ANALYZING THE PERFORMANCES AND BEHAVIORS

OF FOREST-RELATED MARKETS

by

Le La

(Under the Direction of Bin Mei)

ABSTRACT

Understanding the behaviors of wood related markets allows for better investment practices. The forest sector comprises the wood, the paper, the furniture, and publicly traded timber real estate investment trust (REIT), which are analyzed in this dissertation. The first essay in this dissertation deals with the market efficiency of four forest-related markets. Measuring with the notion of entropy, the informational efficiency of all markets is ranked relatively to each other. The results show that the wood market is the most efficient one. The paper and the furniture markets are ranked the second in terms of efficiency. The REIT market was the least informational efficient market. All four markets were also compared to the Treasury bill and the stock markets. The second essay in the dissertation investigates the long-term relationships among four publicly traded REITs using cointegration analysis. Both Johansen procedure and Engle Granger cointegration test indicate that the four REITs do not share the same common trends in the long run. The four companies embrace distinctive business development strategies that allow them to grow in different directions. The last essay examines the influences of 22 regional timber markets in the U.S. South on the stumpage prices in their adjacent areas. The core inspiration for this chapter comes from the importance of modeling timber prices. Using

Bayesian inference instead of the frequentist inference, the parameter estimates are more useful for the stakeholders and the interpretations deliver fresh indications about the interdependency of the regional timber markets. The results reveal which regions can help predicting the future prices in their neighboring areas. The entire dissertation aims to enrich the literature on the forest-related markets and the relationships among them.

INDEX WORDS: Forestry, investment diversification, time series, wood related markets

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by

Le La

B.S., Mississippi State University, 2008

M.S., State University of New York, University at Albany, 2010

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by

Le La

Major Professor: Bin Mei

Committee: Michael L. Clutter
Susana Ferreira
Jack Lutz

Electronic Version Approved:

Julie Coffield
Interim Dean of the Graduate School
The University of Georgia
August 2014

DEDICATION

To my parents – for your love and sense of humor that teach me to persevere

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Pursuing a Doctor of Philosophy degree is not for everyone. After my second semester into the program, I still sometimes caught myself in the moments of self-doubt and pondered if I actually had the ability to get a Ph.D. I would often think my pre-doctoral life was, mostly, a comedy movie that turned into a drama when I started the program. Nevertheless, the ending was a happy one because of so many wonderful and amazing characters in my story.

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Thank you, Mom and Dad, for reminding me about my early thirst for learning whenever I needed a little encouragement. You would tell the story of me when I was four, I said, "Mom, I am going to get higher education when I grow up. I will go up the mountain to study". Your love for me is so great that you let me leave home to see the world and pursue the education opportunities that I wanted. You also said, "Lands can be lost, money can be stolen, but knowledge is an asset that no one can take away from you". Thank you for the education that you had worked so hard for me to have as well as many other things. Mom, Dad, I love you!

TABLE OF CONTENTS

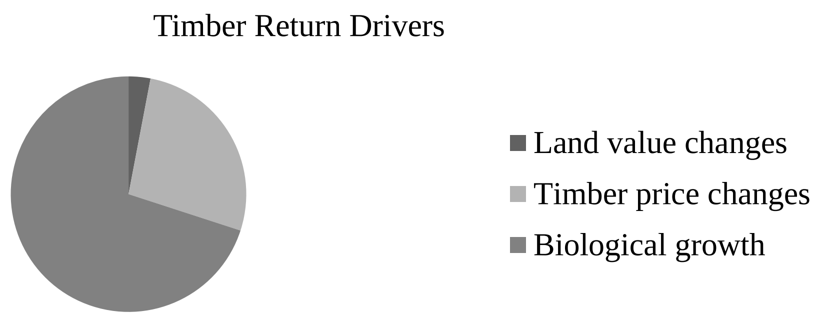
LIST OF FIGURES AND TABLES

CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

The components of timber returns are fascinating and distinctive from many other assets. Different from other commodities such as gold, oil, corn, or cattle, the value of timber asset increases over a long time horizon as trees gradually become mature. The independence of trees' biological growth from the stock markets and other economic variables make timber a valuable asset class for diversification purposes (Binkley et al., 1996; Caulfield, 1998a; Caulfield and Newman, 1999; Conroy and Miles, 1989; Redmond and Cubbage, 1988; Reinhart, 1985, Zinkhan, 1990; and Zinkhan et al., 1992). The return on timberland assets are driven by three components as illustrated below (Caulfield 1998b). The first driver, which is accounted for 2 to 5% of the total return, is the appreciation of bare land value. The second factor is the timber price increase, which constitutes between 25 and 30% of the total return. Lastly, the biological growth is the strongest driver that generates approximately 65 to 75% toward the total profit. The timber price and biological growth components drive the returns on the timber value. When trees grow, not only their volumes increase, but their in-growth also improves the value in terms of wood quality.

The dissertation addresses the investment opportunities in the timber industry, analyzes the market's behaviors and suggests best practices that can improve investment decisions. The timber and timberland sectors comprise different industries and offer different ways for stakeholders to invest. The results from chapter 2 provide insights on the overall performance of the sector. Using the findings in the first research paper, the following two chapters analyze two particular markets in details. Chapter 3 focuses on the REITs' performance which was determined to be the least informationally efficient. Chapter 4 shifts the attention to the most efficient market, the wood industry.



Chapter 2, titled "*Evaluating market Efficiency of the U.S. Forest Industry",* investigates how information should be utilized in four major forest-related markets given every investor's interest in outperforming the markets. Since past price data perpetuate information differently in the furniture, the paper, the wood and the REIT markets, the levels of informational efficiency vary across these markets. Understanding the relative efficiency suggests which market is more likely to be outperformed using historical price data. The more efficient a market is, the less likely public information is useful in creating abnormal return. The first essay of the dissertation examined the familiar issue of market efficiency but with an econophysics approach.

The entropy measurement originated from the field of physics where it is used to measure pressure. According to the second law of thermodynamics, "in all energy exchanges, if no energy enters or leaves the system, the potential energy of the state will always be less than that of the initial state"(Georgescu-Roegen 1971). The second law is also known as entropy. In order to understand this concept in the context of economics, imagine an isolated system such as a cylinder and assume there is no energy exchange between this confined system and the outside space. When every single atoms and molecules in this system are evenly distributed throughout the entire space, the system is at its highest stage of disorder and contains zero energy (Exhibit

A). When the cylinder is compressed, the atoms and molecules are concentrated in half of the confined space. Thus, the system's entropy or chaos decreases since the particles are more in order and their locations are more organized (Exhibit B). In terms of uncertainty, when the isolated system is at the absolute highest disorder or entropy, one is less certain about the position of a particular particle within the cylinder. On the other hands, one will be more confident about the location of the particle when the system is at a lower entropy level. Entropy measurement has become more popular in finance and it has been used to access market efficiency. The following chapter employs this notion to examine the market efficiency in the wood related industries.

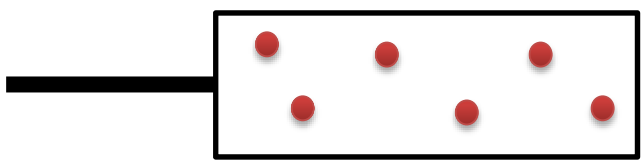


Exhibit A

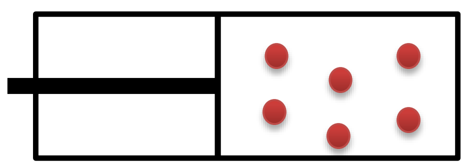


Exhibit B

The second topic in this dissertation solely deals with the REIT market. In the past few decades, a major structural shift took place in the timber industry. From a vertically integrated forest products company (VIFPC) dominated industry, two potent structures have emerged from the regime shift (Hickman 2007). Some VIFPCs sold a substantial amount of their lands, which have then been managed by Timber Investment Management Organizations (TIMOs). Other

VIFPCs separated their manufacturing facilities and their forestland ownerships so that the timberlands are owned by Real Estate Investment Trusts (REITs). There are a number of differences between the two entities. While REITs own their properties, TIMOs acquire and manage timberlands for their investors. Nevertheless, the reformed industry has created more investment opportunities for both large institutional investors and small private investors.

The forest-related markets behave very differently from the stock markets and other commodity markets. A number of studies have showed that the performance of private timber and timberland investments through TIMOs are highly uncorrelated with the stock markets. However, publicly traded REITs are more exposed to the overall macroeconomic performances. Therefore, the later chapter addresses the aspect of using timberland returns to diversify investment portfolios that comprise timber REIT stocks. Chapter 3 is titled "*Portfolio Diversification Through Timber Real Estate Investment Trusts: A Cointegration Analysis*". This essay focuses on the REIT market in which stock prices of four existing companies, Plum Creek, Rayonier, Potlatch, and Weyerhaeuser are analyzed. Based on the conclusions about their stock prices in the long run, the chapter further suggests best practices to improve investment decisions using timberland assets.

The fourth chapter, "*Bayesian Linear Modeling of Timber Prices in the U.S. South*", shifts the focus to the wood market. This discourse looks into the behaviors of 22 regional softwood sawtimber markets in the South to determine the interdependency among them. The interpretations for the results are made using Bayesian inference. The unconventional approach produces more useful and practical information for stakeholders. In addition to the magnitudes of the coefficient parameters, Bayesian modeling allows for the probability of the model estimates. The examples below illustrate one of the advantages from using Bayesian method. While the frequentist approach results in point estimates with probability of either zero or one, Bayesian provide estimates with distribution information. In the example, if the timber price in Northern Georgia increases 1%, the frequentist model predicts that either the price in Southern Georgia will decrease by 5% or it will not. On the other hand, the Bayesian model model that Southern Georgia's price might decrease by 7% with 80% probability or increase by 1% with 20% probability. Using Bayesian statistics allow modeling timber prices in the U.S. South in a more informative and richer context.

	Northern Georgia Prices	
	Increase 1%	Decrease 1%
Southern Georgia Prices	Decrease by 5%	Increase by 5%

Exhibit C: Example of Parameter Estimates under Classical Statistics

	Northern Georgia Prices	
	Increase 1%	Decrease 1%
Southern Georgia Prices	Decrease by 7% with 80% probability	Increase by 7% with 80% probability
	Increase by 1% with 20% probability	Decrease by 1% with 20% probability

Exhibit D: Example of Parameter Estimates under Bayesian Statistics

The three following studies investigate the financial performances of the timber and timberland industries and aim to inform investors about profit opportunities and risks in this sector. Even though all forest related industries rely on the supply and demand of wood products, there exist a number of investment options in this field. Hence, there are a variety of stakeholders such as stockholders, wood-consuming mills, timberland appraisers, and landowners who have a vast interest in understanding the industries' behaviors. The first research paper examines the forest related industries at the macro level whereas the latter two performed thorough analyses at the micro level. The final chapter summarizes and draws the overarching conclusions for this dissertation as well as provides directions for future studies. Further investigations can check the robustness of the chapters' conclusions by using different assumptions and data frequency.

CHAPTER 2

EVALUATING MARKET EFFICIENCY OF THE U.S. FOREST INDUSTRY[1]

[1]La, L. and Mei, B. 2013, *Forest Products Journal*, 63, 232-237, Reprinted here with permission of publisher.

Abstract

The market efficiency of the US forest industry had evolved over the past decade. In this study, the entropy measurement, an econophysic approach, was applied to quantify the informational efficiency of timber real estate investment trusts (REITs), wood, furniture, and paper markets in the United States during the period from 1999 to 2012. In a relative context, indices on Treasury bonds were used to proxy the risk-free rate of returns, while Standard & Poor's (S&P) 500 stock returns were used as a yardstick for risky investments. The analysis indicated that the forest markets were considerably more informationally efficient than the Treasury market. Furthermore, most markets were marginally more efficient compared with the S&P 500 index, with the exception of REIT returns. Therefore, better arbitrage opportunities were present in REIT investments.

Introduction

The economic interpretation of informational efficiency refers to the amount of information contained in prices in a given market. The less informational efficient a market is, the more predictable the future returns will be through various analysis tools. Intuitively, prices reflect only limited available information and behave less erratically in an inefficient market. Therefore, the main application of evaluating the informational efficiency in forest-related markets, including forest products industries (FPI), is to determine the likelihood of consistently outperforming the market by analyzing information such as historical data, financial statements, and private information.

Not only are profitable returns of great interest to investors, but strategies on outperforming the market have intrigued many stakeholders as well. Accurately modeling future prices or returns allows investors to exploit arbitrage opportunities in which profits can be made by buying assets at low prices and simultaneously selling them at higher values (El Karoui et al. 1997). When markets operate inefficiently, the formation of over- and undervalued assets postulates the presence of arbitrage opportunities. On the contrary, if markets are completely efficient, investors cannot obtain arbitrage advantage over other traders because all information is instantaneously incorporated in current prices and accessible by everyone in the market.

According to Fama’s study in 1970, there were three versions of market efficiency: weak form, semistrong form, and strong form. The emphasis of the following study is confined to analyzing the weak form market efficiency, which pertains to past price behaviors (Fama 1970). Therefore, the higher the level of weak efficiency that exists, the less likely for investors to identify under- or overvalued stocks through technical analysis. Performing fundamental analyses on financial statements and utilizing private information were the remaining options for investors to gain excess returns (Sun and Zhang 2001).

The objective of this article is not to provide an absolute answer to whether forest-related markets are efficient. Empirical evidence has suggested the predictability of high-frequency returns from past data, such as daily and weekly stock prices (Fama 1991). Nevertheless, some markets might be less efficient than others and offer greater chances of successfully earning additional returns. In this study, informational efficiency of different markets is measured by the entropy levels they possess.

Literature Review

Informational efficiency studies in the forest products industry

Previous studies on informational efficiency have focused primarily on different stock markets and foreign exchange markets. Although limited research on this topic exists in forest-related industries, available studies have yielded contradictory results. Washburn and Binkley (1990, 1993) indicated that 13 timber markets in the US South operated efficiently in the weak form on an annual and quarterly basis. The authors performed serial correlation tests on the return data from 1976 to 1989 and found independency in deviations from the mean of the series. Their results inferred that no particular rule of movements was present in timber prices because variations in past and current realizations were uncorrelated. According to the notion of weak form efficiency, potential gains would not be achieved by analyzing the path of past prices. However, they found that monthly prices did not capture all available information and were inefficient due to transactional costs in the process of finalizing sales.

In response to the previous results, Hultkrantz (1993) argued that even though prices were not autocorrelated, past information could still be used to investigate future returns if they exhibited stationarity. Therefore, market efficiency should not be claimed on the basis of the unpredictability of future residuals alone. His study showed that the stumpage price series in the US South was stationary with respect to a set of information, including timber growth rate, capital costs, and storage costs. Therefore, investors could examine past price activities in the context of time of sales in order to model the prospect price paths.

In agreement with the latter approach, several studies concurred regarding the presence of stationarity as an indication of informational inefficiency. Through an augmented Dickey-Fuller test, Haight and Holmes (1991) supported the stationarity of softwood sawtimber prices in North Carolina because the time series did not possess a unit root. Moreover, Yin and Newman (1996) further illustrated that 14 southern timber markets operated inefficiently by including one lagged term in their unit root tests. Hence, the result reinforced the hypothesis of market inefficiency. Their study revealed that stumpage prices were indeed stationary over the long horizon and followed a mean-reverting path.

Nevertheless, Prestemon and Holmes (2000) and Prestemon (2003) noted that different assumptions and approaches would lead to contradicting conclusions on stationarity. Different from the findings of Hultkrantz (1993) and Yin and Newman (1996), the latter study aligned with the conjecture that stumpage prices were nonstationary in most southern markets. After adjusting the return time series according to the consumer price index, the author analyzed the monthly data of 27 submarkets in the southern region. As the result of an alternative lag selection procedure, the author applied longer lag lengths in his regressions for the augmented Dickey-Fuller tests. When higher orders of autocorrelation were considered, prices appeared to follow a martingale process in which the conditional expected future price would be equal to the last observed price. The outcomes suggested that technical evaluations would be useful to investors in only a few submarkets of timber.

Entropy measurements in informational efficiency studies

Different from the traditional approach, entropy or information theory is an econophysic framework that has gradually received more interest from economists because of its useful applications in assessing the performance of financial markets. Initially, entropy was used in physics to measure energy through examining thermodynamic processes (Georgescu-Roegen 1971). In 1948, mathematician Claude Shannon applied the concept of entropy into the statistical field in order to calculate information sizes and limits of transmitting signals (Downarowicz 2011). Since its inception, information theory has been used in various fields, including finance, statistics, neurobiology, and computer science (Cover and Thomas 2005). In finance, the entropy value of a market allows analyzing market efficiency in a relative context. Intuitively, when entropy is at zero, its smallest value, future occurrences can be predicted with certainty. On the other hand, when the entropy level is maximized, each possible outcome has an equal chance of happening (Luciano et al. 2011). Therefore, one cannot completely forecast future returns, as the pricing system operates in the most random state. Hence, maximized entropy implies that contemporaneous prices successfully reflect all past prices and that return volatilities are determined by other information so that there are no structured changes in stock prices (Philippatos and Wilson 1972, Gulko 1999, Sung and Anil 2009). In a weakly efficient market, regardless of how well historical price behaviors are understood, investors should be indifferent between making decisions with or without a technical analysis. Likewise, there exists trivial arbitrage opportunity based on previous price information.

In a recent study, Risso (2009) used Shannon entropy to compare 20 stock markets of different countries in terms of informational efficiency. The author showed that the Dow Jones US stock market was more efficient than the British Financial Times and London Stock Exchange from 1997 to 2007. However, both indices were less efficient than the Japanese Nikkei Stock Average. Under a similar methodology, Alvarez-Ramirez et al. (2012a) revealed that the Dow Jones market's informational efficiency depended on the time scale and varied over time. Daily prices were more efficient compared with the monthly and quarterly indices. In addition to Shannon entropy, Renyi and Tsallis are modified measurements of entropy. Bentes et al. (2007) used the three measurements of uncertainty to examine stock prices' volatility clustering. The different entropy indices produced consistent results in showing the Standard & Poor's (S&P) 500 as the most efficient stock market when compared with the Stoxx 50 and the NASDAQ 100.

Data

Relevant daily return data were available from the beginning of July 1999 to the end of December 2012. Forest-related markets, including timber real estate investment trusts (REITs), wood (North American Industry Classification System [NAICS] 321), furniture (NAICS 337), and paper (NAICS 322), were the scope of the research's interest. Because timber companies converted to REITs at different times, a dynamic REIT portfolio comprising Plum Creek (PCL), Rayonier (RYN), Potlatch (PCH), and Weyerhaeuser (WY) was constructed on the basis of their dates of conversion. The value-weighted portfolio initially contained returns from PCL, which was a pioneering REIT entity, and eventually incorporated data from other firms on their official structural changes. Specifically, RYN, PCH, and WY data were included in the portfolio from January 2004, 2006, and 2010, respectively. All REIT return series were obtained from the

Center for Research in Security Prices database from Wharton Research Data Services (WRDS) in 2013, while the wood, furniture, and paper series were acquired from French's online data library (French 2013). The four time series were constructed using the average value-weighted returns, and each contained 3,397 observations.

In order to evaluate the degree of informational efficiency in each FPI, the S&P 500 index and the 3-month Treasury bill rates were utilized as relative thresholds for comparison purposes. The benchmark variables were selected because of the vast financial literature's indications regarding their levels of market efficiency. The US Treasury indices had been influenced by monetary policies and had not tended to change erratically. As it was unconstitutional for the government to default on the US Treasury debts, investments in Treasury bills involve minimal risk and volatility. Although the rates were determined through auctions, the future returns were highly predictable, and the liquid Treasury bill market had often been considered inefficient (Puglisi 1978, Vignola and Dale 1979). On the other hand, the S&P 500 index was chosen as an efficient market yardstick because a number of studies had provided empirical conclusions that supported the informational efficiency of the stock markets (Fama and French 1988, Fama 1991). These data were from WRDS.

Methodology

Entropy measurement

Let $X = (x_1, x_2, \ldots, x_i)$ be a return time series of interest. The Shannon entropy of the market is calculated as follows:

$$S(x) = -\sum_{i=1}^{n} p_i \log_b p_i$$

where p_i is the probability of getting return x_i.

Value of the log base, *b*, refers to the unit of measurement. When $b = 2$, 10, or *e*, the information efficiency will be measured in bit, dit, and nat, respectively. Hence, different units of the log base will result only in different readings of the information size. For consistency purposes, this study used base *e* to calculate the entropies.

Probability assessment

Empirically, a normal distribution assumption is often violated. Hence, the Jarque-Bera test is utilized to determine the presence of kurtosis and skewness in the sample data. Possessing various useful properties, entropy measurement does not rely on the assumption that the sample random variables must propend to a normal distribution (Masud 1987). For that reason, the equidistant histogram approach is implemented on rejection of the null hypothesis. The probability of each interval is then calculated from a histogram-based method. Once the probability of each bin is determined, Shannon entropy is calculated on the basis of the return intervals and their corresponding probability.

Test statistics utilizing rolling windows

On the basis of the sole measurements over the entire sample period, one could not conclude whether the entropy levels between any two markets were profoundly different. Hence, a rolling window approach was utilized to examine the statistical significance of entropy differences among the six markets. Each time series was divided into 31 subsamples in which there were 1,000 observations, with the exception of the last period, with *n* equal to 997. Every subsequent rolling window began after 80 lagged days from its preceding period's starting date so that consecutive episodes were approximately 3 months apart. The same entropy measurement and probability calculation procedures were then applied to the six series for each rolling window. As a result, a sample size of 31 for every variable was generated and allowed for pairwise *t* test comparisons between different forest-related markets.

Business cycles

To examine the changes of informational efficiency for each market, the study further investigated the entropy values according to historical business fluctuations. During economic downturns, the number of businesses shrunk, and the market became less competitive in addition to having lower expected payoffs (Balvers et al. 1990). Thus, under the market efficiency framework, markets were less efficient during recessions due to aggregate cynical expectations (Fama 1990). On the contrary, markets should be more efficient during economic booms because of fierce competition among a greater number of businesses.

Since 1999, the US economy has experienced three complete cycles, which included two contractions and an expansion. According to the National Bureau of Economic Research, a short, mild recession lasted from March to November 2001, followed by an economic recovery and growth for approximately 2 years. Recently, the economy underwent a prolonged contraction from December 2007 to June 2009. The reference dates of the business fluctuations were March 2001 and December 2007, when the economy reached its peaks, and November 2001 and June 2009, during which the economy was in its troughs. According to the discussed time line, four different episodes were generated for each return series. For every economic episode, the data from 3 months prior and 3 months after the turning point date were utilized to calculate Shannon entropies.

Empirical Results

The probability density function for a normal distribution could not be applied, as the Jarque-Bera test rejected the null hypothesis in all six cases (Table 2.1). Therefore, equidistant breaks were utilized to divide each return data set into 20 bins. To a certain extent, Shannon entropy measurements showed similar results to past studies. As expected, future returns were more unpredictable for the S&P 500 index while less stochastic in the case of the Treasury bill rates. When allowing the entropy values of the Treasury bill and the stock markets to act as relative minimum and maximum of informational efficiency, the REIT market lay within the spectrum encompassed by the two benchmarks (Table 2.2). The pairwise *t* tests at the 99 percent confidence interval indicated that such differences between the three markets were statistically significant (Table 2.3). Nevertheless, the REIT index seemed to be closer to the efficient end of the scale. Likewise, the three wood products markets were much more informationally efficient than the Treasury market at the 99 percent confidence interval. In comparing entropies of the FPI to the other markets, the empirical results at the 99 and 95 percent significance levels induced two possible ranking scenarios (Table 2.4). However, at the 90 percent confidence interval, the outcomes provided one consistent inference on the relative efficiency among the six variables (Table 2.5).

In both cases, the wood industry was the most efficient market, followed by the paper industry and the S&P 500 index. Because the test statistics failed to reject the similarity between the paper and stock markets, the result implied that they exhibit the same efficiency. Depending on the selected interval estimations, the furniture industry could be placed first or second as a relatively efficient market. Therefore, at the 95 percent or higher confidence interval, it was ambiguous whether the furniture or the wood time series held the most efficient position among all variables. On the other hand, the paper, furniture, and stock markets were equally efficient at the 90 percent confidence level. Nevertheless, the timber REIT was less efficient than the other FPI, as indicated by the substantial lower entropy levels. In addition, the empirical evidence supported the notion that the timber REIT index operated marginally less efficiently than the stock market did. The statistical significant entropies showed that the Treasury bill was evidently the least informationally efficient market.

During the course of approximately 13 years, the efficiency levels of each market had evolved over time (Fig. 1)[2]. Entropy outcomes of the four economic episodes showed that the informational efficiency of most markets had changed according to the business oscillations (Table 2.6). Entropies of all markets, except for the Treasury bill index, tended to be higher during boom periods than during bust periods. Therefore, markets had performed more efficiently during peaks and, conversely, less efficiently during troughs. Nevertheless, the REIT and furniture markets had gradually improved in terms of informational efficiency when the last contraction ended in June 2009. Their entropy indexes in the last episode were slightly higher than the indexes in the preceding ones.

Discussion and Conclusion

Past studies often determined the informational efficiency of timber-related markets in an absolute context. Nevertheless, entropy measurements were able to quantify the informational efficiency of the given markets despite the model's simplicity. Therefore, in a relative context, this study indicated that the magnitude of efficiency varied across different markets. Among the six markets, the Treasury bill rates operated most inefficiently. Intuitively, changes in

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[2] For a robustness check, the entropy level for each return series assuming a *t* distribution was calculated. The results were generally consistent and are available from the authors on request.

microeconomic conditions happened more frequently than changes in macroeconomic settings because decisions made by individuals and businesses often took place more rapidly than did the central government's decisions. Hence, macroeconomic variables, such as the federal fund rates, bond rates, and Treasury bill rates, tended to be slow in incorporating and reflecting historical information.

On the other hand, the timber REIT market was perceived to be rather less efficient compared with the S&P 500 index. Hence, the present returns did not completely reflect all available historical price behaviors. As an implication, there were arbitrage opportunities for investors to capture additional returns by actively trading REIT stocks. However, the same arguments could not be made for the furniture, paper, and wood industries. FPI had either similar or higher entropy than the stock market did. Although the differences in entropy indexes between the S&P 500 market and the FPI were minimal, only the paper industry appeared to have the same informational efficiency with the stock market in all plausible scenarios.

On the basis of the reported test statistics, the differences in efficiency levels between wood prices and other forest-related markets could raise important economic questions because they were unlikely to happen by chance. At the 90 percent confidence level, the entropy of the wood market returns was indeed higher than the indexes of all other markets. Empirically, the possibility of outperforming the market using historical data seemed to be most trivial in the wood market. Therefore, fundamental analyses would be more appropriate in forecasting wood prices, whereas technical analyses should be effective in predicting future values of timber REITs and could provide some insight into the price behaviors of furniture and paper.

Furthermore, the results showed that the movements of entropy level reflected the financial fluctuations in the US economy. Similar to some past studies, the empirical evidence found that the markets underwent the most efficient period from around 1990 to 2000 in the past century (Alvarez-Ramirez et al. 2012b). The strong and extended period of business expansion during the 1990s aided the efficiency of the US market during the economic boom of 2001. The following brief contraction was due mainly to the September 11 event, and the economy quickly recovered thereafter (Hall 2001). Therefore, the entropy levels slightly decreased as the result of the mild contraction. During the economic growth in 2007, information efficiency was considerably improved, as indicated by the higher entropy indexes. The reported entropies were at their highest around the business peak of 2007, during which the US economy had experienced stable and extended growth. Subsequently, the measures of entropy for the markets tended to be lower during the latest recession, with the exceptions of the REIT, furniture, and Treasury bill markets. Hence, further studies are needed to investigate the abnormal informational efficiency during the recent business cycle. Intuitively, as the number of businesses increase during expansions, the market is more competitive; hence, outperforming the market is less likely.

Many individual stock buyers rely on accessible information, including corporations' historical price data and financial statements, to make their investment decisions. Given constrained resources, investors must exploit the most amount of information and be selective in investing their funds. Therefore, the ordinal positions of different markets in terms of informational efficiency can be a useful guide to overperformance. Knowing whether a price series employs relatively more or less past information enables stockholders to select the appropriate analytical instruments in projecting future returns. Furthermore, the entropy methodology can be extended to examine other publicly traded assets in order to make comprehensive comparisons with forest-related markets.

Figure 2.1. Entropies over 31 subperiods (1999 to 2012).

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Table 2.1. Jarque-Bera test for normal distribution.

Market	χ^2	Degrees of freedom	*P* value
REIT	20,773.270	2	0.000
Furniture	3,691.729	2	0.000
Paper	2,504.294	2	0.000
Wood	1,965.775	2	0.000
S&P 500	7,600.090	2	0.000
Treasury bill	13,977,420.000	2	0.000

Codes for furniture, paper, and wood industries are North American Industry Classification System (NAICS) 337, NAICS 322, and NAICS 321, respectively. REIT = timber real estate investment trusts; S&P 500 = Standard & Poor's 500.

Table 2.2. Comparison of entropy levels for the six markets (1999 to 2012).

Market	Entropy level
REIT	1.439
Furniture	1.818
Paper	1.775
Wood	1.896
S&P 500	1.610
Treasury bill	0.334

Codes for furniture, paper, and wood industries are North American Industry Classification System (NAICS) 337, NAICS 322, and NAICS 321, respectively. REIT = timber real estate investment trusts; S&P 500 = Standard & Poor's 500.

Table 2.3. Pairwise t test statistics for entropy levels among the six markets.

	Wood		Paper		Furniture		S&P 500		Treasury bill	
REIT	0.000	***	0.098	*	0.048	**	0.003	***	0.000	***
	−4.220		*−1.708*		*−2.060*		*−3.201*		*12.016*	
Wood			0.002	***	0.055	*	0.094	*	0.000	***
			3.393		*2.000*		*1.730*		*11.307*	
Paper					0.422		0.471		0.000	***
					−0.815		*−0.731*		*11.767*	
Furniture							0.860		0.000	***
							0.178		*8.758*	
S&P 500									0.000	***
									16.560	

***, **, and * denote statistical significance at the 1, 5, and 10 percent level, respectively; *t* ratios are in italics. Codes for furniture, paper, and wood industries are North American Industry Classification System (NAICS) 337, NAICS 322, and NAICS 321, respectively. REIT = timber real estate investment trusts; S&P 500 = Standard & Poor's 500.

Table 2.4. Rankings based on 95 and/or 99 percent confidence interval.

Rank	Market	
	Scenario 1	Scenario 2
1	Wood	Wood and furniture
2	Paper, furniture, and S&P 500	Paper and S&P 500
3	REIT	REIT
4	Treasury bill	Treasury bill

Rankings: 1 = relatively efficient; 4 = relatively inefficient.
Codes for furniture, paper, and wood industries are North American Industry Classification System (NAICS) 337, NAICS 322, and NAICS 321, respectively. S&P 500 = Standard & Poor's 500; REIT = timber real estate investment trusts.

Table 2.5. Ranking based on 90 percent and higher confidence interval.

Rank	Market
1	Wood
2	Paper, furniture, and S&P 500
3	REIT
4	Treasury bill

Rankings: 1 = relatively efficient; 4 = relatively inefficient.
Codes for furniture, paper, and wood industries are North American Classification System (NAICS) 337, NAICS 322, and NAICS 321, respectively. S&P 500 = Standard & Poor's 500; REIT = timber real estate investment trusts.

Table 2.6. Entropy levels during complete business cycle since 1999.

Reference date	Business cycle	REIT	Wood	Paper	Furniture	S&P 500	Treasury bill
Mar 2001	Peak	2.392	2.599	2.560	2.203	2.499	1.897
Nov 2001	Trough	2.216	2.155	2.286	2.013	2.370	1.836
Dec 2007	Peak	2.442	2.731	2.772	2.508	2.589	1.157
Jun 2009	Trough	2.496	2.495	2.704	2.628	2.380	2.056

Codes for furniture, paper, and wood industries are North American Industry Classification System (NAICS) 337, NAICS 322, and NAICS 321, respectively. REIT = timber real estate investment trusts; S&P 500 = Standard & Poor's 500.

CHAPTER 3

PORTFOLIO DIVERSIFICATION THROUGH TIMBER REAL ESTATE INVESTMENT TRUSTS: A COINTEGRATION ANALYSIS[3]

[3] La, L, and Mei, B. Accepted by *Forest Policies and Economics*, Reprinted here with permission of publisher.

Abstract

Investors who are interested in long-term investments have regarded timberland as an advantageous asset class. The formation of timber real estate investment trusts (REITs) has offered both individual and institutional investors more options to diversify their portfolios through securitized timberlands. Nevertheless, different mixes of REIT stocks will yield various degrees of volatility for the portfolio's performances. The cointegration analyses in this study show that there are no general trends among the historical timber REIT stock prices and the S&P 500 index. Therefore, there is diversification potential in the long run with each timber REIT (except Plum Creek) considered as a unique candidate.

Keywords: asset allocation, forestland investment, portfolio diversification, time series

Introduction

Approximately 33 percent of the U.S. landmass is covered by forested areas. The abundant and productive timber resources in the country have ignited many investment opportunities in the forest sector in the past few decades. Investing in timber assets can be practiced through either direct ownerships or different equity markets in which real estate investment trust (REIT) stocks have become the most common channel of investment.

The first REIT that operates income-producing timberlands was created in 1999 when Plum Creek was converted from a master limited partnership. Since its establishment, the timber REIT structure in the U.S. has become a unique and appealing investment vehicle of which securities can be easily bought and sold. Besides eliminating the double taxation as levied on C-Corporations, a REIT entity allows its shares to be available to both individual and institutional investors. Because securitized timberlands can be traded openly on public stock exchanges, timber REIT assets possess less liquidity risk compared to private-equity timberlands. Furthermore, a number of empirical studies indicate that timberland assets could effectively hedge against inflations and reduce investments' volatility (Caulfield, 1998; Mei et al., 2013; Sun and Zhang, 2001; Washburn and Binkley, 1993). Regardless of market conditions, trees continue to grow as they become mature and merchantable. In an unfavorable market condition, timber harvesting can be postponed until stumpage prices recover to a desired value. In addition, bare land values usually appreciate over time and add more benefits to holding securitized timberlands. Given these investment benefits, timber REIT assets have continuously gained interest from investors in the equity markets.

Although publicly-traded REIT stocks can be quickly sold for cash returns, investments in timberlands are intended for a long planning horizon. Traditionally, timberland-related investments often involve timberland investment management organizations (TIMOs). TIMOs are responsible for identifying, acquiring, and subsequently managing the timberlands on behalf of their clients. Nevertheless, investing through TIMOs requires a significant amount of initial capitals that exceed the majority of small retail and institutional investors' budgets. The appraisal-based valuation approach used by TIMOs also creates barriers to investment. With the emergence of timber REITs, investors find an attractive mean to expand the range of their assets. Combining heterogeneous types of investments helps smooth out unexpected losses because positive returns neutralize the impact of negative returns. Likewise, diversification strategy requires minimal correlations among the assets in the portfolio. Therefore, whether different REIT stock prices share a common trend over time has crucial implications on investment decisions in the timberland industry. At present, the U.S. public timber REIT market is comprised of Plum Creek (PCL), Rayonier (RYN), Potlatch (PCH), Weyerhaeuser (WY), and CatchMark (CTT).[4] The corresponding correlation table shows imperfect correlations between the timber REIT stock prices and the S&P 500 index levels (Table 3.1). Several studies suggest that there is little correlation between the stock market and the performance of the timberland investments (Cascio and Clutter, 2008; Sun and Zhang, 2001). Therefore, the question remains whether portfolios with composite timber REIT equities could perform better than those with a single timber REIT stock in terms of risk managing.

The objective of this study is to determine whether only one or all publicly-traded timber REIT securities should be included for the diversification purpose. Therefore, two cointergation tests, the Engle-Granger and Johansen procedures, are used to examine the long-run equilibrium relationships among the stock prices of four REITs. When cointegrating vectors exist among the

[4] CatchMark went public in December 2013.

four variables, the REIT stock prices will converge over time, and such result indicates a restricted portfolio diversification in the long run. Alternatively, when the companies' stock prices are not cointegrated, the systematic risk can be lessened by investing in multiple REITs. The outcomes of this study can provide some insight for managing investment risk through timber REITs.

Literature Review

Cointegration Analysis

In the economic literature, the notion of cointegration was first introduced prior to the 1980s but the testing procedure had not been formalized until 1987 by Robert F. Engle and Clive W.J. Granger. Testing for cointegration between several time series had frequently been used to analyze the possibility of long-term relationships among the variables of interest. Within the forest economics literature, a number of studies employed cointegration tests to draw inferences and predict behaviors of various forest related markets. In earlier research, the cointegration analysis led to the conclusion that the U.S. pulp prices had an important impact on the Canadian pulp prices since the test statistics suggested a long-run relationship between the two price time series (Alavalapati et al., 1997). Based on cointegration results, Sun and Zhang (2006) found that among eleven southern states, which accounted for the majority of timber harvesting in the country, no individual state was leading the logging sector and the logging market was not perfectly integrated.

Recent research investigated the impacts of different macroeconomic factors on the U.S. forest commodity exports. Sun and Zhang (2003) suggested a negative econometric relationship between exchange rate volatility and the exports of forest products. On the other hand, a positive correlation existed between the economic growths of importing countries and the export volumes of the U.S. (Cheng et al., 2013). Cointegration analyses had also been applied extensively to examine market integration between forest related markets of different countries (Kainulainen and Toppinen, 2006; Olsson et al., 2011; Stordal and Nyrud, 2003; Toivonen et al., 2002).

Timberland Market and Portfolio Diversification

Several seminal studies investigated the diversification of portfolios through forest related investments in both the short run and long run (Aronow et al., 2004; Cascio and Clutter, 2008; Deforest et al., 1991; Redmond and Cubbage, 1988). Investments on timberland assets provided distinctive potentials to minimize volatility since the biological growth factor of timber did not depend on economic expansions and recessions (Mei et al., 2010). The authors stressed that biological growth was the strongest return driver compared to timber price change and bare land value appreciation. Therefore, holding stocks of publicly-traded timber firms would be considered a sound practice for diversification.

On the other hand, Liao et al. (2009) indicated that timberland and softwood were not adequate in reducing the market risk of a portfolio comprised of the Standard and Poor's 500 stocks. Their empirical results implied that changes in the stock market would ultimately influence timber prices and returns on timberland investments. In the paper, Johansen cointegration test revealed one cointegrating vector among seven financial assets and two forestry related investment instruments. Similarly, Sun (2013) concluded that after converting to the REIT structure, the four timber firms had gradually become dependent on the overall performance of the stock market. As publicly-traded entities, timber REIT stock values were more receptive to market fluctuations and provided fewer financial diversification advantages for investors. Furthermore, when compared to private-equity timberland assets, returns on REIT investments were perceived to be less effective in outperforming the market and minimizing the systematic risk (Mei and Clutter, 2010).

To our best knowledge, studies to date have not examined the long-term relationship among stock prices of the four REITs. If the REIT stock prices tend to move in similar directions, investment in various REITs will offer little benefit. In this paper, cointegration analyses are applied to determine whether the timber REIT sector is cointegrated.

Data and Methodology

Data

Historical daily stock price data from December 2009 to December 2013 were available and provided 1018 observations for each timber REIT. Adjusted close prices were used to allow data to be more comparable at different points in time. The starting point of the time window was determined based on the date of conversion announcement from Weyerhaeuser. Within the described period, no new REIT had been formed and none of the existing firms had been dissolved.[5] The stock quotes for all four REITs were obtained from the Center for Research in Security Prices database from Wharton Research Data Services (WRDS, 2013). In order to improve the stationarity property, price time series were converted to natural logarithmic forms. In the remaining discussions, all variables therefore refer to the adjusted data.

Unit Root Test

Prior to performing any cointegration analysis, a time series must be tested for stationarity. The concept of stationarity is important and necessary in characterizing a time series for regression modeling purposes. A stationary time series must have constant mean and variance

[5] CatchMark was not included in the analysis because of data limitation.

over time. In addition, its covariance only depends on the distance between two time periods but not on a specific point in time. When the test statistics indicate the same order of integration for all data series, the conintegration analysis can be applied (Wooldridge, 2013). If the time series is nonstationary and no cointegration exists, the Ordinary Least Squares (OLS) estimations will produce spurious regressions with meaningless interpretations. However, when at least one stationary combination is present among the nonstationary time series, implications of the regression results can be valuable.

A nonstationary time series is said to be integrated of order *q*, denoted as *I(q)*, if the series becomes stationary after being differenced q times (Tsay, 2005). In order to determine the number of unit roots that each price time series contains, the augmented Dickey-Fuller (ADF) test is used. First, data in level is assessed for stationarity. If the null hypothesis of nonstationarity cannot be rejected, the first differenced form will then be analyzed (Enders, 2010). For each stock price series, the ADF tests indicate whether the residual vectors in the following model specifications are stationary.

$$\Delta \ln p_{\mathrm{t}} = \alpha + \theta \ln p_{\mathrm{t}-1} + \gamma_1 \Delta \ln p_{\mathrm{t}-1} + \cdots + \gamma_{\mathrm{k}} \Delta \ln p_{\mathrm{t}-\mathrm{k}} + \varepsilon_{\mathrm{t}} \tag{1}$$

$$\Delta \ln p_{\mathrm{t}} = \alpha + \delta t + \theta \ln p_{\mathrm{t}-1} + \gamma_1 \Delta \ln p_{\mathrm{t}-1} + \cdots + \gamma_{\mathrm{k}} \Delta \ln p_{\mathrm{t}-\mathrm{k}} + \varepsilon_{\mathrm{t}} \tag{2}$$

where p is the stock price, t is the time index, α is a constant term, δ is the coefficient of the linear time trend, θ is the coefficient of the variable in the previous period, γ_{k} is the coefficient of $\Delta \ln p_{\mathrm{t}-\mathrm{k}}$ which is the lagged change of stock price in the log transformed version, k is the number of lag orders, and ε is the disturbance term.

Both versions, one with a time trend and the other without a time trend, are tested in this study. If the error vector obtained from the described model is a stationary process, the null hypothesis is rejected and assessing the data in higher order of difference will not be needed. In order to determine the number of lagged change of stock prices to be included as regressors, Bayesian information criterion (BIC) and Hannan-Quinn information criterion (HQIC) are employed (Hannan and Quinn, 1979; Schwarz, 1978).

Cointegration Tests

Once the appropriate order of integration is verified for each price data, both Engel-Granger and Johansen tests are used to determine if cointegrating vectors exist among the four stock price time series. The former is a two-step method relied on univariate linear regressions whereas the latter is a multivariate test based on a vector autoregressive approach, which allows all variables to be endogenous.

The Engle-Granger procedure first estimates the econometric relationships between all stock prices by using OLS regressions (Engle and Granger, 1987). If the residuals from the OLS estimations are found to be stationary, the null hypothesis of no cointegration is rejected. Nonetheless, choosing different REIT prices as the dependent and independent variables in the long-run equilibrium regressions can lead to conflicting conclusions. Without any certainty on the causal relationships between the stock prices, no particular arrangement is preferable in constructing the models. Consequently, for every model specification, there are four separate Engle-Granger tests, in which each price variable will alternate between the regressor and the regressand. The residual series are then tested for stationarity. Consistent test statistics from all models imply that the cointegration results are unambiguous.

Although the Engle-Granger procedure can be easily executed and its test results become more consistent regardless of the selected predictand when given sufficiently large sample sizes, the test inevitably inherits several weaknesses (Enders, 2010). An important drawback of the procedure is that it can only detect one cointegrating vector even if more than two variables are considered in the analysis. The Johansen procedure, a later econometric instrument, has been developed to address the problem of multiple cointegrating vectors (Johansen, 1988, 1991; Johansen and Juselius, 1990). The test examines the rank of a matrix and uses maximum likelihood estimators to determine the number of stationary combinations among the variables. Applying the Johansen procedure, the following vector autoregressive model is examined

$$\ln\boldsymbol{p}_{\mathrm{t}} = \boldsymbol{\Pi}_1 \ln\boldsymbol{p}_{\mathrm{t-1}} + \cdots + \boldsymbol{\Pi}_{\mathrm{k}} \ln\boldsymbol{p}_{\mathrm{t-k}} + \boldsymbol{\varepsilon}_{\mathrm{t}} \tag{3}$$

where $\boldsymbol{p}$ is a $\mathrm{n} \times 1$ vector comprising the four price variables, t denotes the time index, $\boldsymbol{\Pi}$ is the matrix of parameter coefficients, k denotes the number of lag orders, and $\boldsymbol{\varepsilon}$ is the residual vector. The model presumes that the error terms follow a white noise process. The equation can be rewritten in a more useful form as follows

$$\Delta\ln\boldsymbol{p}_{\mathrm{t}} = \sum_{i=1}^{k-1} \boldsymbol{\Gamma}_{\mathrm{i}}\, \Delta\ln\boldsymbol{p}_{\mathrm{t-i}} + \boldsymbol{\Gamma}\ln\boldsymbol{p}_{\mathrm{t-1}} + \boldsymbol{\varepsilon}_{\mathrm{t}} \tag{4}$$

where $\boldsymbol{\Gamma} = -(\mathbf{I} - \sum_{i=1}^{k} \boldsymbol{\Pi}_{\mathrm{i}})$ and $\boldsymbol{\Gamma}_{\mathrm{i}} = -\sum_{j=i+1}^{k} \boldsymbol{\Pi}_{\mathrm{j}}$.

Model specifications can also contain one or more deterministic elements (Hayashi, 2000). Hence, two additional regressions below are used in the Johansen procedure

$$\Delta\ln\boldsymbol{p}_{\mathrm{t}} = \boldsymbol{\alpha} + \sum_{i=1}^{k-1} \boldsymbol{\Gamma}_{\mathrm{i}}\, \Delta\ln\boldsymbol{p}_{\mathrm{t-i}} + \boldsymbol{\Gamma}\ln\boldsymbol{p}_{\mathrm{t-1}} + \boldsymbol{\varepsilon}_{\mathrm{t}} \tag{5}$$

$$\Delta\ln\boldsymbol{p}_{\mathrm{t}} = \boldsymbol{\alpha} + \boldsymbol{\delta}t + \sum_{i=1}^{k-1} \boldsymbol{\Gamma}_{\mathrm{i}}\, \Delta\ln\boldsymbol{p}_{\mathrm{t-i}} + \boldsymbol{\Gamma}\ln\boldsymbol{p}_{\mathrm{t-1}} + \boldsymbol{\varepsilon}_{\mathrm{t}} \tag{6}$$

where $\boldsymbol{\alpha}$ is a constant vector, $\boldsymbol{\delta}$ is a coefficient vector of the time trend, and other variables are as previously described.

In order to identify the independent cointegrating vectors, the Johansen procedure focuses on $\boldsymbol{\Gamma}$ which is the matrix of parameter coefficients. Particularly, the rank of $\boldsymbol{\Gamma}$ equals the number of cointegrating vectors in the model. Assuming $\boldsymbol{y}_t$ is not an explosive process, rank ($\boldsymbol{\Gamma}$) $\neq 0$ suggests a stationary process and the presence of cointegration. On the other hand, rank ($\boldsymbol{\Gamma}$) = 0 indicates no cointegration. The rank of $\mathbf{\Gamma}$ is determined based on its characteristic roots which can be estimated by use of either the trace test or the maximum eigenvalue test.

Empirical Results

The descriptive statistics of the four price time series were reported in Table 3.2. RYN had the highest average stock price whereas WY had the lowest. In terms of standard deviations, PCH stock showed the lowest volatility while RYN stock exhibited the highest variation. In the subsequent discourse, the reported results were generated by Stata statistical software.

Results from Stationarity Tests

The augmented Dickey-Fuller unit root tests showed that all the time series were integrated of order one. The conclusions were consistent regardless of whether a linear time trend was included in the regression models. The initial step in the analysis involved testing the logarithmic data in level for stationarity. According to BIC and HQIC, the optimal lag lengths that should be used in the ADF test were two in the case of PCH and one in the case of the other three stocks. Since all test results were statistically insignificant, the null hypothesis of a unit root could not be rejected (Table 3.3). Therefore, it was concluded that the original time series were nonstationary and the data in the first difference form must be examined.

BIC and HQIC were performed on the first differenced series prior to implementing the ADF tests. The selection criteria indicated that only one lag should be considered in the OLS models for PCL, RYN and WY. The optimal lag order for PCH data in the first difference was two. The test statistics revealed that the parameter coefficient θ was significantly different from zero at the 1% level; hence, the alternative hypothesis of a stationarity process was chosen for interpretation (Table 3.3). Although there were some differences in the magnitude of the test statistics when a deterministic time trend was contained in the regression model, the variations were marginal to alter the conclusions. Therefore, all variables were verified to be $I(1)$ and could be used for the cointegration analyses.

Results from Cointegration Tests

The empirical results from the Engle-Granger tests strongly suggested that there was limited cointegrating relation among the four stocks (Table 3.4). Two model specifications were considered in this paper because studies had often recommended the inclusion of a drift term and a time trend in the regressions (Pfaff, 2006). Particularly, each model contained a constant but only one had a linear trend. If PCL stock was selected as the regressand, the test statistic suggested the presence of one cointegrating equation. The null hypothesis was rejected at the 10% and 5% level when the linear time trend was absent and present, respectively. However, in both model settings, all cointegration results were indifferent if the choice of the left hand side variable was RYN, PCH, or WY. In these scenarios, the results consistently showed that the null hypothesis of no cointegration could not be rejected. Therefore, the statistical evidences inclined toward the notion that the four REIT stock prices behaved differently from one another in the long run.

The Johansen tests reinforced the claim of no long-run equilibrium relationships among all variables. Table 5 reports the results from the Johansen procedure for models with one, two and three lags. The calculated statistics from both the trace and maximum eigenvalue tests were listed. At the 10% significance level, both tests failed to reject the null hypothesis that rank ($\mathbf{\Gamma}$) equals zero for all scenarios where different lag lengths were considered. The largest estimated eigenvalue was 0.02. The maximum likelihood estimators revealed that the characteristic roots of the matrix $\mathbf{\Gamma}$ were significantly different from unity. Therefore, the econometric analyses indicated no long-run equilibrium among the REIT stock prices although visually investigating the data plot might lead to a contrary conclusion (Figure 1).

Discussion and Conclusions

In the recent years, the weak performance of the stock markets had created more motives for investors to explore ingenious investments to diversify their portfolios. In addition to changes in demand of timber products, the increasing interest in the timberland assets had driven the growth of the REIT market. Investors who sought long-term investments considered timberlands as an advantageous alternative vehicle to generate future incomes. In contrast to typical stocks and bonds, timber assets were strongly driven by the biological growth, which was predictable and independent of the overall economic performance. Given the imperfect correlations between the stock market and the timber REIT prices, this study examined the long-run dynamics between the four REIT stock prices.

In this study, the Engle-Granger test revealed little evidence to support the presence of cointegrating relation among the four REIT stock prices and the S&P 500 index. Moreover, the Johansen procedure outcomes further strengthened the independency of the variables by showing the robust results of no cointegration. Therefore, there is diversification potential in the long run with each timber REIT (except PCL) considered as a unique candidate. Although all timber REITs concentrated on investments in the same sector, their distinct development priorities and business strategies had set them apart in terms of financial performances. Investors might expect to see a common trend among the four REIT stock prices because the profitability of timberlands depends on the overall wood supply and demand. However, market conditions at the local level may vary and the advancement of new technologies may lead to new market segments. As different REITs develop their business plans across different end-products and among different regions, their stock prices evolve with little dependency.

In 2012, Plum Creek, Rayonier, Potlatch, and Weyerhaeuser owned approximately 6.4, 2.7, 1.42, and 6 million acres of timberlands and real estates, respectively. In addition to the differences in size, the heterogeneous allocations of their resources helped differentiate the long-term trends of the REIT prices. All of Plum Creek's properties were situated in 19 states across the Northern and Southern regions. Rayonier and Weyerhaeuser had timber operations both inside and outside of the U.S. Particularly, some of Rayonier's timberlands were set in New Zealand whereas the majority of Weyerhaeuser's international businesses took place in Uruguay and China. In contrast, Potlatch found its niche around the Midwestern U.S. area, which comprised of Arkansas, Idaho and Minnesota.

Since wood is a bulky commodity with the transportation cost making up a significant portion of its marginal cost, regional timber prices tend to be dependent in adjacent but not distant market areas. As regional timber prices are influenced by local market conditions and the fours timber REITs own and manage lands in various places, their stock prices will be less likely to share a common path. In addition, the geographically diverse timberlands allowed REITs to circumvent aggressive competitions for the same local customers and export markets.

Furthermore, the four timber REITs embraced different values and specialized in various timberland related operations (Figure 2). Although the weights of different reportable business segments might vary from year to year, the leading source of operating incomes for Plum Creek had derived from the real estate segment. In the past ten years, Plum Creek generated between 40% and 70% of its profits through selling timberland real estate. The returns from this activity also represented more than 50% of the company's recurring profits in the last three years.

Meanwhile, the resource segment contributed approximately 30% of the total incomes. On the other hand, Rayonier had enjoyed strong and stable revenues from its fiber productions, which included fluff and dissolving pulp. Fiber sales had made up for over 60% of the total profits in the past few years. In the case of Potlatch and Weyerhaeuser, the segment with the highest earnings came from timberland holdings and selling standing timbers and logs. However, Potlatch also generated much of its income from manufacturing wood products. In contrast, Weyerhaeuser earned about 30% of its profits through producing cellulose fibers. Different from Rayonier, the company supplied mainly commodity market pulp.

As REIT stocks offer a number of financial benefits including liquidity and tax advantage, they have attracted a growing number of investors. In the future, more private timber firms may convert to public REITs. Moreover, the recent economic recession and the more competitive forest market have also propelled existing REITs to seek creative and strategic development paths. Rayonier has recently announced its decision to separate its performance fiber sector into an independent entity. The comprehensive restructuring plan is expected to be completed by the middle of 2014. Given various changes in the timber industry, prospective studies should further examine the evolving financial performance and interdependence among different timber REITs. Since stock prices are aggregated reflections of the performances of different business segments, an increase or decrease in the timberlands' value is not the pure contributor to a rise or fall of stock prices. The weight of the impact of timberlands' value on stock prices relative to other business segments can vary across the four timber REITs. In order to understand the individual effect of timberlands on the stock prices, one needs to extract total revenues by business components. This can further help investors in constructing their optimal portfolios.

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Figure 3.1. Stock prices of four REITs from December 2009 to December 2013.

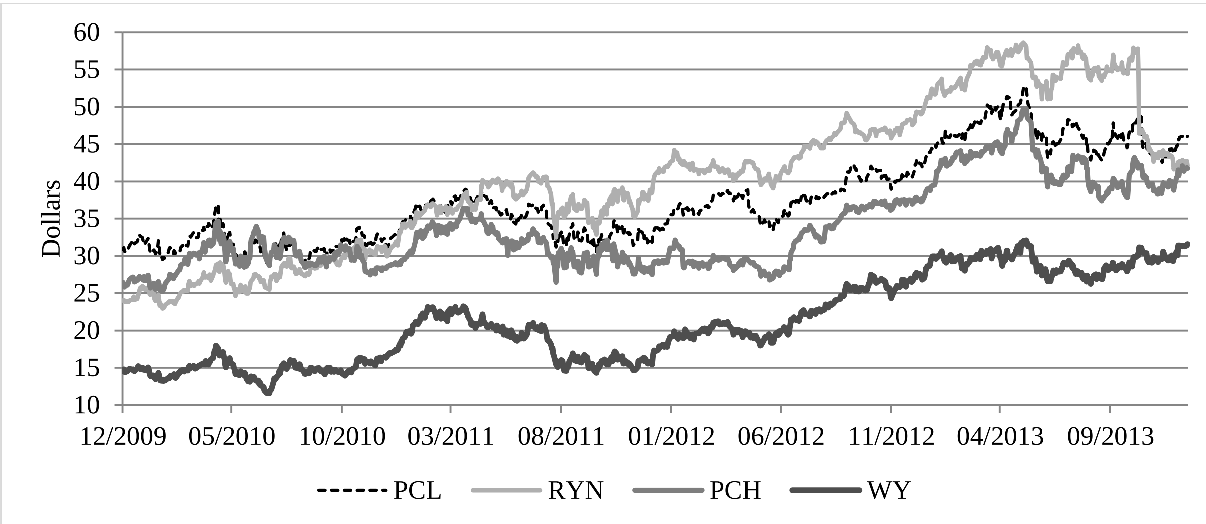
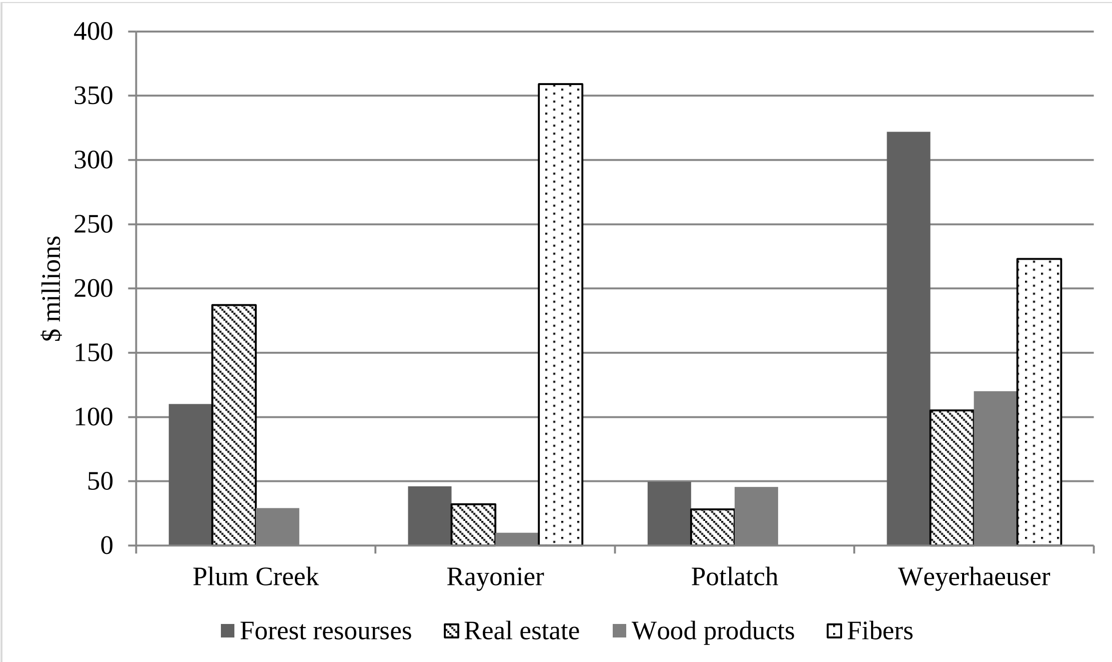


Figure 3.2. REITs' operating incomes by business segment in 2012.



Note: The resource segment refers to timberland holdings, selling standing timbers and logs. The real estate segment refers to sales and development of non-strategic and higher value timberlands. The wood product segment refers to operations of manufactured wood products. The fiber segment refers to cellulose fiber products. Data are obtained from Plum Creek, Rayonier, Potlatch and Weyerhaeuser's annual 10-K reports.

Table 3.1:
Correlation matrix among the S&P 500 index level and the timber REIT stock prices from December 2009 to December 2013.

	S&P 500	PCH	PCL	RYN	WY
S&P 500	1.00				
PCH	0.92	1.00			
PCL	0.94	0.82	1.00		
RYN	0.97	0.91	0.91	1.00	
WY	0.93	0.87	0.83	0.94	1.00

Note: Data are available at the Center for Research in Security Prices database from Wharton Research Data Services.

Table 3.2:
Summary statistics for stock price data.

Variable	Description	Mean	SD	Minimum	Maximum
PCL	Plum Creek stock value	37.65	5.91	28.71	52.80
RYN	Rayonier stock value	40.31	9.88	22.96	58.61
PCH	Potlatch stock value	33.74	5.55	25.21	49.83
WY	Weyerhaeuser stock value	21.20	5.75	11.58	32.11

Table 3.3:
Results from augmented Dickey-Fuller test for stationarity.

Series	Lag orders	Test statistics			
		Data in level		Data in first difference	
		Model 1	Model 2	Model 1	Model 2
PCL	1	-1.28	-2.95	-22.02***	-22.19***
RYN	1	-1.90	-1.17	-22.79***	-20.11***
PCH	2	-1.70	-2.50	-20.13***	-22.86***
WY	1	-0.78	-2.37	-23.15***	-22.59***

Notes: Model 1 includes a constant whereas model 2 includes a constant and a linear time trend.

Table 3.4:
Results from Engel-Granger cointegration tests.

	Test statistics		
Dependent variable	Model 1		Model 2
PCL	-4.37**		-4.37*
RYN	-3.43		-0.85
PCH	-2.97		-2.96
WY	-3.54		-3.41

Notes: Model 1 assumes the absence of a linear time trend while model 2 assumes the presence of a linear time trend. Asterisks * and ** denote statistical significance at the 10% and 5% levels, respectively. Pairwise tests show no cointegrations.

Table 5
Results from Johansen procedure for testing cointegration.

		Model 1			Model 2			Model 3	
Lag orders	Max rank	Trace statistic	Max statistic		Trace statistic	Max statistic		Trace statistic	Max statistic
1	0	28.03*	16.34*		42.65*	20.96*		41.73*	20.89*
	1	11.70	7.36		21.69	12.75		20.84	13.41
	2	4.34	4.21		8.95	5.33		7.42	7.355
	3	0.13	0.13		3.62	3.62		0.07	0.07
2	0	27.59*	16.40*		40.62*	20.70*		39.12*	20.68*
	1	11.19	6.34		19.92	11.26		18.44	11.41
	2	4.85	4.65		8.66	5.17		7.03	6.75
	3	0.20	0.20		3.49	3.49		0.27	0.27
3	0	26.52*	15.66*		39.86*	18.64*		39.14*	18.81*
	1	10.86	6.99		21.22	13.09		20.33	13.55
	2	3.87	3.67		8.13	5.34		6.78	6.76
	3	0.20	0.20		2.80	2.80		0.02	0.02

Notes: Model 1 does not include any deterministic regressors. Model 2 includes a drift term but not a linear time trend. Model 3 considers both a constant and a linear time trend. Asterisk * indicates the rank selected by the maximum likelihood estimators. Adding S&P 500 index into the cointegration space does not change the conclusion of no cointegration.

CHAPTER 4

BAYESIAN LINEAR MODELING OF TIMBER PRICES IN THE U.S. SOUTH[6]

[6] La, L. and Mei, B. Submitted to *Natural Resource Modeling*, 05/01/2014.

Abstract

Stumpage prices among neighboring timber regions have been shown to influence one another to various degrees. To further the understanding of timber price's behaviors, this study employs Bayesian methods to generate statistical inferences about the reciprocal relationships of pine sawtimber prices in the U.S. South. Contrasting to the frequentist approach, the results from the Bayesian inference deliver different intuitions about the parameters of the predictors.

Introduction

The Southern region of the United States provides favorable environmental characteristics for growing timber such as productive soils, high annual precipitations and warm average temperatures. The abundance of undeveloped lands in the South also encourages numerous investment opportunities in the forest industry. Thus, there are many stakeholders including wood-consuming mills, timber brokers, appraisers, and timberland owners and investors, whose interests lie in accurately modeling timber prices. From the timber suppliers' perspective, projecting stumpage prices will help determine the economically optimal rotation age. For instance, a landowner will decide to delay harvesting if he or she anticipates a significant price increase in the future, ceteris paribus. Furthermore, predicting timber prices allows for evaluation of the future financial performance of timberland investments. Based on the predicted stumpage prices, stockholders can obtain valuable insights on expected returns and associated risks that enable them to enhance their investment portfolios.

In the forest industry, local timber prices might reflect shifts of stumpage production costs in adjacent areas. Since mills can obtain their wood materials from different surrounding locations, stumpage prices are often determined in competitive settings. Modeling the dynamic interactions among timber prices in neighboring regions can help understand future stumpage costs. Given a positive correlation between timber prices in two adjacent regions, one should expect a price increase for stumpage in the following quarter if the neighboring state experiences a rise in stumpage costs. Intuitively, when the demand from wood buyers grows, a consequential increase of regional prices might spill over to the adjacent areas. A substantial number of active timber operations are located throughout 11 states in the U.S. South which comprises Alabama (AL), Arkansas (AR), Florida (FL), Georgia (GA), Louisiana (LA), Mississippi (MS), North

Carolina (NC), South Carolina (SC), Tennessee (TN), Texas (TX), and Virginia (VA). The Southern region has been producing most of the timber output in the country and its harvest share has consistently increased since the mid-1900s (Prestemon and Abt [2002]). Given relevant price data, an analysis on their relationships is needed.

Through a Bayesian framework, this study examines the responses of stumpage prices in a particular region conditional on price's movements in adjacent areas. Contrasting to the frequentist statistics, the Bayesian approach does not result in only point estimates or fixed model parameters. Different from the classical inference, Bayesian inference produces posterior distributions for the unknown parameters of interest conditioning on their prior distributions and new information. When new realizations become available, the Bayesian methods allow the unknown parameters to be described probabilistically with changeable distributions (Neath and Langenfeld [2012]). Therefore, based on the existing timber price data, the projected coefficients in the model specifications can be presented with credible intervals. Overall, the results reveal that more relationships can be determined when no information is used to formulate the prior distributions. The informative priors produce more results that are ambiguous. Furthermore, the test statistics from two different prior assumptions reinforce seven deterministic relationships between different lagged returns and contemporaneous returns. Under the noninformative prior distribution assumption, there are high probabilities that one-period lagged prices have negative impacts on prices in the current period for most timber regions.

Literature review

Dynamics of timber prices in the U.S. South

Several studies had investigated the interactions among wood prices in the Southern States. Applying the Johansen's procedures, Nagubadi et al. [2001] concluded that the Law of One Price did not hold for the hardwood stumpage markets in Alabama, Arkansas, Louisiana, Mississippi, Tennessee, and Texas. Timber prices in these states did not share a long-run trend. Yin et al. [2002] also employed the cointegration analysis to show that the Southern timber markets were not perfectly integrated but were separated into contiguous market segments. Since a significant portion of the marginal costs of the commodity often accrued from transporting, distanced locations were unlikely to belong to one market. Bingham et al. [2003] suggested that both pine sawlog and pulpwood markets were not integrated in the Southern region. The authors suggested that the market for pine sawlog encompassed four or five sub regions while the market for pine pulpwood entailed three separate segments.

Nevertheless, other studies had suggested the presence of interdependency across regional lumber markets to different extents. Murray and Wear [1998] applied the cointegration test and found a bidirectional feedback between the Southern and Pacific North West lumber markets. Under various model specifications, Mei et al. [2010] revealed that only seven of the 13 timber regions defined the long-run behaviors of the stumpage prices in the South. Their conclusions were drawn from intensively analyzing several univariate and multivariate models under distinctive price process assumptions.

Bayesian linear regression models

In the classical econometric literature, inferences were often based on the frequentist view. The orthodox statistical approach had been utilized in research extensively because it did not require complex and exhaustive computational efforts. However, the advancements of technologies had allowed for faster and more efficient computing power that increased the implementations of the Bayesian methods. As a result, a growing number of literatures had devoted to analyzing economic and financial data using Bayesian inferences (Aguilar and West [2000], Bondarenko and Bossaerts [2000], Brav [2000], Pastor [2000], Polson and Tew [2000], Watanabe [2000], Avramov [2002]). Among a variety of topics, Bayesian modeling had been predominantly applied to market efficiency studies, asset pricing, time-varying returns, and portfolio analysis (Beck et al. [2012]).

Brunauer et al. [2013] recently used the Bayesian regression methods to predict the U.S. house prices in real terms. The authors applied Bayesian inference to determine the probability distributions of the regression coefficients for individual attributes and locational characteristics in the forecast model. Kulcsár and Tarnóczi [2012] also employed Bayesian formulation in their linear regression models in order to study the correlation of exchange rates and stock markets between two European countries. Geweke [1989], West [1997] and West and Harrison [1997] described in details the use of the Bayesian framework in linear regression analyses in their early works. Elliott et al. [2013] illustrated an empirical application on the use of Bayesian statistics to estimate the Ordinary Least Squares (OLS) regression models which aimed to forecast the U.S. stock returns based on 12 financial factors. Cremers [2002] investigated the predictability of the S&P 500 index monthly excess returns using 14 technical, price level, liquidity, interest rate, and macroeconomic variables.

Nevertheless, Bayesian models and methods have not been presented in any studies relating to timber price analysis. Given the differences between the frequentist and Bayesian interpretations and a number of advantages of the latter approach, this study attempts to deepen the development of modeling tools for the softwood stumpage prices in the U.S. South.

Data

Timber prices in the South have been surveyed and compiled by Timber Mart-South (TMS) whose continuity is supported by Frank Norris Foundation since 1976. The historical price data on three pine products, sawtimber, chip-and-saw, and pulpwood, are currently recorded on a quarterly basis. TMS creates its reporting regions based on combinations of terrain characteristics, mill types, harvesting volumes, and species mixes (Mei et al. [2010]). For every regional market, TMS has been publishing three sets of price for each wood product, the low average, the high average and the mid average values. The low, high and mid averages are the mean values of the lowest 10%, the highest 10%, and the mid 80% of the reported prices. Thus, the presented data are not the absolute dollar values but the average of different price groups. In this analysis, the utilized data are based on the average of the relative mid prices.

As the prices tended to be sensitive to location and distance, each state was delineated into two regions that provided a total of 22 price time series to be examined (Figure 1). Therefore, the study exhausted the quarterly pine sawtimber prices of each region from 1977Q1 to 2013Q4. To improve the property of stationarity, the raw prices were converted to return series by transforming the initial data using natural logarithm followed by first differencing. The transformation allowed for convenient interpretations of the available data as returns. The existing data provided a sample size of 148 observations. The data are divided into two periods, which represent the old and the new information sets. The old set includes the first 30 observations while the new set contains the remaining 118 realizations. In the remaining discussions, the adjusted return time series are denoted by the two letter state abbreviations accompanied by a number, which indicates different regions. The study also utilizes lagged variables in the model specifications. When the return notations are followed by a single numeric digit, 1 or 2, they refer to the one-period and the two-period lagged return variables, respectively.

Methodology

Model specifications

The relationships among returns on pine sawtimber in the neighboring areas are the core concern of the study. For each return series, its regression model incorporates only return variables in the adjacent regions as the explanatory variables. Based on the geographic characteristics, the number of regressors in the model specifications varies for each timber return. The following generalized univariate linear regression is employed to explain the variability of the timber returns in each region.

$$r_{k,t} = \alpha + \beta_1 r_{1,t-1} + \dots + \beta_n r_{k,t-p} + \epsilon_t \qquad (1)$$

where r_k is the timber returns in region k, α is the drift term, $\beta_1, \dots, \beta_n$ are the coefficient parameters to be estimated, t denotes the time index, p denotes the lag order, and ϵ is the disturbance. The numbers of k and p in the model specifications vary for different timber regions. The optimal numbers of lags are determined by Bayesian information criterion (BIC) and Hannan-Quinn information criterion (HQIC).

The frequentist framework perceives data as repeatable random variable and the true parameters remain constant under the repeated trials. In contrast, Bayesians view data as fixed information and the parameters can evolve with new information being added to the existing knowledge. The conclusions about the βs are described probabilistically. Assuming the error terms are normally distributed, the Poisson distribution likelihood function is given by:

$$L\left(\alpha, \beta_1, \dots, \beta_n, \sigma \middle| r_{k,t}, r_{1,t-1}, \dots, r_{k,t-p}\right) = (2\pi\sigma^2)^{-\frac{1}{2}}$$

$$\exp\left\{(-\frac{1}{2\sigma^2}\sum_{i=1}^{t}(r_{k,i} - \alpha - \beta_1 r_{1,i-1} - \cdots - \beta_n r_{k,t-p})^2\right\} \qquad (2)$$

where σ is the model variance and other variables are as previously described (Gill [2008]).

Prior and posterior distributions

The fundamental difference between frequentists and Bayesians is their interpretations of the notion of probability. Frequentists define probability as the relative likelihood or “long-run frequency” that an event will occur when a sizable number of trials take place. This probability will eventually converge to the true population distribution given a growing sample size. In contrast, Bayesians refer probability to “degree of belief” which induces a prior distribution for an event based on different sets of information such as experience, intuition, and opinion. Bayes estimates do not necessarily approach the same constants when different premises about the priors are considered, regardless of large samples (Diaconis and Freedman [1986], Samaniego and Reneau [1994]).

In order to calibrate the posterior distributions of the model coefficients using Bayes’ theorem, the prior distributions must be assumed in addition to the described maximum likelihood function. The two main and opposing classes of priors are informative and noninformative prior distributions (Press [2003]). Under informative or subjective priors, rational assertions about the prior distributions are often derived from the use of data in past studies or human’s knowledge. On the other hand, if no information on the prior distributions is accessible or model uncertainty is significant, uninformed or objective priors can be employed. When subjective information is not desired and minimal bias in fabricating the prior distributions is sought, noninformative priors are more appropriate (Samaniego [2010]). This study estimates the parameters under both prior distribution forms in order to test the robustness of the results.

Noninformative priors

The common noninformative prior distribution that appears in the vast literature is the Jeffreys' prior. Although the Jeffreys' prior is improper because the densities of the mean and variance do not integrate to one, its posterior is proper in this case (Press [1989]). The joint noninformative distributions for the model parameters presuming the Jeffreys' prior are as follows (Lee [2004]).

$$p(\boldsymbol{\beta}, \sigma^2) \propto \frac{1}{\sigma^2} \tag{3}$$

where $\boldsymbol{\beta}$ is a $(n+1) \times 1$ vector of parameters with its first element being the intercept and σ is as previously described.

Using (2) and (3), the joint posterior distributions of the model estimates can be derived accordingly by use of Bayes' rule (Winkler [1972]):

Posterior Probability $\propto$ Likelihood Function $\times$ Prior Probability, or

$$p\left(\boldsymbol{\beta}, \sigma^2 \middle| r_{k,t}, r_{1,t-1}, \dots, r_{k,t-p}\right) \propto L\left(\boldsymbol{\beta}, \sigma^2 \middle| r_{k,t}, r_{1,t-1}, \dots, r_{k,t-p}\right) p(\boldsymbol{\beta}, \sigma^2) \tag{4}$$

The marginal posterior distribution of $\boldsymbol{\beta}$ is obtained by integrating the joint posterior with respect to σ^2. It can be shown that $\boldsymbol{\beta}$ follows the Student's *t*-distribution with $t-(n+1)$ degree of freedom (Gill [2008]). In addition, the posterior mean and variance of $\boldsymbol{\beta}$ are given by:

$$\mathrm{E}\left(\boldsymbol{\beta} \middle| r_{k,t}, r_{1,t-1}, \dots, r_{k,t-p}\right) = \widehat{\boldsymbol{\beta}}$$

and

$$\mathrm{var}\left(\boldsymbol{\beta} \middle| r_{k,t}, r_{1,t-1}, \dots, r_{k,t-p}\right) = \hat{\sigma}^2 (\boldsymbol{X}'\boldsymbol{X})^{-1} \frac{t-(n+1)}{t-(n+1)-2},$$

respectively (Rachev [2008]). Under the noninformative or diffuse priors assumption, the estimated mean $\widehat{\boldsymbol{\beta}}$ and variance-covariance matrix $\hat{\sigma}^2 (\boldsymbol{X}'\boldsymbol{X})^{-1}$ can be conveniently generated by the OLS method using the new information set. In this case, the posterior means remain unchanged while the posterior variance increases by the term $\frac{t-(n+1)}{t-(n+1)-2}$ to reflect the degree of uncertainty about σ^2.

Informative priors

Researchers can also assume that the coefficient vector, $\boldsymbol{\beta}$, follows a normal distribution and assert a "degree of belief", π, to this assumption. Then, the prior distributions of $\boldsymbol{\beta}$ and σ^2can be expressed as follows.

$$\boldsymbol{\beta}|\sigma \sim \mathrm{N}(\boldsymbol{\beta}_0, \hat{\sigma}^2\pi^{-1}(\boldsymbol{X}'\boldsymbol{X})^{-1})$$

and

$$\sigma^2 \sim \mathrm{Inv} - \chi^2(t_0 - n, \hat{c}_0^2)$$

where $\boldsymbol{\beta}_0$ is the vector of prior means and 0 < π ≤ 1. Values of $\widehat{\boldsymbol{\beta}}_0, t_0$ and $\hat{c}_0^2$ are obtained from the old information set. A small value of π implies little confidence about the assumptions pertaining to the priors. As the value of π increases, the posterior means will move toward the value of the prior means. Intuitively, if the prior means are believed to be true with high certainty, the posterior means will be more similar to the prior values. In this study, π is set to 1. The prior means and variances are determined with OLS regressions using the data in the first period. Likewise, the marginal posterior distributions for $\boldsymbol{\beta}$ are given by:

$$\mathrm{E}\left(\boldsymbol{\beta}|r_{k,t}, r_{1,t-1}, \dots, r_{k,t-p}\right) = (\pi(\boldsymbol{X}'\boldsymbol{X}) + (\boldsymbol{X}'\boldsymbol{X}))^{-1}(\pi(\boldsymbol{X}'\boldsymbol{X})\boldsymbol{\beta}_0 + \pi(\boldsymbol{X}'\boldsymbol{X})\widehat{\boldsymbol{\beta}})$$

and

$$\mathrm{var}\left(\boldsymbol{\beta}|r_{k,t}, r_{1,t-1}, \dots, r_{k,t-p}\right) = \hat{c}^2(\pi(\boldsymbol{X}'\boldsymbol{X}) + \boldsymbol{X}'\boldsymbol{X}))^{-\mathbf{1}}\frac{t-(n+1)}{t-(n+1)-2},$$

where $\widehat{\boldsymbol{\beta}}$ is the coefficient vector from the new information set (Rachev [2008]). Values of $\widehat{\boldsymbol{\beta}}$ and $\hat{c}^2$ are acquired based on the second period's data. The posterior means are the weighted averages of the prior means, $\boldsymbol{\beta}_0$, and the OLS estimated means from the later observations, $\widehat{\boldsymbol{\beta}}$. The “degree of belief”, π, is reflected in the posterior means and variances.

Empirical results

Based on the results from BIC and HQIC, the optimal lag order to be used in the regression models was one for all the return variables with the exceptions of TX1 and TX2. The information criteria suggested a lag of two for the return series in these areas. For each region, the explanatory variables are represented by one’s own lagged returns and the lagged returns in the adjacent areas (Tables 1 and 2).

Results under noninformative assumptions

AL1 timber region is adjacent to AL2, GA1, MS1, and TN2. According to the test results, the impacts of the lagged GA1 and MS1 variables are strongly different from zero since their posterior distributions comprise vastly positive values. The 90% symmetric Bayesian intervals for GA1.1 and MS1.1 variables are (0.0227, 0.3248) and (0.0582, 0.3012), respectively. In other words, with a 90% probability, a 1% change in GA1 and MS1 timber prices in the past quarter leads to a 0.02-0.32% and 0.09-0.30% increase in AL1 timber price in the present quarter. Although, the analogue of the frequentist confidence interval is the Bayesian credible interval, the two notions have distinctive interpretations. In this study, the Bayesian interpretation indicates that the probability for the parameter of MS1.1 to take any value between 0.0582 and 0.3527 is 90%. Using the classical interpretation, the probability that a fixed parameter falls within any confident intervals is always either zero or one since the interval covers the true parameter or it does not.

Under the classical approach, the parameter estimates from OLS regressions are frequently tested for significance. The hypothesis of the coefficients being equal to a particular value is either rejected or cannot be rejected. Such approach does not permit analysts to ascribe probabilities or "degree of belief" to different competing hypotheses. However, one might be interested in knowing the likelihood that a given hypothesis is true. Bayesians have the tools for comparing opposing theories. For instance, the changes of AL1, LA2, and TN2 returns in the previous period have unclear effects on the current AL1 timber returns as their posterior masses are allocated significantly on both positive and negative intervals. Bayesians can compare the hypothesis of AL1.1 being negative to the one of AL1.1 being positive. Since more than half of the posterior mass is negative, the former hypothesis has the higher probability of being true. Similar conclusions cannot be established using the usual inference.

AL2 timber region is neighboring to AL1, FL2, GA2, and MS2. The test results show that the posterior of the lagged variable of AL2 is distributed below zero. Hence, AL2.1 has a clear inverse impact on AL2, meaning for an increase in lagged AL2 the current return in Southern Alabama is expected to decrease. In contrast, both lagged AL1 and MS2 have positive correlations with the contemporary AL2 since their posteriors are concentrated on the positive space. Moreover, FL2.1 and GA2.1 have ambiguous effects on AL2 returns as their posterior distributions cover considerably both positive and negative values.

Under the uninformative assumptions, one's own lagged returns exhibit negative relationships with the contemporary returns for all regions except AL1, AR2, MS2, and TX1. It is interesting to note that the one-period lagged returns in GA1, MS1, MS2 and VA1 are the four variables that have explanatory power on three different regional returns. Hence, they appear to be the dominating timber regions in the South. The past returns of the remaining regions, except

AR2, can help predict the timber returns in one or two of their neighboring regions. Further detailed test statistics can be found in Table 4.1.

Results under informative assumptions

Given the strong belief that the prior coefficients are normally distributed with the means $\boldsymbol{\beta}_0$ and the variances $\hat{\sigma}^2(\boldsymbol{X}'\boldsymbol{X})^{-1}$, the informative posterior means are much closer to the prior means while the uninformative posterior means are further from the prior means. In the case of AL1, all predicting variables, except GA1.1, have their distribution masses spread evenly on both negative and positive intervals. Hence, it is more difficult to determine the signs of the coefficient vectors. Nevertheless, the one-period lagged returns of GA1 appear to be positively correlated with current return in AL1. In the case of AL2, all explanatory variables seem to have little effect on the variability of its timber returns.

For the regions in the remaining states, similar interpretations can be made and the detail statistical results are reported in Table 2. Only FL1, GA1, MS2, NC1, SC1 and TN1 can help to predict the returns in at least one region. Furthermore, GA1.1 and NC1.1 are the only two leading variables, which have unambiguous correlations with the current timber returns in their own or adjacent areas. The other 16 return time series do not indicate any clear relationships between the past and the current regional timber returns.

There are seven cases where a defined relationship between two returns is the same under both prior assumptions. For instance, the relationships between the past and current returns in LA1, SC2 and TN1 are negatively correlated. In addition, GA1.1 and FL.1 have positive impacts on AL1 and FL2, respectively. Lastly, the one-period lagged returns in MS2 have positive impacts with both regions in Louisiana. AR2 is the only region, which has no clear effect on neighboring states regardless of the premises about the priors.

Discussion and conclusions

The literature on timber price modeling has been dominated with the use of frequentist inference. The classical approach, which requires less complicated computations, has been well understood and applied by many researchers. Nevertheless, Bayesian analyses of the same timber price data are important and worth conducting. The later method incorporates two types of information to create the posterior probability of an unknown entity. The first kind of information comes from a person's belief about the unknown variable. The other information, which is summarized in the maximum likelihood function, characterizes the observed data. Thus, the posteriors are updated when new observed information is available.

The Bayesian framework employs the given dataset to provide the credible intervals for the coefficients of interest. In the noninformative scenario, the results show that the one-period lagged return variable of a region tend to have unambiguous negative relationship with the current return in the same area. The exceptions are AL1, AR2, MS2, and TX1 whose one-period lagged returns have unclear influence on their contemporary returns. Under the informative assumptions, only LA1, SC1 and TN1 past returns have clear negative impacts with their current returns.

The cross effects of lagged return variables on adjacent timber regions vary from case to case. FL2, GA1 and MS2 are the only three areas whose one-period lagged returns have explicit impacts on prices in certain adjacent areas regardless of the assumed priors. The uninformative and informative prior scenarios have one and 16, respectively, lagged return variables whose significant portions of their posterior masses lie in both positive and negative regions. Hence, depending on the prior distributions, these variables have little explanatory power over the variability of the contemporaneous returns.

Bayesian inference can be more meaningful for the stakeholders since the models can be interpreted in terms of probability. Hence, the information allows softwood sawtimber sellers and buyers to identify both the high and low points of an increase or decrease in future returns with a particular “degree of belief”. Likewise, Bayesian models enable investors to calculate the expected returns in a relative context. One’s willingness to accept the risk of earning a negative return on his or her investments might depend on the dollar value of the possible losses. Given the same probability of losing, an investor can chose the investing option that has a smaller possibility of financial losses.

A key step in the Bayesian estimation is to determine the priors. Although unbiased priors are an attractive attribute, private news, stakeholders’ opinions, and other sources of information can also be used to better formulate the prior distributions. Further studies should investigate different premises about the priors by use of reliable facts or insights from professionals in the forest industry.

Figure 4.1: Timber Mart-South's reporting regions

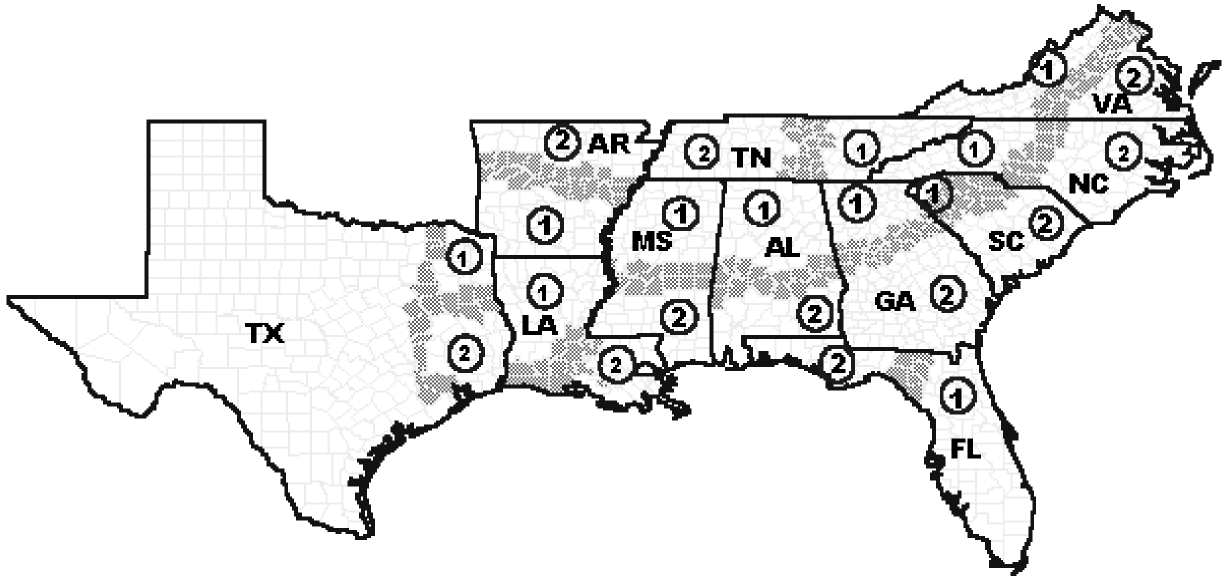


Table 4.1: Bayesian inference for estimated parameters assuming noninformative priors

Timber Region	Parameter	Posterior Mean	Posterior Std. Dev.	$b_{0.01}$	$b_{0.05}$	$b_{0.25}$	$b_{0.75}$	$b_{0.95}$	$b_{0.99}$
AL1	Intercept	0.0004	0.0090	-0.0209	-0.0145	-0.0057	0.0065	0.0153	0.0216
	AL1.1	-0.1176	0.1051	-0.3660	-0.2921	-0.1887	-0.0464	0.0569	0.1309
	AL2.1	0.0165	0.1061	-0.2344	-0.1597	-0.0553	0.0884	0.1927	0.2675
	GA1.1	0.1738	0.0910	-0.0413	0.0227	0.1122	0.2353	0.3248	0.3888
	MS1.1	0.1797	0.0732	0.0067	0.0582	0.1302	0.2292	0.3012	0.3527
	TN2.1	-0.0053	0.0550	-0.1353	-0.0966	-0.0426	0.0319	0.0859	0.1247
AL2	Intercept	0.0006	0.0091	-0.0209	-0.0145	-0.0055	0.0068	0.0157	0.0221
	AL2.1	-0.3654	0.1093	-0.6238	-0.5468	-0.4394	-0.2914	-0.1840	-0.1070
	AL1.1	0.3176	0.1062	0.0665	0.1413	0.2457	0.3895	0.4940	0.5687
	FL2.1	0.0642	0.1145	-0.2064	-0.1258	-0.0133	0.1417	0.2542	0.3348
	GA2.1	0.0564	0.1538	-0.3072	-0.1989	-0.0477	0.1605	0.3117	0.4200
	MS2.1	0.2032	0.0901	-0.0098	0.0536	0.1422	0.2642	0.3528	0.4162
AR1	Intercept	0.0006	0.0116	-0.0269	-0.0187	-0.0073	0.0085	0.0199	0.0281
	AR1.1	-0.2819	0.1251	-0.5777	-0.4896	-0.3666	-0.1971	-0.0741	0.0140
	AR2.1	0.0415	0.0925	-0.1772	-0.1121	-0.0211	0.1041	0.1951	0.2602
	LA1.1	0.0262	0.1196	-0.2565	-0.1723	-0.0547	0.1072	0.2247	0.3089
	MS1.1	0.2828	0.0907	0.0684	0.1322	0.2214	0.3442	0.4333	0.4972
	TX1.1	0.0232	0.1443	-0.3180	-0.2164	-0.0745	0.1209	0.2628	0.3644
AR2	Intercept	0.0021	0.0152	-0.0338	-0.0231	-0.0082	0.0124	0.0274	0.0381
	AR2.1	-0.1168	0.1172	-0.3939	-0.3114	-0.1961	-0.0374	0.0778	0.1604
	AR1.1	-0.0386	0.1458	-0.3832	-0.2806	-0.1372	0.0601	0.2035	0.3061
	TN2.1	0.0923	0.0921	-0.1253	-0.0605	0.0300	0.1546	0.2451	0.3099

FL1	Intercept	0.0025	0.0088	-0.0184	-0.0122	-0.0035	0.0085	0.0172	0.0234
	FL1.1	-0.3393	0.0912	-0.5549	-0.4907	-0.4010	-0.2776	-0.1879	-0.1237
	FL2.1	0.1230	0.1082	-0.1328	-0.0566	0.0498	0.1963	0.3027	0.3789
	GA2.1	0.0469	0.1421	-0.2890	-0.1890	-0.0493	0.1431	0.2828	0.3828
FL2	Intercept	0.0021	0.0081	-0.0170	-0.0113	-0.0033	0.0076	0.0156	0.0213
	FL2.1	-0.2071	0.1009	-0.4457	-0.3747	-0.2754	-0.1388	-0.0396	0.0314
	AL2.1	0.1177	0.0858	-0.0851	-0.0247	0.0597	0.1758	0.2602	0.3206
	FL1.1	0.2537	0.0836	0.0561	0.1149	0.1971	0.3103	0.3925	0.4514
	GA2.1	0.1229	0.1347	-0.1956	-0.1008	0.0317	0.2141	0.3466	0.4414
GA1	Intercept	0.0024	0.0099	-0.0212	-0.0142	-0.0044	0.0091	0.0189	0.0259
	GA1.1	-0.2036	0.1101	-0.4639	-0.3864	-0.2781	-0.1290	-0.0208	0.0567
	AL1.1	-0.0031	0.1039	-0.2487	-0.1756	-0.0734	0.0673	0.1694	0.2426
	GA2.1	0.1435	0.1759	-0.2723	-0.1484	0.0245	0.2626	0.4355	0.5593
	NC1.1	0.0702	0.0565	-0.0634	-0.0236	0.0320	0.1085	0.1641	0.2039
	SC1.1	0.0117	0.0864	-0.1925	-0.1317	-0.0468	0.0702	0.1551	0.2159
	TN1.1	0.0882	0.0625	-0.0595	-0.0155	0.0459	0.1305	0.1920	0.2359
GA2	Intercept	0.0015	0.0063	-0.0134	-0.0090	-0.0028	0.0058	0.0120	0.0164
	GA2.1	-0.2529	0.1177	-0.5313	-0.4484	-0.3326	-0.1732	-0.0575	0.0254
	AL2.1	0.1101	0.0669	-0.0482	-0.0010	0.0648	0.1554	0.2212	0.2684
	FL1.1	0.0632	0.0687	-0.0992	-0.0509	0.0167	0.1096	0.1772	0.2255
	FL2.1	0.0672	0.0804	-0.1230	-0.0664	0.0127	0.1216	0.2007	0.2574
	GA1.1	0.1048	0.0711	-0.0633	-0.0133	0.0567	0.1529	0.2228	0.2729
	SC2.1	0.0004	0.0711	-0.1678	-0.1177	-0.0477	0.0486	0.1185	0.1686
LA1	Intercept	0.0018	0.0095	-0.0205	-0.0139	-0.0046	0.0082	0.0175	0.0242
	LA1.1	-0.5166	0.1064	-0.7681	-0.6932	-0.5886	-0.4446	-0.3400	-0.2651
	AR1.1	0.0294	0.1001	-0.2072	-0.1367	-0.0383	0.0972	0.1956	0.2661

	LA2.1	0.0272	0.1005	-0.2105	-0.1397	-0.0408	0.0953	0.1941	0.2649
	MS2.1	0.3830	0.0961	0.1559	0.2235	0.3180	0.4481	0.5425	0.6102
	TX1.1	0.3033	0.1333	-0.0119	0.0820	0.2131	0.3936	0.5247	0.6185
	TX2.1	0.0206	0.1141	-0.2492	-0.1689	-0.0567	0.0979	0.2101	0.2904
LA2	Intercept	0.0014	0.0102	-0.0228	-0.0156	-0.0055	0.0083	0.0184	0.0256
	LA2.1	-0.3900	0.1054	-0.6391	-0.5649	-0.4613	-0.3186	-0.2150	-0.1409
	LA1.1	0.0973	0.1041	-0.1488	-0.0755	0.0268	0.1678	0.2701	0.3434
	MS2.1	0.4579	0.0986	0.2249	0.2942	0.3912	0.5246	0.6215	0.6909

Table 4.2: Bayesian inference for estimated parameters assuming informative priors

Timber Region	Parameter	Prior Mean	Posterior Mean	Posterior Std. Dev.	$b_{0.01}$	$b_{0.05}$	$b_{0.25}$	$b_{0.75}$	$b_{0.95}$	$b_{0.99}$
AL1	Intercept	0.0098	0.0051	0.0241	-0.0519	-0.0350	-0.0112	0.0214	0.0452	0.0622
	AL1.1	-0.5082	-0.3129	0.2823	-0.9804	-0.7816	-0.5040	-0.1218	0.1558	0.3546
	AL2.1	0.1952	0.1059	0.2851	-0.5683	-0.3675	-0.0872	0.2989	0.5793	0.7800
	GA1.1	0.8174	0.4956	0.2444	-0.0821	0.0899	0.3302	0.6610	0.9013	1.0733
	MS1.1	0.0123	0.0960	0.1966	-0.3688	-0.2304	-0.0371	0.2291	0.4224	0.5607
	TN2.1	0.0084	0.0015	0.1477	-0.3477	-0.2437	-0.0985	0.1015	0.2467	0.3507
AL2	Intercept	0.0102	0.0054	0.0223	-0.0474	-0.0317	-0.0097	0.0205	0.0425	0.0582
	AL2.1	-0.2917	-0.3286	0.2684	-0.9630	-0.7741	-0.5102	-0.1469	0.1170	0.3059
	AL1.1	0.0805	0.1990	0.2609	-0.4177	-0.2340	0.0225	0.3756	0.6321	0.8158
	FL2.1	0.4211	0.2427	0.2811	-0.4219	-0.2240	0.0524	0.4329	0.7093	0.9072
	GA2.1	-0.2518	-0.0977	0.3777	-0.9906	-0.7247	-0.3533	0.1580	0.5293	0.7952
	MS2.1	-0.0370	0.0831	0.2213	-0.4401	-0.2843	-0.0667	0.2329	0.4505	0.6063
AR1	Intercept	0.0149	0.0078	0.0217	-0.0435	-0.0283	-0.0069	0.0224	0.0438	0.0590
	AR1.1	0.3755	0.0468	0.2333	-0.5047	-0.3405	-0.1111	0.2048	0.4342	0.5984
	AR2.1	0.2473	0.1444	0.1725	-0.2633	-0.1419	0.0277	0.2611	0.4307	0.5521
	LA1.1	-0.1445	-0.0591	0.2229	-0.5862	-0.4292	-0.2100	0.0918	0.3110	0.4679
	MS1.1	0.1290	0.2059	0.1691	-0.1938	-0.0748	0.0915	0.3203	0.4866	0.6056
	TX1.1	-0.3806	-0.1787	0.2690	-0.8148	-0.6254	-0.3608	0.0034	0.2680	0.4574
AR2	Intercept	0.0146	0.0084	0.0245	-0.0495	-0.0323	-0.0082	0.0250	0.0490	0.0663
	AR2.1	0.1943	0.0388	0.1887	-0.4073	-0.2745	-0.0890	0.1665	0.3520	0.4848
	AR1.1	0.0590	0.0102	0.2346	-0.5445	-0.3793	-0.1486	0.1691	0.3998	0.5650
	TN2.1	0.1016	0.0970	0.1482	-0.2533	-0.1490	-0.0033	0.1973	0.3430	0.4473

FL1	Intercept	0.0101	0.0063	0.0216	-0.0448	-0.0296	-0.0083	0.0209	0.0422	0.0574
	FL1.1	0.3078	-0.0157	0.2227	-0.5423	-0.3855	-0.1665	0.1350	0.3540	0.5108
	FL2.1	0.4881	0.3055	0.2643	-0.3193	-0.1333	0.1266	0.4845	0.7444	0.9304
	GA2.1	-0.6215	-0.2873	0.3470	-1.1078	-0.8635	-0.5222	-0.0524	0.2889	0.5332
FL2	Intercept	0.0171	0.0096	0.0222	-0.0429	-0.0273	-0.0054	0.0247	0.0465	0.0622
	FL2.1	0.3717	0.0823	0.2769	-0.5724	-0.3774	-0.1052	0.2698	0.5420	0.7370
	AL2.1	-0.0972	0.0103	0.2355	-0.5464	-0.3806	-0.1491	0.1697	0.4012	0.5670
	FL1.1	0.6188	0.4363	0.2294	-0.1061	0.0554	0.2810	0.5916	0.8172	0.9787
	GA2.1	-0.7707	-0.3239	0.3697	-1.1980	-0.9377	-0.5742	-0.0736	0.2899	0.5502
GA1	Intercept	0.0128	0.0076	0.0202	-0.0402	-0.0260	-0.0061	0.0213	0.0411	0.0554
	GA1.1	0.5693	0.1828	0.2238	-0.3463	-0.1887	0.0313	0.3343	0.5544	0.7120
	AL1.1	-0.4586	-0.2308	0.2112	-0.7302	-0.5815	-0.3738	-0.0879	0.1198	0.2685
	GA2.1	-0.1033	0.0201	0.3575	-0.8251	-0.5734	-0.2219	0.2621	0.6136	0.8653
	NC1.1	0.3980	0.2341	0.1149	-0.0376	0.0433	0.1563	0.3119	0.4250	0.5059
	SC1.1	-0.0183	-0.0033	0.1755	-0.4183	-0.2948	-0.1221	0.1155	0.2881	0.4117
	TN1.1	0.0570	0.0726	0.1270	-0.2276	-0.1382	-0.0133	0.1586	0.2835	0.3729
GA2	Intercept	0.0107	0.0061	0.0178	-0.0360	-0.0234	-0.0059	0.0182	0.0357	0.0482
	GA2.1	-0.8354	-0.5442	0.3322	-1.3295	-1.0957	-0.7690	-0.3193	0.0073	0.2411
	AL2.1	-0.0315	0.0393	0.1889	-0.4073	-0.2743	-0.0886	0.1671	0.3529	0.4858
	FL1.1	0.2414	0.1523	0.1938	-0.3058	-0.1694	0.0211	0.2835	0.4740	0.6104
	FL2.1	0.0117	0.0395	0.2270	-0.4971	-0.3374	-0.1142	0.1931	0.4163	0.5761
	GA1.1	0.5304	0.3176	0.2006	-0.1567	-0.0155	0.1818	0.4534	0.6507	0.7919
	SC2.1	0.3837	0.1920	0.2007	-0.2825	-0.1412	0.0562	0.3279	0.5253	0.6666
LA1	Intercept	0.0133	0.0076	0.0216	-0.0436	-0.0283	-0.0071	0.0222	0.0435	0.0587
	LA1.1	-0.3517	-0.4341	0.2434	-1.0095	-0.8382	-0.5989	-0.2694	-0.0300	0.1413
	AR1.1	0.4426	0.2360	0.2290	-0.3054	-0.1442	0.0810	0.3911	0.6163	0.7775

	LA2.1	-0.0071	0.0101	0.2300	-0.5338	-0.3719	-0.1457	0.1658	0.3920	0.5539
	MS2.1	0.4018	0.3924	0.2198	-0.1273	0.0274	0.2436	0.5412	0.7574	0.9121
	TX1.1	-0.5033	-0.1000	0.3051	-0.8212	-0.6064	-0.3065	0.1065	0.4065	0.6212
	TX2.1	0.2153	0.1179	0.2611	-0.4994	-0.3156	-0.0588	0.2947	0.5515	0.7353
LA2	Intercept	0.0100	0.0057	0.0262	-0.0561	-0.0377	-0.0120	0.0234	0.0492	0.0676
	LA2.1	-0.2246	-0.3073	0.2695	-0.9445	-0.7547	-0.4897	-0.1248	0.1402	0.3299
	LA1.1	-0.1727	-0.0377	0.2662	-0.6671	-0.4797	-0.2179	0.1425	0.4043	0.5917
	MS2.1	0.7004	0.5792	0.2521	-0.0169	0.1606	0.4085	0.7498	0.9977	1.1752

CHAPTER 5

CONCLUSION

The investment opportunities in timber and timberlands have increased in the past few decades. Employing and analyzing historical price data allow researcher to better understand the interactions among different wood related markets and suggest sound investment practices. However, the analytical tools that researchers used in past studies have been limited to the traditional methods. Although some studies had looked into the informational efficiency of different forest markets, the popular methodologies that appeared in these papers often involved time series analysis such as serial correlation and stationarity tests. Applying the unconventional econophysics method, the first essay concludes that the furniture, the wood, the paper, and the REIT markets are all relatively efficient in terms of information. However, they are ranked differently among themselves.

Chapter 3 narrows the analysis to only one market, the REITs' returns. Since investing in timber and timberlands has been considered an effective way to achieve portfolio diversification, the second essay focuses on the dependency among four existing REITs, Plum Creek, Rayonier, Potlatch and Weyerhaeuser. The cointegration tests developed by both Johansen and Engle-Granger are applied in this chapter. It is clear from the test results that the stock prices do not share the same common trend in the long run. Differences in the locations of their timberlands and the revenue segments of focus can play important factors in determining their long run developments.

Chapter 4 analyzes in depth the relationships among 22 regional timber markets in the U.S. South. The study indicates that the some markets are more influential on the wood prices in their adjacent areas while some markets have little effect on the timber prices in the neighboring regions. The methodology described in this chapter is not based on the usual inference. While the classical statisticians rely on relative frequency of an event as the consistent indications of probability for such occurrence, Bayesians believe everything can change in the future. Hence, the probability of any event should only be partially constructed based on past probability and must be updated with new available information. Therefore, the Bayesians perceive past data as fixed while frequentists believe data can be generated with repeated trials. In additions, the traditional school of thought considers that the underling parameters are constant. Bayesians accept that the parameters are unknown and can only be approximated with a certain "degree of believe". In this chapter, the Bayesian regression methodology describes the parameter estimates probabilistically. Therefore, instead of point estimates, a credible interval with probability information is presented for every variable in the model specifications. Such results are more useful since stakeholders can predict the relative decrease and increase in the future prices. If prices are going to decrease, by at most or at least how much will they decrease? The classical approach does not address these kinds of questions adequately while Bayesian inference has been known for being able to answer them effectively. According to the results in Chapter 4, some regions can influence more than half of their neighboring areas in terms of timber prices. On the other hand, some regions have no effect on any states. The results are drawn based on the posterior distribution masses of each variable.

There are potential research opportunities that can arise from the topics and methodologies in this dissertation. In addition to the four fundamental wood related markets, the renewable energy sector has gained much attention in the past few years. Many European countries are interested in increasing the consumption of wood pellets. In the last several years, timber suppliers in the U.S. South have experienced a significant flux of demand for wood pellets from other northern parts of the States, Canada, Australia and many European countries (Bernetti, Fagarazzi, & Fratini, 2004; Conrad, Bolding, Aust, & Smith, 2010). The primary uses of wood pellets are for heating homes and co-firing to generate electricity. Although the extra revenue from sales of wood pellets is valuable, it is less than ten percent of total profit in the forest industry whereas lumber, paper and packaging products remain the foremost return drivers (Washburn 2012). Renewable energy advocacy and changes in environmental policies have played important driving forces in increasing wood pellet consumptions (Chau et al., 2009; Lu & Rice, 2011). However, the political regimes have been inconsistent and behind in ratifying critical laws such as carbon tax credit that can change the forest industry. Therefore, timber and timberland owners want to know how other economic variables might propagate this emerging demand for wood pellets.

Some studies have shown that oil prices do affect the market of biomass and biofuel energy (Chang & Su, 2010; Sopha & Klockner, 2011). As fossil fuel becomes more expensive, the substitution effect will create incentives for consumers to switch to alternative energy sources. In addition, wood pellets are frequently traded goods among Canada, U.S. and European countries (Cocchi 2011). Hence, exchange rates might also alter the prices of timber products. Since wood pellets are made of sawdust and there is no other major use for the raw material, prices for chip-and-saw can be used. Therefore, more studies can shed some light on the explanatory power of the U.S. dollar index and crude oil prices over the behavior of chip-and-saw prices in the U.S. South. Future analyses can utilize both cointegration testing and Bayesian inference to determine the relationships among these variables and predict their impacts on future wood pellet prices. One can also use entropy measurements to investigate the informational efficiency of the wood pellet market. Its relative informational efficiency should also be compared to the other forest-related markets.

REFERENCES

Aguilar, O., and M. West. 2000. Bayesian Dynamic Factor Models and Portfolio Allocation. J Bus Econ Stat 18(3):338-357.

Alavalapati, J.R.R., Luckert, M.K., Adamowicz, W.L., 1997. A cointegration analysis of Canadian wood pulp prices. American journal of agricultural economics 79, 975-986.

Alvarez-Ramirez, J., E. Rodriguez, and G. Espinosa-Paredes. 2012b. Is the U.S. stock market becoming weakly efficient over time? Evidence from 80-year-long data. Phys. A Stat. Mechanics Appl. 391:5643–5647.

Alvarez-Ramirez, J., E. Rodriguez, and J. Alvarez. 2012a. A multiscale entropy approach for market efficiency. Int. Rev. Financial Anal. 21:64–69.

Aronow, M.E., Binkley, C.S., Washburn, C.L., 2004. Explaining timberland values in the United States. Journal of Forestry 102, 14-18.

Avramov, D. 2002. Stock Return Predictability and Model Uncertainty. Journal of Financial Economics 64(3):423-458.

Balvers, R. J., T. F. Cosimano, and B. McDonald. 1990. Predicting stock returns in an efficient market. J. Finance 45(4):1109–1128.

Beck, K., B. Niendorf, and P. Peterson. 2012. The Use of Bayesian Methods in Financial Research. Investment Management and Financial Innovations 9(3):68-75.

Bentes, S., R. Menezes, and D. Mendes. 2007. Long memory and volatility clustering: Is the empirical evidence consistent across stock markets? Phys. A Stat. Mechanics Appl. 387:3826–3830.

Bernetti, I., Fagarazzi, C., & Fratini, R. (2004). A methodology to anaylse the potential development of biomassenergy sector: an application in Tuscany. Forest Policy and Economics, 6(3-4), 415-432.

Bingham, M.F., J.P. Prestemon, D.J. MacNair, and R.C. Abt. 2003. Market Structure in U. S. Southern Pine Roundwood. Journal of Forest Economics 9(2):97-117.

Binkley, C.S., C.F. Raper, and C.L. Washburn (1996): Institutional ownership of US timberland. History, rationale and implications for forest management – Journal of Forestry 9 (Sep 1996), 21 – 28.

Bondarenko, O., and P. Bossaerts. 2000. Expectations and Learning in Iowa. Journal of Banking and Finance 24(9):1535-1555.

Brav, A. 2000. Inference in Long-Horizon Event Studies: A Bayesian Approach with Application to Initial Public. Journal of Finance 55(5):1979-2016.

Brunauer, W., S. Lang, and N. Umlauf. 2013. Modelling House Prices Using Multilevel Structured Additive Regression. Statistical Modelling: An International Journal 13(2):95-123.

Cascio, A.J., Clutter, M.L., 2008. Risk and required return assessments of equity timberland investments in the United States. Forest Products Journal 58, 61-70.

Caulfield, J.P. (1998a): Timberland in institutional portfolios and the question of persistence – Forest Products Journal, Apr. 1998, 48(4), 23 – 28.

Caulfield, J.P. (1998b): Timberland return drivers and investing styles for an asset that has come of age – Real Estate Finance, winter 1998, 14(4), 65 – 78.

Caulfield, J.P. and D.H. Newman (1999): Dealing with timberland investment risk: Theory versus practice for institutional owners – Journal of Forest Economics 5:2 1999, 253 – 268.

Conroy, R. and M. Miles (1989): Commercial forestland in the pension portfolio: the biological beta – Financial Analysts Journal, Vol. 45, September - October 1989, 46-54.

Chang, T. H., & Su, H. M. (2010). The substitutive effect of biofuels on fossil fuels in the lower and higher crude oil price periods. Energy, 35(7), 2807-2813.

Chau, J., Sowlati, T., Sokhansanj, S., Preto, F., Melin, S., & Bi, X. (2009). Economic sensitivity of wood biomass utilization for greenhouse heating application. Applied Energy, 86(5), 616-621.

Cheng, B., Mei, B., Wan, Y., 2013. An Econometric Analysis of US Exports of Forest Products. Forest Products Journal 63, 224-231.

Cocchi, M., Nikolaisen L., Junginger M., Goh C., Heinimo J., Bradley D., Hess R., Jacobson J. Ovard L., Thran D., Hennig C., Deutmeyer M., Schouwenberg P., & Marchal D. (2011). Global Wood Pellet Indudstry Market and Trade Study. IEA Bioenergy.

Conrad, J. L., Bolding, M. C., Aust, W. M., & Smith, R. L. (2010). Wood-to-energy expansion, forest ownership changes, and mill closure: Consequences for US South's wood supply chain. Forest Policy and Economics, 12(6), 399-406.

Cover, T. and J. Thomas. 2005. Elements of Information Theory. Wiley Interscience, New York. 613 pp.

Cremers, K.J.M. 2002. Stock return predictability: A Bayesian model selection perspective. Rev Financ Stud 15(4):1223-1249.

Deforest, C.E., Cubbage, F.W., Redmond, C.H., Harris, T.G., 1991. Hedging with Trees - Timber Assets and Portfolio Performance. Forest Products Journal 41, 23-30.

Diaconis, P., and D. Freedman. 1986. On the Consistency of Bayes Estimates. The Annals of Statistics 14(1):1-360.

Downarowicz, T. 2011. Entropy in Dynamical Systems. Cambridge University Press, Cambridge, England.

El Karoui, N., S. Peng, and M. Quenez. 1997. Backward stochastic differential equations in finance. Math. Finance 7(1):1.

Elliott, G., A. Gargano, and A. Timmermann. 2013. Complete Subset Regressions. J Econometrics 177(2):357-373.

Enders, W., 2010. Applied econometric time series, 3rd ed. John Wiley & Sons Inc, Hoboken, N.J.

Engle, R.F., Granger, C.W.J., 1987. Cointegration and Error Correction - Representation, Estimation, and Testing. Econometrica 55, 251-276.

Frank Norris Foundation. 1977–2011. Timber Mart-South. Warnell School of Forestry and Natural Resources, University of Georgia, Athens, GA.

Fama, E. 1970. Efficient capital markets: A review of theory and empirical work. J. Finance 25(2):383–417.

Fama, E. 1990. Stock returns, expected returns, and real activity. J. Finance 45(4):1089–1108.

Fama, E. 1991. Efficient capital markets: II. J. Finance 46(5):1575–1617.

Fama, E. and K. French. 1988. Permanent and temporary components of stock prices. J. Polit. Econ. 96(2):246–273.

French, K. R. 2013. Data library. http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Accessed August 01, 2013.

Georgescu-Roegen, N. 1971. The Entropy Law and the Economic Process. Harvard University Press, Cambridge, Massachusetts.

Geweke, J. 1989. Bayesian Inference in Econometric Models Using Monte Carlo Integration. Econometrica 57(6):1317-1339.

Gill, J. 2008. Bayesian Methods : A Social and Behavioral Sciences Approach. Boca Raton : Chapman & Hall/CRC.

Gulko, L. 1999. The entropic market hypothesis. Int. J. Theor. Appl. Finance 2:293–330.

Haight, R. and T. Holmes. 1991. Stochastic price models and optimal tree cutting: Results for loblolly pine. Nat. Resour. Model. 5(4):423–443.

Hall, R. 2001. The Business Cycle Peak of March 2001. National Bureau of Economic Research, Cambridge, Massachusetts.

Hannan, E.J., Quinn, B.G., 1979. Determination of the Order of an Autoregression. Journal of the Royal Statistical Society Series B-Methodological 41, 190-195.

Hayashi, F., 2000. Econometrics. Princeton University Press, Princeton, N.J.

Hickman, C. (2007). TIMOs and REITs. USDA Forest Services. Accessed at http://www.fs.fed.us/spf/coop/library/timo_reit.pdf

Hultkrantz, L. 1993. Informational efficiency of markets for stumpage: Comment. Am. J. Agric. Econ. 75(1):234–238.

Johansen, S., 1988. Statistical-Analysis of Cointegration Vectors. Journal of Economic Dynamics & Control 12, 231-254.

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

Johansen, S., Juselius, K., 1990. Maximum-Likelihood-Estimation and Inference on Cointegration - with Applications to the Demand for Money. Oxford Bulletin of Economics and Statistics 52, 169-210.

Kainulainen, T., Toppinen, A., 2006. Testing integration in main European paper markets under floating and fixed exchange rates. Forest Policy and Economics 9, 372-379.

Kulcsár, E., and T. Tarnóczi. 2012. The Comparative Analysis of Romanian and Hungarian Stock Market Indices and Exchange Rates. Annals of the University of Oradea, Economic Science Series 21(2):564-570.

Lang, A. (2012). Macroeconomic Trends and the Forest Products Sector in the South. Forsik Consulting. Website: http://www.forestlandowners.com/displaycommon.cfm?an=1&subarticlenbr=306

Lee, P.M. 2004. Bayesian Statistics : An Introduction. London : Arnold.

Liao, X.C., Zhang, Y.Q., Sun, C.Y., 2009. Investments in Timberland and Softwood Timber as Parts of Portfolio Selection in the United States: A Cointegration Analysis and Capital Asset Pricing Model. Forest Science 55, 471-479.

Lu, N., & Rice, R. W. (2011). Characteristics of Wood Fuel Pellet Manufacturers and Markets in the United States, 2010. Forest Products Journal, 61(4), 310-315.

Luciano, Z., T. Benjamin, S. Francesco, Z. Massimiliano, P. Darío, and R. Osvaldo. 2011. Commodity predictability analysis with a permutation information theory approach. Phys. A Stat. Mechanics Appl. 390:876–890.

Masud, M. 1987. Introduction to Information Theory. Prentice Hall, Englewood Cliffs, New Jersey.

Mei, B., Clutter, M.L., 2010. Evaluating the Financial Performance of Timberland Investments in the United States. Forest Science 56(5), 421-428.

Mei, B., Clutter, M.L., Harris, T.G., 2013. Timberland Return Drivers and Timberland Returns and Risks: A Simulation Approach. Southern Journal of Applied Forestry 37, 18-25.

Mei, B., M. Clutter, and T. Harris. 2010. Modeling and Forecasting Pine Sawtimber Stumpage Prices in The U.S. South by Various Time Series Models. Can J Forest Res 40(8):1506-1516.

Murray, B.C., and D.N. Wear. 1998. Federal Timber Restrictions and Interregional Arbitrage in U.S. Lumber. Land Economics 74(1):76-91.

Nagubadi, V., I.A. Munn, and A. Tahai. 2001. Integration of Hardwood Stumpage Markets in the Southcentral United States. Journal of Forest Economics 7(1):69-98.

Neath, A.A., and N. Langenfeld. 2012. A Note on the Comparison of the Bayesian and Frequentist Approaches to Estimation. P. 1-12 in Advances in Decision Sciences. Hindawi Publishing Corporation.

Olsson, O., Hillring, B., Vinterback, J., 2011. European wood pellet market integration - A study of the residential sector. Biomass & Bioenergy 35, 153-160.

Pastor, L. 2000. Portfolio Selection and Asset Pricing Models. Journal of Finance 55(1):179-223.

Pfaff, B. (2007). Using the cars package. Website: http://rss.acs.unt.edu/Rdoc/library/vars/doc/vars.pdf

Pfaff, B., 2006. Analysis of integrated and cointegrated time series with R. Springer, New York.

Philippatos, G. and C. Wilson. 1972. Entropy, market risk, and the selection of efficient portfolios. Appl. Econ. 4(3):209.

Polson, N.G., and B.V. Tew. 2000. Bayesian Portfolio Selection: An Empirical Analysis of the S&P 500 Index 1970-1996. J Bus Econ Stat 18(2):164-173.

Press, S.J. 1989. Bayesian Statistics : Principles, Models, and Applications. New York : Wiley.

Press, S.J. 2003. Subjective and Objective Bayesian Statistics : Principles, Models, and Applications. Hoboken, NJ : Wiley-Interscience.

Prestemon, J. and T. Holmes. 2000. Timber price dynamics following a natural catastrophe. Am. J. Agric. Econ. 82(1):145.

Prestemon, J. P. 2003. Evaluation of U.S. southern pine stumpage market informational efficiency. Can. J. Forest Res. 33(4):561–572.

Prestemon, J.P., and R.C. Abt. 2002. Southern Forest resource assessment. Timber Products Supply and Demand. In General Technical Report - Southern Research Station, USDA Forest Service. United States Department of Agriculture, Forest Service, Washington; USA.

Puglisi, D. 1978. Is the futures market for Treasury bills efficient? J. Portfolio Manag. 4(2):64–67.

Rachev, S.T. 2008. Bayesian Methods in Finance. Wiley, Hoboken, N.J. xviii, 329 p. p.

Redmond, C.H., Cubbage, F.W., 1988. Portfolio Risk and Returns from Timber Asset Investments. Land Economics 64, 325-337.

Reinhart, J. (1985): Institutional investment in U.S. timberlands – Forest Products Journal, 35(5), 13-18.

Risso, W. A. 2009. The informational efficiency: The emerging markets versus the developed markets. Appl. Econ. Lett. 16(5):485–487.

Samaniego, F.J. 2010. A Comparison of the Bayesian and Frequentist Approaches to Estimation. New York : Springer.

Samaniego, F.J., and D.M. Reneau. 1994. Toward a Reconciliation of the Bayesian and Frequentist Approaches to Point Estimation. J Am Stat Assoc 89(427):947-957.

Schwarz, G., 1978. Estimating the Dimension of a Model. The Annals of Statistics, 461.

Sopha, B. M., & Klockner, C. A. (2011). Psychological factors in the diffusion of sustainable technology: A study of Norwegian households' adoption of wood pellet heating. Renewable & Sustainable Energy Reviews, 15(6), 2756-2765.

Stordal, S., Nyrud, A.Q., 2003. Testing roundwood market efficiency using a multivariate cointegration estimator. Forest Policy and Economics 5, 57-68.

Sun, C. and D. Zhang. 2001. Assessing the financial performance of forestry-related investment vehicles: Capital asset pricing model vs. arbitrage pricing theory. Am. J. Agric. Econ. 83(3):617–628.

Sun, C., 2013. On the market risk of securitized timberlands. Journal of Forest Economics 19, 110-127.

Sun, C., Zhang, D., 2001. Assessing the financial performance of forestry-related investment vehicles: Capital asset pricing model vs. arbitrage pricing theory. American Journal of Agricultural Economics 83, 617-628.

Sun, C., Zhang, D., 2003. The effects of exchange rate volatility on US forest commodities exports. Forest Science 49, 807-814.

Sun, C., Zhang, D., 2006. Timber harvesting margins in the southern United States: A temporal and spatial analysis. Forest Science 52, 273-280.

Sung, P. and B. Anil. 2009. Maximum entropy autoregressive conditional heteroskedasticity model. J. Econometrics 150:219–230.

Toivonen, R., Toppinen, A., Tilli, T., 2002. Integration of roundwood markets in Austria, Finland and Sweden. Forest Policy and Economics 4, 33-42.

Tsay, R.S., 2005. Analysis of financial time series, 2nd ed. Wiley, Hoboken, N.J.

Vignola, A. and C. Dale. 1979. Is the futures market for Treasury bills efficient? J. Portfolio Manag. 5(2):78–81.

Washburn C. (2012, March). Applied Forest Economics At Work. Presentation at Sothern Forest Economics Workers Annual Meeting, Charlotte, NC.

Washburn, C. and C. Binkley. 1990. Informational efficiency of markets for stumpage: Comment. Am. J. Agric. Econ. 72(2):394–405.

Washburn, C. and C. Binkley. 1993. Informational efficiency of markets for stumpage: Reply. Am. J. Agric. Econ. 75(1):239–242.

Washburn, C.L., Binkley, C.S., 1993. Do Forest Assets Hedge Inflation. Land Economics 69, 215-224.

Watanabe, T. 2000. Bayesian Analysis of Dynamic Bivariate Mixture Models: Can They Explain the Behavior of Returns and Trading Volume? J Bus Econ Stat 18(2):199-210.

West, M. 1997. Time Series Decomposition. Biometrika 84(2):489-494.

West, M., and J. Harrison. 1997. Bayesian Forecasting and Dynamic Models. New York : Springer.

Winkler, R.L. 1972. An Introduction to Bayesian Inference and Decision. New York, Holt, Rinehart and Winston.

Wooldridge, J.M., 2013. Introductory econometrics : a modern approach, 5th ed. South-Western Cengage Learning, Mason, Ohio.

WRDS, 2013. Wharton Research Data Services. The Wharton School at the University of Pennsylvania.

Yin, R. and D. Newman. 1996. Are markets for stumpage informationally efficient? Can. J. Forest Res. 26(6):1032–1039.

Yin, R., D. Newman, and J. Siry. 2002. Testing for Market Integration Among Southern Pine Regions. Journal of Forest Economics 8(2):151-166.

Zinkhan, F. C. (1990): Timberland as an Asset for Institutional Portfolios – Real Estate Review, 19, 69-74.

Zinkhan, F. C., W. R. Sizemore, G. G. Mason, and T. J. Ebner (1992): Timberland investments: a portfolio perspective – Portland, OR, Timber Press.