GARCH effects in another market: Modeling and forecasting kraft prices and conditional volatility

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Abstract

This paper empirically studies price movements and volatility in several Kraft prices by using monthly data. Paper shows that ARMA models with GARCH specifications for the conditional volatility can characterize the prices quite well. The performance of alternative models in terms of in-sample and out-of-sample are investigated by using several statistical loss functions reveal that ARMA models with GARCH effects outperform in predicting future price changes in one-to-twelve months ahead. Out-of-sample forecasting experiments reveal also that $ARMA-GARCH$ models outperform simple AR models and exponential smoothing models in several forecast horizons ranging from one month to six months ahead. In longer terms, including nine and twelve months ahead, $GARCH$ models perform comparable to simple exponential and AR models with varying degree of success depending upon the loss function and *ex-post* measure of actual volatility used.

Keywords: Kraft prices, GARCH model, forecasting.

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1 Introduction

Characterization and understanding of volatility in any market is important as volatility provides a measure of overall market risk. Moreover characterization and understanding of risk is crucial for risk management purposes. Given the importance of the issue, there exists an extant literature on modeling and forecasting volatility and risk in assets, exchange rates and commodity markets. For an excellent survey of the literature and references see Anderson et al. (2005). Despite the importance of the issue very little research has been done in understanding volatility dynamics in Pulp and Paper markets. This paper seeks to fill this gap and contribute the volatility dynamics literature on commodities markets by developing alternative empirical models for volatility in Kraft prices and evaluating alternative models in terms of in-sample and out-of-sample predictive ability by using several statistical loss functions. To our best knowledge, Fromson (1997) is the only study which investigates the price volatility in Pulp and Paper industry. Fromson (1997) studies the volatility in pulp prices, but does not model volatility directly. This is the first study that undertakes modeling and forecasting Kraft price changes and conditional volatilities. In addition to a general interest to gain insights into the volatility dynamics in Kraft markets, there are several reasons why the findings of this exercise might be useful in practice for risk managers in the Kraft industry. At a substantive level, one may be interested in forecasting the volatility in Kraft and related markets. From a practical point of view, lacking with a formal and official futures market, firms in the Kraft industry might be forced to divert resources and funds from productive activities to predicting price movements and hedging activities that might potentially increase the burden and cost for the industry as a whole. Unpredictable price movements may also lead firms to be exposed to future income loses that may cause variability in firms present value of future income streams. It is also well known that volatility in the prices could lead to a number of serious consequences for the whole industry, like financial losses, excess capacity and difficulties in long-term financial planning. On the other hand, a better characterization of volatility dynamics and having the capability to forecast the volatility in the market prices can enable firms in industry to develop better risk management strategies in different horizons ranging from very short run to long run, and enhance their capability to make long-term strategic planning. Moreover, firms can prepare better production plans and they can prevent some degree of negative consequences of excess capacity in times of great uncertainty.

The literature on other commodities market has found that several commodity price change (and/or commodity return) series to be well described by $martingale{-}GARCH(1,1)$ models. See among many others, Baillie and Myers (1991), Baillie, Myers and Song (2006), and the references in Anderson et al. (2005) and Baillie (2006). In contrast to the results from commodity and assets markets, we find that the conditional mean process for monthly Kraft prices changes can be characterized approximately an Autoregressive Moving Average (ARMA) model rather than by a martingale process. This finding indicates that Kraft prices that are investigated have considerable persistence and cyclical dynamics in price changes and past information on the prices can be useful in predicting the future behavior of prices. This result also reveals that contrary to other commodity markets, Kraft markets are not efficient in the sense that the information on the past realizations of prices can predict the future movements of prices. Similar to other commodity markets however, our findings reveal that there is considerable evidence on time-variation in the volatilities of Kraft prices which can be modeled adequately by GARCH models.

Studies on volatility in financial, exchange rates and commodities markets tend to show that so called “GARCH effects” diminishes as the frequency of observations decreases. In other words, the GARCH effects are found to be prominent in daily and weekly data and less so for monthly data (see the papers cited in the previous paragraph). Our findings reveal that contrary to other commodity markets, there are significant GARCH effects at the monthly frequency in Kraft markets. Since high frequency price data is not available for Kraft prices, our results are limited to monthly series. Our findings show presence of considerable GARCH effects in the monthly Kraft prices. This finding is similar to early findings in exchange rate and financial asset returns (see for instance Engle 1986, Akgiray 1989) and studies on inflation rate dynamics (see for instance Baillie, Chung and Tieslau 1996) which report evidence of GARCH effects in the conditional volatility of several financial asset returns and inflation rates, (see also Anderson et al. 2005 for further references).

Majority of the studies which investigate volatility in financial and commodities markets explore predictive ability of alternative models in terms of their forecasting performance for the conditional volatility. In this paper, we both investigate performance of GARCH and other models in terms of not only their predictive ability for the future volatility but also future movements of price changes. From a methodological point of view, this exercise should provide useful insights as it allows us to explore if explicit modeling of higher conditional moments by GARCH models add anything new to ARMA models' predictive ability or not. Our out-of-sample forecasting exercises for the conditional mean (i.e. price change series) indicate that ARMA models with GARCH effects outperform the simple exponential and pure ARMA models with constant volatility in both short and longer horizons in terms of several statistical criteria. Hence, incorporating the information from higher moments of price movements enhances forecasting performance of our time series models. The out-of-sample forecasting predictive ability of GARCH models are compared with those of simple AR and exponential smoothing models. The results show that GARCH models outperform alternative models in predicting the dynamics of future conditional volatility in one-to-six months horizons and performs comparable in nine and twelve months horizons. In this study, we use several measures for the unobserved volatility, including absolute monthly price change, squared monthly price change and following the results in Anderson and Bollerslev (1998), quarterly sum of monthly absolute and squared price changes. Our findings show that irrespective of the *ex-post* volatility measure used, GARCH models outperform alternative models in one-to-nine months horizons in terms of several loss functions criteria used. GARCH models performs relatively poorly in twelve months horizons however. The rest of this study is organized as follows, section 2 provides a preliminary investigation of the data, section 3 presents and discusses briefly the empirical methods and findings of the study. In section 4, we display and discuss our out-of-sampling exercises results for the Kraft prices and their volatilities. The last section concludes the paper.

2 Data and Preliminary Analysis

The data used in this study are monthly US delivery prices from 01/1983 to 06/2001 for Northern Hardwood Kraft, Northern Softwood Kraft, Southern Softwood Kraft and Southern Hardwood Kraft. The values are in U.S dollars per metric ton of Kraft. The panels of Table 1 presents summary statistics and Lijung-Box tests for serial correlations for Kraft prices, percentage change in prices and absolute value of price changes over the sample period together with results from the application of unit root tests. Results indicate presence of substantial variation in prices of all Kraft types considered. Average monthly percentage changes in prices seem to be low with relatively high standard deviation. In a typical month, the average percentage change in prices seems to be in the order of about %0.9 with a standard deviation of about %5 per month. This indicates an average annualized price change of about %11 with an annualized standard deviation of %60, again indicating quite large variation in prices. Skewness and kurtosis values indicate that relative to normal distribution percentage price change series are negatively skewed with very large excess kurtosis values pointing the evidence of fat tails. This implies that relative to a normally distributed random variable, more negative realizations of price changes occur in our sample. The absolute percentage price change series have quite high skewness and kurtosis values consistent with the percentage change series. The reported statistics measures are quite similar to the results from other commodity and financial markets.

The reported Lijung-Box tests clearly indicate that all the series, prices, price changes and absolute percentage series, are highly serially autocorrelated. Compared to the empirical findings from the other commodity markets, findings here indicate that not only the prices and absolute price changes, but also the price changes are also serially correlated. This is striking as most studies on commodity and financial markets have found that price changes usually have very low serial correlation (i.e. price changes are close to a Martingale or a white noise process) while level series, i.e. prices, and absolute or squared changes in prices tend to be serially correlated. In order to further investigate the time series properties of Kraft prices, Table 1 also reports results from unit root tests applied to the price series, price changes and absolute price changes. As can be seen from the Table, both ADF (Said and Dickey 1984) and Phillips-Perron (PP, Phillips and Perron 1988) tests fail to reject a unit root null for all series at 5 percent significance level, except for South Hardwood for which ADF reject the null of unit root at 5% level while Phillips-Perron test fails to reject the same null. All the tests reject presence of a unit root in the price change series and absolute value of price changes at 5% significance level. This is expected with some evidence of unit root on the level series. Consistent with this evidence, we model the price change series by fitting $ARMA$ models.[1] Overall,

[1] Note that given the finding of a unit root for the price series, this implies that monthly price series follow an Integrated ARMA ($ARIMA$) process.

the analysis in this part reveal that Kraft prices are highly correlated, with some evidence of time varying volatility and excess kurtosis in price changes and absolute price changes.

3 ARMA and GARCH models for Kraft prices and their volatilities

We utilize ARMA and GARCH models in this study to empirically investigate the joint dynamics of price movement and time-varying volatility in Kraft market. Econometric modeling of the time-varying volatility occurred relatively recently in 1980s. The Autoregressive Conditional Heteroscedasticity (ARCH) models introduced first by Engle (1982) and modified by Bollerslev (1986) and labeled as Generalized ARCH (GARCH) model and their extensions have become popular both among practitioners and researchers. GARCH models are able to describe certain properties of economic time series, such as volatility clustering and excess kurtosis. GARCH family of models allows one to model persistence and serial correlation in volatility dynamics parsimoniously. The GARCH processes approximate volatility dynamics in moving averages of lagged squared errors and lagged auto regressions of variances. Today's conditional variance functions are linked to the lagged conditional variances and lagged squared errors in a linear fashion. They are flexible enough to model joint dynamics of conditional mean, say prices and the conditional variances in a market. The GARCH family of models has been used in exchange rate, stock and other commodity markets extensively both to model volatility dynamics and forecasting. A survey of this extant literature can be found in Diebold and Lopez (1995), Bollerslev, Engle, and Nelson (1994), Diebold (2004) and Anderson et al. (2005). Since all of the models employed in this study are not new, rather it is the implementation of the models in the context of Kraft prices which is novel, we do not provide a throughout presentation of models here and refer readers to look at the aforementioned papers.

Table 2 report estimation results and diagnostic statistics for the estimated pure $ARMA$ and $ARMA-GARCH$ models. The sample period is 01/1983-06/2000. The observations for the last year of the sample is left out for forecasting exercises. After careful investigation several alternative specifications in terms of extensive diagnostic tests, we have found an $AR(3)$ model with a seasonal moving average component in the second lag (i.e. $AR(3)$ with an $MA(2)$ seasonal factor, from now on this model will be referred by pure $ARMA$ or simply $ARMA$ model) characterizes the time series dynamics of all price change series relatively better than the alternatives.[2] The columns two through five report the results from the $AR(3)$ with an $MA(2)$ seasonal component model for the conditional mean series. Careful inspection of the results in the Table reveals that squared residuals of the model displays serial correlation, suggestive of an $ARCH$ type process. The last row of the Table report results from LM test for presence of $ARCH$ affects in the residuals. Both presence of serial correlation tests and LM tests for ARCH effects in the residuals indicate that the estimated models will be mis-specified if one ignores the serial correlation in the higher moments of residuals from the estimated $ARMA$ models.

After some preliminary investigation with several different specifications, for all Kraft types, except for the Southern softwood, we have found that a low order $GARCH(1, 1)$ specification models the conditional volatility dynamics quite well. On the other hand, for the Southern Softwood, a $GARCH(3, 1)$ specification provided best fit in terms of residual diagnostics. The following $AR(3)-GARCH(1,1)$ model with a $MA(2)$ seasonal

[2] Several diagnostic tools and information criteria (such as Akaike and Bayesian) are used in selecting the alternative specifications. The results of $ARMA(p, q)$ modeling are not fully reported to conserve space. These can be obtained upon request.

component (from now on we will refer this model by $ARMA-GARCH$ model),

$$r_t = \mu + \phi_1 r_{t-1} + \phi_2 r_{t-2} + \phi_3 r_{t-3} + \varepsilon_t + \theta_2 \varepsilon_{t-2} \tag{1}$$
$$\sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 + \alpha_1 \varepsilon_{t-1}^2$$

where $\varepsilon_t = \eta_t \sigma_t$, and η_t is a Gaussian white noise process with $\sigma_\eta = 1$, is found to the best fitting model for Northern hardwood series. For Northern softwood and Southern hardwood series, an $AR(3)-GARCH(1,\,1)$ model found to be the best fitting model. For the Southern softwood series however, an $AR(3)-GARCH(3,1)$ model fit the best (i.e. a $GARCH(3,\,1)$ specification $\sigma_t^2 = \omega + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2 + \beta_3 \sigma_{t-3}^3 + \alpha_1 \varepsilon_{t-1}^2$, is estimated). Note that in the pure $ARMA$ model $\sigma_t^2 = \sigma^2$ for all t. The $GARCH$ model allows us to model conditional volatility in the market explicitly and makes it a function of the past shocks (e.g. unexpected inventory accumulation, or changes in the domestic and international market conditions, or technology shocks etc.) and past level of volatility. These properties of models are quite appealing as they allow one to model volatility clustering and impacts of extreme events relatively easily. Note that the parameter α_1 shows the extent to which a volatility shock today feeds through into next period's volatility while $\alpha_1+\beta_1$ in $GARCH(1,1)$ model and $\alpha_1+\beta_1+\beta_2+\beta_3$ in the $GARCH(3,1)$ model measure the rate at which this effect dies out over time (Campbell et al., 1997, p.483). In other words, α_1 indicates the level of persistency in "volatility of volatility" therefore, the larger is this parameter the more "persistent" the volatility and hence the risk in the market is. Note also that the unconditional variance (i.e. $E(\varepsilon_t^2)$) is given by $\sigma^2 = E(u_t^2) = \omega/(1-\alpha_1-\beta_1)$, provided $\alpha_1+\beta_1 < 1$ in the case of $GARCH(1,1)$ model and by $\sigma^2 = E(u_t^2) = \omega/(1-\alpha_1-\beta_1-\beta_2-\beta_3)$, provided that $\alpha_1+\beta_1+\beta_2+\beta_3 < 1$ in the case of $GARCH(3,\,1)$ model.

Estimation results from the $ARMA-GARCH$ models are presented in the remaining columns of Table 2. It should be emphasized that for Northern softwood and Southern hardwood series the seasonal moving average component becomes insignificant with the introduction of GARCH errors. The parameter estimates indicate that all GARCH parameters are statistically significantly different from zero and $ARMA-GARCH$ models outperforms pure $ARMA$ in terms of in-sample fit in several dimensions for the series we consider in this study. As can be seen from Table, likelihood values, and likelihood ratio LR tests as well as the Bayesian information criteria, SIC, select the $ARMA-GARCH$ models. Note both Lijung-Box test for the serial correlation in the squared residuals and p-values for the presence of ARCH effects indicate that $GARCH$ models are superior. It should also be noted that despite the increase in the skewness statistics in the residuals from $ARMA-GARCH$ models, there is significant decline in the excess kurtosis values compared to the Kurtosis values from pure $ARMA$ models.

The estimated α_1 values indicate that volatility of Northern hardwood and Southern softwood price changes are much more persistent than the Northern softwood and Southern hardwood. Estimated parameter values also reveal that sum of α_1 and β_1 (and also β_2 and β_3) are close to unity which is similar to findings from other commodity and financial markets.[3] Estimated parameter values also indicate that estimated $GARCH$ models are stationary. The last row of Table 2 also provide implied unconditional standard deviation from the $GARCH$ models. The reported results are quite close to the standard deviation estimates presented in Table 1 for the price change series. Overall reported findings reveal that $ARMA-GARCH$ models perform better in modeling the dynamics of Kraft prices than the pure ARMA models.

[3]Another model that can be entertained is the long memory GARCH model of for example, Baillie, Bollerslev and Mikkelsen (1996). The given the limited size of the data, we do not pursue this here.

4 Out-of-Sample Forecasting of Kraft Price Change and Volatilities

In this part of the paper, we utilize the models from the previous part to compare and contrast their out-of-sample forecasting performance in terms of various statistical criteria both for the prices changes and their volatilities. Specifically, our purpose is to consider the out-of-sample predictive ability of simple Exponential smoothing, ARMA models without GARCH effects and ARMA with GARCH in the errors models for predicting Kraft price changes and their volatility.

4.1 Predictive Ability of Alternative Models for Monthly Price

In order to evaluate predictive ability of alternative models for the level series, i.e. Kraft price change series, we use three statistical loss functions: root mean squared error (MSE), mean percentage absolute error (APE), and Theil's U-statistic U. Mean squared error provides a quadratic loss function which disproportionately weights large forecast errors more heavily relative to mean percentage absolute error, and hence the former may be particularly useful in forecasting situations when large forecast errors are disproportionately more serious than small errors. This may, however, also be viewed as a disadvantage if large errors are not disproportionately more serious. MAPE is a relative measure, compared to MSE, it is a percentage error, and hence its value is bounded between 0 and 1. MAPE also has the advantage that for a random walk in the prices (i.e. a zero forecast for the percentage price changes), the criterion will take the value one, so that if the forecasting model gives a MAPE smaller than one, it is superior to the random walk model. Theil's statistic compares the proportion of forecast errors from a given model to that of a benchmark model, usually a random walk model. Hence a value of one implies that the model under consideration and the benchmark model are equally (in)accurate, while a value of less than one implies that the model is superior to the benchmark.

The results for the Kraft price change forecasts under statistical evaluation methods discussed above are presented in panels of Table 3. The forecasts from Exponential, pure ARMA, and ARMA-GARCH models are obtained and statistical evaluation measures computed for one, three, six, nine and twelve months ahead(i.e. 2000:07, 2000:9, 2000:12, 2001:03, and 2001:06). ARMA-GARCH model seems to be the winner in terms all criteria for almost all the forecast horizons considered. This finding is consistent with the findings from the in-sample fit of the $ARMA-GARCH$ models. The obvious loser is the simple exponential smoothing model in any of the forecasting horizon. As we would expect, statistical measures increases for all models as the forecast horizon increases for all Kraft types. This indicates our models tend to forecast less accurately as the forecast horizon gets longer. This, however, is more severe for exponential smoothing and pure $ARMA$ models than the $ARMA-GARCH$ models.

4.2 Predictive Ability of Alternative Models for Kraft Price Volatilities

The predictive ability of alternative models for the conditional volatility of Kraft price changes are evaluated by using MSE, Mean Absolute Error (MAE) and Bias Proportions (BP) and percentage of over predictions ($\%OP$)[4]. In all of these measures, the smaller is the statistical measure the more accurate is the forecast from a given model. We

[4]Note that bias proportions measure how far the mean of the forecast is from the mean of the actual series, see also Brooks and Persand (2003) for more on forecast evaluation for conditional volatility. We have also sued loss functions such as $MAPE$ and Theil's U statistic discussed in the previous section. Since results were qualitatively similar, we do not report the results from all loss functions to conserve space. These can be obtained from the author upon request.

compare predictive ability of $GARCH$ model with that of an $AR(p)$ model fitted to absolute (and squared) price changes, where the lag order p is chosen by AIC criteria, and a simple exponential smoothing method. Unlike price changes, volatilities are not directly observable from the market. Therefore, in order to evaluate the predictive ability of forecasts from alternative models, we need to make an auxiliary assumption about how the *ex-post* or realized volatilities are calculated. The vast majority of existing papers, use absolute returns or its power transformations, such as squared returns of the frequency of the data as the measure of realized volatility. Consistent with this approach a measure of ex-post monthly volatility will be absolute value of the price change or the squared price change. While this method is simple and intuitively plausible, Andersen and Bollerslev (1998) suggest that "same-frequency" squared (and absolute) returns are an unbiased but extremely noisy measure of the latent volatility. They argue that a much better approximation to volatility would be obtained by summing the absolute values or squares of higher frequency price changes or returns. The usefulness of this approach is somewhat limited as it requires existence of high frequency price data. Since in this paper we focus on forecasting one, three, six nine and twelve-month ahead, in addition to the absolute price changes and their squares, we also utilize a measure similar to Andersen and Bollerslev (1998)'s in which we sum three-month absolute prices changes and squared price changes. In other words, we use $\sum_{i=1}^{3} |r_{t-i}|$ and $\sum_{i=1}^{3} r_{t-i}^2$ where r_{t-i} is the monthly price change over the month i. All and all, we use four measures of latent volatility process, namely absolute and squared monthly price changes, and three-month sum of monthly squared and absolute price changes as measures of *ex-post* volatility (see also the discussion in Brooks and Persand (2003) on the appropriateness of such volatility measures).

In Tables 4 and 5, we report results from alternative models with three statistical loss functions discussed above for the realized volatility measures, absolute price changes and three-month sum of absolute price changes.[5] Reported results in Table 4 reveal that GARCH model achieves the lowest root mean squared error and mean absolute error measures for 1, 3, and 6 months horizons under any *ex-post* measure volatility. The MSE and MAE values for the GARCH model is considerably low compared to alternative models for one through six months ahead forecasts. For nine and twelve months-ahead forecasts, MSE and MAE provides mixed results, selecting either the simple exponential model or the GARCH model. Exponential smoothing model beats GARCH model in most of the cases in nine and twelve months forecasts by MSE criteria. MAE criteria selects GARCH model in nine months in most cases under any measure of actual volatility. MAE chooses exponential smoothing model in twelve months forecast we use the absolute price change and (squared price change, not reported in the table), as the actual volatility measure, and GARCH model if we use the three month sum of absolute(squared) price change in majority of Kraft types. Overall, GARCH model outperforms alternative models in short to medium terms in terms of loss functions which are based on mean squared error and absolute error, while for longer horizons results are mixed and both exponential and GARCH models can perform equally well.

In Table 5, we report evaluation of alternative models for forecasting future volatility in terms of two more criteria, namely the percentage of times a given model over predicts the volatility in three, six, nine and twelve months and bias proportions discussed as in Brooks and Presand (2003) Pindyck and Rubinfeld (1998). As the results in the Table indicate GARCH model beats alternatives in terms of achieving the lowest $\%OP$ measures for all horizons under any measure of *ex-post* volatility measure used. Both AR and exponential smoothing models over predicts at least fifty percent of the time under any measure of actual volatility for all Kraft types. Moreover, they tend to over

[5] The results from squared price changes and sum of three-month squared price changes are qualitatively similar and not reported for space considerations. These results can be obtained from the author upon request.

predict more frequently under absolute/squared price change *ex-post* measure of volatility than the three-month sum of absolute/squared price change measure. GARCH model also outperforms the alternative models in terms of BP measure in three, six and nine months ahead under monthly absolute/squared price change measure of actual volatility. On the other hand, results are mixed in twelve months ahead forecasts in terms of bias proportions criteria. In twelve-month forecasting, exponential smoothing model is the winner for all Kraft types in terms of BP under monthly absolute(squared) price change measure of volatility and AR model becomes the winner under three-month sum of absolute(squared) monthly price change measure of actual volatility. Overall results in Table 5 reveal that GARCH model performs quite well in terms of obtaining lower $\%OP$ and BP compared to alternative models. Findings reveal that $ARMA-GARCH$ model performs quite well not only in terms of predicting monthly price changes but also their volatilities for all Kraft prices considered in this study.

5 Conclusion

In this study we investigated modeling monthly price changes and conditional volatility in several Kraft prices. We have found that the price series are highly persistent with some evidence of stochastic trends. Our findings also revealed time-varying volatility in price changes. Then, we formally, modeled the stochastic trend and cyclical dynamics in price changes and second conditional moments ARMA model, and ARMA-GARCH models. Our findings indicated that within the sample, $ARMA$ models with $GARCH$ in the errors models the time series dynamics of monthly Kraft prices quite well. We have also conducted several exercises to measure the predictive ability of our $ARMA-GARCH$ models with some relatively simple alternatives and found that $ARMA-GARCH$ models does beat the alternative models in out-of-sample forecasting of monthly price changes in terms of several statistical loss functions.

In order to further investigate the gain in including $GARCH$ terms for the conditional volatility of price changes, we have also conducted expansive forecasting experiments from $ARMA - GARCH$ and two simple models, namely the $AR(p)$ model that is fitted to monthly absolute(squared) price change and three-month sum of absolute(squared) price change series and the simple exponential smoothing model. By using several statistical loss functions and different measures of *ex-post* actual volatility measures, we have found that $ARMA-GARCH$ models performed better than the alternatives in short to medium term forecasts, namely forecasts from one-month to six months ahead. In nine and twelve months horizons, both $ARMA - GARCH$ and alternative models performed well in varying degrees. Overall, findings in the paper indicate usefulness of $GARCH$ models in terms of characterizing the time series dynamics of price series in Kraft markets and forecasting price movements both in terms of levels and in terms of conditional volatility.

It should be noted that even in the low frequency monthly series, we have found considerable evidence of GARCH effects in Kraft prices. The findings of the paper indicate that inclusion of GARCH effects should enhanced the performance of $ARMA$ models considerably in several dimensions. Our findings also reveal that from a risk management point of view it might be useful to incorporate the information from the higher conditional moments of prices as the results show in this paper, second conditional moments varies over time and it is not constant. This indicates the overall market risk is time-varying and a dynamic approach is needed in designing optimal hedging policies. We should also emphasize that the findings of the paper are exploratory and further research needs to address the issue further by using high frequency data from several Kraft markets. A general investigation of these issues should also enhance our understanding of price dynamics in other Pulp and Paper markets.

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Table 1: Summary statistics and Lijung-Box test for serial correlations

	min	max	mean	med	m_3	m_4	sdev	ADF	$P-P$	$Q(6)$	Q(12)
Series					Northern Hardwood						
P_t	340.0	860.0	532.5	510.0	0.7	2.6	129.4	-2.60	-2.68	960.2	1229.1
r_t	-31.0	13.1	0.1	0.0	-1.2	12.5	4.8	-4.11^{*}	-4.00^{*}	91.2	93.2
$\|r_t\|$	0.0	31.0	2.8	1.4	2.9	16.6	3.9	-5.44^{*}	-13.22^{*}	24.0	28.9
					Northern Softwood						
P_t	400.0	985.0	595.0	575.0	0.7	2.7	136.7	-2.68	-2.48	1010.0	1374.3
r_t	-20.6	10.9	0.1	0.0	-0.7	8.8	3.9	-4.69^{*}	-4.55^{*}	112.8	117.2
$\|r_t\|$	0.0	20.6	2.4	1.2	2.3	11.0	3.2	-3.63^{*}	-12.09^{*}	28.3	44.2
					Southern Hardwood						
P_t	325.0	850.0	514.3	490.0	0.7	2.7	130.7	$-3.01^{\dagger}$	-2.73	947.3	1205.1
r_t	-32.4	13.7	0.1	0.0	-1.1	11.7	5.1	-3.97^{*}	-3.88^{*}	93.4	94.9
$\|r_t\|$	0.0	32.4	2.9	1.4	2.7	15.4	4.1	-6.20^{*}	-12.20^{*}	23.4	31.7
					Southern Softwood						
P_t	345.0	880.0	546.6	520.0	0.7	2.7	135.1	-2.73	-2.65	966.0	1265.3
r_t	-29.2	12.6	0.1	0.0	-1.1	10.9	4.7	-5.90^{*}	-5.86^{*}	103.7	105.0
$\|r_t\|$	0.0	29.2	2.8	1.6	2.7	14.6	3.8	-6.04^{*}	-11.405^{*}	34.4	46.3

Key: P_t is the monthly price for four Kraft types. r_t is the monthly price change and $|r_t|$ is the absolute value of the monthly price change. *med* is the sample median, m_3 is the sample skewness, m_4 is the Kurtosis and *sdev* is the sample standard deviation. The MacKinnon simulated 1% and 5% critical values for ADF and PP tests are -3.461, -2.875 respectively. $*$ and $\dagger$ indicate rejection of unit root null at 1% and 5% significance levels respectively. $Q(6)$ and $Q(12)$ stand for the Lijung-Box statistics for testing serial correlation for a given series up to 6 and 12 months period respectively. The 5% asymptotic critical values for $Q(6)$ and $Q(12)$ are 12.592 and 21.026 respectively.

Table 2: Estimated $ARMA(p, q)$ and $ARMA(p, q) - GARCH(m,\ k)$ models for monthly Kraft Price changes

	$ARMA(p,\ q)$ Results				$ARMA(p,\ q) - GARCH(m,\ k)$ Results			
	N.Hd.	N.Sd.	S.Hd.	S.Sd.	N.Hd.	N.Sd.	S.Hd.	S.Sd.
$\hat{\mu}$	0.379	0.313	0.391	0.354	1.068	0.816	0.804	0.580
	(0.592)	(0.619)	(0.617)	(0.586)	(1.286)	(0.989)	(2.123)	(0.903)
$\hat{\phi}_1$	0.293	-0.416	0.299	0.365	0.288	0.231	0.230	0.276
	(0.137)	(0.176)	(0.119)	(0.120)	(0.108)	(0.059)	(0.104)	(0.095)
$\hat{\phi}_2$	-0.430	0.408	-0.445	-0.446	-0.135	0.164	0.232	-0.143
	(0.186)	(0.124)	(0.145)	(0.153)	(0.113)	(0.063)	(0.092)	(0.101)
$\hat{\phi}_3$	0.287	0.311	0.275	0.253	0.500	0.440	0.381	0.473
	(0.108)	(0.095)	(0.103)	(0.120)	(0.076)	(0.069)	(0.066)	(0.069)
$\hat{\theta}_2$	0.769	0.778	0.813	0.771	0.567	.	.	0.562
	(0.136)	(0.183)	(0.099)	(0.109)	(0.067)	.	.	(0.068)
$\hat{\omega}$	.	.	.	.	1.767	0.750	0.831	1.145
	.	.	.	.	(0.796)	(0.441)	(0.324)	(0.477)
$\hat{\beta}_1$	.	.	.	.	0.466	0.715	0.700	0.148
	.	.	.	.	(0.121)	(0.067)	(0.117)	(0.059)
$\hat{\beta}_2$	.	.	.	.	.	.	.	0.605
	.	.	.	.	.	.	.	(0.048)
$\hat{\beta}_3$	.	.	.	.	.	.	.	-0.214
	.	.	.	.	.	.	.	(0.014)
$\hat{\alpha}_1$	.	.	.	.	0.502	0.225	0.212	0.423
	.	.	.	.	(0.108)	(0.065)	(0.043)	(0.076)
ll	-580.2	-540.7	-588.5	-571.8	-548.4	-512.8	-568.7	-530.6
SIC	5.762	5.379	5.843	5.680	5.531	5.160	5.141	5.410
$p - Q(12)$	0.816	0.011	0.684	0.592	0.713	0.300	0.160	0.505
$p - Q^2(12)$	0.000	0.000	0.004	0.000	0.193	0.366	0.561	0.157
m_3	0.127	0.382	0.206	0.228	0.634	0.959	0.533	0.621
m_4	7.240	5.309	7.079	6.820	4.007	4.236	4.642	3.817
$p - ARCH$	0.018	0.000	0.014	0.001	0.140	0.228	0.700	0.359
LR	.	.	.	.	63.6*	55.8*	39.6*	82.4*
$\hat{\sigma}$	.	.	.	.	6.65	3.54	3.1	5.49

Key: Values in parentheses underneath the parameter estimates are the robust Newey-West standard errors. ll is the log likelihood value, SIC is the Schwartz Information Criterion, $p - Q(12)$ and $p - Q^2(12)$ are the values for the Lijung-Box test applied to the residuals and squared standardized residuals from the estimated models respectively. $pARCH$ is the maximal $p-$ value for test of presence of ARCH effects in the residuals lags 1 throughout 6. m_3 and m_4 represent the estimated excess Skewness and Kurtosis statistics from the residuals. LR is the robust likelihood ratio test for testing the null of $ARMA$ model against the alternative of $ARMA - GARCH$ model. $*$ indicates rejection of the null at 5% level. N.Hd., N.Sd., S.Hd., and S.Sd. stand for Northern hardwood, Northern softwood, Southern hardwood and Southern softwood respectively.

Table 3: Forecast Comparisons for monthly Kraft price changes

steps	1-month			3-month			6-month			9-month			12-month		
							Northern Hardwood								
	MSE	*APE*	*U*	*MSE*	*APE*	*U*	*MSE*	*APE*	*U*	*MSE*	*APE*	*U*	*MSE*	*APE*	*U*
EXP	3.31	55.6	.	1.74	21.3	0.47	1.56	21.1	0.47	3.56	31.2	0.49	5.58	48.1	0.49
ARMA	2.94	63.8	.	1.50	20.1	0.40	**1.30**	18.5	0.41	1.97	25.5	0.42	2.94	42.3	0.42
GARCH	**1.59**	**34.4**	.	**1.04**	**11.5**	**0.23**	1.33	**11.3**	**0.34**	**1.89**	**18.3**	**0.38**	**2.50**	**34.5**	**0.32**
							Northern Softwood								
EXP	4.90	85.2	.	2.54	33.1	0.81	1.99	17.9	0.80	2.80	26.0	0.77	4.91	55.1	0.50
ARMA	4.02	91.2	.	2.53	30.4	0.71	**1.66**	15.2	0.79	**1.69**	22.3	0.70	2.47	38.7	0.45
GARCH	**1.35**	**30.6**	.	**0.02**	**10.2**	**0.22**	1.164	**5.1**	**0.34**	1.70	**12.1**	**0.35**	**2.17**	**32.2**	**0.36**
							Southern Hardwood								
EXP	3.21	61.402	.	1.92	25.0	0.55	2.21	19.8	0.55	3.33	29.1	0.55	5.50	**38.1**	0.57
ARMA	2.91	62.114	.	1.72	20.7	0.45	**1.40**	16.0	0.45	2.00	**22.1**	0.44	3.59	39.1	0.43
GARCH	**1.37**	**29.2**	.	**0.81**	**9.7**	**0.18**	1.156	**6.6**	**0.31**	**1.79**	23.5	**0.32**	**3.14**	38.5	**0.34**
							Southern Softwood								
EXP	3.68	78.0	.	2.67	37.8	0.70	2.21	36.7	0.84	2.99	49.9	0.81	5.50	78.9	0.77
ARMA	3.53	77.7	.	2.13	25.9	0.61	1.63	23.2	0.59	2.01	34.1	0.51	3.07	43.3	0.40
GARCH	**1.53**	**33.7**	.	**0.90**	**11.2**	**0.21**	**1.12**	**8.6**	**0.32**	**1.52**	**17.78**	**0.30**	**2.70**	**32.6**	**0.32**

Key: EXP stands for the simple exponential smoothing model, ARMA is the ARMA model without GARCH effects in the conditional second moments, GARCH is the ARMA-GARCH model discussed in the text. *MSE* is the mean squared error, *APE* is the mean absolute percentage error and *U* is the Theil's *U*-statistic. The shaded values indicate the lowest value of loss function among the alternatives.

Table 4: Volatility Forecast Comparisons from alternative models

a. Monthly absolute price change as *ex-post* measure of volatility

steps	1-month		3-month		6-month		9-month		12-month	
	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
					Northern Hardwood					
AR_p	10.10	10.10	16.30	15.56	15.30	14.89	14.49	14.13	19.23	17.81
EXP	4.01	4.01	6.83	6.58	8.11	6.36	**5.52**	5.04	**5.21**	**4.80**
$GARCH$	**0.00**	**0.00**	**0.01**	**0.03**	**1.20**	**0.49**	5.64	**3.26**	9.18	6.29
					Northern Softwood					
AR_p	8.29	8.29	15.05	14.08	13.77	13.21	13.31	12.90	23.03	19.52
EXP	2.98	2.98	5.77	5.48	5.42	5.20	**4.72**	4.22	**5.06**	**4.64**
$GARCH$	**0.00**	**0.00**	**0.02**	**0.00**	**1.18**	**0.48**	6.48	**3.75**	9.95	6.86
					Southern Hardwood					
AR_p	11.55	11.55	17.93	17.29	16.88	16.47	16.75	16.42	29.03	19.52
EXP	8.81	8.81	11.68	11.52	11.53	11.43	9.88	9.19	**8.69**	7.53
$GARCH$	**0.00**	**0.00**	**0.00**	**0.00**	**1.22**	**0.50**	**7.19**	**4.25**	9.95	**4.43**
					Southern Softwood					
AR_p	8.29	8.29	15.00	13.32	12.06	11.92	11.11	10.31	20.34	17.12
EXP	2.98	2.98	5.71	5.82	5.12	4.17	**4.12**	4.28	**5.05**	**4.48**
$GARCH$	**0.00**	**0.00**	**0.02**	**0.00**	**1.16**	**0.47**	5.18	**3.44**	8.17	4.69

b. Three-month sum of monthly absolute price change as *ex-post* volatility measure

	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
					Northern Hardwood					
AR_p	10.10	10.10	12.93	12.49	13.60	13.35	12.28	11.78	12.47	12.14
EXP	4.01	4.01	**3.53**	3.51	5.06	4.82	**5.10**	4.56	**10.27**	**8.01**
$GARCH$	**0.00**	**0.00**	3.77	**3.08**	**2.92**	**2.03**	8.39	**3.62**	16.56	11.63
					Northern Softwood					
AR_p	8.29	8.29	11.72	11.01	12.05	11.70	10.84	10.41	15.27	13.73
EXP	2.98	2.98	**2.49**	**2.45**	3.98	3.69	5.46	4.38	**11.83**	8.68
$GARCH$	**0.00**	**0.00**	3.71	3.03	**2.88**	**2.00**	**3.61**	**3.24**	11.88	**6.66**
					Southern Hardwood					
AR_p	11.55	11.55	14.53	14.08	15.15	14.91	13.90	13.59	20.47	17.70
EXP	8.81	8.81	8.40	8.39	10.00	9.86	**8.75**	8.06	**11.35**	10.21
$GARCH$	**0.00**	**0.00**	**3.83**	**3.13**	**2.97**	**2.06**	10.93	**7.08**	13.85	**10.04**
					Southern Softwood					
AR_p	8.29	8.29	11.72	11.05	12.05	11.70	10.84	10.41	15.27	13.73
EXP	2.98	2.98	**2.49**	**2.45**	3.98	3.69	**5.46**	**4.38**	**11.83**	**8.68**
$GARCH$	**0.00**	**0.00**	0.02	0.00	**2.88**	**2.00**	9.61	6.24	12.03	**8.68**

Key: MSE is the mean squared error and MAE is the mean absolute error. AR_p, EXP and $GARCH$ refer to the forecasting models from an $AR(p)$, simple exponential smoothing, and $ARMA-GARCH$ models respectively.

Table 5: Volatility Forecast Comparisons from alternative models

a. Monthly absolute price change as *ex-post* measure of volatility

steps	3-month		6-month		9-month		12-month	
	$\%OP$	BP	$\%OP$	BP	$\%OP$	BP	$\%OP$	BP
				Northern Hardwood				
AR_p	100.0	0.91	100.0	0.95	100.0	0.83	0.83	0.80
EXP	100.0	0.93	100.0	0.95	100.0	0.66	0.75	**0.20**
$GARCH$	**0.00**	**0.05**	**0.17**	**0.17**	**0.33**	**0.33**	**0.25**	0.47
				Northern Softwood				
AR_p	100.0	0.88	83.3	0.91	76.7	0.83	75.0	0.79
EXP	100.0	0.90	100.0	0.92	88.9	0.66	75.0	**0.03**
$GARCH$	**00.0**	**0.02**	**00.0**	**0.17**	**22.2**	**0.33**	**16.7**	0.48
				Southern Hardwood				
AR_p	100.0	0.92	100.0	0.95	100.0	0.89	91.7	0.71
EXP	100.0	0.97	100.0	0.88	88.9	0.86	83.3	0.67
$GARCH$	**00.0**	**0.00**	**00.0**	**0.20**	**11.0**	**0.33**	**16.7**	**0.46**
				Southern Softwood				
AR_p	100.0	0.88	100.0	0.91	88.9	0.79	66.7	0.72
EXP	100.0	0.90	100.0	0.92	88.9	0.41	66.7	**0.11**
$GARCH$	**00.0**	**0.00**	**00.0**	**0.16**	**22.2**	**0.34**	**16.7**	0.48

b. Three-month sum of monthly absolute price change as *ex-post* volatility measure

	$\%OP$	BP	$\%OP$	BP	$\%OP$	BP	$\%OP$	BP
				Northern Hardwood				
AR_p	100.0	0.74	100.0	79.0	77.8	0.28	58.3	**0.00**
EXP	100.0	0.99	100.0	91.0	100.0	**0.17**	83.3	0.09
$GARCH$	**00.0**	**0.67**	**16.7**	**0.48**	**44.4**	0.45	**58.3**	0.49
				Northern Softwood				
AR_p	100.0	0.79	100.0	0.82	66.7	**0.15**	66.7	**0.13**
EXP	100.0	0.97	100.0	0.86	88.9	0.29	83.3	0.18
$GARCH$	**00.0**	**0.67**	**0.00**	**0.48**	**11.0**	0.45	**25.0**	0.48
				Southern Hardwood				
AR_p	100.0	0.93	100.0	0.93	77.8	0.43	66.7	**0.10**
EXP	100.0	1.00	100.0	0.97	91.7	0.53	75.0	0.11
$GARCH$	**00.0**	**0.67**	**16.7**	**0.48**	**33.3**	**0.42**	**33.3**	**0.49**
				Southern Softwood				
AR_p	100.0	0.80	100.0	0.82	66.7	0.15	50.0	**0.13**
EXP	100.0	0.92	100.0	0.86	100.0	**0.05**	66.7	0.18
$GARCH$	**0.00**	**0.67**	**0.00**	**0.48**	**0.22**	0.31	**0.17**	0.47

Key: $\%OP$ is the percentage of over predictions and BP is the bias proportions.