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Forecasting Commodity Prices with Switching Regimes: The Case of Fishmeal Prices

by

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Abstract

The objective of this paper is to present a parsimonious forecasting model of the fishmeal price. The focus is on the impact of the soybean meal market on the fishmeal price together with the stocks-to-use as an indicator of demand and supply conditions. Volatile fishmeal supply due to El Niño events appears to lead to temporal changes in demand conditions and thereby multiple price regimes. In particular, there seem to be two different price regimes: one where the fishmeal price is highly correlated with the soybean meal price and another where fishmeal supply is scarce and the fishmeal price is weakly correlated with the soybean meal price, especially during El Niño events. The results from the Markov-switching autoregression (MS-AR) provide empirical evidence of two such price regimes for fishmeal. In terms of forecasting performance, it is unclear whether the MS-AR model improves over linear models.

Keywords: Forecasting, Markov Switching Models, Fishmeal

Introduction

Reliable forecasts of commodity prices are an important tool for risk management. In the industrial production of poultry, pork, and farmed fish, feed ingredients such as proteins, cereals, and oils constitute the largest cost components. One such feed ingredient, fishmeal, is used as a protein source for several kinds of animal and fish production. For example, in salmon aquaculture, the average level of fishmeal used in feed is usually around 35%, which makes it the largest feed input (Tacon, 2005). This is important because feed accounts for over 50% of the variable costs for producing a farmed salmon. A study by Guttormsen (2002) indicates that substitutability between feed and other inputs in salmon aquaculture is close to zero, which highlights the vulnerability of feed producers and salmon farmers to changing raw material prices. Good price forecasts are therefore important for making hedging decisions like those suggested in earlier studies (Gjerde, 1989; Vukina & Anderson, 1993).

The main objective of this paper is to examine whether a Markov-switching vector autoregressive (MS-VAR) model improves modeling and forecasting of historical fishmeal prices. Autoregressive integrated moving average (ARIMA) and restricted vector autoregressive (VAR) models have shown good forecasting performance of agricultural and aquaculture commodity prices compared with more basic forecasting methods like naïve models, extrapolation, and other univariate models (Allen, 1994; Guttormsen, 1999). Commodity prices, however, have certain nonlinear characteristics in their movements due to the workings of commodity markets, which might call for a nonlinear modeling approach.

By construction, commodity prices have a floor because producers do not charge prices below zero. Consequently, prices may spike upwards, but they are limited in their downward movements, creating an asymmetry in their behavior. Storage accentuates the asymmetric price pattern because it is more effective at eliminating exceedingly low prices by pulling stocks out of the market than vice versa, since it is not possible to carry negative inventories (Wright & Williams, 1982). In other words, in periods with supply shortages, stocks are usually depleted and thereby create higher and more volatile prices while in periods with normal supply, producers can stabilize prices by withholding stocks from the market when prices, for example, are undesirably low.

An asymmetry of price movements as described above will often imply a log-normal distribution and can therefore be dealt with in forecasting models using logarithms of prices. In some markets, however, price movements are best described as being the result of multiple price regimes. For example, studies support the presence of multiple price regimes in the fishmeal market (Asche & Tveterås, 2004; Kristofersson & Anderson, 2005; Tveterås & Tveterås, 2004).[1] More specifically, these studies indicate that there are two price regimes, one with high price levels and inelastic demand and another with low price levels and more elastic demand, implying a kinked demand curve for fishmeal.

Deaton and Laroque (1992) have pointed out that a convex demand curve combined with large harvest variability leads to high volatility in prices. This observation appears to be a fitting description of the fishmeal market, given the large year-to-year variation in fish catches targeted for fishmeal production. Even if the demand curve for fishmeal is more appropriately described as kinked rather than smoothly convex, the effect of volatile supply on prices remains the same. The asymmetry of commodity price movements caused by multiple price regimes complicates accurate modeling and forecasting since it makes linear estimation methods inappropriate in the sense that the underlying price mechanism is not linear.

Several modeling techniques are available to deal with commodity prices characterized by nonlinear relationships caused by multiple price regimes such as threshold autoregressive (TAR) models, artificial neural network (ANN) models, or Markov-switching (MS) models. Switching models can be useful in commodity markets with multiple price regimes since they potentially provide a 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 accurately described as being the 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.

To investigate whether temporal decoupling with the soybean meal price is a fair description of the fishmeal market, I will apply a Markov-switching vector autoregressive (MS-VAR) model. Usually, Markov-switching models are reserved for financial and macroeconomic data dealing with issues as business cycles, core inflation, and interest rate volatility, but they can be equally useful when modeling commodity prices.[2] However, the main objective of introducing a Markov-switching model in this study is not to model price movements as such but to improve fishmeal price forecasts.

This paper is organized as follows. The next section gives the background of the fishmeal market, highlighting its demand and supply characteristics. The following sections present the MS-VAR modeling approach, the data, the empirical results, and a summary and conclusions.

Background

Variation due to changing biological conditions is the main source of the large fluctuations in the industrial fisheries used for fishmeal. The El Niño weather phenomenon that takes place approximately every 3 to 7 years can cause downfalls in fishmeal supply that are unfamiliar even in agricultural production, as the Anchoveta, the world's largest fisheries situated in the Southeast Pacific, are nearly depleted due to the lack of nutritious surface water.[3] The industrial fisheries are characterized by natural variability in pelagic fish stocks and, like many other fisheries, they have struggled with adequate fisheries management systems. These are important factors behind the supply fluctuations which translate into volatile fishmeal prices. In particular, El Niño events have a negative impact on fishmeal supply and thereby inflate fishmeal prices. For end users like salmon producers, the variable fishmeal supply translates into uncertainty and risk.

The demand side of the fishmeal market is characterized by buyer segments with distinct demand schedules for marine proteins. For instance, salmon feed producers prefer fishmeal as the main protein source because of the high nutritional value of marine proteins in terms of essential fatty and amino acids. Substitutability between fishmeal and alternative protein sources is low for salmon feed in the short run (Drakeford & Pascoe, 2008). This is important since the salmon industry is one of the largest consumers of fishmeal in aquaculture. However, marine proteins are also used in livestock feeds such as pig and poultry. Fishmeal has been used in pig and poultry feeds for several decades, and there is evidence of a kinked demand curve for fishmeal prior to aquaculture's entrance into 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 pigs associated with using fishmeal instead of alternative protein sources in feeds for young animals. Poultry producers, by contrast, seem to treat fishmeal just as one of several alternative protein sources for feed so that the relative price of fishmeal compared to soybean meal, for example, is the main determinant of demand.

The rapid expansion of industrialized aquaculture production has changed the consumption pattern of fishmeal. Because of its high willingness to pay for marine proteins, aquaculture has displaced the poultry sector as the largest consumer of fishmeal. Figure 1 shows that aquaculture's share of fishmeal consumption increased from 10% to 45% from 1988 to 2002 while poultry's share decreased from 60% to 22%. These changes clearly reflect that the poultry sector is more price sensitive than either the pig or the aquaculture sectors.

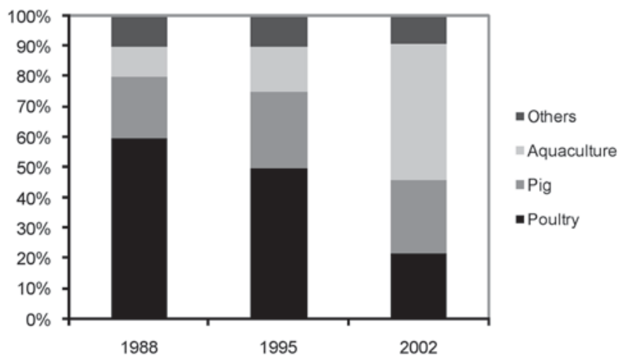

Figure 1. Consumption share of fishmeal by sector. (Source: Tveterås & Tveterås, 2004)

Of the various alternative protein sources, soybean meal is the most widely available and, in some aspects, has a similar nutritional profile as fishmeal. Empirical findings indicate that these two protein markets have been strongly integrated since prior to the emergence of aquaculture their prices tended to move proportionally over time (Asche & Tveterås, 2004). However, the link between the fishmeal and the soybean meal market has become weaker with the growth of the aquaculture sector (Kristofersson & Anderson, 2005). Consequently, we can hypothesize that there is a kinked demand curve for fishmeal. The vertical part of the demand curve, which is prevalent at higher price levels, is dominated by the aquaculture and the pig sectors because of their more inelastic demand for marine proteins. However, when the fishmeal price becomes sufficiently low, the poultry sector enters the market. This makes aggregated fishmeal demand more elastic due to the substitution with soybean meal, and, accordingly, demand at low prices is characterized by a more horizontal demand curve. If such a description were appropriate, we would expect there to be one price regime at higher price levels that is primarily determined by the supply of fishmeal and another price regime at lower price levels that is primarily determined by the soybean meal price. In this study, these are the underlying assumptions that provide the rationale for introducing a Markov-switching model to forecast fishmeal prices.

Methodology

In a competitive market, prices are determined simultaneously by supply and demand. The purpose of this study is not to develop a supply and demand system since it is too costly to obtain data for such structural models other than on an annual basis. Instead, the study focused on leading indicators, which are commonly used in short-term financial and agricultural forecasting (Allen, 1994). A leading indicator refers to a variable whose movements tend to precede those of another variable. As discussed in the preceding section, the variable of interest in this study is the fishmeal price, and the hypothesized leading indicators are the soybean meal price and the stocks-to-use ratio of fishmeal.

Time-series forecasting methods are constantly evolving with an array of modeling approaches to choose from, some more sophisticated than others. Unfortunately, the forecasting performance is not improving at the same pace. What can be perceived as somewhat disappointing forecasts has to be evaluated in view of an inherently uncertain future. Singer (1997, p. 39) expressed this uncertainty in the following manner: "Because of the things we don't know [that] we don't know, the future is largely unpredictable. But some developments can be anticipated, or at least imagined, on the basis of existing knowledge."

Modelling these developments, wich according to Singer can be anticipated is crucial for forecasting performance. As Clements and Hendry (1996) note, shifts in deterministic components are one of the major reasons why forecasts break down. This can explain why naïve forecasts often win over more sophisticated forecasting models: naïve models do not contain any deterministic components so they avoid forecast breakdowns associated with deterministic shifts. Nevertheless, there have been improvements in forecasting performance over the years. In particular, ARIMA and restricted VAR models have shown comparatively good performance. In addition to these two models, which are currently used widely, there exist an array of other models like switching models, autoregressive fractionally integrated moving average (ARFIMA) models and other linear and nonlinear forecasting techniques that have yet to prove their superiority in forecasting performance.

The usual approach in VAR modeling is to treat parameters as fixed over time. In an MS-VAR model, parameters are allowed to vary over time, implying a nonlinear 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 are a number of ways available to restrict the regime changes and parameters in an MS-VAR model, including restricting the number of regimes and the 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 to characterize the probability law for transition between regimes. The algorithm 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. It must be noted that these estimated probabilities of regime changes imply that the MS-VAR model is characterized by exogenous regime shifting in contrast to comparative models such as the threshold autoregressive (TAR) model.

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

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

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

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

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+1} does not depend on past regimes. It depends only on the present regime. The Markov-switching regression model is defined as

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

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

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

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: first, the Gaussian VAR model as the conditional data-generating process and second, the Markov process as the regime-generating process, that is, 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.

Data

Price data originate from continental Europe, which is one of the biggest markets for fishmeal. More precisely, they are monthly averages of quoted prices for fair and average quality (FAQ) fishmeal with 64/65% protein contents delivered cost and freight to Hamburg, Germany while the soybean meal has 44/45% protein content delivered from Argentina to Rotterdam cost, insurance and freight. The Fishmeal Exporters Organization (FEO) provided the data that are used for constructing the stocks-to-use indicator.[4] 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 scarcity and higher prices. In this case, stocks-to-use is constructed with production and inventory data from FEO, which represents some of the largest fishmeal producing countries, namely Peru, Chile, Norway, Denmark, and Iceland. These countries account for a large part of the global fishmeal exports with approximately 82% of the fishmeal exports in 2000 (United Nations Food and Agricultural Organization [FAO], 2000).

The data are on a monthly basis and span from January 1988 to December 2001, as seen in Figure 2. In the figure, the soybean meal price has been normalized to the fishmeal price for January 1988, making it easier to observe comovements. The actual soybean meal price for that month was 225 USD/ton. These are the three variables used in the VAR and MS-VAR models.[5] Augmented Dickey Fuller tests indicate that the price series are a I(1) process, as shown in Table 1, and are therefore differenced. The sense of purpose of such differencing can be discussed in a forecasting context since it implies a loss of information. Nonstationarity need not be a problem as such, since well-behaved residuals imply cointegration. However, in our case, differenced data provide more robust models, and it 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*
Fishmeal price	-2.5427	-4.6513**
Soybean meal price	-1.9102	-5.9989**
Stocks-to-use	-3.2089	-7.6364**

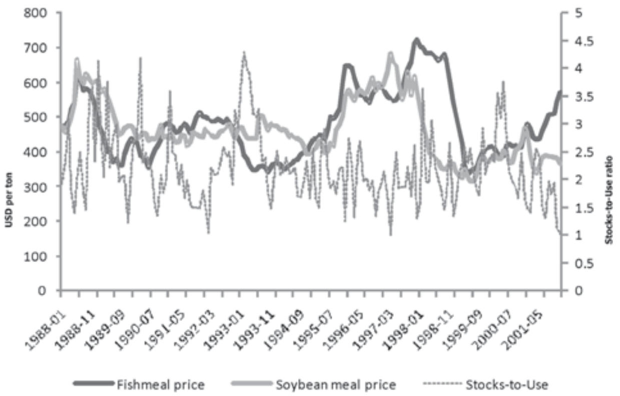

Figure 2. Monthly fishmeal and soybean meal prices from Hamburg and Rotterdam together with a stocks-to-use indicator for fishmeal.
(Source: Fishmeal Exporters Organization)

Empirical Results

The VAR model is first estimated unrestricted with all three variables as endogenous to avoid potential endogeneity problems. The three variables are the fishmeal price (FP), the soybean meal price (SP), and stocks-to-use ratio (S:U). 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. Granger Causality tests indicate that both soybean meal price and stocks-to-use are exogenous in the VAR system, which implies that it can be reduced to an AR model.

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

Before applying the MS-VAR, it makes sense to pretest for nonlinearity. One such test, RESET, tests the null of linearity against a general alternative hypothesis of nonlinearity. This test is applied to the estimated AR(1) model reported in the first column in Table 2. With a p-value of 0.0516, the reported test statistic implies that we barely keep the null hypothesis at a 5% level. This suggests that the model is only borderline linear. Another way to check for linearity is by examining for parameter constancy. Figure 3 shows how key parameter estimates (i.e., of the two leading indicator variables) evolve through recursive estimation of the model, in which the model is reestimated by adding observations iteratively until all observations are used. In the first runs of the model, the magnitude of the estimated parameters usually changes significantly since relatively few observations are used. Provided that the model is correctly specified, the parameter values should converge as more observations are added.

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

The graph in the upper-left hand of Figure 3 shows the recursive parameter estimates along with the ±2 standard deviation of the first differenced logarithm of the soybean meal price (DlnSP). The graph does not show rapid convergence as one would expect of a correctly specified model. In fact, if we compare two periods, from January 1994 to December 1996 and from January 1999 to December 2001, which represent pre- and post- El Niño periods, the average parameter estimate drops from 0.37 to 0.20. This corresponds to a fall in the parameter value

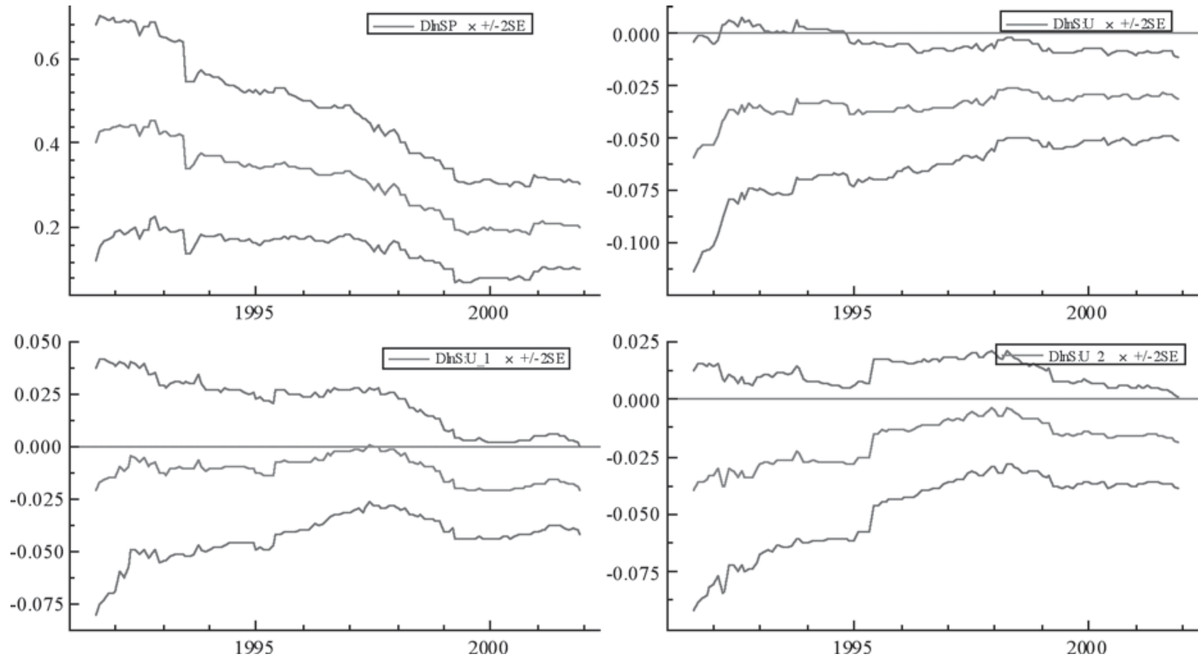

Figure 3. Recursive estimations for evaluation of parameter constancy.

of over 40%. The smaller coefficient magnitude supports our hypothesis that the role of the soybean meal price has diminished during the period where the aquaculture sector has become the largest buyer of fishmeal (see Figure 1).

The parameter estimate for the simultaneous period value of stocks-to-use in the upper right-hand corner seems relatively stable and statistically significant. However, the two lagged values of stocks-to-use,

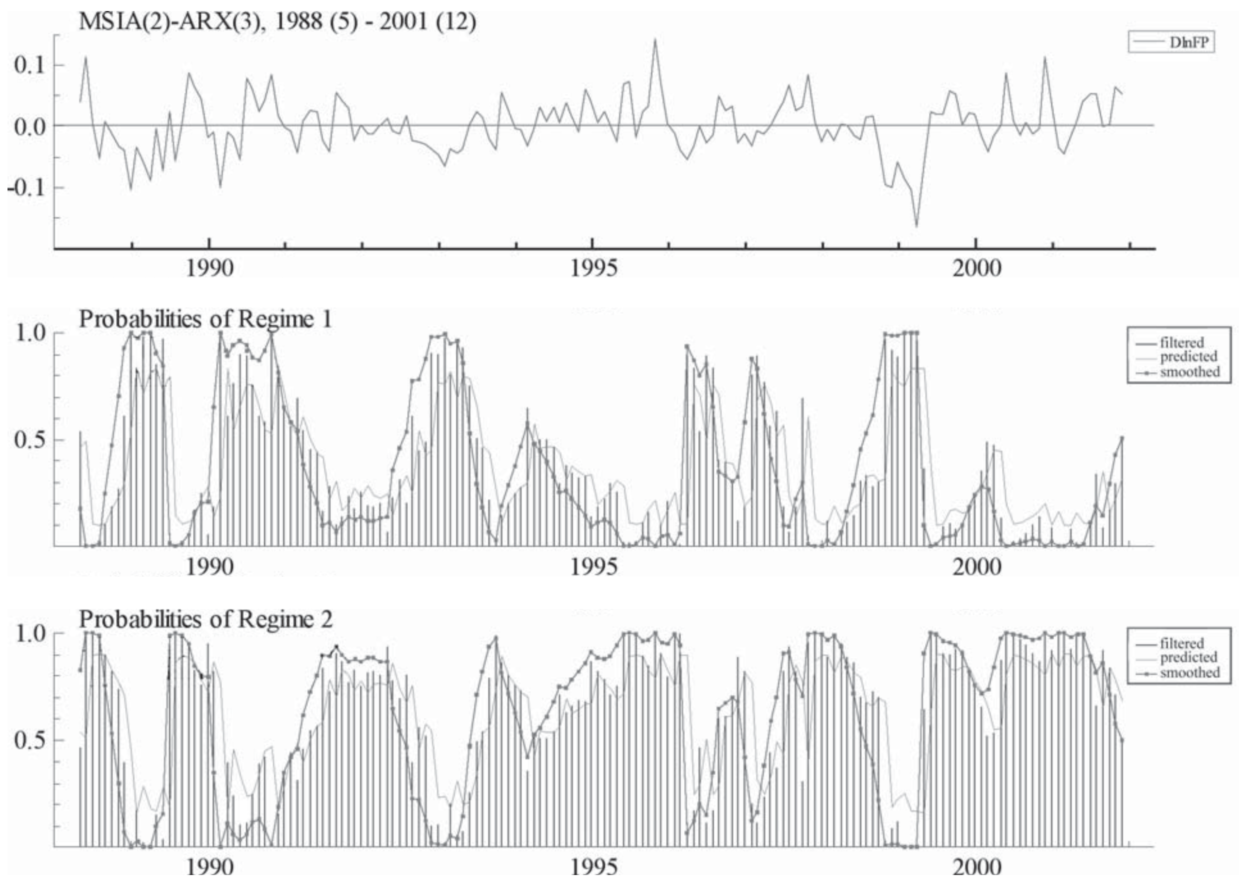

Figure 4. Plot of DlnFP and the probability distributions of Regimes 1 and 2 occurring from the MS-AR(2) model.

DlnSU_1 and DlnSU_2, both show a tendency to become statistically significant during the period from January 1999 to December 2000 if we allow for a 10% significance level. This suggests that, as the soybean meal price has become a less important determinant of the fishmeal price, the role of stocks-to-use as a predictor of price has increased.

With empirical evidence supporting the presence of regime shifts in the fishmeal market, we proceed to estimate the Markov-switching model for the fishmeal price. The lag-length specification of the MS-AR model is based on Aikake and Bayes information criteria. In the end, a model with two regimes and three lags is chosen, with the estimated parameters reported in the two right-hand columns in Table 1. The results are interesting as the estimates provide further evidence of two price regimes. In Regime 1, 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. In Regime 2, only soybean meal prices are significant, except for the own-price lag. This indicates that in Regime 1, there is a detachment of the fishmeal market from the soybean meal market where the price of fishmeal is mainly determined by the supply of fishmeal while in Regime 2, the soybean meal price is the price leader.

There are several measurements of forecasting performance, but mean squared predicted error (MSPE) is frequently used because it strikes a balance between accuracy and precision of a forecast. This is the measurement used in this study for forecast comparison. According to the MSPE, the AR model performs better than the MS-AR model. In Table 3, we see that 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, which has an MSPE of 0.0209. In Figure 5, the forecasts from the naïve, AR, and MS-AR models 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 to that of the AR.

Table 3
Mean Squared Predicted Error

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

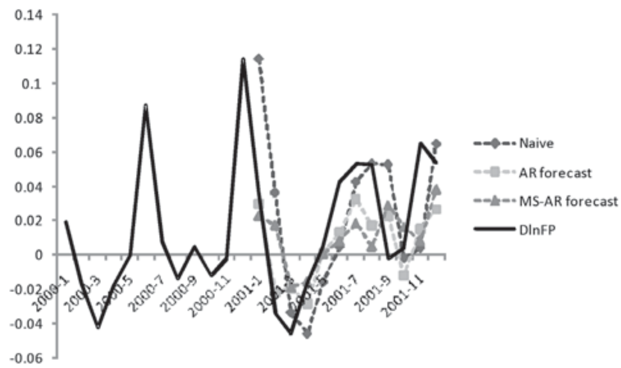

Figure 5. One step ahead within sample forecasts of the differenced fishmeal price based on Naïve, AR, and MS-AR model.

Summary and Conclusions

This paper has examined the modeling and forecasting of historical fishmeal prices, comparing the AR and MS-AR models with a naïve model. The purpose of introducing a Markov-switching model for the fishmeal price is to achieve higher accuracy in the price modeling and to produce better forecasts. Empirical evidence supports the belief that there is more than one price regime in the fishmeal market, not least because of volatile supply and structural changes in the makeup of buyer segments. In particular, the increased presence of the aquaculture sector has probably induced a more kinked demand curve for fishmeal. Furthermore, the economic theory suggests that storage accentuates asymmetries in commodity price movements, which is highly relevant for the fishmeal market. The severe impact of El Niño on fishmeal production makes the fishmeal market somewhat unique by inducing shortfalls in the supply that are not often observed in other markets. In these periods, fishmeal stocks run low, making the fishmeal price sensitive to supply changes.

Two leading indicators were chosen for explaining the fishmeal price: the soybean meal price and stocks-to-use. Initially, an unrestricted VAR model is estimated, that is, as a system with three endogenous variables. As both the soybean meal price and stocks-to-use are found to be strongly exogenous in relation to the fishmeal price, the VAR and MS-VAR models are reduced to single equation AR and MS-AR models with the fishmeal price as the left-hand side variable. In terms of modeling, the results of the MS-AR model are encouraging in the sense that they give a plausible account of the underlying price mechanism. The results indicate that the fishmeal market decouples periodically from the soybean market, likely because of tighter supply, and subsequently the stocks-to-use ratio becomes more important for predicting the fishmeal price. This is in accordance with what we should expect with a kinked demand curve for fishmeal combined with volatile supply.

While the MS-AR model seems to offer a plausible explanation of fishmeal price regimes, its forecasting performance is less convincing, at least when compared to the AR model. In fact, the AR model outperforms the Markov-switching model when comparing MSPE. As a result, the study does not provide any evidence that the MS-AR model improves the quality of forecasts of the fishmeal price.

It is well known that in-sample fit is no guarantee for good forecasting performance. A general problem is that in-sample estimation error usually increases with the size of the model, which again translates into larger forecast errors. Another important point is that we are not able to fully exploit the regime switching of the MS-AR model in a forecasting context. The reason is that the future regime is not forecasted. Instead, the forecast produced by the MS-AR model is based on a weighted average of the two regimes. In other words, the forecast is calculated using a weighted average of both sets of parameter estimates corresponding to the two regimes. This system is not necessarily the most desirable when there are two distinct regimes.

Another criticism of the models in terms of forecasting relates to the leading indicators. We can question whether the two leading indicators in the estimated AR and MS-AR models in fact are leading, since the contemporary values of the soybean meal price and stocks-to-use are the strongest predictors of the fishmeal price. This implies that forecasts of both the soybean meal price and stocks-to-use are required to produce a true forecast of the fishmeal price. This is an obvious weakness as it introduces additional sources of forecast errors. For these variables to act as pure leading indicators, higher frequency data such as weekly or daily data would probably be required.

The structural changes on the demand side have continued after the data period covered in this study, with the aquaculture sector moving away even more from the fishmeal consumption of the poultry sector. Unfortunately, I have not been able to obtain data on fishmeal stocks for the period after December 2001. Thus, it would be ideal for future research to expand the model in this paper to include prices of aquaculture products since high prices for farmed fish could lead to higher demand for fishmeal. To my knowledge, there are only available aggregate price indices for seafood, but not for farmed fish specifically (Tveterås, 2005). The FAO has a project to develop an aquaculture price index that could prove useful to model fishmeal prices in the future.

Another potential extension of this study relates to how regimes are estimated. If we believe that there are two distinct regimes, it would be desirable to make forecasts based on either of the two regimes instead of using a weighted average. However, this requires that we be able to forecast the regimes. Thus, a suggestion is to estimate a model with endogenous regime switching. In the fishmeal market, the price level should be a promising predictor of the state of the regime for the same reasons that have been discussed earlier in this paper (i.e., related to the kinked demand curve).

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Endnotes

1 Another example is the soybean meal market (e.g. Goodwin, Schnepf, & Dohlman, 2005)

Footnotes

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

3 The small pelagic species used for fishmeal production are free migrating schooling fish that inhabit the surface waters, as opposed to demersal fish species.

4 FEO is now a part of the International Fishmeal and Fishoil Organization (IFFO) after merging with the International Fish Meal and Oil Manufacturers Associations (IFOMA) in 2003.

5 Unit root tests and VAR model estimation is done in PcGive, while MS-VAR model is estimated using MSVAR package for OX created by Krolzig (1998).

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