Project Report:

Forecasting Containerboard Prices*

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* This report is mainly based on the master thesis by Lidia Marko.

Abstract

In this report, we analyzed the pattern of containerboard price movement, including the existence of trend and seasonality component, the stationarity property, and the casualty relationship between price and inventory. Price forecasts based on various time series forecasting methods are produced and compared with the published forecasts. We also conducted a forecasting excise to produce quarterly price forecasts using selected methods for year 2003-2005.

Forecasting Containerboard Prices

1. Introduction

Linerboard price behavior was hardly predictable especially over the last decades. The industry-wide linerboard price could increase more than 60% in one year, as happened in 1994. Unpredictable price behavior could lead to a number of serious consequences for the industry, such as excess capacity, financial losses, and difficulties in long-term financial planning. Despite the importance of these issues for the industry, there has been little research focused on linerboard prices. The goal of this study is to employ advanced time series techniques to analyze linerboard price movements and to produce price forecasts.

We will first analyze the historic patterns of linerboard price, focusing on price trend, seasonality, and the stationarity property. Secondly, we will evaluate the performance of the existing price forecasts in the industry using different objective measures. Then we will review briefly forecasting techniques based on univariate time series, including naïve forecast, exponential smoothing, and Box-Jenkins approach. These methods will be utilized to forecast linerboard price.

Moreover, we will also apply system method such as Vector Autoregressive Models (VAR) to forecast price by incorporating inventory in the forecasting system, because inventory is believed to be an important indicator of price change. To do so, we will also examine the nature of inventory series, and then conduct Granger causality test on the causality relationship between price and inventory.

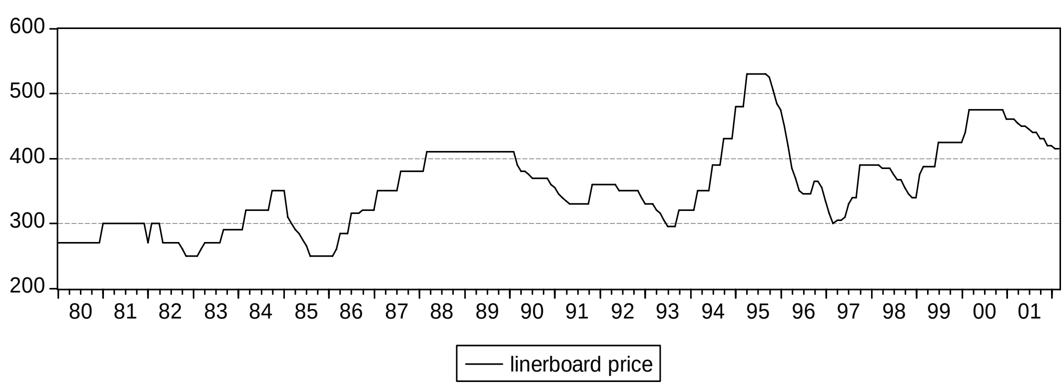
The performance of each forecasting method will be compared and evaluated. We will also produce price forecasts that are comparable with the published forecasts in the industry, and then evaluate relative performance of different forecasting techniques. Finally, we will forecast linerboard price for year 2003-2005 using different forecasting methods.

2. The Behavior of Linerboard Price

2.1 Historic Pattern of Linerboard Price Movement

The linerboard price in the United States has historically been highly cyclical, rising during the middle and late stages of economic recovery and falling down under weakening demand. The nominal price movement is last twenty years is shown in Figure 2.1.

Figure 2.1 Linerboard Price (1980-2002)



As can been seen, the price peaked in 1995, and then dropped dramatically. From September 1995 to July 1996, the linerboard price plummeted by about 35%.

Presently, the linerboard price movement is in the middle of the current cycle. It reached the peak level in 2000, and began to move down. The current cycle is different from both 1988 and 1995. This price landing is softer than the previous ones. In a two-year period starting in July 2001, the price dropped by about 18%, a relatively moderate price falling.

Figure 2.1 only shows the pattern of nominal price. However, it would be interesting to see how real price moved in the same period. Sometimes real price is more important in analyses because nominal price changes can just be caused by inflation. There are a number of ways in calculating real prices. We utilize Producer Price Index (PPI) of all commodities to deflate the nominal price with December 1982 the base date.[1]

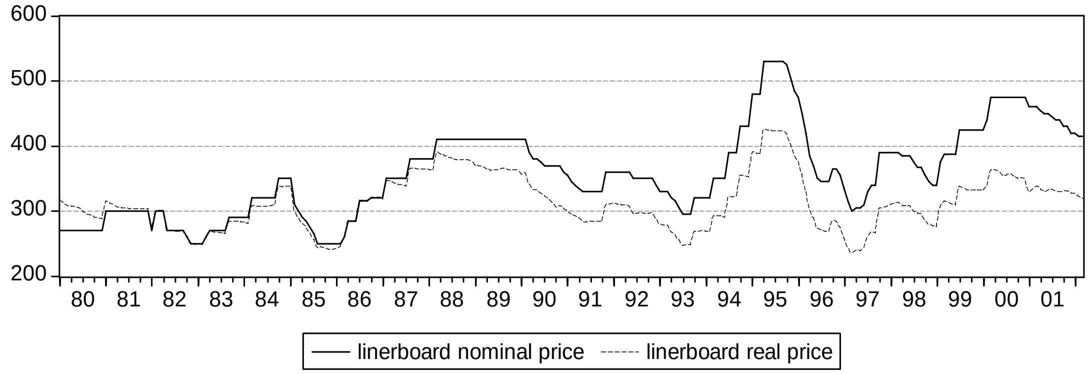
The real price is calculated below:

$$Real\ Price = \frac{Nominal\ Price}{PPI} * 100 \tag{2.1}$$

The movement of real price is given in Figure 2.2. In general the real price follows the pattern of the nominal price, but with slightly less fluctuations with a standard deviation of $43 vs. $63 for nominal price. It appears that the current real price is not much higher than that in early 1980s, and even lower than that in later 80s. Some statistics for the nominal price and real prices are given in Table 2.1.

[1] According to Bureau of Labor Statistics, the Producer Price Index (PPI) is a family of indexes that measures the average change over time in selling prices received by domestic producers of goods and services. PPIs measure price change from the perspective of the seller. All commodities PPI reflects the change in selling prices of over 3,200 commodities.

Figure 2.2 Nominal and Real Linerboard Prices (1980-2002)



The price data utilized forecasting are monthly data from January 1980 to December 1999, and are collected from *Pulp and Paper Week*. The price information for 2000-2003 is not used in forecasting models, because monthly inventory data needed for VAR model are not available for these years.

Table 2.1 Linerboard Price Descriptive Statistics

Statisctics	Nominal price	Real price
Mean	347.48	310.17
Median	347.50	305.18
Maximum	530.00	425.36
Minimum	250.00	235.66
Std. Dev.	63.08	42.87

2.2 Trend and Seasonality Pattern in Price

In order to analyze whether there is an upward or downward trend in price movement, we use regression analysis to test possible trend pattern. The following two equations are estimated with linear trend and quadratic trend:

$$X = \beta_0 + \beta_1 * Trend + \varepsilon \qquad (2.2)$$

$$X = \beta_0 + \beta_1 * Trend + \beta_2 * Trend^2 + \varepsilon \qquad (2.3)$$

On the other hand, the price series is on monthly base, we also check for seasonality. The regression models are augmented with monthly dummy variables with January as the base month.

$$X = \beta_0 + \beta_1 Trend + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \beta_6 D_6 + \beta_7 D_7 + \\ + \beta_8 D_8 + \beta_9 D_9 + \beta_{10} D_{10} + + \beta_{11} D_{11} + + \beta_{12} D_{12} + \varepsilon \qquad (2.4)$$

$$X = \beta_0 + \beta_1 Trend + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \beta_6 D_6 + \beta_7 D_7 + \\ + \beta_8 D_8 + \beta_9 D_9 + \beta_{10} D_{10} + + \beta_{11} D_{11} + + \beta_{12} D_{12} + \beta_{13} Trend^2 + \varepsilon \qquad (2.5)$$

The estimation results for nominal and real price time series are presented in Tables 2.2 and 2.3. Since our tests show that autocorrelation exists for the regression error in each model, the standard errors are calculated based on Newey - West (NW) robust standard errors for unknown form of heteroskedasticity and autocorrelation.

It turns out nominal price series contains a positive linear trend. Linear trend parameter estimate coefficient is significant at 1% significance level. Quadratic trend coefficient is significant only at 10% level. It appears that the nominal price in the last two decades show an upward trend with a slower speed of increase. The result also shows that nominal price does not have any seasonality. The p-values of the most seasonal dummy coefficients are very large and therefore insignificant.

The real price also contains both linear and quadratic trends. Linear and quadratic trend parameter coefficient estimates are significant at 1% and 5% percent significance levels, respectively. The upward trend of real price is flatter than that of nominal price.

Table 2.2 Trend and Seasonality in Nominal Price Time Series

Variable	Eqiation 2	Eqiation 3	Eqiation 4	Eqiation 5
Intercept	252.09 (28.65)***	230.71 (21.43)***	251.63 (20.81)***	230.37 (16.70)***
Trend	0.68 (10.37)***	1.13 (4.62)***	0.68 (10.12)***	1.13 (4.52)***
$Trend^2$		-0.0016 (-1.88)*		-0.0016 (-1.84)*
D_2			-0.26 (-0.04)	-0.25 (-0.04)
D_3			2.61 (0.29)	2.63 (0.30)
D_4			4.11 (0.36)	3.21 (0.28)
D_5			-1.57 (-0.12)	-1.54 (-0.13)
D_6			-4.33 (-0.31)	-4.32 (-0.32)
D_7			-1.36 (-0.10)	-1.36 (-0.10)
D_8			-1.20 (-0.09)	-1.21 (-0.09)
D_9			-0.42 (-0.03)	-0.43 (-0.04)
D_{10}			4.74 (0.46)	4.72 (0.47)
D_{11}			3.64 (0.43)	3.63 (0.44)
D_{12}			0.68 (0.11)	0.67 (0.11)

Therefore, the real price increases very slowly. Similar to the nominal price, real price time series does not comprise seasonal components. None of the seasonal dummies coefficients are significant at 10% significance level.

Table 2.3 Trend and Seasonality in Real Price Time Series

Variable	Eqiation 2	Eqiation 3	Eqiation 4	Eqiation 5
Intercept	300.98 (34.71)***	278.59 (26.28)***	301.03 (24.92)***	278.69 (23.02)***
Trend	0.08 (1.06)	0.64 (2.57)***	0.07 (1.03)	0.64 (4.07)***
Trend2		-0.002 (-2.31)**		-0.0016 (-3.70)***
D2			0.035 (0.005)	0.011 (0.001)
D3			2.05 (0.22)	2.01 (0.15)
D4			1.80 (0.15)	1.75 (0.13)
D5			-2.38 (-0.19)	-2.45 (-0.18)
D6			-4.99 (-0.35)	-5.06 (0.37)
D7			-1.93 (-0.14)	-2.01 (0.88)
D8			-1.63 ()	-1.70 (0.13)
D9			-1.05 (-0.08)	-1.11 (-0.08)
D10			3.86 (0.34)	3.82 (0.28)
D11			3.15 (0.35)	3.13 (0.23)
D12			0.96 (0.14)	0.96 (0.07)

2.3 Unit Root Testing for the Price Series

If price moves following the random walk model, it will not generally return to any particular trend or level. In this case, the series is not stationary. In other word, whether the price series has unit roots is an important time-series characteristic. For regression analysis, unit root in price will result in spurious regression. Moreover, some forecasting tools, such as Autoreggressive Moving Average Model (ARMA) model in the Box-Jenkins approach, cannot be directly applied if the series is not stationary. Therefore, we conduct unit root test for the price.

In order to perform the unit root test, it is important to know whether the data contain any trend and seasonal components. Including too many deterministic regressors in the unit root test will result in lost power; while not including enough of them will bias the test in favor of the unit root null. Based on the regression results of trend and seasonality, we include intercept and trend in the equation. In order to select an appropriate number of lags in the unit root test, we start with the number of lags at 12 and then reduce the model using t or F-tests since we work with a monthly data.

The following equation is estimated for the Augmented Dickey-Fuller (ADF) unit root test:

$$\Delta X = \gamma X_{t-1} + \alpha t + \sum_{i=1}^{p} \beta \Delta X_{t-i+1} + \varepsilon \,, \qquad (2.6)$$

where X_t is the value of the tested variable (price) and t is the time trend. If the t-statistic of the last lag p is insignificant, we proceed with the model with lag length $p-1$, until the last lag becomes statistically significant. Further, a Likelihood Ratio (LR) test is also conducted on the joint significance of the excluded lags. After the lag length has been determined, we also conducted diagnostic checking of the residuals by the Ljung-Box Q-statistics. If there is no strong evidence of serial correlation in the residuals, then an appropriate lag length is chosen.

Based on the procedure above, we select a lag length of 6. The sixth lag coefficient is statistically significant at the 6% level, and the lags 7-12 appear to be jointly insignificant. Statistics and p-value of LR test are 3.09 and 0.81 respectively. Finally, a diagnostic checking of the residuals by the Ljung-Box Q-statistics shows that there is no serial correlation in the residuals

Table 2.4 contains the result of the unit root testing. The *t*-statistics are computed for coefficients and referred to the MacKinnon (1996) one-sided p-values table[2]. If absolute computed value exceeds the critical value, the null hypothesis that time series is non-stationary is rejected. Based on the results, we can see that price turns out to be stationary.

Table 2.4. Unit Root Test Results

Variables	Lag	Test statistics	P-value
Price	6	-4.089371(ADF)	0.0075

[2] Critical values: 1% level -3.997930; 5% level -3.429229; and 10% level -3.138092.

3. The Performance of Price Forecasting in the Industry

In order to measure forecast performance and to compare alternative forecasts, two most commonly used measures are—the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). The RMSE has been commonly used. It is calculated using the following formula:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_i - F_i)^2}{n}}, \qquad (3.1)$$

where X_i is the actual price; F_i is the forecasted value; and n is the number of forecasts for a specific forecast horizon. The disadvantages of the RMSE are: (1) it is very sensitive to outliers (extreme forecast errors), and (2) it is not scale free.

To avoid the problem of scaling, the MAPE is often used:

$$MAPE = \frac{\sum_{i=1}^{n} 100 * \left|(X_i - F_i)/X_i)\right|}{n} \qquad (3.2)$$

The MAPE calculates the forecast error as a percentage of the actual value. The drawback of the MAPE measure is that it puts a heavier penalty on the forecasts that exceed the actual value than on those that fall behind the actual value since MAPE distribution used in its calculation is right-skewed and asymmetric. As a result MAPE is bounded on the low side by an error of 100 % but not bound exists on the high side[3].

[3] For example if the actual value of the price equal to $300 is over forecasted by $300 (forecasted value=$600) then MAPE=100%. Since the price can not be negative we can not under forecast the price by more then $300 or by 100%. Thus, the MAPE puts a heavier penalty on the forecasts that exceed the actual value.

The journal *Pulp and Paper Forecaster* by Miller Freeman Inc. publishes regular forecasts of prices for major grades of containerboard. Although we do not have an access on the forecasting models they used, we can still evaluate the forecasting performance based on some objective measures. The quarterly forecasts are available in the journal from January 1996 to April 2000. The grades covered are: containerboard, corrugating medium, unbleached linerboard (42-lb/1,000 ft^2), and export kraft liner (175+ g/m^2). For the export liner, the forecast data is available only up to December of 1999. The data are collected manually and then are regrouped in order to obtain one-, two-, and three-step forecasts, where one-step (two, three-step) forecast refer to one quarter (two, three-step) ahead forecast, etc. In Figures 3.1-3.4, the graphs of the actual price and one-, two-, and three-step-ahead forecasts are represented.

Figure 3.1 Actual Containerboard Price and Forecasts from the "Forecaster"

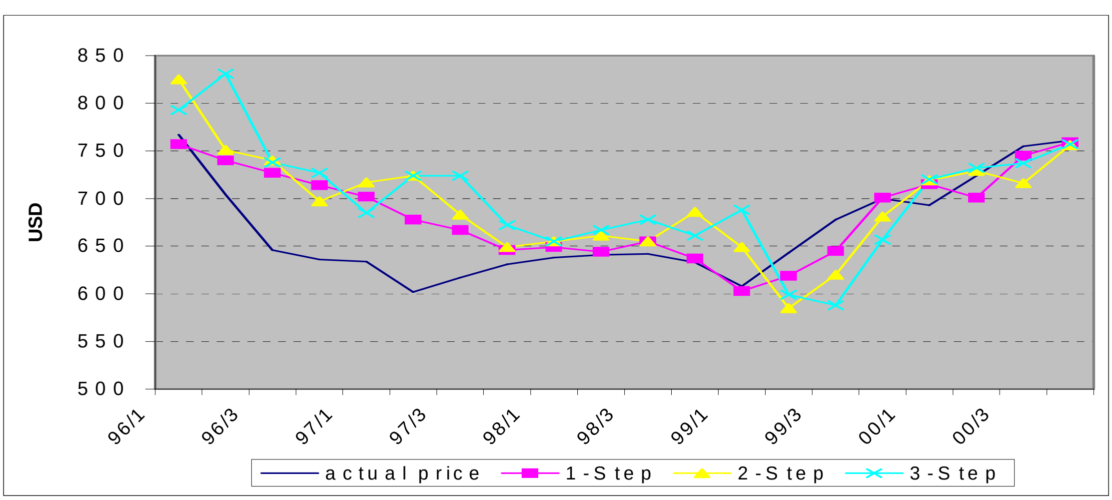


Figure 3.2 Actual Linerboard Price and Forecasts from the "Forecaster"

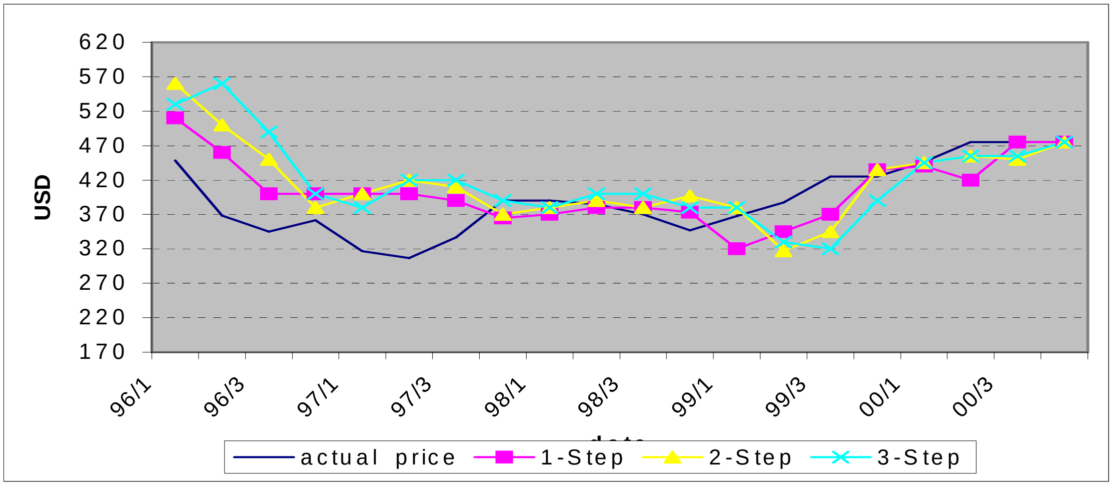


Figure 3.3 Actual Corrugating Medium Price and Forecasts from the "Forecaster"

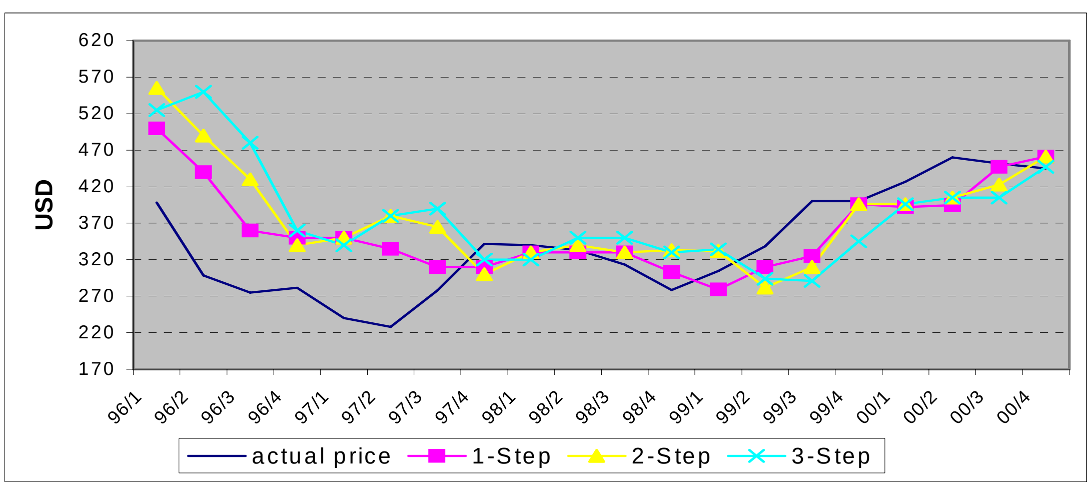
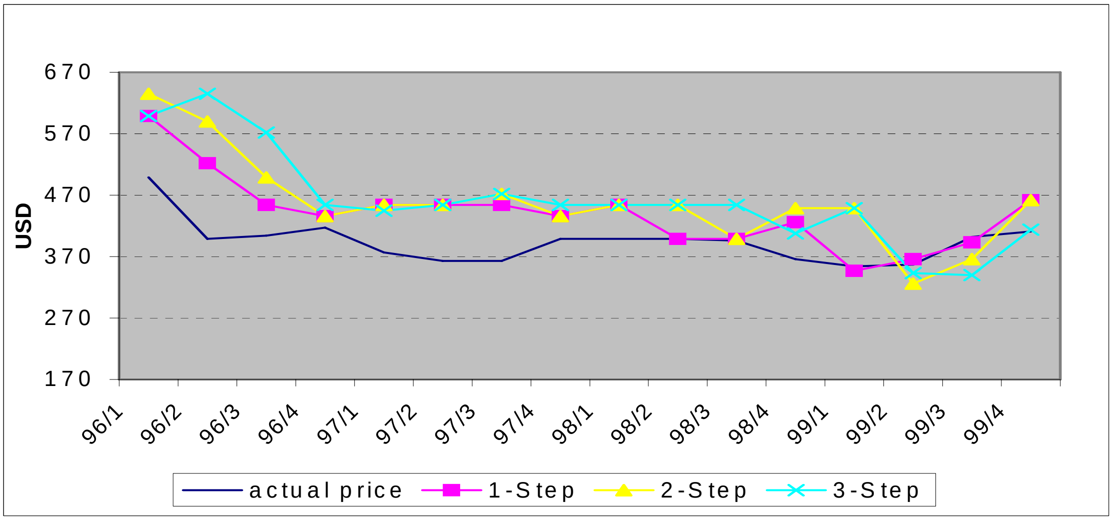


Figure 3.4 Actual Export Liner Price and Forecasts from the "Forecaster"



As we can see in the graphs, in general the forecast performance for all three horizons is relatively adequate. For the years 1996-1997 the forecasts are less accurate and consistently exceed the actual prices. In contrast, in 1998-2000 forecasted values are improved and quite close to the actual ones.

As expected, one-step-ahead forecasts are generally more accurate than two-, or three-step forecasts. The shorter horizon implies that the forecaster faces less uncertainty in the future. Both the RMSE and MAPE show that one-step-ahead forecasts for containerboard, unbleached linerboard, corrugating medium, and export liner price are the most accurate (see Table 3.1). For the second- and third-step ahead forecasting, the accuracy of the forecasts decreases significantly. The MAPE range of the three-step-ahead forecasts varies from 8.31% for the containerboard forecasts to 25.4% for the corrugating medium price forecasts. The three-quarter ahead price forecasts of the corrugating medium is on average over- or under-predicted by 25 percent.

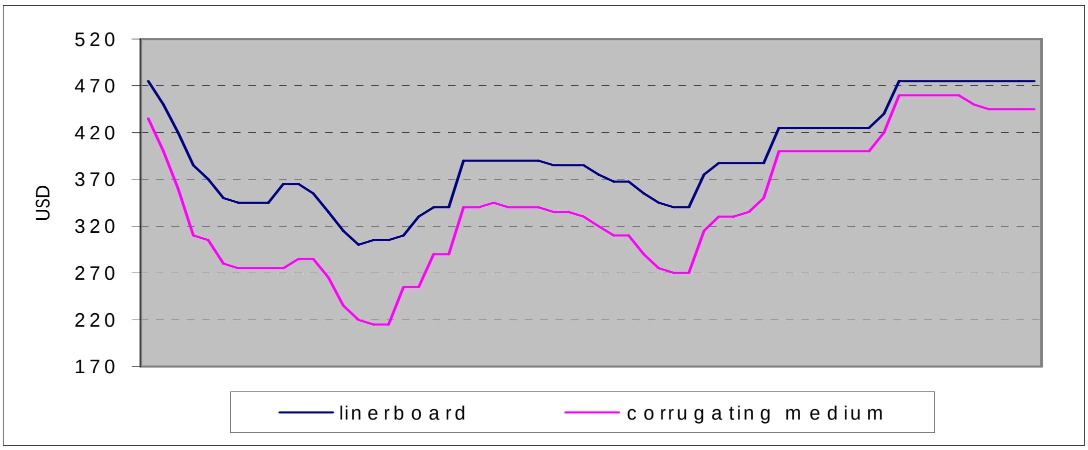
Table 3.1 RMSE and MAPE of Price Forecasts

Grade	Error measurement	1 step ahead	2 step ahead	3 step ahead
Containerboard	MAPE	4.3702	6.938355	8.310461
Unbleached linerboard	MAPE	10.65847	13.00216	14.4374
Export liner	MAPE	12.35728	18.49232	19.82277
Corrugating medium	MAPE	16.14924	22.22057	25.39659
Containerboard	RMSE	38.91594	54.43666	65.81337
Unbleached linerboard	RMSE	48.63147	64.08824	73.67204
Export liner	RMSE	61.89507	86.11547	95.96614
Corrugating medium	RMSE	63.87064	87.55552	100.5182

It seems that the most accurate forecasts for all horizons are for containerboard prices, then for unbleached linerboard, export liner, and corrugating medium. This is not surprising. Containerboard price has experienced less fluctuation than the prices of the other grades (see Figure 3.1). Corrugating medium prices usually follow quite closely the linerboard prices; therefore the accuracy of forecasts for linerboard and corrugating medium forecasts are similar (see Figure 3.4).

However, in the first quarter of 1996 the price of corrugating medium is significantly over-forecasted as well as in the first and second quarter of 1997. During these periods, corrugating and linerboard prices plummet down, and the forecasts of both grades fail to predict such an abrupt decrease in the prices. For some reason, corrugating medium forecast is very inaccurate for these quarters, and its Absolute Percentage Error (APE) of the three-step-ahead forecast exceeds 45% (see Table 3.3).

Figure 3.4 Linerboard and Corrugating Medium Monthly Prices (1996-2000)



Overall, the performance of the published forecasts appears to be quite accurate for the containerboard and for unbleached linerboard prices. For nine months ahead forecast the MAPE did not exceed 9% and 15 % for containerboard and unbleached linerboard prices, respectively. However, for export liner and corrugating medium, the forecasts are less reliable. When the forecast errors are converted to dollar values, the MAPE of the three-quarter-ahead forecast on average represents $80 for the price of export liner and $90 for corrugating medium.[4] Such errors are quite large.

[4] The average prices of export liner and corrugating medium over the period 1996 to 1999 are multiplied by the value of the average MAPE over the same period.

Table 3.3 APE of Corrugating Medium and Linerboard Forecast

Corrugating Medium				Unbleached Linerboard			
Quarter	1-Step	2-Step	3-Step	Quarter	1-Step	2-Step	3-Step
96/3	3.64	23.64	23.64	96/3	2.90	13.04	10.14
96/4	7.41	18.52	29.63	96/4	4.35	10.14	15.94
97/1	8.33	31.25	45.83	97/1	7.94	20.63	26.98
97/2	0.00	26.09	45.65	97/2	0.00	19.35	29.03
97/3	3.70	3.70	3.70	97/3	0.00	1.47	5.88
97/4	0.00	10.45	7.46	97/4	0.00	7.89	3.95

4. Forecasting Price Using Univariate Models

Despite the importance of producing an accurate price forecasting for the industry, few studies has been devoted to price forecasting. Most of the academic studies concentrate on econometric models of price formation (see Buongiorno and Gilles (1980), Buongiorno and Lu (1989), Chas-Amil and Buongiorno (1999), Buongiorno et al. (1982), Stier (1985), and Booth et al. (1991). Some other studies, such as Alavalapati et al. (1997) and Naininen and Toppinen (1999), use cointegration method to study the relationship between paper product price movements and the exchange rate.

Brannlund et al. (1999) is the only study, as far as we know, that focuses directly on forecasting of prices of paper products. It introduces a new forecasting technique – Maximum Autocorrelation Factors (MAF). This method is based on the idea, like the vector autoregressive model, that time series of prices and quantities from different sectors of the forest industry are mutually correlated over time. They compare the results of the MAF estimation with the results from the univariate method (ARIMA) estimation and naïve forecast. It turns out that for the Swedish forest industry it is difficult to forecast prices significantly better than naïve forecast. ARIMA models produced second best forecasts followed by the MAF technique.

In the following sections, we will give a brief review of some commonly used forecasting methods, including naïve forecast, exponential smoothing, ARIMA model, and VAR model; and then use the monthly price data from January 1980 to December 1999 published in *PPW* to forecast monthly price for January to December 2000. The results are evaluated using MAPE and MRSE error measurements.

4.1 Naïve and Exponential Smoothing Methods

Naïve forecasting is a quantitative tool that uses only historical data of the variable being forecasted in the analysis. It provides a convenient way to generate quick and easy forecasts for short time horizon; i.e. a month, a quarter, at most a year ahead. This method has minimal data requirements and is easy to implement since generally it requires only simple arithmetic to generate the forecast. The drawback of this technique is that its forecast will miss turning points. The naïve forecast is based only on recent actual values of the variable. Hence, the forecast will not change direction (up or down) until after the actual data has shown this change. The naïve method generally expects the data to have no trend and if a trend is present in the data it will usually treat the trend as a linear one. The forecasts for the time series containing trend are generated according to following formula:

$$\hat{X}_{t+1} = X_t + (X_t - X_{t-1}) \qquad (4.1)$$

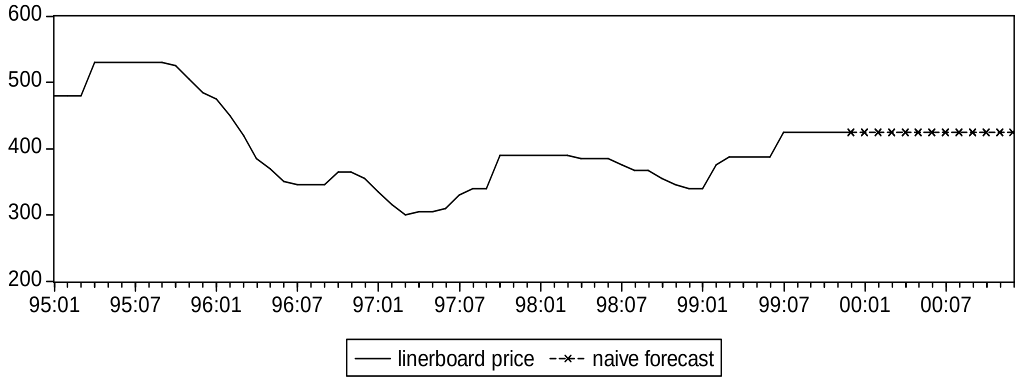
The results of the twelve months one-step ahead price forecast starting January 2000 can be found in Table 4.1. As we have mentioned before, naïve forecast is based only on the recent price values. Since the second half of 1999, linerboard prices have been fixed at $425 per short ton, producing the forecast for the whole year equaling the same value.

Table 4.1 Linerboard Price Forecast for Year 2000

Date	Naïve	Exp. Smoothing Nonseasonal	Exp. Smoothing Seasonal	ARIMA (3,1,0)	VAR
Jan-00	425,00	428,24	426,85	425,37	427,62
Feb-00	425,00	431,44	429,31	425,79	429,60
Mar-00	425,00	434,64	433,89	426,24	431,11
Apr-00	425,00	437,84	437,09	426,79	432,30
May-00	425,00	441,04	436,55	427,36	433,23
Jun-00	425,00	444,24	436,50	427,95	433,96
Jul-00	425,00	447,44	443,33	428,56	434,52
Aug-00	425,00	450,64	446,66	429,19	434,95
Sep-00	425,00	453,84	450,12	429,82	435,27
Oct-00	425,00	457,04	459,70	430,47	435,51
Nov-00	425,00	460,23	461,65	431,11	435,70
Dec-00	425,00	463,43	461,36	431,76	435,85

In Figure 4.1 we can see the actual price values from January 1995 and forecasted linerboard price for year 2000.

Figure 4.1 Naïve Forecast of Linerboard Price



Another simple and commonly used method of adaptive forecasting is the exponential smoothing technique. In this method the forecasted values are the weighted averages of past observations with heavier weights given to recent values and exponentially decreasing weights to earlier values. This technique has been successfully employed in practice to predict the future values of many types of time series, such as price, sales, or inventory data. Exponential smoothing method under some circumstances may be more feasible, accurate, cheaper, and easier to use than more complicated forecasting techniques. At the same time, on average it produces more reliable results than the naïve forecast.

There are several exponential smoothing methods. The most basic method of exponential smoothing is the single exponential smoothing with one parameter. This method is appropriate for series that move randomly above and below a constant mean with no trend or seasonal patterns. The forecast of y is a weighted average of the past values of y_t, where weights decline exponentially with time (equation 4.2). The forecasts from simple smoothing are constant for all future observations.

$$\hat{y}_t = \alpha \sum_{s=0}^{t-1} (1-\alpha)^s y_{t-s} , \quad (4.2)$$

Other exponential smoothing methods include: Holt-Winters non-seasonal algorithm with two parameters and seasonal Holt-Winters additive algorithm with three parameters. The first method is appropriate for series with a linear time trend and no seasonal variation. The second one is often being utilized for series with a linear time trend and additive seasonal variation.

We have already discovered that the price data contains linear trend, hence simple exponential smoothing cannot be applied to the data. Regression analyses also showed that the price series is not likely to contain seasonality. Yet, we still use both non-seasonal and seasonal approaches utilizing Holt-Winters algorithm. The α, β, and γ parameters are determined by minimizing of sum of squared errors.[5] They are shown in Table 4.2. The results of parameter estimation show that γ parameter is equal to zero, which is consistent with our previous finding that the price does not have a seasonal element.

The forecasts produced from both models are very close as Figures 4.2 and 4.3 indicate. Table 4.1 contains numerical value of forecasts. In contrast to the Naïve forecast, exponential smoothing method captures the upward movement of the price.

[5] β, and γ parameters reflect trend and seasonal components of the data.

Table 4.2 Parameters of Exponential Smoothing

	α (general)	β (trend)	γ (seasonal)
Nonseasonal HW	.99	.2	N/A
Seasonal HW	0.97	0.22	0

Figure 4.2 Nonseasonal Exponential Smoothing Forecast of Linerboard Price

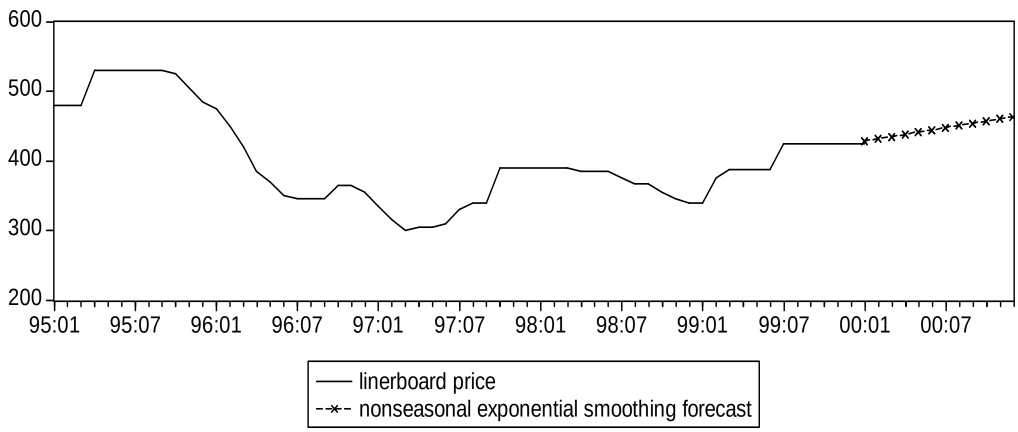
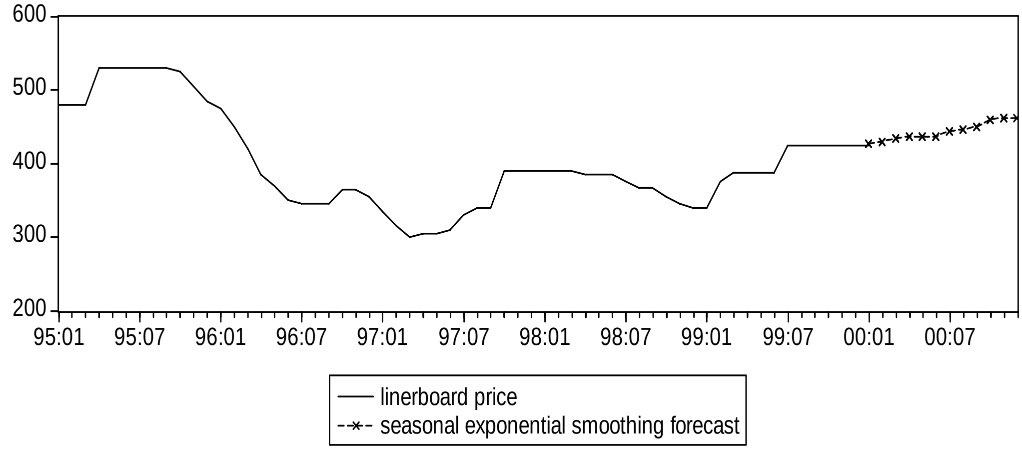


Figure 4.3 Seasonal Exponential Smoothing Forecast of Linerboard Price



4.2 Using ARIMA model for Price Forecasting

According to Makridakis (1997), autoregressive (AR) models were first introduced by Yule in 1926 and subsequently supplemented by Slutsky, who in 1937 presented moving average (MA) process. Wold in 1938 combined both AR and MA and showed that ARMA processes can be used to model a large class of stationary time series. In other words, a time series X can be modeled as a combination of past X_t values and/or past e_t:

$$X_t = \theta_1 X_{t-1} + \theta_2 X_{t-2} + \ldots + \theta_p X_{t-p} + \phi_1 e_{t-1} - \phi_2 e_{t-2} - \ldots - \phi_q e_{t-q} + e_t \quad (4.3)$$

The process of fitting a model to a real lifetime series requires four steps. First, the original time series must be transformed to become stationary around its mean and variance. Second, appropriate order of p and q must be specified. Third, the value of the parameters θ and ϕ must be estimated using some non-linear optimization procedure that minimizes the sum of square errors or some other appropriate loss function.

The implementation of the theoretical framework introduced by Wold became possible only in the late 1960s when the first computers, capable of performing all necessary calculations, appeared. In 1970, Box and Jenkins published a landmark book on time series analysis and forecasting and popularized the use of the ARIMA method. They introduced the guidelines for making time series stationary; suggested autocorrelation and partial autocorrelation as a tool for determining the appropriate values of p and q; proposed to check the residuals for white noise to determine whether the model is adequate or not. This methodology became known as Box-Jenkins or ARIMA approach, where ‘I’ stands for ‘integrated,’ signifying that time series might need to be differenced to become stationary. The last stage of fitting ARIMA model is actually performing and evaluating the forecast from the chosen model using such error measures as the MRSE and Mean Absolute Percentage Error MAPE.

In Box-Jenkins methodology of ARIMA modeling, it must be first established that a given time series is stationary before trying to identify the orders of AR and MA processes. In Box-Jenkins approach, this is done by visual analysis of the sample’s autocorrelations (AC) and partial autocorrelations (PAC). Figure 4.4 shows the AC and PAC of the linerboard price. The sample autocorrelations of the undifferenced series exhibit smooth patterns at high lags, so it is likely that the price series is not stationary. Hence, differencing may be necessary.

The next step is to examine the sample AC and PAC of the first differenced series. They are shown together with two standard error limits in Figure 4.5. The pattern of the sample AC at high lags is not at all smooth. The first three sample AC are moderately large, while the next two values are quite small, suggesting that a MA(3) model for the first-differenced series is possible. However, similar pattern is also present in the sample PAC, so that an AR(3) model might be appropriate. We can limit the choice of the model to ARIMA with difference of order one, with up to AR(3) orders of the autoregressive term and up to MA(3) orders of the moving average term.

To facilitate the process of choosing the best model, we use Eviews macro, which we wrote specifically for automatic ARIMA modeling of a non-seasonal time series. We estimated all possible models up to order 4 for both MA and AR parameters. The SBC points out that ARIMA (1,1,1), ARIMA (3,1,0), and ARIMA(0,1,3) might be adequate models for forecasting.

Figure 4.4 AC and PAC of Linerboard Price Time series

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob</th></tr>
<tr><td>.|*******|</td><td>.|*******|</td><td>1</td><td>0.974</td><td>0.974</td><td>230.64</td><td>0.000</td></tr>
<tr><td>.|*******|</td><td>*|. |</td><td>2</td><td>0.941</td><td>-0.150</td><td>446.94</td><td>0.000</td></tr>
<tr><td>.|*******|</td><td>*|. |</td><td>3</td><td>0.903</td><td>-0.106</td><td>646.92</td><td>0.000</td></tr>
<tr><td>.|*******|</td><td>**|. |</td><td>4</td><td>0.855</td><td>-0.206</td><td>826.76</td><td>0.000</td></tr>
<tr><td>.|****** |</td><td>.|. |</td><td>5</td><td>0.803</td><td>-0.048</td><td>986.08</td><td>0.000</td></tr>
<tr><td>.|****** |</td><td>.|. |</td><td>6</td><td>0.748</td><td>-0.054</td><td>1124.9</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>7</td><td>0.690</td><td>-0.047</td><td>1243.5</td><td>0.000</td></tr>
<tr><td>.|***** |</td><td>.|. |</td><td>8</td><td>0.630</td><td>-0.039</td><td>1342.9</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>9</td><td>0.574</td><td>0.054</td><td>1425.7</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>10</td><td>0.517</td><td>-0.051</td><td>1493.1</td><td>0.000</td></tr>
<tr><td>.|**** |</td><td>.|. |</td><td>11</td><td>0.461</td><td>-0.001</td><td>1547.0</td><td>0.000</td></tr>
<tr><td>.|*** |</td><td>.|* |</td><td>12</td><td>0.412</td><td>0.078</td><td>1590.3</td><td>0.000</td></tr>
<tr><td>.|*** |</td><td>.|. |</td><td>13</td><td>0.369</td><td>0.051</td><td>1625.2</td><td>0.000</td></tr>
<tr><td>.|** |</td><td>*|. |</td><td>14</td><td>0.324</td><td>-0.102</td><td>1652.2</td><td>0.000</td></tr>
<tr><td>.|** |</td><td>.|. |</td><td>15</td><td>0.285</td><td>0.018</td><td>1673.1</td><td>0.000</td></tr>
<tr><td>.|** |</td><td>.|. |</td><td>16</td><td>0.249</td><td>-0.009</td><td>1689.2</td><td>0.000</td></tr>
<tr><td>.|** |</td><td>.|* |</td><td>17</td><td>0.218</td><td>0.073</td><td>1701.6</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>18</td><td>0.194</td><td>0.036</td><td>1711.4</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>19</td><td>0.171</td><td>-0.035</td><td>1719.0</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>20</td><td>0.152</td><td>0.017</td><td>1725.2</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>21</td><td>0.139</td><td>0.053</td><td>1730.3</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|. |</td><td>22</td><td>0.128</td><td>-0.037</td><td>1734.7</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>.|* |</td><td>23</td><td>0.123</td><td>0.082</td><td>1738.7</td><td>0.000</td></tr>
<tr><td>.|* |</td><td>|. |</td><td>24</td><td>0.121</td><td>0.016</td><td>1742.7</td><td>0.000</td></tr>
</table>

Figure 4.5 AC and PAC of Differenced Linerboard Price Time series

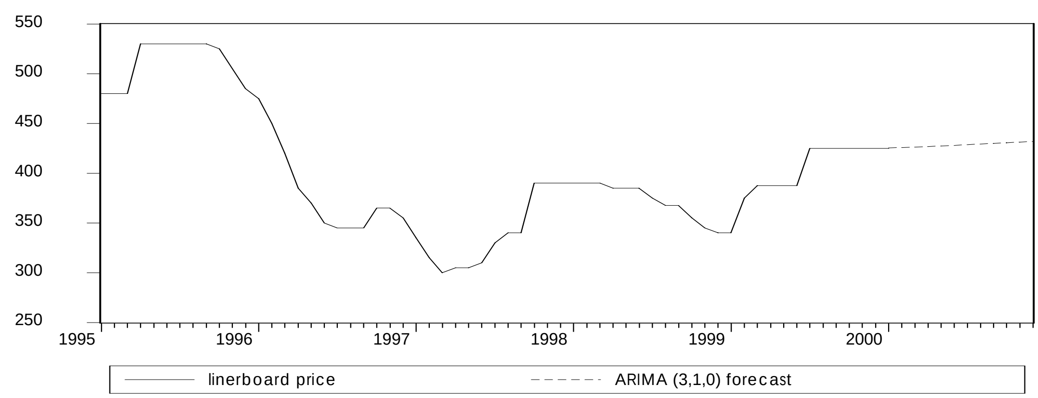
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|*		.|*		1	0.176	0.176	7.5161	0.006
.|*		.|*		2	0.135	0.108	11.975	0.003
.|**		.|**		3	0.264	0.234	29.006	0.000
.|*		.|.		4	0.087	0.002	30.878	0.000
.|*		.|.		5	0.076	0.015	32.296	0.000
.|*		.|*		6	0.156	0.084	38.274	0.000
.|.		.|.		7	0.035	-0.025	38.577	0.000
*|.		*|.		8	-0.085	-0.139	40.366	0.000
.|.		.|.		9	0.019	-0.010	40.456	0.000
.|.		.|.		10	-0.018	-0.012	40.539	0.000
*|.		*|.		11	-0.103	-0.066	43.237	0.000
*|.		*|.		12	-0.071	-0.060	44.500	0.000
.|.		.|*		13	0.013	0.069	44.544	0.000
*|.		*|.		14	-0.148	-0.093	50.173	0.000
*|.		*|.		15	-0.119	-0.070	53.799	0.000
*|.		*|.		16	-0.140	-0.128	58.867	0.000
*|.		*|.		17	-0.176	-0.065	66.941	0.000
*|.		.|.		18	-0.072	0.031	68.307	0.000
*|.		.|.		19	-0.103	-0.045	71.077	0.000
*|.		*|.		20	-0.149	-0.063	76.934	0.000
*|.		.|.		21	-0.058	0.039	77.811	0.000
*|.		*|.		22	-0.144	-0.104	83.309	0.000
*|.		.|.		23	-0.097	-0.025	85.813	0.000
*|.		*|.		24	-0.118	-0.112	89.527	0.000

ARIMA (1,1,1) cannot be used for forecasting since the residual test does not show white noise. The next model, ARIMA (3,1,0), seems to be adequate. This model autocorrelations are inside the two standard error boundaries computed as

$\pm 2/\sqrt{T}$, where T is total number of observations in the sample. If the autocorrelations are within these bounds, they are not significantly different from zero at (approximately) 5% significance level and therefore represent white noise. We also could not reject the null hypothesis of white noise even at 10% significance level when Breush-Pagan test for autocorrelation in residuals is used. Hence, we will perform forecasting using ARIMA (3,1,0) model.

The forecasts shows moderate increasing in price values for the next twelve months but this increase is smaller than the one predicted when exponential smoothing methods are utilized (see Figure 4.6 and Table 4.1).

Figure 4.6 ARIMA Forecast of Linerboard Price



5. Price Forecasting Using System Models

Two decades ago, Christopher Sims (1980) proposed Vector Autoregressions (VAR). As Stock and Watson (2001) have put it, a univariate autoregression is a single-equation, single-variable linear model, in which the current value of a variable is explained by its own lagged values. A VAR is an *n*-equation; *n*-variable linear model, in which each variable is in turn explained by its own lagged values, plus current and past values of the remaining *n-1* variables. This simple framework provides a systematic way to capture rich dynamics in multiple time series.

VAR models are commonly used for forecasting systems of interrelated time series and for analyzing dynamic impact of random disturbances on systems of variables. The VAR approach sidesteps the need for structural modeling by treating every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system. The mathematical representation of a VAR model including linerboard price and inventories level is:

$$y_t = A_1 y_{t-1} + ... + A_p y_{t-p} + Bx_t + \varepsilon_t \tag{5.1}$$

where y_t is a vector of endogenous variables, x_t is a vector of exogenous variables, $A_1.....A_p$ and B are matrices of coefficients to be estimated, and ε_t is a vector of innovations that may be contemporaneously correlated but are uncorrelated with their own lagged values and uncorrelated with all of the right-hand side variables.

Since only lagged values of the endogenous variables appear on the right-hand side of the equations, simultaneity is not an issue and an OLS yields consistent estimates. Moreover, even though the innovations may be contemporaneously correlated, the OLS is efficient and equivalent to a GLS since all equations have identical regressors.

One of the important factors influencing linerboard price movements in short run is a change in total inventory levels at mills and box plants. Linerboard manufacturers produce their product to meet the needs of box plants. The demand for fiber boxes is strongly dependent on the general economic conditions. Changes in demand cause fluctuations in inventories, and as a result, instability in price level. Suppose that the linerboard price (P) and total inventory (Inv) are jointly determined by a VAR process and let a constant be the only exogenous variable. Assuming that the VAR contains two lagged values of the endogenous variables, it may be written as:

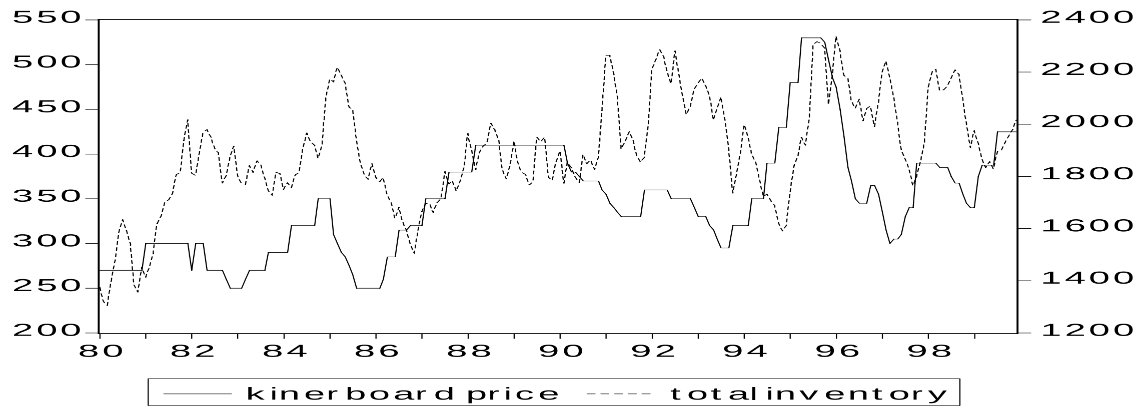
$$P_t = a_{11}P_{t-1} + b_{12}Inv_{t-1} + b_{11}P_{t-2} + b_{12}Inv_{t-2} + c_1 + \varepsilon_{1t} \qquad (5.2)$$

$$Inv_t = a_{21}P_{t-1} + a_{22}Inv_{t-1} + b_{21}P_{t-2} + b_{22}Inv_{t-2} + c_2 + \varepsilon_{2t} \qquad (5.3)$$

where a_{ij}, b_{ij}, c_i are the parameters to be estimated.

For the analysis we use monthly data on price and inventory for unbleached linerboard. Figures 5.1 allow us to visually examine the relationship between the variables of interest. According to the chart, there is a negative correlation between inventories and price variables. Increase in inventories stock is likely to cause the decrease in price. However, price adjustments do not take place instantly. There is a time lag between the price and inventories changes. The lag length varies depending on the point of the time interval.

Figure 5.1 Price and Inventories at Mills and Box Plants



5.1 The Inventory Series

Before conducting the VAR estimation, we need to check if the inventory data contains trend or seasonality to determine whether any exogenous variable should be included in the model. We utilize the regression technique introduced in Section 2 to check for trend and seasonality in the linerboard price time series. The results of the estimation are presented in Table 5.1. Inventory seems to comprise linear, quadratic trend, and some seasonal component. The p-values of October and November seasonal dummies (D10 and D11) coefficients are significant at 5% level. Given this results intercept and trend are included into inventory unit root test equation[6]. Table 5.2 below shows the results of the unit root testing. The *t*-statistics are computed for coefficients and referred to the MacKinnon table. According to the results the null of a unit root can be rejected at 1% significance level.

[6] The lags length procedure introduced in Section 2 demonstrates 12 lags should be included in unit root equation.

Standard unit root test equation does not include seasonal dummy variables. To account for seasonality we modify the ADF procedure for the inventory variable. First, we regress inventory variable on the monthly dummies. The residuals from this regression can be viewed as the deseasonalized values of the inventory. Further, we use the residuals to estimate the test equations. Dickey, Bell, and Miller (1986) have shown that the limiting distribution for γ is not affected by the removal of the deterministic seasonal component. Therefore, the test is valid and we can use MacKinnon's critical values. The unit root testing of the deseasonalized show that t-statistic equals –5.41. It means that we can reject the null of a unit root at 1% significance level (critical value of the MacKinnon empirical distribution at 1% level is –3.46). Hence, we can conclude that inventory as well as price data is stationary and can be utilized in VAR modeling

Table 5.1 Trend and Seasonality in Linerboard Inventory

Variable	Eqiation 2	Eqiation 3	Eqiation 4	Eqiation 5
Intercept	1699.77 (34.61)***	1607.67 (23.74)***	1741.21 (26.13)***	1649.28 (20.35)***
Trend	1.63 (4.66)***	3.96 (3.24)	1.65 (4.60)***	3.97 (3.13)***
$Trend^2$		(-2-.0097 (-2.08)**		-0.009 (-2.00)**
D_2			-10.36 (-0.33)	-10.45 (-0.35)
D_3			-20.41 (-0.46)	-20.59 (-0.5)
D_4			-21.86 (-0.43)	-22.10 (-0.46)
D_5			-52.28 (-0.96)	-52.56 (-1.01)
D_6			-52.21 (-0.91)	-52.50 (-0.96)
D_7			4.16 (0.07)	3.87 (0.07)
D_8			-34.32 (-0.59)	-34.59 (-0.63)
D_9			-63.91 (-1.18)	-64.14 (-1.24)
D_{10}			-115.60 (-2.26)**	-115.77 (-2.35)**
D_{11}			-113.40 (-2.41)**	-113.50 (-2.50)**
D_{12}			-44.16 (-1.12)	-44.16 (-1.18)

Notes: Numbers in parenthesis are t-statistics values. ***, **, * indicate that regression coefficients are significantly different from zero at the 1%, 5% and 10% significance level, respectively. All statistics are calculated using Newey – West standard errors.

Table 5.2 Inventory Time Series Unit Root Test Results

Variables	Lag	Test statistics	P-value
Inventory	12	-5.430392 (ADF)	0.0000

5.2 Granger Causality Testing

Since in VAR model each variable can be explained by its own lagged values, current, and past values of the other variables, we conduct the Granger causality test which shows the direction of Granger causality between price and inventory. According to Granger (1969), the question of whether one time series causes another can be answered as follows: X_1 is said to be Granger caused by X_2, if the past values of X_2 help in the prediction of X_1, or equivalently, if the coefficients on the lagged values of X_2 are statistically significant. Using this definition, an econometric implementation of the Granger-causality test can be conducted in the following way. First, we estimate the following equation by the OLS:

$$\mathrm{X}_{1t} = \alpha_0 + \alpha_1 X_{1t-1} + ... + \alpha_p X_{t-p} + \beta_2 X_{2t-2} + ... + \beta_p X_{2t-p} + \varepsilon \qquad (5.4)$$

Then, we conduct an F-test of the null hypothesis $H_0: \beta_0=\beta_1=\beta_2=....=\beta_p$. If the null is not rejected, X_2 does not Granger cause *X1*. A few issues should be noted in carrying out the Granger causality test. First, it is a bivariate test and thus must be used between two time series. Second, the test is normally interpreted as a test whether one variable helps forecast another, rather than a test of whether one variable causes another. Therefore, Granger causality measures precedence in information content but does not itself indicates causality. Also, bidirectional or two-way causality case is quite frequent.

Finally, since the causality test is sensitive to the choice of the lag length *(p)*, we need to determine statistically and practically sensible number of lags included in the model. The number might be different from the number of lags used in the unit root testing since in this case not one but two variables are included in the test equation. For this purpose a number of different criteria can be used - likelihood ratio statistics, finite prediction error, Akaike, Schwartz, and Hannan-Quinn criterion. The problem is that these criteria often point out at different lag length and consequently lead to contradictory results. We choose to utilize the SIC criterion since it tends to point out the most parsimonious models. In our case, the SIC criterion indicates that one lag should be included in price/inventory Granger test.

The results of Granger test for the level data neither reject nor strongly support the hypothesis that inventory causes changes in the price variable. It turns out that there is a bi-directional causality between lagged inventory and price[7]. But when we utilize price and lagged inventory change (growth) variable, instead of the level values, lagged inventories are found to significantly help explain changes in current price fluctuations. Contrary to that, price growth variable does not Granger cause inventory movements. The results of the tests are consistent with Toppinen et al (1996) results. Their study focused on the relationship between Finnish pulp export prices and international pulp inventories. They found that Granger causality existed from inventory to price but not vice versa.

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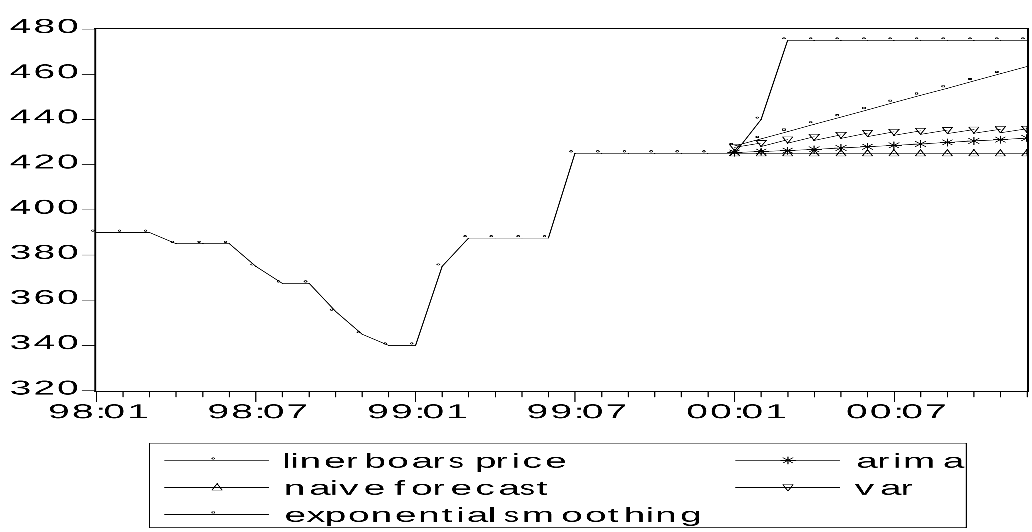
[7] Results are the same for not-seasonally adjusted and deseasonalized data.

5.3 Forecasting using VAR Models

A crucial element in a VAR model is the lag length. The importance of the lag length has been demonstrated by Hafer and Sheemen (1989). They show that forecast accuracy from VAR models varies substantially depending on alternative lag length. Ivanov and Kilian (2000) argue that the lag length determination procedure, based on the AIC criterion, performs well in most cases for monthly data. According to this criterion, the VAR model that includes linear trend two lags of both variables should be utilized in forecasting. The resultant forecast is represented in Table 4.1. The values of this forecast are close to those of the ARIMA model. Figure 5.2 shows the actual linerboard price from 1980 to 1999, and 2000 forecasts obtained from all the above-mentioned models.

Figure 5.2 Different Methods Price Forecasts



5.4 Evaluation of Different Models

In order to investigate the accuracy of the results rendered by different forecasting methods, we calculate the MRSEs and the MAPEs for each forecasting method. As Table 3.1 shows both forecast error measures point out that exponential smoothing method produce the most accurate forecast in this case.

Table 5.3 Different Methods MAPE and MRSE

Method	Naïve	Exp. Smoothing	ARIMA	VAR
MAPE	9.06	4.78	8.36	7.40
MRSE	45.85	25.28	42.29	37.36

Exponential smoothing MAPE is 2.62 percentage points lower than the MAPE of the second best model VAR. The ARIMA and Naïve methods produce less accurate forecasts than the other two techniques. Their MAPEs are 3.58 and 4.28 percentage larger than that of exponential smoothing technique.

It is worth to point out that in this exercise a simple exponential smoothing outperforms the ARIMA and VAR methods. This result is consistent with the some previous studies, for example, Newbold and Granger (1974), Makridakis and Hibon (1979), Fildes et al. (1998). They point out that simple forecasting methods sometimes might render better forecasts than statistically sophisticated ones.

Moreover, in our case, during 1999 - and 2000 year the linerboard prices are either fixed or steadily grow following an upward trend (see Figure 5.3). In this situation exponential smoothing method that takes into account mainly recent values of the price and linear trend element may produce better results than those which incorporate more complex algorithms. At the same time exponential smoothing would fail to predict the change in the direction of the trend and would generate less precise results if we were to forecast for year 2001 when price went down (see Figure 5.4). Advanced techniques are likely to produce more accurate forecast in this case.

Figure 5.3 Linerboard Price (1999-2000)

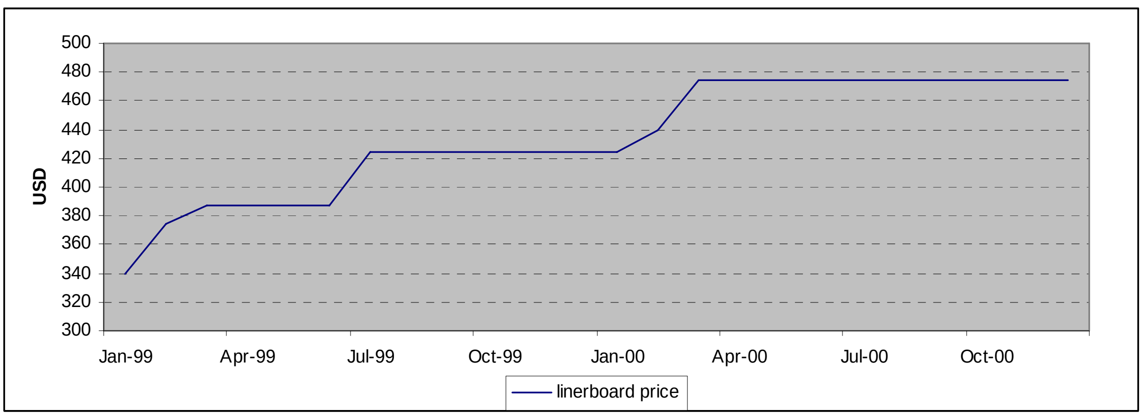
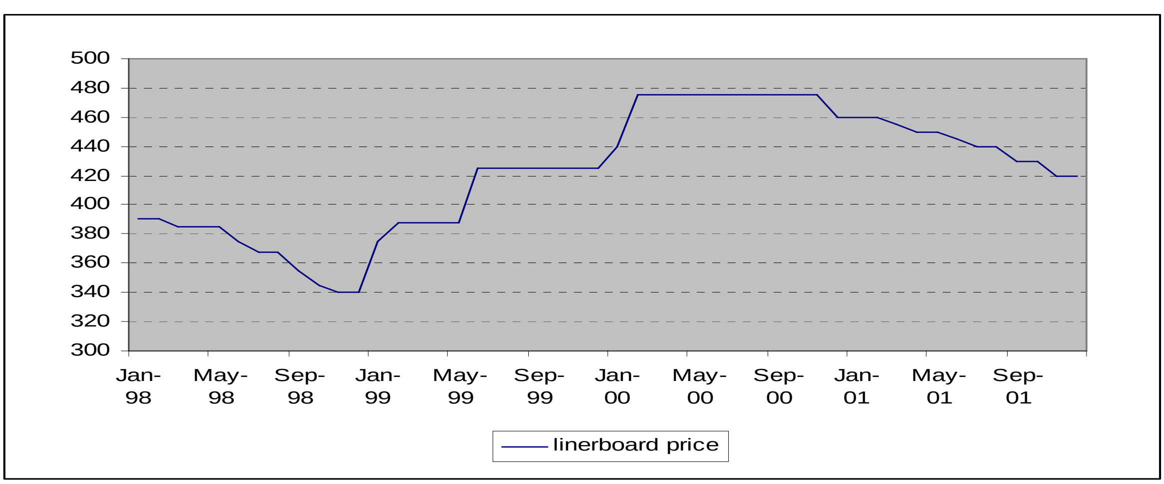


Figure 5.4 Linerboard Price (1998-2001)



6. Comparing Price Forecasts

In order to compare the performance of the above techniques with the existing forecast, we use these methods to forecast prices analogous (the same time span and forecasting horizons) to the forecasts published in *Forecaster*. We limit the forecasting exercise to unbleached linerboard. Simple forecasting techniques - nonseasonal Holt-Winter method - as well as more advanced ones, such as the univariate ARIMA approach and multivariate VAR model, are applied to the log value of the existing data. Based on these models, the sequence of the out-of-sample forecasts is produced for all quarters within the period from 1996 to 2000. The results of the published and produced forecasts are represented in Table 6.1. MRSE and MAPE are calculated for each forecasting horizon.

Table 6.1 Different Forecasting Methods Comparison (unbleached linerboard)

Method	MRSE			MAPE		
	1-Step	2-Step	3-Step	1-Step	2-Step	3-Step
Published forecasts	48.63	64.09	73.67	10.66	13.00	14.44
Holt-Winter	32.78	69.15	115.11	7.71	15.09	23.07
ARIMA	27.22	48.36	62.75	6.28	10.67	13.67
VAR	30.08	49.94	58.33	5.98	10.36	12.68

The results show that simple exponential smoothing (Holt-Winter) method outperforms the published one-step ahead forecast but fails to improve the accuracy for the longer horizons. More complicated techniques render more accurate results in all horizons (see Figures 6.1-6.5).

Figure 6.1 Linerboard Price and ARIMA Model Forecasts

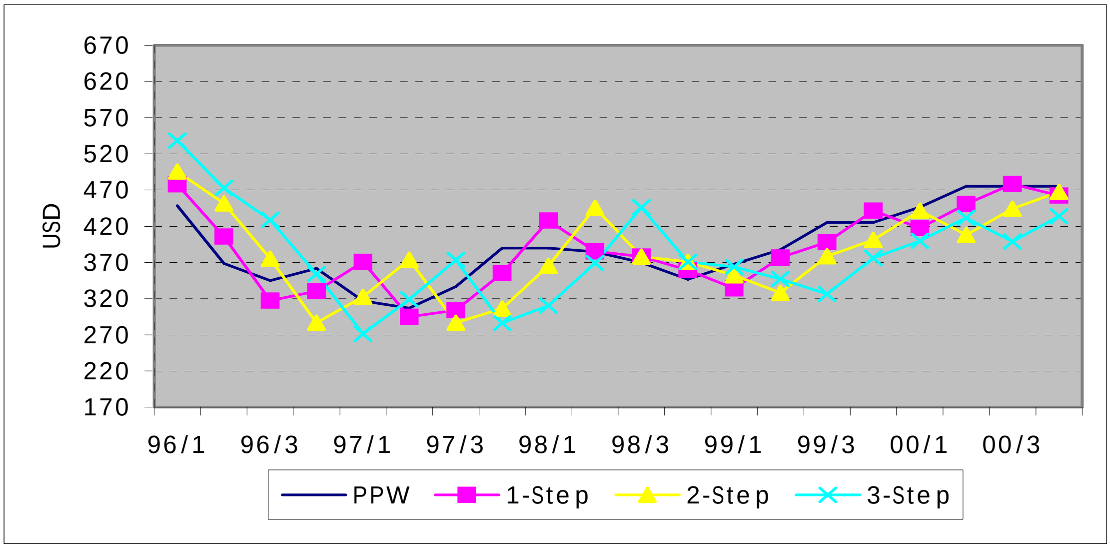


Figure 6.2 Linerboard Price and VAR Model Forecasts.

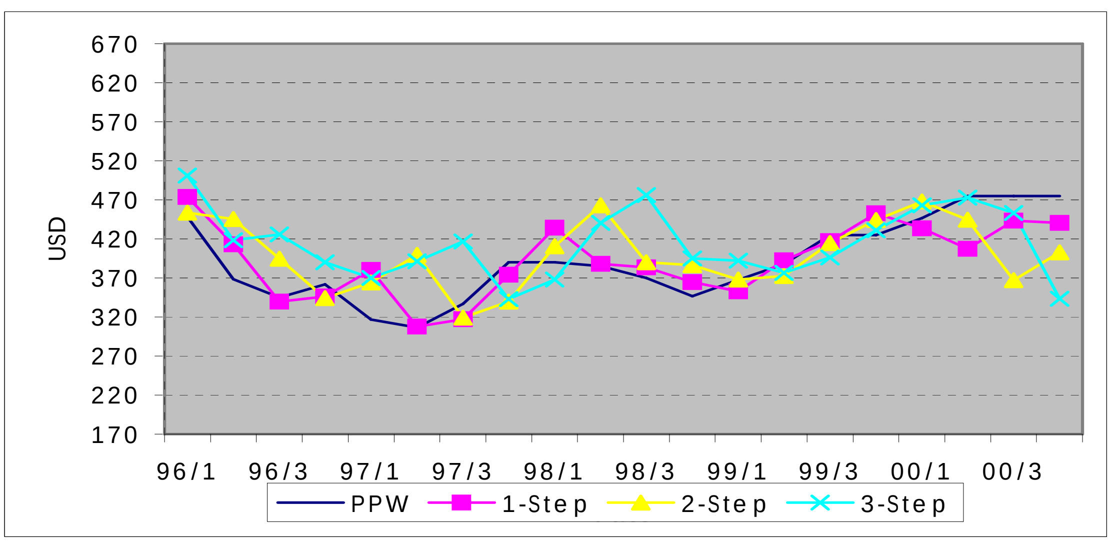


Figure 6.3 Linerboard Price and One-step Ahead Forecasts.

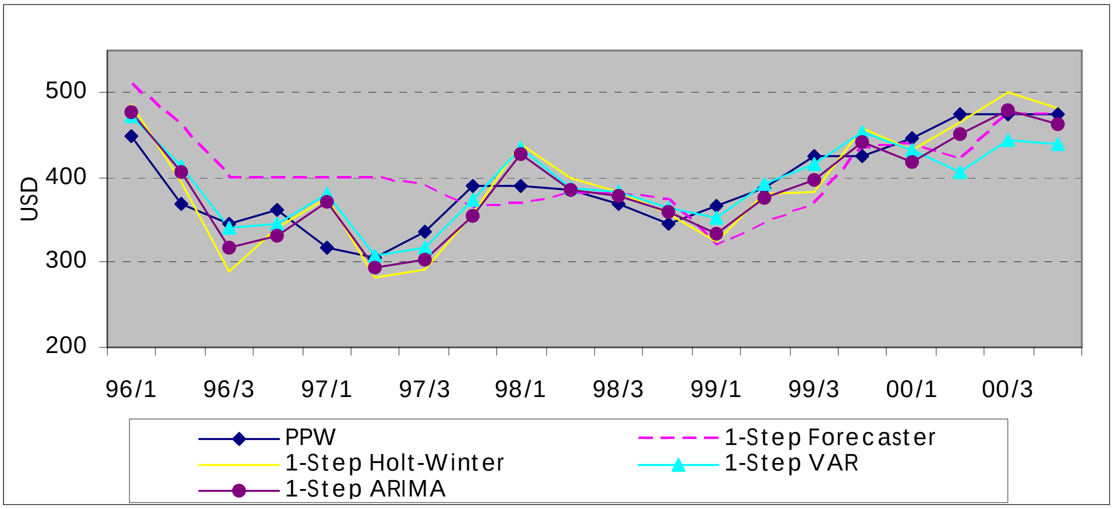


Figure 6.4 Linerboard Price and Two-step Ahead Forecasts

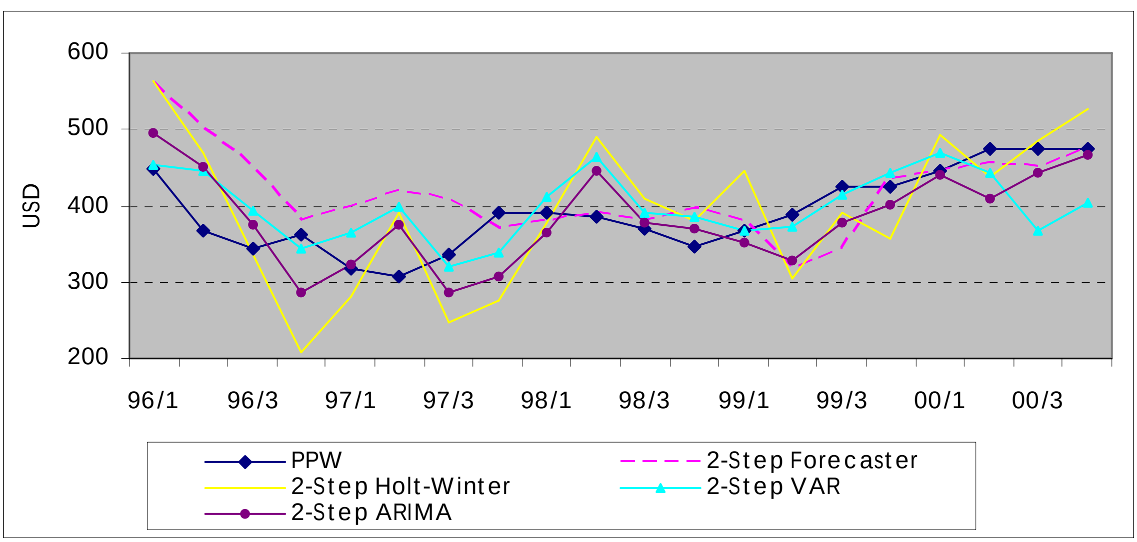
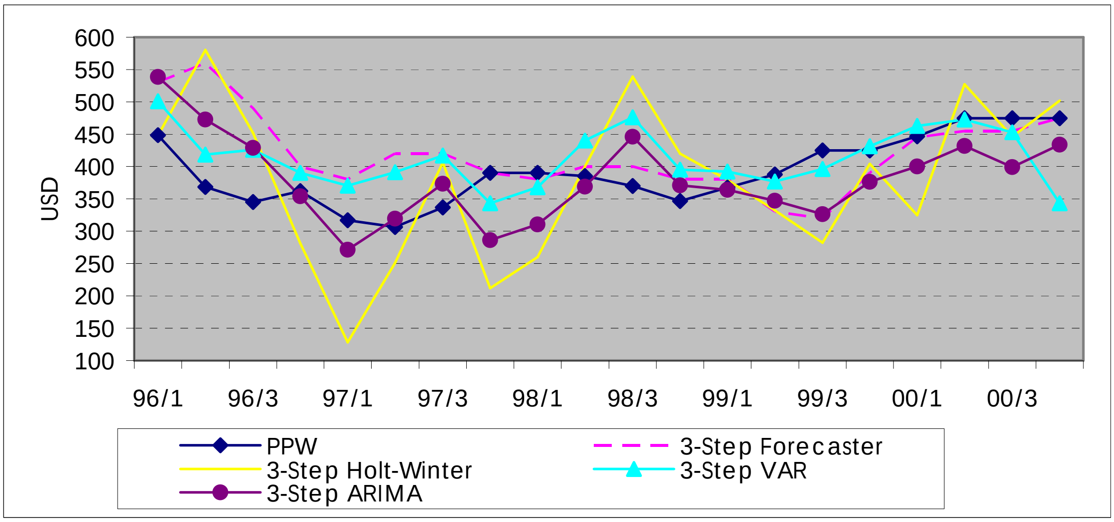


Figure 6.5 Linerboard Price and Three-step Ahead Forecasts



The difference between the ARIMA and VAR forecasts is small. On average, the MAPE is lower by 4.5, 2.5, and 1.25 percentage points for the one-, two-, and three-step-ahead forecasts respectively than for the published forecasts. When the MAPE error percentages are converted into dollar values, they constitute as much as $22 per short ton improvement of the one step-ahead forecast in the fourth quarter of 2000.

All three methods can be employed to forecast price movement. However, for short-term forecast, especially when the price has not changed significantly in the recent months prior to starting point of forecast, exponential smoothing method may be preferred. The VAR and ARIMA approaches can be applied when forecasting for a longer horizon and when the price exhibits considerable variations.

7. Forecasting Future Price (2003 - 2005)

In this section, we produce quarterly linerboard price forecasts for year 2003 to 2005 using different methods. Because the inventory data on linerboard are available only up to December 1999, we can not use VAR model for the forecasting exercise. Figure 7.1 presents the ARIMA and exponential smoothing quarterly forecasts from April 2003 to December 2005.

Interestingly, the two models predict quite different directions or price behavior (see Table 7.1). Exponential smoothing nonseasonal Holt-Winters incorporates recent downward trend and points out at a gradual decrease in price during next two years. In contrast, the ARIMA takes into account historical price behavior and points at possible increases in linerboard prices.

Figure 7.1 Linerboard Price Forecast for 2003-2005

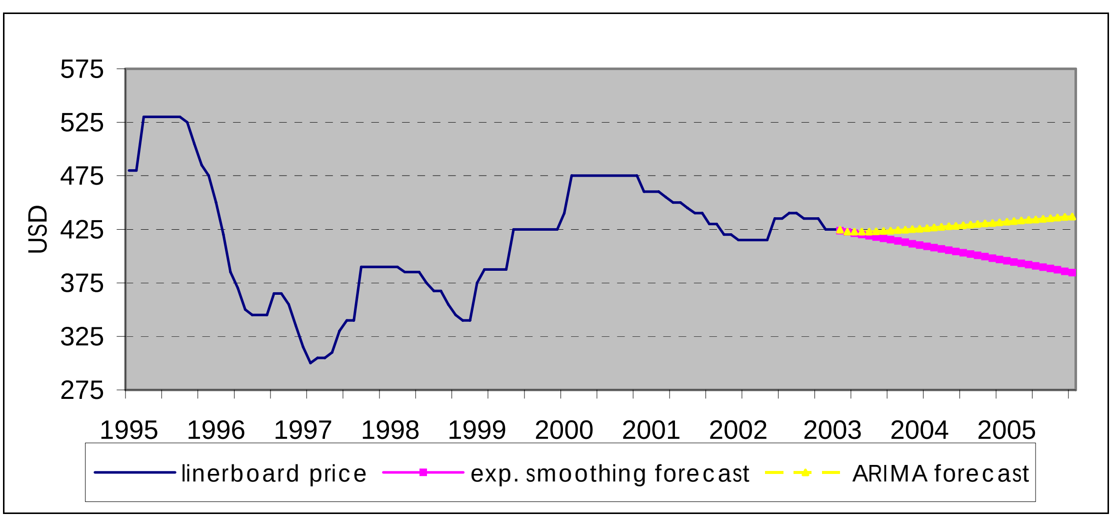


Table 7.1 Quarterly Forecast for 2003-2005

	Exp. Smoothing	ARIMA
2003:02	422,55	422,64
2003:03	418,88	422,63
2003:04	415,20	423,65
2004:01	411,53	425,07
2004:02	407,86	426,63
2004:03	404,18	428,24
2004:04	400,51	429,87
2005:01	396,83	431,50
2005:02	393,16	433,13
2005:03	389,49	434,77
2005:04	385,81	436,40

8. Conclusions

In this study, we investigate the pattern of containerboard price, and compare the performance of price forecasts based on various forecasting methods. We also produce price forecasts for year 2003-2005.

The main findings can be summarized as follows. First, the nominal price contains the upward linear trend component. The real price has the linear trend as well. However, the real price upward trend is flatter than that of the nominal price. Neither nominal nor real prices contain seasonality. The unit root testing determined that nominal price does not have unit root and, therefore, it can be utilized for ARMA and VAR modeling. Second, the results of Granger test showed that there was bidirectional causality between previous month inventory and current price. When inventory change is utilized instead of the levels, lagged inventories found to be an important factor explaining changes in current price fluctuations, while price change does not Granger cause inventory movements. Third, for short term forecasting, when price variation is small, Holt-Winters exponential smoothing renders the most adequate performance. For long term forecast and when the price varies considerably, the VAR model performs better than all other forecasting techniques. The ARIMA model forecasts outperform the published forecast as well.

Clearly, the performance of price forecasting depends on the characteristics of price movement and forecasting horizon. Due to the complicated nature of price movement, it is preferable to generate forecasts using alternative methods. Hence, mixed forecasts, combining different techniques, are likely to produce better results in price forecasting for containerboard.

References

Alavalapati, J., Admowicz W., and M. Luckert (1997). “A Cointegration Analysis of Canadian Wood Pulp Prices”, *American Journal of Agricultural Economics*, 79, pp. 975-986.

Akaike, H. (1969). “Fitting autoregressive models for prediction”, *Annals of the Institute of Statistical Mathematics,* 21, pp. 243-247.

Arstrong, J.S., and F. Collopy (1992). “Error measures for generalizing about forecasting methods: Empirical comparisons”, *International Journal of Forecasting* 8, pp. 69-80.

Barro, R. and H. Crossman (1971). “A General Disequilibrium Model of Income and Employment”, *American Economic Review,* 62, pp. 82-93.

Baudin, A. (2001). “Inventory and Price Variations of Coniferous Sawnwood in the UK Market,” *Supply Chain Management for Paper and Timber Industries*, Vaxjo, pp. 77-98.

Booth D.L., Kanetkar V., Vertinsky I., and D. Whistler (1991). “An Empirical Model of Capacity Expansion and Pricing in an Oligopoly with Barometric Price Leadership: A Case Study of the Newsprint Industry in North America,’ *Journal of Industrial Economics* v. XXXIX(3),pp. 255-276.

Brannlund, R., Lofgren K.G., and S. Sjostedt (1999). “Forecasting Prices of Paper Products: Focusing on the Relations between Autocorrelation Structure and Economic Theory”, *Journal of Forest Economics* 5(1), pp. 23-44.

Buongiorno J, Farimani M., and W.J. Chuang (1982). “Econometric Model of Price Formation in the United States Paper and Paperboard Industry”, *Wood and Fiber Science* 15(1), pp. 28-39.

Buongiorno J. and H.C. Lu (1989). “Effect of Costs, Demand, and Labor Productivity on the Prices of Forest Products in the United States”, *Forest Science* 35(2), pp. 349-363.

Buongiorno, J. and J.K. Gilless (1980). “Effect of Input Costs, Economies of Scale, and Technological Change on International Pulp and Paper Prices”, *Forest Science* 26(2), pp. 261-275.

Cheng, B. (1999). “Causality Between Taxes and Expenditures: Evidence from Latin American Countries”, *Journal of Economics and Finance* 23(2), pp. 184-192.

Dickey, D., Bell, W., and R. Miller, (1986). “Unit Roots in Time series Models: Tests and Implications”, *American Statistician*, 40, pp. 12-26.

Ekstein, O. and G. Fromm (1968). “The Price Equation,” *American Economic Review*, 58(5), pp. 1159-1183.

Fildes, R., Hibon M., Makridakis S., and N. Meade (1998). “The Accuracy of Extrapolative Forecasting Methods: Additional Empirical Evidence”, *International Journal of Forecasting* 14, pp. 339-358.

Geweke, J., Meese R., and W. Dent (1984). “Comparing Alternative Tests of Causality in Temporal Systems: Analytic Research Results and Experimental Evidence”, *Journal of Money, Credit, and Banking*, 16, pp. 403-434.

Granger C.W.J. (1969). “Investigating Causal Relationship by Econometrics and Cross Sectional Method”, *Econometrica* 37, pp. 424-438.

Hay, G. (1970), “Production, Price, and Inventory Theory, “*American Economic Review*, 60, pp. 531-545.

MacKinnon, J. G. (1996). "Numerical Distribution Functions for Unit Root and Cointegration Tests," *Journal of Applied Econometrics*, 11, 601-618.

Makridakis, S. and M. Hibon (1979). “Accuracy of Forecasting: an Empirical Investigation”, *Journal of the Royal Statistical Society,* A142, pp. 97-145.

Makridakis, S. and M. Hibon (1997). “ARMA Models and the Box-Jenkins Methodology”, *Journal of Forecasting* 16, pp. 147-163.

Newbold, P., and C.W. Granger (1974). “Experience with Forecasting Univariate Time series and the Combination of Forecasts”, *Journal of the Royal Statistical Society* A137, pp. 131-165.

Stier J. C. (1985). “Implications of Factor Substitutions, Economies of Scale, and Technological Change for the Cost of Production in the United States Pulp and Paper Industry”, *Forest Science* 31(4), pp. 803-812.

Stigler , G.J. and J.K. Kindahl (1970). “The Behavior of Industrial Prices”, Columbia University Press, New York.

Toppinen, A., Laaksonen, S., and R. Hanninen (1996). “Dynamic Forecasting Model for the Finnish Pulp Export Price”, Silva Fennica, 30(4).

Venieris Y.P. (1973). “Sales Expectations, Inventory Fluctuations, and Price Behavior”, *Southern Economic Journal*, 40(2), pp. 246-261.

Appendix List of Abbreviations

AC	Autocorrelations
ADF	Augmented Dickey-Fuller Unit Root Test
AR	Autoregressive
ARIMA	Autoreggressive Integrated Moving Average Model
MA	Moving Average
MAPE	Mean Absolute Percentage Error
NSA	Not Seasonally Adjusted
PAC	Partial Autocorrelations
PPW	Pulp and Paper Week
RMSE	Root Mean Squared Error
SA	Seasonally Adjusted
VAR	Vector Autoregressive Model