, "estimate"], ef[3, "sign"], sep=""),
    paste("","ef[3,"t.value"], ", sep=""),
    paste(ef[4, "estimate"], ef[4, "sign"], sep=""),
    paste("","ef[4,"t.value"], ", sep=""))
  vect <- cbind(vect, vect2)
}
item <- c("pos.coeff","pos.t.value", "neg.coeff","neg.t.value")
ve <- data.frame(cbind(item, vect)); colnames(ve) <- col.name

ThCo02 <- rbind(diag, ve)[c(1,10:13, 7:9),]
ThCo22 <- cbind("LB~PS",t(ThCo22[,c(3,5)]))
colnames(ThCo22) <- cbind("Pairs of Prices", t(ThCo22[,1]))
```r
##### 4Ac LA + PS
dpd <- LA # y
idp <- PS # x

# TAR best threshold ====================
t3 <- ciTarThd(y=dpd, x=idp, model="tar", lag=0); t3$basic; plot(t3)
th.tar <- t3$basic
for (i in 1:12) {
  t3a <- ciTarThd(y=dpd, x=idp, model="tar", lag=i)
  th.tar[i+2] <- t3a$basic[,2]
}
th.tar

# MTAR best threshold ====================
t4 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=0); plot(t4)
th.mtar <- t4$basic
for (i in 1:12) {
  t4a <- ciTarThd(y=dpd, x=idp, model="mtar", lag=i)
  th.mtar[i+2] <- t4a$basic[,2]
}
th.mtar

t.tar <- -25.087; t.mtar <- 10

##### lag selection ====================
(g1 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12,
  adjust=T, thresh= 0)); plot(g1)
(g2 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12,
  adjust=T, thresh= 0)); plot(g2)
(g3 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12,
  adjust=T, thresh= t.tar)); plot(g3)
(g4 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12,
  adjust=T, thresh= t.mtar)); plot(g4)

# Figure of threshold value selection
(t5 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=6)); plot(t5)

win.graph(width=5.1,height=3.3,pointsize=9); bringToTop(stay=T)
par(mai=c(0.7,0.7,0.1,0.1),family="serif")
plot(path.sse~path.thr, data=t5$path, type="l",
  ylab="Sum of Squared Errors", xlab="Threshold value")
fig3 <- ggplot(data=t5$path) +
  geom_line(aes(x=path.thr, y=path.sse)  ) +
  labs(x="Threshold value", y="Sum of squared errors") +
```

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G <- 6
(f1 <- ciTarFit(y=dpd, x=idp, model=\"tar\", lag=G, thresh=0))
(f2 <- ciTarFit(y=dpd, x=idp, model=\"tar\", lag=G, thresh=t.tar))
(f3 <- ciTarFit(y=dpd, x=idp, model=\"mtar\", lag=G, thresh=0))
(f4 <- ciTarFit(y=dpd, x=idp, model=\"mtar\", lag=G, thresh=t.mtar))

r0 <- cbind(summary(f1)$dia, summary(f2)$dia, summary(f3)$dia, summary(f4)$dia)
(r1 <- r0[, c(1,2,4,6,8)])
col.name <- c("item","tar","c.tar","mtar","c.mtar")
diag <- r1[c(2, 6:7, 12:14, 8, 9, 11), col.name]
rownames(diag) <- 1:nrow(diag); diag

e1 <- summary(f1)$out; e2 <- summary(f2)$out
e3 <- summary(f3)$out; e4 <- summary(f4)$out
(r2 <- rbind(e1, e2, e3, e4))

ee <- list(e1, e2, e3, e4); vect <- NULL
for (i in 1:4) {
  ef <- data.frame(ee[[i]]); ef
  vect2 <- c(paste(ef[3, "estimate"], ef[3, "sign"], sep=""),
    paste("", ef[3, "t.value"], ""), sep=""),
    paste(ef[4, "estimate"], ef[4, "sign"], sep=""),
    paste("", ef[4, "t.value"], ""), sep=""))
  vect <- cbind(vect, vect2)
}
item <- c("pos.coeff","pos.t.value", "neg.coeff","neg.t.value")
ve <- data.frame(cbind(item, vect)); colnames(ve) <- col.name

ThCo03 <- rbind(diag, ve)[c(1,10:13, 7:9),]
ThCo3 <- cbind("LA~PS", t(ThCo03[,c(3,5)]))
colnames(ThCo3) <- cbind("Pairs of Prices", t(ThCo03[,1]))

#### 4Ad LA + PD

dpd <- LA # y
idp <- PD # x
# TAR best threshold ====================
t3 <- ciTarThd(y=dpd, x=idp, model="tar", lag=0); t3$basic; plot(t3)
th.tar <- t3$basic
for (i in 1:12) {
  t3a <- ciTarThd(y=dpd, x=idp, model="tar", lag=i)
  th.tar[i+2] <- t3a$basic[,2]
}

th.tar

# MTAR best threshold ====================
t4 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=0); plot(t4)
th.mtar <- t4$basic
for (i in 1:12) {
  t4a <- ciTarThd(y=dpd, x=idp, model="mtar", lag=i)
  th.mtar[i+2] <- t4a$basic[,2]
}

th.mtar

t.tar <- -26.014; t.mtar <- 9

##### lag selection ====================
(g1 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12,
     adjust=T, thresh= 0)); plot(g1)
(g2 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12,
     adjust=T, thresh= 0)); plot(g2)
(g3 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12,
     adjust=T, thresh= t.tar)); plot(g3)
(g4 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12,
     adjust=T, thresh= t.mtar)); plot(g4)

# Figure of threshold value selection
(t5 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=3)); plot(t5)

win.graph(width=5.1,height=3.3,pointsize=9); bringToTop(stay=T)
par(mai=c(0.7,0.7,0.1,0.1),family="serif")
plot(path.sse~path.thr, data=t5$path, type="l",
     ylab="Sum of Squared Errors", xlab="Threshold value")
fig3 <- ggplot(data=t5$path) +
  geom_line(aes(x=path.thr, y=path.sse) ) +
  labs(x="Threshold value", y="Sum of squared errors") +
  # scale_y_continuous(limits=c(5100,5650)) +
  # scale_x_continuous(breaks=c(-10:10)) +
  opts( axis.text.x =theme_text(size=8,family="serif", vjust=0.8) )+

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G <- 3
(f1 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=0))
(f2 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=t.tar))
(f3 <- ciTarFit(y=dpd, x=idp, model="mtar", lag=G, thresh=0))
(f4 <- ciTarFit(y=dpd, x=idp, model="mtar", lag=G, thresh=t.mtar))

r0 <- cbind(summary(f1)$dia, summary(f2)$dia, summary(f3)$dia, summary(f4)$dia)
(r1 <- r0[, c(1,2,4,6,8)])
col.name <- c("item", "tar", "c.tar", "mtar", "c.mtar")
diag <- r1[2, 6:7, 12:14, 8, 9, 11, col.name]
rownames(diag) <- 1:nrow(diag); diag

e1 <- summary(f1)$out; e2 <- summary(f2)$out
e3 <- summary(f3)$out; e4 <- summary(f4)$out
(r2 <- rbind(e1, e2, e3, e4))

ee <- list(e1, e2, e3, e4); vect <- NULL
for (i in 1:4) {
  ef <- data.frame(ee[i]); ef
text <- c(paste(ef[3, "estimate"], ef[3, "sign"], sep=""),
                         paste("(" , ef[3, "t.value"], ")", sep=""),
                         paste(ef[4, "estimate"], ef[4, "sign"], sep=""),
                         paste("(" , ef[4, "t.value"], ")", sep=""))
  vect <- cbind(vect, vecttext)
}
item <- c("pos.coeff", "pos.t.value", "neg.coeff", "neg.t.value")
ve <- data.frame(cbind(item, vecttext)); colnames(ve) <- col.name

ThCo04 <- rbind(diag, ve)[c(1, 10:13, 7:9),]
ThCo4 <- cbind("LA~PD", t(ThCo04[, c(3, 5)]))
colnames(ThCo4) <- cbind("Pairs of Prices", t(ThCo04[, 1]))

#### 4Ac PS + PD
dpd <- PD # y
idp <- PS # x

# TAR best threshold
(t3 <- ciTarThd(y=dpd, x=idp, model="tar", lag=0); t3$basic; plot(t3)
th.tar <- t3$basic
for (i in 1:12) {
  t3a <- ciTarThd(y=dpd, x=idp, model="tar", lag=i)
  th.tar[i+2] <- t3a$basic[,2]
}
th.tar

# MTAR best threshold -------------------------------
t4 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=0); plot(t4)
th.mtar <- t4$basic
for (i in 1:12) {
  t4a <- ciTarThd(y=dpd, x=idp, model="mtar", lag=i)
  th.mtar[i+2] <- t4a$basic[,2]
}
th.mtar

t.tar <- 6.326; t.mtar <- 2

##### lag selection -------------------------------
(g1 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12,
  adjust=T, thresh= 0)); plot(g1)
(g2 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12,
  adjust=T, thresh= 0)); plot(g2)
(g3 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12,
  adjust=T, thresh= t.tar)); plot(g3)
(g4 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12,
  adjust=T, thresh= t.mtar)); plot(g4)

# Figure of threshold value selection
(t5 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=0)); plot(t5)

win.graph(width=5.1,height=3.3,pointsize=9); bringToTop(stay=T)
par(mai=c(0.7,0.7,0.1,0.1),family="serif")
plot(path.sse~path.thr, data=t5$path, type="l",
  ylab="Sum of Squared Errors", xlab="Threshold value")
fig3 <- ggplot(data=t5$path) +
geom_line(aes(x=path.thr, y=path.sse) ) +
labs(x="Threshold value", y="Sum of squared errors") +
# scale_y_continuous(limits=c(5100,5650)) +
# scale_x_continuous(breaks=c(-10:10)) +
  opts( axis.text.x =theme_text(size=8,family="serif", vjust=0.8 ) )+
  opts( axis.text.y =theme_text(size=8,family="serif", hjust=0.8 ) )+
  opts( axis.title.x=theme_text(size=9,family="serif" ) )+
  opts( axis.title.y=theme_text(size=9,family="serif", angle=90 ) )
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#### final estimation ====================

\[ G = 0 \]

\[
(f1 \leftarrow \text{ciTarFit}(y=dpd, x=idp, \text{model}="\text{tar}", \text{lag}=G, \text{thresh}=0))
\]

\[
(f2 \leftarrow \text{ciTarFit}(y=dpd, x=idp, \text{model}="\text{tar}", \text{lag}=G, \text{thresh}=t.tar))
\]

\[
(f3 \leftarrow \text{ciTarFit}(y=dpd, x=idp, \text{model}="\text{mtar}", \text{lag}=G, \text{thresh}=0))
\]

\[
(f4 \leftarrow \text{ciTarFit}(y=dpd, x=idp, \text{model}="\text{mtar}", \text{lag}=G, \text{thresh}=t.mtar))
\]

\[
r0 \leftarrow \text{cbind}(\text{summary}(f1)\text{dia}, \text{summary}(f2)\text{dia}, \text{summary}(f3)\text{dia}, \text{summary}(f4)\text{dia})
\]

\[
(r1 \leftarrow r0[, c(1,2,4,6,8)])
\]

\[
col.name \leftarrow c("\text{item","tar","c.tar","mtar","c.mtar")
\]

\[
diag \leftarrow r1[c(2, 6:7, 12:14, 8, 9, 11), \text{col.name}]
\]

\[
\text{rownames(diag)} \leftarrow 1:\text{nrow(diag)}; \text{diag}
\]

\[
e1 \leftarrow \text{summary}(f1)\text{out}; e2 \leftarrow \text{summary}(f2)\text{out}
\]

\[
e3 \leftarrow \text{summary}(f3)\text{out}; e4 \leftarrow \text{summary}(f4)\text{out}
\]

\[
r2 \leftarrow \text{rbind}(e1, e2, e3, e4)
\]

\[
\text{ee} \leftarrow \text{list}(e1, e2, e3, e4); \text{vect} \leftarrow \text{NULL}
\]

\[
\text{for (i in 1:4) \{}
\]

\[
\text{ef} \leftarrow \text{data.frame(ee[i]); ef}
\]

\[
\text{vect2} \leftarrow \text{c(paste(ef[3, }"\text{estimate}"\text{], ef[3, }"\text{sign}"\text{], sep=""), pastex("," \text{ef[3, }"\text{t.value}"\text{], "}\text{" sep=""), pastex("," \text{ef[4, }"\text{estimate}"\text{], ef[4, }"\text{sign}"\text{], sep=""), pastex("," \text{ef[4, }"\text{t.value}"\text{], "}\text{" sep="")})}
\]

\[
\text{vect} \leftarrow \text{cbind(vect, vect2)}
\}
\]

\[
\text{item} \leftarrow c("\text{pos.coeff","pos.t.value", "neg.coef","neg.t.value")}
\]

\[
\text{ve} \leftarrow \text{data.frame(cbind(item, vect)); colnames(ve) \leftarrow col.name}
\]

\[
\text{ThCo05} \leftarrow \text{rbind(diag, ve)}[c(1,10:13, 7:9),]
\]

\[
\text{ThCo5} \leftarrow \text{cbind("PD~PS", t(ThCo05[.,c(3,5)]))}
\]

\[
\text{colnames(ThCo5)} \leftarrow \text{cbind("Pairs of Prices", t(ThCo05[.,1]))}
\]

##### 4Af LB + PD

\[
dpd \leftarrow \text{PD \# y}
\]

\[
idp \leftarrow \text{LB \# x}
\]

# TAR best threshold ========================

\[
t3 \leftarrow \text{ciTarThd}(y=dpd, x=idp, \text{model}="\text{tar}", \text{lag}=0); t3$basic; \text{plot(t3)}
\]

\[
\text{th.tar} \leftarrow t3$basic
\]

\[
\text{for (i in 1:12) \{}
\]

\[
\text{t3a} \leftarrow \text{ciTarThd}(y=dpd, x=idp, \text{model}="\text{tar}", \text{lag}=i)
\]
th.tar[i+2] <- t3a$basic[,2]
}
th.tar

# MTAR best threshold ====================
t4 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=0); plot(t4)

th.mtar <- t4$basic
for (i in 1:12) {
    t4a <- ciTarThd(y=dpd, x=idp, model="mtar", lag=i)
    th.mtar[i+2] <- t4a$basic[,2]
}
th.mtar

t.tar <- -16.655; t.mtar <- 5.885

##### lag selection ====================

(g1 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12,
adjust=T, thresh=0)); plot(g1)

(g2 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12,
adjust=T, thresh=0)); plot(g2)

(g3 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12,
adjust=T, thresh=t.tar)); plot(g3)

(g4 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12,
adjust=T, thresh=t.mtar)); plot(g4)

# Figure of threshold value selection
(t5 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=7)); plot(t5)

win.graph(width=5.1,height=3.3,pointsize=9); bringToTop(stay=T)

par(mai=c(0.7,0.7,0.1,0.1),family="serif")

plot(path.sse~path.thr, data=t5$path, type="l",
                               ylab="Sum of Squared Errors",
                               xlab="Threshold value")

fig3 <- ggplot(data=t5$path) +
   geom_line(aes(x=path.thr, y=path.sse)) +
   labs(x="Threshold value", y="Sum of squared errors") +
   opts(axis.text.x =theme_text(size=8,family="serif", vjust=0.8)) +
   opts(axis.text.y =theme_text(size=8,family="serif", hjust=0.8)) +
   opts(axis.title.x=theme_text(size=9,family="serif", angle=90)) +
   opts(axis.title.y=theme_text(size=9,family="serif", angle=90))

win.graph(width=4.5,height=3,pointsize=9); bringToTop(stay=T); fig3

##### final estimation ====================

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G <- 7
(f1 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=0))
(f2 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=t.tar))
(f3 <- ciTarFit(y=dpd, x=idp, model="mtar", lag=G, thresh=0))
(f4 <- ciTarFit(y=dpd, x=idp, model="mtar", lag=G, thresh=t.mtar))

r0 <- cbind(summary(f1)$dia, summary(f2)$dia, summary(f3)$dia, summary(f4)$dia)
(r1 <- r0[, c(1,2,4,6,8)])
col.name <- c("item", "tar", "c.tar", "mtar", "c.mtar")
diag <- r1[c(2, 6:7, 12:14, 8, 9, 11), col.name]
rownames(diag) <- 1:nrow(diag); diag

e1 <- summary(f1)$out; e2 <- summary(f2)$out
e3 <- summary(f3)$out; e4 <- summary(f4)$out
(r2 <- rbind(e1, e2, e3, e4))

ee <- list(e1, e2, e3, e4); vect <- NULL
for (i in 1:4) {
  ef <- data.frame(ee[i]); ef
  vect2 <- c(paste(ef[3, "estimate"], ef[3, "sign"], sep=""),
             paste("(" , ef[3, "t.value"], ")", sep=""),
             paste(ef[4, "estimate"], ef[4, "sign"], sep=""),
             paste("(" , ef[4, "t.value"], ")", sep=""))
  vect <- cbind(vect, vect2)
}
item <- c("pos.coeff", "pos.t.value", "neg.coeff", "neg.t.value")
ve <- data.frame(cbind(item, vect)); colnames(ve) <- col.name

ThCo06 <- rbind(diag, ve)[c(1,10:13, 7:9),]
ThCo6 <- cbind("PD-LB", t(ThCo06[,c(3,5)]))
colnames(ThCo6) <- cbind("Pairs of Prices", t(ThCo06[,1]))

##### 4Ag LB + PS
dpd <- PS # y
idp <- LB # x

# TAR best threshold ================
t3 <- ciTarThd(y=dpd, x=idp, model="tar", lag=0); t3$basic; plot(t3)
th.tar <- t3$basic
for (i in 1:12) {
  t3a <- ciTarThd(y=dpd, x=idp, model="tar", lag=i)
  th.tar[i+2] <- t3a$basic[2]
}
th.tar

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# MTAR best threshold

t4 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=0); plot(t4)
th.mtar <- t4$basic
for (i in 1:12) {
  t4a <- ciTarThd(y=dpd, x=idp, model="mtar", lag=i)
  th.mtar[i+2] <- t4a$basic[,2]
}
th.mtar

# Figure of threshold value selection
(t5 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=7)); plot(t5)

# final esitmation
G <- 7
(f1 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=0))
(f2 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=t.tar))
(f3 <- ciTarFit(y=dpd, x=idp, model="mtar", lag=G, thresh=0))
(f4 <- ciTarFit(y=dpd, x=idp, model="mtar", lag=G, thresh=t.mtar))

r0 <- cbind(summary(f1)$dia, summary(f2)$dia, summary(f3)$dia, summary(f4)$dia)
(r1 <- r0[, c(1,2,4,6,8)])
col.name <- c("item", "tar", "c.tar", "mtar", "c.mtar")
diag <- r1[, c(2, 6:7, 12:14, 8, 9, 11), col.name]
rownames(diag) <- 1:nrow(diag); diag

e1 <- summary(f1)$out; e2 <- summary(f2)$out
e3 <- summary(f3)$out; e4 <- summary(f4)$out
(r2 <- rbind(e1, e2, e3, e4))

ee <- list(e1, e2, e3, e4); vect <- NULL
for (i in 1:4) {
  ef <- data.frame(ee[[i]]); ef
  vect2 <- c(paste(ef[3, "estimate"], ef[3, "sign"], sep=""),
              paste("", ef[3, "t.value"], "), sep=""),
          paste(ef[4, "estimate"], ef[4, "sign"], sep=""),
          paste("", ef[4, "t.value"], "), sep=""))
  vect <- cbind(vect, vect2)
}
item <- c("pos.coeff", "pos.t.value", "neg.coeff", "neg.t.value")
ve <- data.frame(cbind(item, vect)); colnames(ve) <- col.name

ThCo07 <- rbind(diag, ve)[c(1,10:13, 7:9),]
ThCo7 <- cbind("PS~LB", t(ThCo07[,c(3,5)]))
colnames(ThCo7) <- cbind("Pairs of Prices", t(ThCo07[,1]))

##### 4Ah LA + PS
dpd <- PS  # y
idp <- LA  # x

# TAR best threshold ====================
t3 <- ciTarThd(y=dpd, x=idp, model="tar", lag=0); t3$basic; plot(t3)
th.tar <- t3$basic
for (i in 1:12) {
  t3a <- ciTarThd(y=dpd, x=idp, model="tar", lag=i)
  th.tar[i+2] <- t3a$basic[,2]
}
th.tar

# MTAR best threshold ==============
t4 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=0); plot(t4)
th.mtar <- t4$basic
for (i in 1:12) {
  t4a <- ciTarThd(y=dpd, x=idp, model="mtar", lag=i)
  th.mtar[i+2] <- t4a$basic[,2]
}
th.mtar

t.tar <- -18.642; t.mtar <- -12.916

##### lag selection ===============
(g1 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12, adjust=T, thresh=0)); plot(g1)
(g2 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12, adjust=T, thresh=0)); plot(g2)
(g3 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12, adjust=T, thresh=t.tar)); plot(g3)
(g4 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12, adjust=T, thresh=t.mtar)); plot(g4)

# Figure of threshold value selection
(t5 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=6)); plot(t5)

win.graph(width=5.1,height=3.3,pointsize=9); bringToTop(stay=T)
par(mai=c(0.7,0.7,0.1,0.1),family="serif")
plot(path.sse~path.thr, data=t5$path, type="l",
     ylab="Sum of Squared Errors", xlab="Threshold value")

fig3 <- ggplot(data=t5$path) +
  geom_line(aes(x=path.thr, y=path.sse ) ) +
  labs(x="Threshold value", y="Sum of squared errors") +
  # scale_y_continuous(limits=c(5100,5650)) +
  # scale_x_continuous(breaks=c(-10:10)) +
  opts( axis.text.x =theme_text(size=8,family="serif", vjust=0.8 ) )+
  opts( axis.text.y =theme_text(size=8,family="serif", hjust=0.8 ) )+
  opts( axis.title.x=theme_text(size=9,family="serif") )+
  opts( axis.title.y=theme_text(size=9,family="serif", angle=90 ) )
win.graph(width=4.5,height=3,pointsize=9); bringToTop(stay=T); fig3

##### final estimation ============

G <- 6
(f1 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=0))
(f2 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=t.tar))
(f3 <- ciTarFit(y=dpd, x=idp, model="mtar",lag=G, thresh=0))
(f4 <- ciTarFit(y=dpd, x=idp, model="mtar",lag=G, thresh=t.mtar))
r0 <- cbind(summary(f1)$dia, summary(f2)$dia, summary(f3)$dia, summary(f4)$dia)
(r1 <- r0[, c(1,2,4,6,8)])
col.name <- c("item","tar","c.tar","mtar","c.mtar")
diag <- r1[,c(2, 6:7, 12:14, 8, 9, 11), col.name]
rownames(diag) <- 1:nrow(diag); diag

e1 <- summary(f1)$out; e2 <- summary(f2)$out
e3 <- summary(f3)$out; e4 <- summary(f4)$out
(r2 <- rbind(e1, e2, e3, e4))

ee <- list(e1, e2, e3, e4); vect <- NULL
for (i in 1:4) {
  ef <- data.frame(ee[[i]]); ef
  vect2 <- c(paste(ef[3, "estimate"], ef[3, "sign"], sep=""),
             paste("", ef[3, "t.value"], ",", sep=""),
             paste(ef[4, "estimate"], ef[4, "sign"], sep=""),
             paste("", ef[4, "t.value"], ",", sep=""))
  vect <- cbind(vect, vect2)
}  item <- c("pos.coeff","pos.t.value", "neg.coeff","neg.t.value")
ve <- data.frame(cbind(item, vect)); colnames(ve) <- col.name

ThCo08 <- rbind(diag, ve)[c(1,10:13, 7:9),]
ThCo8 <- cbind("PS~LA",t(ThCo08[,c(3,5)]))
colnames(ThCo8) <- cbind("Pairs of Prices", t(ThCo08[,1]))

##### 4Ai LA + PD
dpd <- PD # y
idp <- LA # x

# TAR best threshold =========================
t3 <- ciTarThd(y=dpd, x=idp, model="tar", lag=0); t3$basic; plot(t3)
th.tar <- t3$basic
for (i in 1:12) {
  t3a <- ciTarThd(y=dpd, x=idp, model="tar", lag=i)
  th.tar[i+2] <- t3a$basic[,2]
}
th.tar

# MTAR best threshold =========================
t4 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=0); plot(t4)
th.mtar <- t4$basic
for (i in 1:12) {
  t4a <- ciTarThd(y=dpd, x=idp, model="mtar", lag=i)
}
th.mtar[i+2] <- t4a$basic[,2]
}
th.mtar

t.tar <- 32.571; t.mtar <- -22.908

##### lag selection ====================
(g1 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12, adjust=T, thresh= 0)); plot(g1)
(g2 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12, adjust=T, thresh= 0)); plot(g2)
(g3 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12, adjust=T, thresh= t.tar)); plot(g3)
(g4 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12, adjust=T, thresh= t.mtar)); plot(g4)

# Figure of threshold value selection
(t5 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=3)); plot(t5)

win.graph(width=5.1,height=3.3,pointsize=9); bringToTop(stay=T)
par(mai=c(0.7,0.7,0.1,0.1),family="serif")
plot(path.sse~path.thr, data=t5$path, type="l",
     ylab="Sum of Squared Errors", xlab="Threshold value")

fig3 <- ggplot(data=t5$path) +
    geom_line(aes(x=path.thr, y=path.sse)) +
    labs(x="Threshold value", y="Sum of squared errors") +
    # scale_y_continuous(limits=c(5100,5650)) +
    # scale_x_continuous(breaks=c(-10:10)) +
    opts(axis.text.x =theme_text(size=8,family="serif", vjust=0.8 ))+
    opts(axis.text.y =theme_text(size=8,family="serif", hjust=0.8 ))+
    opts(axis.title.x=theme_text(size=9,family="serif" ))+
    opts(axis.title.y=theme_text(size=9,family="serif", angle=90 ) )
win.graph(width=4.5,height=3,pointsize=9); bringToTop(stay=T); fig3

#### final estimation ====================

G <- 3
(f1 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=0))
(f2 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=t.tar))
(f3 <- ciTarFit(y=dpd, x=idp, model="mtar",lag=G, thresh=0))
(f4 <- ciTarFit(y=dpd, x=idp, model="mtar",lag=G, thresh=t.mtar))

r0 <- cbind(summary(f1)$dia, summary(f2)$dia, summary(f3)$dia, summary(f4)$dia)
(r1 <- r0[, c(1,2,4,6,8)])
col.name <- c("item","tar","c.tar","mtar","c.mtar")
diag <- r1[c(2, 6:7, 12:14, 8, 9, 11), col.name]
rownames(diag) <- 1:nrow(diag); diag
e1 <- summary(f1)$out; e2 <- summary(f2)$out
e3 <- summary(f3)$out; e4 <- summary(f4)$out
(r2 <- rbind(e1, e2, e3, e4))

ee <- list(e1, e2, e3, e4); vect <- NULL
for (i in 1:4) {
  ef <- data.frame(ee[i]); ef
  vect2 <- c(paste(ef[3, "estimate"], ef[3, "sign"], sep=""),
             paste("", ef[3, "t.value"], "", sep=""),
             paste(ef[4, "estimate"], ef[4, "sign"], sep=""),
             paste("", ef[4, "t.value"], "", sep=""))
  vect <- cbind(vect, vect2)
}
item <- c("pos.coeff","pos.t.value", "neg.coeff","neg.t.value")
ve <- data.frame(cbind(item, vect)); colnames(ve) <- col.name

ThCo09 <- rbind(diag, ve)[c(1,10:13, 7:9),]
ThCo9 <- cbind("PD~LA",t(ThCo09[,c(3,5)]))
colnames(ThCo9) <- cbind("Pairs of Prices", t(ThCo09[,1]))

##### 4Aj PS + PD
dpd <- PS  # y
dip  <- PD  # x

# TAR best threshold ==============================
t3 <- ciTarThd(y=dpd, x=idp, model="tar", lag=0); t3$basic; plot(t3)
th.tar <- t3$basic
for (i in 1:12) {
  t3a <- ciTarThd(y=dpd, x=idp, model="tar", lag=i)
  th.tar[i+2] <- t3a$basic[,2]
}

th.tar

# MTAR best threshold ===========================
t4 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=0); plot(t4)
th.mtar <- t4$basic
for (i in 1:12) {
  t4a <- ciTarThd(y=dpd, x=idp, model="mtar", lag=i)
  th.mtar[i+2] <- t4a$basic[,2]
}

th.mtar
t.tar <- -5.475; t.mtar <- -1.7

##### lag selection ====================
(g1 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12, adjust=T, thresh= 0)); plot(g1)
(g2 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12, adjust=T, thresh= 0)); plot(g2)
(g3 <- ciTarLag(y=dpd, x=idp, model="tar", maxlag=12, adjust=T, thresh= t.tar)); plot(g3)
(g4 <- ciTarLag(y=dpd, x=idp, model="mtar", maxlag=12, adjust=T, thresh= t.mtar)); plot(g4)

# Figure of threshold value selection
(t5 <- ciTarThd(y=dpd, x=idp, model="mtar", lag=0)); plot(t5)

win.graph(width=5.1,height=3.3,pointsize=9); bringToTop(stay=T)
par(mai=c(0.7,0.7,0.1,0.1),family="serif")
plot(path.sse~path.thr, data=t5$path, type="l",
     ylab="Sum of Squared Errors", xlab="Threshold value")
fig3 <- ggplot(data=t5$path) +
    geom_line(aes(x=path.thr, y=path.sse)) +
    labs(x="Threshold value", y="Sum of squared errors") +
    # scale_y_continuous(limits=c(5100,5650)) +
    # scale_x_continuous(breaks=c(-10:10)) +
    opts(axis.text.x =theme_text(size=8,family="serif", vjust=0.8 ))+
    opts(axis.text.y =theme_text(size=8,family="serif", hjust=0.8 ))+
    opts(axis.title.x=theme_text(size=9,family="serif" ))+
    opts(axis.title.y=theme_text(size=9,family="serif", angle=90 ))
win.graph(width=4.5,height=3,pointsize=9); bringToTop(stay=T); fig3

#### final estimation ====================
G <- 0
(f1 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=0))
(f2 <- ciTarFit(y=dpd, x=idp, model="tar", lag=G, thresh=t.tar))
(f3 <- ciTarFit(y=dpd, x=idp, model="mtar",lag=G, thresh=0))
(f4 <- ciTarFit(y=dpd, x=idp, model="mtar",lag=G, thresh=t.mtar))

r0 <- cbind(summary(f1)$dia, summary(f2)$dia, summary(f3)$dia, summary(f4)$dia)
(r1 <- r0[ c(1,2,4,6,8) ])
col.name <- c("item","tar","c.tar","mtar","c.mtar")
diag <- r1[c(2,6:7,12:14,8,9,11), col.name]
rownames(diag) <- 1:nrow(diag); diag

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e1 <- summary(f1)$out; e2 <- summary(f2)$out
e3 <- summary(f3)$out; e4 <- summary(f4)$out
(r2 <- rbind(e1, e2, e3, e4))

ee <- list(e1, e2, e3, e4); vect <- NULL
for (i in 1:4) {
ef <- data.frame(ee[i]); ef
evect2 <- c(paste(ef[3, "estimate"], ef[3, "sign"], sep=""),
paste("", ef[3, "t.value"], ""), sep=""),
paste(ef[4, "estimate"], ef[4, "sign"], sep=""),
paste("", ef[4, "t.value"], ""), sep=""))
vect <- cbind(vect, vect2)
}
item <- c("pos.coeff", "pos.t.value", "neg.coeff", "neg.t.value")
ve <- data.frame(cbind(item, vect)); colnames(ve) <- col.name

ThCo010 <- rbind(diag, ve)[c(1,10:13, 7:9),]
ThCo10 <- cbind("PS~PD", t(ThCo010[,c(3,5)]))
colnames(ThCo10) <- cbind("Pairs of Prices", t(ThCo010[,1]))

# Threshold Estimation
ThresholdEstimation <- rbind(ThCo4, ThCo9, ThCo1, ThCo6, ThCo3,
ThCo8, ThCo2, ThCo7, ThCo5, ThCo10)
(tab4 <- data.frame(ThresholdEstimation))

# 4b. E C M
setwd("K:/Sun/10.File Zhuo Ning/Vertical")

# 4ba LA+PS
ra1 <- ecmAsyFit(y=LA, x=PS, lag=5)
rb1 <- ecmAsyFit(y=LA, x=PS, lag=5, split=F, model="linear")
rc1 <- ecmAsyFit(y=LA, x=PS, lag=5, split=T, model="mtar", thresh=10)

names(ra1); names(rb1); names(rc1)
class(ra1); class(rb1); class(rc1)
ra1; rb1; rc1
summary(ra1); summary(rb1); summary(rc1)
ecmDiag(ra1); ecmDiag(rb1); ecmDiag(rc1)

teb <- ecmAsyTest(rb1); teb$out
tec <- ecmAsyTest(rc1); tec
(ECM1 <- data.frame(tec$out[c(2,3,14,15,1),c(1:6)]))

# 4bb LA+PD
ra2 <- ecmAsyFit(y=LA, x=PD, lag=3)
rb2 <- ecmAsyFit(y=LA, x=PD, lag=3, split=F, model="linear")
rc2 <- ecmAsyFit(y=LA, x=PD, lag=3, split=T, model="mtar", thresh=9)

names(ra2); names(rb2); names(rc2)
class(ra2); class(rb2); class(rc2)
ra2; rb2; rc2
summary(ra2); summary(rb2); summary(rc2)
ecmDiag(ra2); ecmDiag(rb2); ecmDiag(rc2)

teb <- ecmAsyTest(rb2); teb$out
tec <- ecmAsyTest(rc2); tec

(ECM2 <- data.frame(tec$out[c(2,3,10,11,1),c(1:6)]))

# 4bc LB+PS
ra3 <- ecmAsyFit(y=LB, x=PS, lag=4)
rb3 <- ecmAsyFit(y=LB, x=PS, lag=4, split=F, model="linear")
rc3 <- ecmAsyFit(y=LB, x=PS, lag=4, split=T, model="mtar", thresh=4.984)

names(ra3); names(rb3); names(rc3)
class(ra3); class(rb3); class(rc3)
ra3; rb3; rc3
summary(ra3); summary(rb3); summary(rc3)
ecmDiag(ra3); ecmDiag(rb3); ecmDiag(rc3)

teb <- ecmAsyTest(rb3); teb$out
tec <- ecmAsyTest(rc3); tec

(ECM3 <- data.frame(tec$out[c(2,3,12,13,1),c(1:6)]))

# 4bd LB+PD
ra4 <- ecmAsyFit(y=LB, x=PD, lag=4)
rb4 <- ecmAsyFit(y=LB, x=PD, lag=4, split=F, model="linear")
rc4 <- ecmAsyFit(y=LB, x=PD, lag=4, split=T, model="mtar", thresh=-11.414)

names(ra4); names(rb4); names(rc4)
class(ra4); class(rb4); class(rc4)
ra4; rb4; rc4
summary(ra4); summary(rb4); summary(rc4)
ecmDiag(ra4); ecmDiag(rb4); ecmDiag(rc4)

teb <- ecmAsyTest(rb4); teb$out
tec <- ecmAsyTest(rc4); tec

(ECM4 <- data.frame(tec$out[c(2,3,12,13,1),c(1:6)]))

# 4be PD+PS
ra5 <- ecmAsyFit(y=PD, x=PS, lag=7)
rb5 <- ecmAsyFit(y=PD, x=PS, lag=7, split=F, model="linear")
rc5 <- ecmAsyFit(y=PD, x=PS, lag=7, split=T, model="mtar", thresh=2.635)

names(ra5); names(rb5); names(rc5)
class(ra5); class(rb5); class(rc5)
ra5; rb5; rc5
summary(ra5); summary(rb5); summary(rc5)
ecmDiag(ra5); ecmDiag(rb5); ecmDiag(rc5)

teb <- ecmAsyTest(rb5); teb$out
tec <- ecmAsyTest(rc5); tec

(ECM5 <- data.frame(tec$out[c(2,3,18,19,1),c(1:6)]))

# 4bf LA+PS
ra6 <- ecmAsyFit(y=PS, x=LA, lag=6)
rb6 <- ecmAsyFit(y=PS, x=LA, lag=6, split=F, model="linear")
rc6 <- ecmAsyFit(y=PS, x=LA, lag=6, split=T, model="mtar", thresh=-12.916)

names(ra6); names(rb6); names(rc6)
class(ra6); class(rb6); class(rc6)
ra6; rb6; rc6
summary(ra6); summary(rb6); summary(rc6)
ecmDiag(ra6); ecmDiag(rb6); ecmDiag(rc6)

teb <- ecmAsyTest(rb6); teb$out
tec <- ecmAsyTest(rc6); tec

(ECM6 <- data.frame(tec$out[c(2,3,16,17,1),c(1:6)]))

# 4bg LA+PD

ra7 <- ecmAsyFit(y=PD, x=LA, lag=5)
rb7 <- ecmAsyFit(y=PD, x=LA, lag=5, split=F, model="linear")
rc7 <- ecmAsyFit(y=PD, x=LA, lag=5, split=T, model="mtar", thresh=-22.908)

names(ra7); names(rb7); names(rc7)
class(ra7); class(rb7); class(rc7)
ra7; rb7; rc7
summary(ra7); summary(rb7); summary(rc7)
ecmDiag(ra7); ecmDiag(rb7); ecmDiag(rc7)

teb <- ecmAsyTest(rb7); teb$out
tec <- ecmAsyTest(rc7); tec

(ECM7 <- data.frame(tec$out[c(2,3,14,15,1),c(1:6)]))

# 4bh LB+PS

ra8 <- ecmAsyFit(y=PS, x=LB, lag=5)
rb8 <- ecmAsyFit(y=PS, x=LB, lag=5, split=F, model="linear")
rc8 <- ecmAsyFit(y=PS, x=LB, lag=5, split=T, model="mtar", thresh=10.803)

names(ra8); names(rb8); names(rc8)
class(ra8); class(rb8); class(rc8)
ra8; rb8; rc8
summary(ra8); summary(rb8); summary(rc8)
ecmDiag(ra8); ecmDiag(rb8); ecmDiag(rc8)

teb <- ecmAsyTest(rb8); teb$out
tec <- ecmAsyTest(rc8); tec

(ECM8 <- data.frame(tec$out[c(2,3,14,15,1),c(1:6)]))

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# 4bi LB+PD
ra9 <- ecmAsyFit(y=PD, x=LB, lag=7)
rb9 <- ecmAsyFit(y=PD, x=LB, lag=7, split=F, model="linear")
rc9 <- ecmAsyFit(y=PD, x=LB, lag=7, split=T, model="mtar", thresh=5.885)

names(ra9); names(rb9); names(rc9)
class(ra9); class(rb9); class(rc9)
ra9; rb9; rc9
summary(ra9); summary(rb9); summary(rc9)
ecmDiag(ra9); ecmDiag(rb9); ecmDiag(rc9)

teb <- ecmAsyTest(rb9); teb$out
tec <- ecmAsyTest(rc9); tec

(ECM9 <- data.frame(tec$out[c(2,3,18,19,1),c(1:6)]))

# 4bj PD+PS
ra10 <- ecmAsyFit(y=PS, x=PD, lag=7)
rb10 <- ecmAsyFit(y=PS, x=PD, lag=7, split=F, model="linear")
rc10 <- ecmAsyFit(y=PS, x=PD, lag=7, split=T, model="mtar", thresh=-2.066)

names(ra10); names(rb10); names(rc10)
class(ra10); class(rb10); class(rc10)
ra10; rb10; rc10
summary(ra10); summary(rb10); summary(rc10)
ecmDiag(ra10); ecmDiag(rb10); ecmDiag(rc10)

teb <- ecmAsyTest(rb10); teb$out
tec <- ecmAsyTest(rc10); tec

(ECM10 <- data.frame(tec$out[c(2,3,18,19,1),c(1:6)]))

(ECMEst <- rbind(ECM2, ECM4, ECM1, ECM3, ECM5, ECM7, ECM9, ECM6, ECM8, ECM10))
(tab5 <- data.frame(ECMEst))

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APPENDIX B

R CODE FOR CHAPTER III
# CHAPTER III SPATIAL PRICE LINKAGE BETWEEN FOREST PRODUCTS
MARKETS IN THE SOUTH AND PACIFIC NORTHWEST

Modifed March 27th, 2012.

```r
library(RODBC); library(urca); library(vars);
library(strucchange); library(car); library(TSA);library(fUnitRoots)
library(erer); library(apt);library(tsDyn)
options(width=130)

##### 1. Import Data

getwd();setwd("C:/aaWood/ZN.RSM/"); getwd()

wood <- odbcConnectExcel2007('lumber price 2.xlsx')
sheet <- sqlTables(wood); sheet$TABLE_NAME
tim <- sqlFetch(wood, "calculation"); odbcClose(wood)
dim(tim); names(tim); head(tim); tail(tim)

### 1.1 First pair: D, Pine (W), KD, 2m4, #2, R & D, Fir, KD, 2m4, Std&Btr

Dim24Raw <- tim[1:480, c("Fir1", "Pine1")]
colnames(Dim24Raw) <- c("DimFir1", "DimPine1"); head(Dim24Raw)
Dim24 <- ts(Dim24Raw, start=c(1971,1), freq=12); Dim24[1:5,]
dim24Raw <- log(Dim24); head(dim24Raw); dim24 <- ts(dim24Raw,
start=c(1971,1), freq=12)
colnames(dim24) <- tolower(c("LogDimFir1", "LogDimPine1"))
dim24[1:5,]

Pine1 <-Dim24[, "DimPine1"]; Fir1 <-Dim24[, "DimFir1"]
LogPine1 <-dim24[, "logdimpine1"]; LogFir1 <-dim24[, "logdimfir1"]

##### Data Arrangement

original1=log(Pine1/Fir1)

##### Basic Statistics

bsStat11 <- bsStat(Dim24, digit=3); bsStat(dim24, digit=3)
bsStat12 <- basicStats(Pine1);bsStat13 <- basicStats(Fir1)
bsStatDim24 <- data.frame(t(rbind(bsStat11$sobno,bsStat11$mean,bsStat11$stde,
t(rbind(bsStat14,bsStat15)))))
colnames(bsStatDim24) <- c("Obno", "Mean","Stde","Skew","Kurt")
rownames(bsStatDim24) <- c("WDIM1","SDIM1")
bsStatDim24
basicStats(LogPine1);basicStats(LogFir1)
basicStats(original1)
```
### 1.2 Second pair: D, Pine, 2m10, #2, Random & D, Fir, KD, 2m10, #2&Btr

Dim210Raw <- tim[25:492, c("Fir2", "Pine2")]
colnames(Dim210Raw) <- c("DimFir2", "DimPine2"); head(Dim210Raw)
Dim210 <- ts(Dim210Raw, start=c(1973,1), freq=12); Dim210[1:5,]

dim210Raw <- log(Dim210); head(dim210Raw)
dim210 <- ts(dim210Raw, start=c(1973,1), freq=12)
colnames(dim210) <- tolower(c("LogDimFir2", "LogDimPine2"))
dim210[1:5,]

Pine2 <- Dim210[, "DimPine2"]; Fir2 <- Dim210[, "DimFir2"]
LogPine2 <-dim210[, "logdimpine2"]; LogFir2 <-dim210[, "logdimfir2"]

##### Data Arrangement

original2=log(Pine2/Fir2)

##### Basic Statistics

bsStat21 <- bsStat(Dim210, digit=3); bsStat(dim210, digit=3)
bsStat22 <- basicStats(Pine2);bsStat23 <- basicStats(Fir2)
bsStatDim210 <- data.frame(t(rbind(bsStat21$obno,bsStat21$mean,bsStat21$stde, t(rbind(bsStat24,bsStat25)))))
colnames(bsStatDim210) <- c("Obno", "Mean","Stde","Skew","Kurt")
rownames(bsStatDim210) <- c("WDIM2","SDIM2")
bsStatDim210

basicStats(LogPine2);basicStats(LogFir2)
basicStats(original2)

### 1.3 Fourth pair: Pine, StressGrades

#KD #1 2m4 R & Fir, StressGrade, #1&Btr 2m4 R

StressRaw <- tim[25:492, c("Fir4", "Pine4")]
colnames(StressRaw) <- c("StressFir", "StressPine"); head(StressRaw)
Stress <- ts(StressRaw, start=c(1973,1), freq=12); Stress[1:5,]

stressRaw <- log(Stress); head(stressRaw)
stress <- ts(stressRaw, start=c(1973,1), freq=12)
colnames(stress) <- tolower(c("LogStressFir", "LogStressPine"))
stress[1:5,]

Pine4 <- Stress[, "StressPine"]; Fir4 <- Stress[, "StressFir"]
LogPine4 <-stress[, "logstresspine"]; LogFir4 <-stress[, "logstressfir"]

##### Data Arrangement

original4=log(Pine4/Fir4)
### Basic Statistics

```r
bsStat41 <- bsStat(Stress, digit=3); bsStat(stress, digit=3)
bsStat42 <- basicStats(Pine4); bsStat43 <- basicStats(Fir4)
bsStatStress <- data.frame(t(rbind(bsStat41$obno, bsStat41$mean, bsStat41$stde,
                              t(rbind(bsStat44, bsStat45)))))
colnames(bsStatStress) <- c("Obno", "Mean", "Stde", "Skew", "Kurt")
rownames(bsStatStress) <- c("WSTR", "SSTR")
bsStatStress
```

```r
basicStats(LogPine4); basicStats(LogFir4)
basicStats(original4)
```

```r
(tab1 <- rbind(bsStatDim24, bsStatDim210, bsStatStress))
```

### 2. Unit Root

```r
## 2.1 Dim24
summary(adf.xa2 <- ur.df(LogPine1, type="none", lags=16)); plot(adf.xa2)
summary(adf.dxb2 <- ur.df(diff(LogPine1), type="none", lags=16))

summary(adf.ya2  <- ur.df(LogFir1, type="none", lags=25)); plot(adf.ya2)
summary(adf.dyb2 <- ur.df(diff(LogFir1), type="none", lags=25))

ff2 <- data.frame(matrix(0, nrow=2, ncol=7))
colnames(ff2) <- c("ADF.level", "ADF.dif", "PP.level", "PP.dif", "KPSS.level", "KPSS.dif", "lag")

```r
gg2 <- c(16, 25); diggit <- 2
```

```r
for (i in 1:length(gg2)) {
  x <- ts(dim24[, i], start=c(1971, 1), freq=12)
y <- diff(x);
  adf.x  <- ur.df(x, type="none", lags=gg2[i])
adf.y  <- ur.df(y, type="none", lags=gg2[i])
  pp.x   <- pp.test(x, type = "Z(t_alpha)"
  pp.y   <- pp.test(y, type = "Z(t_alpha)"
  kpss.x <- kpss.test(x)
kpss.y <- kpss.test(y)
  ff2[i,1] <- round(adf.x@teststat[1,1], digit)
  ff2[i,2] <- round(adf.y@teststat[1,1], digit)
  ff2[i,3] <- round(data.frame(pp.x$statistic)[1,1], digit)
  ff2[i,4] <- round(data.frame(pp.y$statistic)[1,1], digit)
  ff2[i,5] <- round(data.frame(kpss.x$statistic)[1,1], digit)
  ff2[i,6] <- round(data.frame(kpss.y$statistic)[1,1], digit)
  ff2[i,7] <- gg2[i]
}
```
rownames(ff2)[i] <- colnames(dim24)[i]

(tab.22 <- ff2)

##2.2 Dim210
summary(adf.xa4  <- ur.df(LogPine2, type=c("none"), lags=23)); plot(adf.xa4)
summary(adf.dxb4 <- ur.df(diff(LogPine2), type=c("none"), lags=23))

summary(adf.ya4  <- ur.df(LogFir2, type=c("none"), lags=20)); plot(adf.ya4)
summary(adf.dyb4 <- ur.df(diff(LogFir2), type=c("none"), lags=20))

ff4 <- data.frame(matrix(0, nrow=2, ncol=7))
colnames(ff4) <- c("ADF.level","ADF.dif","PP.level","PP.dif","KPSS.level","KPSS.dif", "lag")
gg4 <- c(23,20)
for (i in 1:length(gg4)) {
  x <- ts(dim210[, i], start=c(1973,1), freq=12)
y <- diff(x);
  adf.x  <- ur.df(x, type=c("none"), lags=gg4[i])
adf.y  <- ur.df(y, type=c("none"), lags=gg4[i])
  pp.x   <- pp.test(x, type = "Z(t_alpha)"
  pp.y   <- pp.test(y, type = "Z(t_alpha)"
  kpss.x <- kpss.test(x)
  kpss.y <- kpss.test(y)
  ff4[i,1] <- round(adf.x@teststat[1,1], digit)
  ff4[i,2] <- round(adf.y@teststat[1,1], digit)
  ff4[i,3] <- round(data.frame(pp.x$statistic)[1,1], digit)
  ff4[i,4] <- round(data.frame(pp.y$statistic)[1,1], digit)
  ff4[i,5] <- round(data.frame(kpss.x$statistic)[1,1], digit)
  ff4[i,6] <- round(data.frame(kpss.y$statistic)[1,1], digit)
  ff4[i,7] <- gg4[i]
  rownames(ff4)[i] <- colnames(dim210)[i]
}

(tab.24 <- ff4)

##2.3 Stress
summary(adf.xa8  <- ur.df(LogPine4, type=c("none"), lags=16)); plot(adf.xa8)
summary(adf.dxb8 <- ur.df(diff(LogPine4), type=c("none"), lags=16))

summary(adf.ya8  <- ur.df(LogFir4, type=c("none"), lags=25)); plot(adf.ya8)
summary(adf.dyb8 <- ur.df(diff(LogFir4), type=c("none"), lags=25))
ff8 <- data.frame(matrix(0, nrow=2, ncol=7))
colnames(ff8) <- c("ADF.level","ADF.dif",
                 "PP.level","PP.dif","KPSS.level","KPSS.dif", "lag")

gg8 <- c(16,25)
for (i in 1:length(gg8)) {
  x <- ts(stress[, i], start=c(1973,1), freq=12)
  y <- diff(x);
  adf.x  <- ur.df(x, type=c("none"), lags=gg8[i])
  adf.y  <- ur.df(y, type=c("none"), lags=gg8[i])
  pp.x   <- pp.test(x, type = "Z(t_alpha)"")
  pp.y   <- pp.test(y, type = "Z(t_alpha)"")
  kpss.x <- kpss.test(x)
  kpss.y <- kpss.test(y)
  ff8[i,1] <- round(adf.x@teststat[1,1], digit)
  ff8[i,2] <- round(adf.y@teststat[1,1], digit)
  ff8[i,3] <- round(data.frame(pp.x$statistic)[1,1], digit)
  ff8[i,4] <- round(data.frame(pp.y$statistic)[1,1], digit)
  ff8[i,5] <- round(data.frame(kpss.x$statistic)[1,1], digit)
  ff8[i,6] <- round(data.frame(kpss.y$statistic)[1,1], digit)
  ff8[i,7] <- gg8[i]
  rownames(ff8)[i] <- colnames(stress)[i]
}

(tab.28 <- ff8)

######## Summary ########################################################

ADF <- rbind(tab.22,tab.24,tab.28)

(tab2 <- ADF)

###### 3. C o i n t e g r a t i o n ###########################################
# JJ cointegration
##3.1 Dim24
VARselect(dim24, lag.max=24, type="const") #Lag=2
VARselect(dim24, lag.max=24, type="trend") #Lag=2
VARselect(dim24, lag.max=24, type="both")  #Lag=2
VARselect(dim24, lag.max=24, type="none")  #Lag=2
summary(VAR(dim24, type="const", p=1))

K <- 2
summary( j21 <- ca.jo(cbind(LogFir1,LogPine1),type='eigen',ecdet="trend",K=K ))
summary( j22 <- ca.jo(cbind(LogFir1,LogPine1),type='eigen',ecdet="const",K=K ))
summary( j23 <- ca.jo(cbind(LogFir1,LogPine1),type='eigen',ecdet="none", K=K ))
summary( j24 <- ca.jo(cbind(LogFir1,LogPine1),type='trace',ecdet="trend",K=K ))
summary( j25 <- ca.jo(cbind(LogFir1,LogPine1),type='trace',ecdet="const",K=K ))
summary( j26 <- ca.jo(cbind(LogFir1,LogPine1),type='trace',ecdet="none",K=K ))
slotNames(j21)
out21 <- cbind("eigen", "trend", K, round(j21@teststat, 3), j21@cval)
out22 <- cbind("eigen", "const", K, round(j22@teststat, 3), j22@cval)
out23 <- cbind("eigen", "none", K, round(j23@teststat, 3), j23@cval)
out24 <- cbind("trace", "trend", K, round(j24@teststat, 3), j24@cval)
out25 <- cbind("trace", "const", K, round(j25@teststat, 3), j25@cval)
out26 <- cbind("trace", "none", K, round(j26@teststat, 3), j26@cval)
jjci <- rbind(out21, out22, out23, out24, out25, out26)
jjci2 <- cbind("DIM1",jjci)
colnames(jjci2) <- c("Product","test 1", "test 2", "lag", "statistic",
  "c.v 10%", "c.v 5%", "c.v 1%")
rownames(jjci2) <- 1:nrow(jjci2)
(tab32 <- data.frame(jjci2))

##3.2 Dim210
VARselect(dim210, lag.max=24, type="const")  #Lag=2
VARselect(dim210, lag.max=24, type="trend")  #Lag=2
VARselect(dim210, lag.max=24, type="both")   #Lag=2
VARselect(dim210, lag.max=24, type="none")   #Lag=2
summary(VAR(dim210, type="const", p=1))

K <- 2
summary( j41 <- ca.jo(cbind(LogFir2,LogPine2),type='eigen',ecdet="trend",K=K ))
summary( j42 <- ca.jo(cbind(LogFir2,LogPine2),type='eigen',ecdet="const",K=K ))
summary( j43 <- ca.jo(cbind(LogFir2,LogPine2),type='eigen',ecdet="none",K=K ))
summary( j44 <- ca.jo(cbind(LogFir2,LogPine2),type='trace',ecdet="trend",K=K ))
summary( j45 <- ca.jo(cbind(LogFir2,LogPine2),type='trace',ecdet="const",K=K ))
summary( j46 <- ca.jo(cbind(LogFir2,LogPine2),type='trace',ecdet="none",K=K ))
slotNames(j41)
out41 <- cbind("eigen", "trend", K, round(j41@teststat, 3), j41@cval)
out42 <- cbind("eigen", "const", K, round(j42@teststat, 3), j42@cval)
out43 <- cbind("eigen", "none", K, round(j43@teststat, 3), j43@cval)
out44 <- cbind("trace", "trend", K, round(j44@teststat, 3), j44@cval)
out45 <- cbind("trace", "const", K, round(j45@teststat, 3), j45@cval)
out46 <- cbind("trace", "none", K, round(j46@teststat, 3), j46@cval)
jjci <- rbind(out41, out42, out43, out44, out45, out46)
jjci4 <- cbind("DIM2",jjci)
colnames(jjci4) <- c("Product","test 1", "test 2", "lag", "statistic",
  "c.v 10%", "c.v 5%", "c.v 1%")
rownames(jjci4) <- 1:nrow(jjci4)
(tab34 <- data.frame(jjci4))

##3.3 Stress
VARselect(stress, lag.max=24, type="const")  #Lag=4

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VARselect(stress, lag.max=24, type="trend")  #Lag=4
VARselect(stress, lag.max=24, type="both")  #Lag=4
VARselect(stress, lag.max=24, type="none")  #Lag=4
summary(VAR(stress, type="const", p=1))

K <- 4
summary(j81 <- ca.jo(cbind(LogFir4,LogPine4),type='eigen',ecdet="trend",K=K ))
summary(j82 <- ca.jo(cbind(LogFir4,LogPine4),type='eigen',ecdet="const",K=K ))
summary(j83 <- ca.jo(cbind(LogFir4,LogPine4),type='eigen',ecdet="none",K=K ))
summary(j84 <- ca.jo(cbind(LogFir4,LogPine4),type='trace',ecdet="trend",K=K ))
summary(j85 <- ca.jo(cbind(LogFir4,LogPine4),type='trace',ecdet="const",K=K ))
summary(j86 <- ca.jo(cbind(LogFir4,LogPine4),type='trace',ecdet="none",K=K ))
slotNames(j81)
out81 <- cbind("eigen", "trend", K, round(j81@teststat, 3), j81@cval)
out82 <- cbind("eigen", "const", K, round(j82@teststat, 3), j82@cval)
out83 <- cbind("eigen", "none", K, round(j83@teststat, 3), j83@cval)
out84 <- cbind("trace", "trend", K, round(j84@teststat, 3), j84@cval)
out85 <- cbind("trace", "const", K, round(j85@teststat, 3), j85@cval)
out86 <- cbind("trace", "none", K, round(j86@teststat, 3), j86@cval)
jjci <- rbind(out81, out82, out83, out84, out85, out86)
jjci8 <- cbind("STR",jjci)
colnames(jjci8) <- c("Product","test 1", "test 2", "lag", "statistic",
                  "c.v 10%", "c.v 5%", "c.v 1%")
rownames(jjci8) <- 1:nrow(jjci8)
(tab38 <- data.frame(jjci8))

(tab3 <- rbind(tab32,tab34,tab36,tab38))

######## 4. TVECM ###############################################
## 4.1 tsDyn::TVECM

#4.1.1 Dim24
v13 <- VECM(dim24, lag=1)
summary(v13)
tv13 <- TVECM(dim24, lag=1, nthresh=1, trim=0.05)
summary(tv13)

#4.1.2 Dim210
v23 <- VECM(dim210, lag=1)
summary(v23)
tv23 <- TVECM(dim210, lag=1, nthresh=1, trim=0.05)
summary(tv23)

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# 4.1.3 Stress
v43 <- VECM(stress, lag=2)
summary(v43)

tv43 <- TVECM(stress, lag=2, nthresh=1, trim=0.05)
summary(tv43)

## 4.2 tsDyn::TVECM.HStest

### 4.2.1 Dim24

tvtest12 <- TVECM.HStest(dim24, lag=1, trim=0.05, intercept=TRUE, nboot=1000)
summary(tvtest12)

### 4.2.2 Dim210

tvtest22 <- TVECM.HStest(dim210, lag=1, trim=0.05, intercept=TRUE, nboot=1000)
summary(tvtest22)

### 4.2.3 Stress

tvtest42 <- TVECM.HStest(stress, lag=2, trim=0.05, intercept=TRUE, nboot=1000)
summary(tvtest42)

### 4.3 tsDyn::TVECM.SeoTest

### 4.3.1 Dim24

SeoTest14 <- TVECM.SeoTest(dim24, lag=1, beta=1, trim=0.05, nboot=10, plot=FALSE, check=FALSE)
summary(SeoTest14)

### 4.3.2 Dim210

SeoTest24 <- TVECM.SeoTest(dim210, lag=1, beta=1, trim=0.05, nboot=10, plot=FALSE, check=FALSE)
summary(SeoTest24)

### 4.3.3 Stress

SeoTest44 <- TVECM.SeoTest(stress, lag=2, beta=1, trim=0.05, nboot=10, plot=FALSE, check=FALSE)
summary(SeoTest44)

### 4.4 tsDyn::LSTAR

# Lag select

### 4.4.1 m selection by AR model
mod.ar1 <- linear(x=original1, m=11)
summary(mod.ar1)
mod.ar2 <- linear(x=original2, m=10)
summary(mod.ar2)
mod.ar4 <- linear(x=original4, m=7)
summary(mod.ar4)
## 4.4.2 d selection by STAR.Test

```r
source('STAR.Test.r')
source('STAR.Test2.r')

(dd1 <- STAR.Test2(y=original1, p=11, d=4, nam.var='DIM24'))   #LSTAR
(dd2 <- STAR.Test2(y=original2, p=10, d=9, nam.var='DIM210'))  #LSTAR
(dd4 <- STAR.Test2(y=original4, p=7, d=3, nam.var='STR'))      #LSTAR

(ma1 <- STAR.Test(y=original1, p=11, d=4, nam.var='DIM24'))   #LSTAR
(ma2 <- STAR.Test(y=original2, p=10, d=9, nam.var='DIM210'))  #LSTAR
(ma4 <- STAR.Test(y=original4, p=7, d=3, nam.var='STR'))      #LSTAR
```

## 4.4.3 Model Estimation

### Dim24

```r
(mod.lstar1 <- lstar(original1, m=11, d=4))
summary(mod.lstar1)
plot(mod.lstar1)
```

### Dim210

```r
(mod.lstar2 <- lstar(original2, m=10, d=9))
summary(mod.lstar2)
plot(mod.lstar2)
```

### Stress

```r
(mod.lstar4 <- lstar(original4, m=7, d=3))
summary(mod.lstar4)
plot(mod.lstar4)
```