**Forecasting Commodity prices with switching regimes:
A MS-VAR approach for fish meal price**

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Abstract: The objective of this paper is to present a parsimonious forecasting model of the fish meal price. The focus is on the soybean meal market's impact on the fish meal price together with the stocks-to-use as an indicator of demand and supply conditions. A salient feature of the fish meal market is the impact of El Niño events on fish meal supply. This possibly leads to two different price regimes, one where the fish meal price is highly correlated with the soybean meal price, and another, during El Niño events, where fish meal supply is low and the fish meal price is not strongly correlated with the soybean meal price. The results from the Markov-switching autoregressions indicate two price regimes where one is mostly governed by the soybean meal price while the other is governed by the level of stocks-to-use.

Keywords: Fish meal market, price regimes, Markov-switching autoregression.

1. Introduction

The main objective of this paper is to examine whether a Markov-switching vector autoregressive (MS-VAR) model improves modeling and forecasting of fish meal prices. Traditionally, autoregressive integrated moving average (ARIMA) and restricted vector autoregressive (VAR) models have showed the best forecasting performance in agricultural economics compared with more basic forecasting methods like naïve models, extrapolation, and other univariate models (Allen, 1994; Guttormsen, 1999). Commodity price movements have, however, certain built-in non-linear characteristics due to the nature of commodity markets, which might call for a non-linear approach like the MS-VAR model.

Reliable forecasts of commodity prices are an important tool for risk management. Not the least for salmon aquaculture, considering that feed costs account for over 50% of the variable costs, where fish meal together with fish oil are by far the largest feed inputs in terms of costs. A study by Guttormsen (2002) indicates that substitutability between feed and other inputs in salmon aquaculture is close to zero, further emphasizing the vulnerability of feed producers and fish farmers to changing raw material prices. Good forecasts are therefore important for making hedging decisions like ones suggested in earlier studies (Gjerde, 1989; Vukina and Anderson, 1993).

Commodity markets have a price floor by construction, as one does not observe negative prices. Consequently prices are able to spike upwards, but are limited in their downward movements, creating an asymmetry in price movements. Storage accentuates the asymmetric price pattern by being more effective at eliminating exceedingly low prices, by pulling out stocks from the market, than vice versa, since it is impossibility to carry negative inventories (Wright and Williams 1982). In other words, in periods with supply shortages stocks are

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usually depleted and thereby create higher and more volatile prices, while in periods with normal supply producers can stabilize prices by e.g. withholding stocks from the market when prices are getting undesirable low. The asymmetry of commodity price movements complicates accurate modeling and forecasting since it leaves linear estimation methods inappropriate in the sense that the underlying price mechanisms is not linear.

A MS-VAR model might alleviate these difficulties. Usually Markov switching models are reserved for financial and macroeconomic data dealing with issues like business cycles, core inflation, and interest rate volatility.[1] Yet, Markov switching models might also be called for in commodity markets with multiple price regimes since it potentially provides more accurate description of the price formation process and better forecasts. It is not obvious, however, that asymmetries in commodity prices are pronounced enough to justify such an approach, or for that matter best described as being a result of multiple price regimes. It is therefore important to consider whether a commodity market is plausibly described as having more than one price regime. A few studies suggest this is the case for the fish meal market (Tveterås and Tveterås, 2002; Asche and Tveterås, 2000).

More specifically these studies indicate that there is one regime where prices are high and demand is inelastic and another regime where prices are low and demand is more elastic. This implies a kinked demand curve for fish meal. Deaton and Laroque (1992) pointed out that a convex demand curve combined with large harvest variability leads to large variability in prices. Considering the highly volatile fish meal supply caused by large natural variations in the industrial fisheries this seems like a fitting description of the fish meal market. Even if the

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[1] The following references is only a small sample from the large literature on regime switching in financial and macroeconomic literature; Hamilton (1989, 1991); Perez-Quiros and Timmermann (2001); Smith (2002); Morana and Beltratti (2002); Clements and Krolzig (2002); Krolzig (2001).

demand curve for fish meal might be more appropriately described as kinked rather than convex the implications are still the same.

This paper is organized as follows. The next section gives background of the fish meal market with emphasis on the demand and supply characteristics. Section 3 presents the MS-VAR modeling approach. In Section 4 the data are presented followed by the empirical results in Section 5, and then finally conclusion in Section 6.

2. Background

The large variations in the industrial fisheries are caused by the El Niño weather phenomenon that takes place approximately every 3 to 7 years. This can cause shortages in supply that are unfamiliar even in agricultural production, as some of the worlds largest fisheries situated in the Pacific outside South America are near depleted due to the lack of nutritious surface water.[2] Other important characteristics of the industrial fisheries include natural variability in pelagic fish stocks and fishery management, which has not always been up to the task. All of these are important factors behind the supply fluctuations, which also translates into volatile fish meal prices. In particular, El Niño events have a negative impact on fish meal supply and thereby fish meal prices. For the end user, the compound feed producer, the variable fish meal supply translates into uncertainty and risk.

Salmon feed producers prefer fish meal as the main protein source because of the high nutritional value of marine proteins in terms of essential fatty and amino acids. However, marine proteins are also used in livestock feeds. Fish meal has been used in pig and poultry feeds for several decades already, preceding aquaculture's expansion, and there is even

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[2] Pelagic species used for fish meal production are free migrating fish species that inhabits the surface waters, as opposed to demersal fish species.

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evidence of a kinked demand curve for fish meal before aquaculture became a player in this market (Hansen, 1980). The so-called Unidentified Growth Factor can be an explanatory factor in this respect. The term refers to the increased growth rate of animals associated with using fish meal instead of alternative protein sources in feeds for young animals. The growth of intensive aquaculture production has changed the consumption pattern of fish meal, because of its higher willingness to pay for marine proteins compared to the pig and poultry sector. Since the end of the 1990s aquaculture has been the largest consumer of fish meal.

There are alternative protein sources to fish meal for both fish and livestock feeds. Soybean meal is the most widely available with somewhat similar nutritional profile as fish meal. Empirical findings indicate that these two markets are strongly integrated, as prices tend to move proportionally over time (Asche and Tveterås, 2000). Fish meal prices still exhibit short-term deviations from soybean meal prices. Furthermore, the degree of substitutability between fish meal and alternative protein sources varies with the particular aquaculture and animal species, and substitution from one protein source to another is complicated by logistical and technical reasons. For example most producers have limited storage space available. This limits how much can by purchased of a certain feed input at any given time, even if relative prices favor substitution from one to the other feed ingredient. Another sluggishness in substitution is that animals and aquatic species needs time to adapt to new feeding regimes.

3. Methodology

In a competitive market prices are determined by demand and supply. The purpose of this study is not to develop a supply and demand system since it is too costly to attain data for such extensive models for other than on an annual basis. Instead I concentrate on leading

indicators, which is commonly used in short-term financial and agricultural forecasting (Allen, 1994).

Time-series forecasting methods is constantly evolving with an array of modeling approaches to choose from, some more sophisticated than others. Unfortunately, forecasting performance is not improving at the same pace as forecasting techniques are developing. What can be perceived as somewhat disappointing forecasts has to be evaluated in view of an inherently uncertain future. How models handle the uncertainty is, nevertheless, crucial for forecasting performance. As Clements and Hendry (1996) note, shifts in deterministic components are one of the major reasons why forecasts break down, which can explain why naïve forecasts often 'win' over more advanced forecasting models. As naïve models do not contain any deterministic components they avoid forecast breakdowns associated with deterministic shifts. Still, there have been improvements in forecasting performance over the years. In particular, ARIMA and restricted VAR models have shown good performance. More recent models like switching models, generalized autoregressive conditional heteroscedacity (GARCH), autoregressive fractionally integrated moving average (ARFIMA) and other non-linear forecasting techniques have yet to prove their forecasting abilities.

The usual approach in VAR modeling is to treat parameters as fixed over time. In an MS-VAR model we alternatively let the parameters vary over time implying a non-linear data generating process. Hamilton (1989, 1990) developed a procedure for estimating regime shifts using a Markov chain to represent the regime generating process, which was further formalized with the MS-VAR framework by Krolzig (1997). There is a number of ways to restrict the MS-VAR model. This includes restricting parameters to be constant over regimes, either autoregressive or intercept parameters, like parameters in a regular VAR model.

The unrestricted parameters will change in accordance with regime changes. These changes are governed by an explicitly stated probability law and can be derived using the Expected Maximum likelihood (EM) algorithm. The purpose of this algorithm is to identify regime shifts, to estimate parameters associated with each regime, and characterize the probability law for transition between regimes. This is based on the state space form of the Kalman filter, but unlike the linear Kalman filter the EM algorithm is capable of nonlinear inference. It is also a numerical robust algorithm for maximizing sample likelihood. I use the MS-VAR package for OX for model estimation.

The general idea behind such Markov switching models is that the parameters of a K-dimensional time series process depend on an unobservable regime $s_t \in \{1, ..., M\}$.

$$p(y_t \mid Y_{t-1}, X_t, s_t) = \begin{cases} f(y_t \mid Y_{t-1}, X_t, \theta_1) & \text{if} \quad s_t = 1 \\ \quad \vdots \\ f(y_t \mid Y_{t-1}, X_t, \theta_M) & \text{if} \quad s_t = M \end{cases} \qquad (2)$$

where $Y_{t-1} = \{y_{t-j}\}_{j=0}^{\infty}$ denotes the history of y_t and X_t are exogenous variables. The θ_m is the VAR parameter vector associated with regime m. The regime generating process is an ergodic Markov chain with a finite number of states defined by the transition probabilities:

$$p_{ij} = \Pr(s_{t+j} = j \mid s_t = i), \qquad \sum_{j=1}^{M} p_{ij} = 1 \qquad \forall i, j \in \{1, ..., M\} \qquad (3)$$

Thus, the conditional distribution of any future regime s_{t+1} given the past regimes $s_0, s_1, \ldots, s_{t-1}$ and present regime s_t is independent on past regimes and depends only on the present regime. The Markov-switching regression model is defined as

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y_t = \begin{cases} X_t \beta_1 + u_t & u_t \mid s_t \sim NID(0, \Sigma_1) & \text{if} \quad s_t = 1 \\ \vdots & & \\ X_t \beta_M + u_t & u_t \mid s_t \sim NID(0, \Sigma_M) & \text{if} \quad s_t = M \end{cases} \tag{4}
$$

The most general form of a Markov-switching vector autoregressive (MS-VAR) process is given by

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y_t = v(s_t) + A_1(s_t) y_{t-1} + \ldots + A_p(s_t) y_{t-p} + u_t, \qquad u_t \mid s_t \sim NID(0, \Sigma(s_t)), \tag{5}
$$

where all the parameters $\theta = \{v, A_1, \ldots, A_p\}$ are dependent on regime s_t, where s_t is a random variable that can assume only an integer value {1,2,…,N}. There are two components of a VAR model: 1) the Gaussian VAR model as the conditional data generating process, and 2) the Markov process as the regime generating process, i.e., the density of y_t is conditional on pre sample values Y_{t-1} and the different states s_t. The conditional density of y_t will be a mixture of normal distributions given that there is more than one state.

4. Data

Price data are collected from continental Europe, which is one of the biggest markets for fish meal. More precisely they are monthly averages of quoted prices for fair and average quality (FAQ) fish meal with 64/65 % protein contents delivered c&f Hamburg, Germany, while the soybean meal has 44/45 % protein content delivered from Argentina to Rotterdam cif. Fish

meal Exporters Organisation (FEO) provides the data that are used for constructing the stocks-to-use indicator. Stocks-to-use, which is calculated by dividing carryover stocks with total use, is often used in agricultural price modeling as an indicator of demand and supply conditions. A low value indicates limited availability of stocks, which one would normally associate with higher prices. In this case it is constructed with production and inventory data from FEO, which represents some of the largest fish meal producing countries, namely Peru, Chile, Norway, Denmark and Iceland. These countries account for a large part of the global fish meal exports with e.g. approximately 82 % of the fish meal exports in 2000 (FAO, 2000).

The data are on a monthly basis and span from January 1988 to December 2001, as seen in Figure 1. These are the three variables used in the VAR and MS-VAR models.[3] Augmented Dickey Fuller tests indicate that the price series are I(1) process, as shown in Table 1, and are therefore differenced. The purposefulness of such differencing can be discussed in a forecasting context. Non-stationarity need not be a problem as such, since well-behaved residuals imply cointegration. However, in our case differenced data provide more robust models, and is therefore the preferred approach. All three variables are transformed to logarithms.

Table 1. Augmented Dickey-Fuller tests

Data series	Test statistic, levels	Test statistic, first differences
Fish meal price	-2.5427	-4.6513**
Soybean meal price	-1.9102	-5.9989**
Stocks-to-use	-3.2089	-7.6364**

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[3] The MS-VAR models are estimated using MSVAR package for OX created by Krolzig (1998).
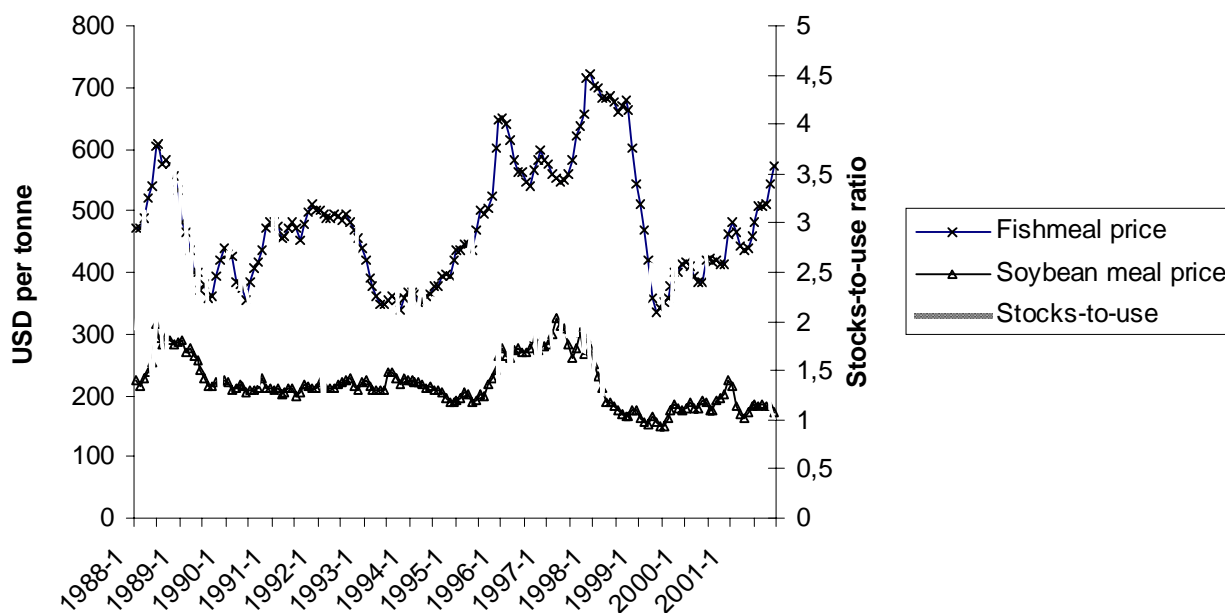
Figure 1. Monthly fish meal and soybean meal price data from Hamburg and Rotterdam together with a stocks-to-use indicator for fish meal (OilWorld; FEO).

5. Empirical Results

The VAR model is first estimated unrestricted with all the 3 variables as endogenous to avoid potential endogeneity problems. Two dummies are included in the VAR model in order to account for outliers. The model specification also contains a dummy for El Niño in 1997/98, which has been chosen based on Chow tests for structural breaks. Tests for Granger non-causality of whether soybean meal and stocks-to-use are Granger caused by any of the other two variables are not rejected with the respective Wald statistics of 2.8639 [0.8257] and 7.6285 [0.2666].[4] Following the VAR model is reduced to an AR model.

This leads to the two different models reported in Table 2; an AR(1) and a MS-AR(3) model. The AR(1) has two exogenous variables where only significant lags are included. In addition

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[4] p-values in brackets.

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there are seasonal dummies and dummies for the two outliers. Lag length is based on specification tests. First, we notice that the both own lagged variable and the exogenous variables DlnSP (soybean meal price) and DlnS/U (stocks-to-use) have sensible signs; own price lag is positive, soybean meal price, which is a substitute, is positive, and, finally, stocks-to-use is negative.

Table 2. Parameter estimates of an AR model and a MS-AR model with two regimes

Variable	AR(1)	MS(2)-AR(3) regime 1	MS(2)-AR(3) regime 2
DlnFP_1	0.3102**	0.4269**	0.3099**
DlnFP_2		0.0956	-0.1604
DlnFP_3		0.3162*	-0.0116
DlnSP	0.2032**	-0.0880	0.3247**
DlnSP_1		0.0421	0.0010
DlnSP_2		0.0770	0.0386
DlnSP_3		0.0763	-0.0198
DlnS/U	-0.0315**	-0.0621**	-0.0098
DlnS/U_1	-0.0204	-0.0542**	-0.0046
DlnS/U_2	-0.0181	-0.0663**	0.0002
DlnS/U_3		-0.0510**	0.0228
Seasonal	-0.0032		
Seasonal_1	-0.0090		
Seasonal_2	-0.0240*		
Seasonal_3	-0.0042		
Seasonal_4	0.0048		
Seasonal_5	0.0158		
Seasonal_6	0.0137		
Seasonal_7	-0.0094		
Seasonal_8	0.0053		
Seasonal_9	0.0168		
Seasonal_10	0.0204*		
d9511	0.1042**		
d9810-9904	-0.0679**		

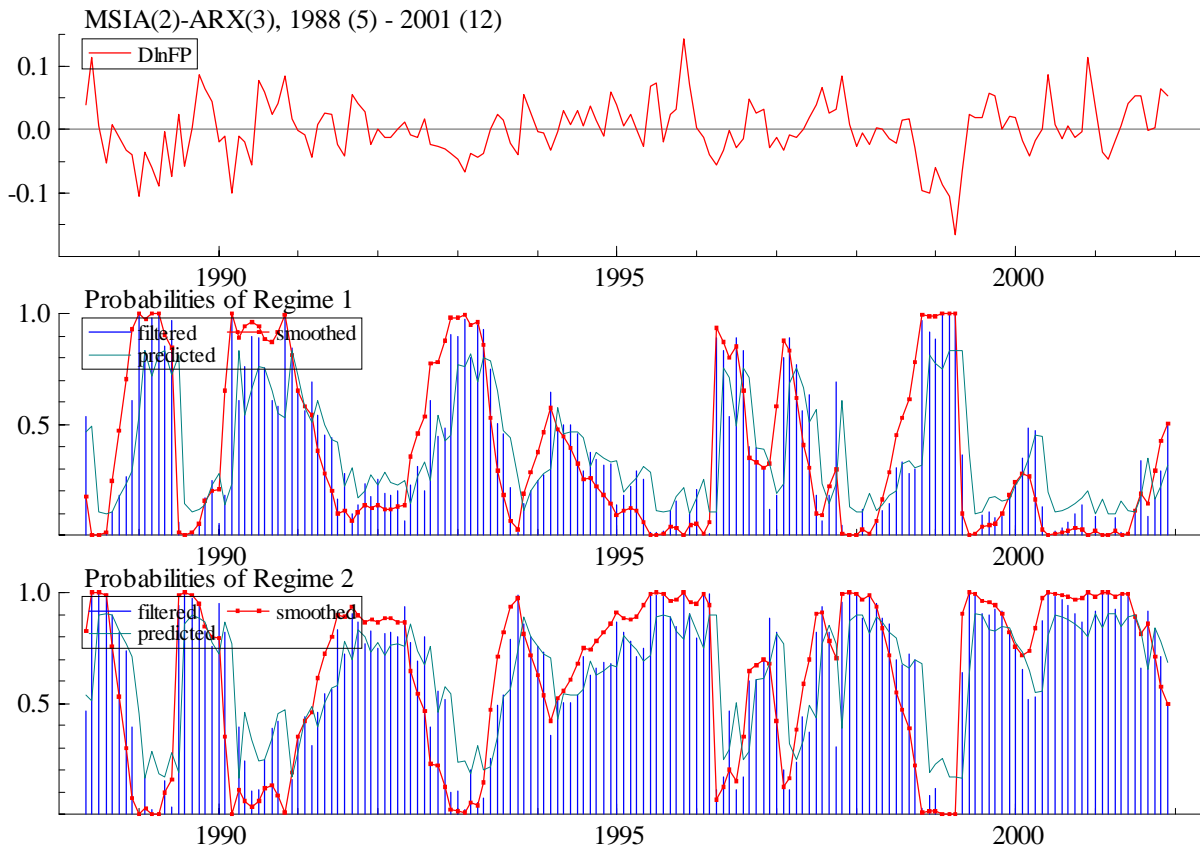*indicates 5% significance level, while ** indicates 1% significance level

Figure 2. Plot of DlnFP and the probability distributions of regime 1 and 2 occurring from the MS-AR(2) model

Next the specification of the MS-AR model is based on Aikake criterion and similar criteria. In the end a model with two regimes and three lags is chosen, with the estimated parameters as shown in Table 1. The results are interesting as they provide evidence of the two price regimes. In regime one, which is the least prevailing in the estimated sample, all the soybean meal price coefficients are insignificant, while all the stocks-to-use variables are significant. While in regime 2 only soybean meal prices are signinficant except for the own price lag. This indicate that in regime 1 there is a detachment of the fish meal market from the soybean meal market where the price of fish meal is mainly determined by the supply of fish meal, while in regime two the soybean meal price is the price leader.

When it comes to forecasting the AR model outperform the MS-AR model based on Mean Sqaured Predicted Error (MSPE). From Table 3 we see the AR model has lower MSPE, with

0.0077 against 0.0128 of the MS-AR model. However, both the AR and MS-AR perform better than a NAÏVE model. In Figure 3 the forecasts from the Naïve, AR, and MS-AR model are plotted against the actual values of DlnFP. The fact that the own-price lag is just as significant in the MS-AR model as in the AR model is probably an indicator that the forecasting abilities are not superior of the AR.

Table 3. Mean Squared Predicted Error

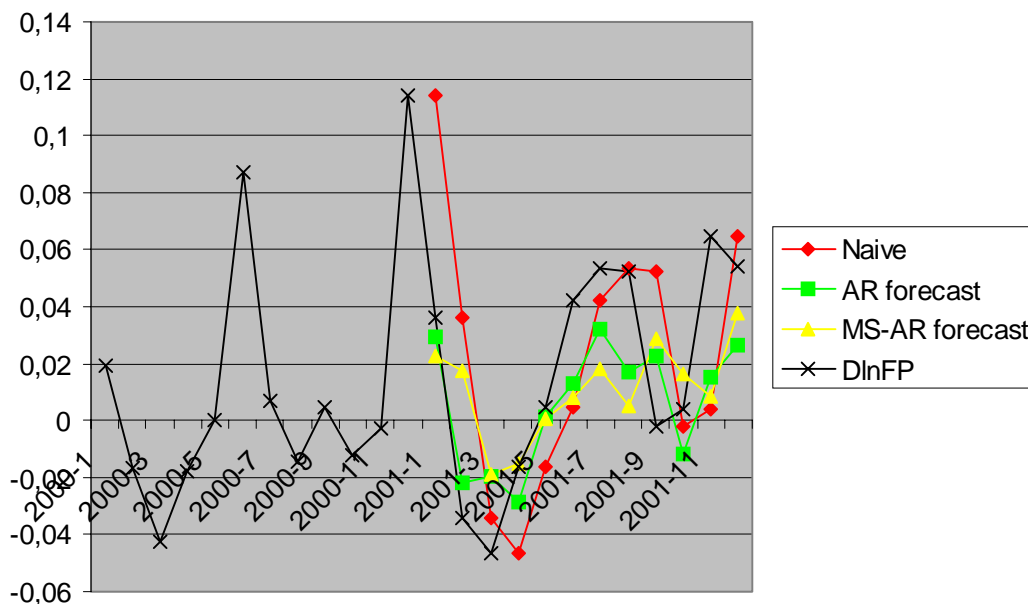| Data series	MSPE
MS-AR	0.0128
AR	0.0077
NAIVE	0.0209

Figure 3. One step ahead within sample forecasts of the differenced fish meal price based on Naïve, AR, and MS-AR model

6. Concluding remarks

This paper compares modeling and forecasting of a fish meal price using both VAR and MS-VAR models. The motivation for introducing a Markov switching model for the fish meal price is both as a means for more accurate modeling of the fish meal price and for producing

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better forecasts. There is empirical evidence of more than one price regimes in the fish meal market. Furthermore, economic theory of storage supports the notion that commodity price movements are non-linear, which in the case of the fish meal market seems to provide a good description. The severe impact of El Niño on fish meal production makes the fish meal market somewhat unique by inducing shortfalls in the supply that are not often observed in other markets. In these periods fish meal stocks run low, which makes the fish meal price very sensitive to supply changes.

Two leading indicators have been chosen for explaining the fish meal price, the soybean meal price and stocks-to-use. Initially an unrestricted VAR models is estimated, i.e., as a system with three endogenous variables. As both the soybean meal price and stocks-to-use are found to not be Granger caused by any of the other two variables, the VAR and MS-VAR models reduced to single equation models with the fish meal price as the left-hand side variable. Model wise, the results of the MS-VAR model are encouraging in the sense that they seem to give a plausible account of the underlying price mechanism. The results indicate the in periods the fish meal market decouples from the soybean market when supply gets tighter, and subsequently stocks-to-use gets more important in explaining the fish meal price. This is in accordance with what we should expect with a kinked demand curve for fish meal. Forecasting performance of the MS-VAR is, however, not so convincing relative to regular VAR model. It is a known fact that in sample fit is no guarantee for good forecasting performance, and this seems to be such a case.

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