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Dynamic econometric modeling for market analysis

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ABSTRACT: Structural-Time series models have not gained much ground in commodity market modeling despite the overwhelming popularity of time series approaches in forecasting and dynamic analyses. This study tries to adopt a structural model for the commodity market and estimates important econometric specifications. This paper contributes by applying developments in seasonal cointegration and structural-time series analysis to the study of commodity markets. The conclusions may be summarized as follows. First, quarterly data in the commodity market have seasonal unit roots and also in a forecasting context, seasonally cointegrated VECMs perform uniformly better that their nonseasonal counterpart. Finally, DSEM with seasonal cointegration, however, perform better than VECMs at longer forecast horizons.

***Key words*:**forecasting, seasonal cointegration, commodity market, seasonally cointegrated

INTRODUCTION

A market analysis studies the attractiveness and the dynamics of a special market within a special industry. It is part of the industry analysis and this in turn of the global environmental analysis. Through all these analyses the chances, strengths, weaknesses and risks of a company can be identified. Finally, with the help of a SWOT analysis, adequate business strategies of a company will be defined (Dickey and Fuller 1979). The market analysis is also known as a documented investigation of a market that is used to inform a firm's planning activities, particularly around decisions of inventory, purchase, work force expansion/contraction, facility expansion, purchases of capital equipment, promotional activities, and many other aspects of a company.

The economic mechanism used to shed some light on stockholding decisions is based on the classical storage model and seems to ignore some crucial properties of commodity price behaviour such as the dependency of prices on inventory levels and their relationship with convenience yield. All these issues negatively affect the empirical performance in predicting the spot price (Elliot et al. 1996).

We focus our attention on the framework proposed by (Dickey,1984). The economic mechanism underlying our model can be summarized as follows: once the spot price is determined by the interaction between demand and supply, both producers and industrial consumers hold inventories to stabilize the impacts of stochastic fluctuations on stockholding and production plans. In this setting, the storage theory represents the way to account for the economic benefits from stockholding activities through the nexus between convenience yield and inventories.

Various questions arise regarding the quality of grain market information generated from existing econometric models. For example, the high grain prices in spring 1996 were not forecasted accurately the previous summer because the relevant levels of the supply and demand factors were not accurately forecasted either. Actual crop size was smaller than expected, and use of this crop turned out to be larger than expected. Thus, ending stocks for the 1995-1996 crop years for grains were small (Dickey and Fuller 1979). In trying to address these problems, economic theory of commodity markets may help explain the dynamic nature of these markets and why changes occurring in the markets are gradual, with responses taking time to stabilize (Engle et al, 1997).

The convenience yield is intended to approximate the economic benefits from holding inventories and such a definition does not depend on the final stockholding purposes, since it can include both precautionary and speculation motives. In fact, economic agents may hold inventories not only to speculate on higher commodity prices in the future, but also to be insured against shortages which could stop the production process (Engle, 1982).

In this context, we specify a model in which the patterns of the spot price determining the exchanges on the market are investigated and a criterion governing the stockholding choices may be obtained. With respect to (Dickey,1984), we derive the estimated equations from a continuous time framework and we model the cash market in a more general fashion. Denoting net demand as the difference between production and consumption, the cash market is characterized by the relationship between spot prices and net demand. In particular, we write the net demand as the difference between the exogenous supply function and the stochastic demand. This modeling strategy is coherent with one of the most peculiar features of the metal market in which the economic uncertainty massively affects the demand rather than the supply side of the market (Holt and Aradhyula, 1990).

A literature review on econometric commodity modeling is presented in this section. Early in the history of commodity modeling, economic theory was the backbone of model specification. These models played an important role in structural analyses and were formulated as simultaneous equation models (SEMs). In spite of their economic appeal, their historical forecasting performance was poor, giving way to the use of time series models (TSM). TSMs for forecasting, however, have been accompanied by much criticism because of their "ad hoc" nature, and for decades, after the introduction of Box-Jenkins models, researchers have been making progress on the marriage between the SEMs and TSMs philosophies. These two types of approaches were known in other fields to have good forecasting performance. Engle et al, (1987) provide a comprehensive review of commodity models and their history. Efforts to expand and improve SEMs are continual and often driven by the availability of more extensive and accurate data, by the introduction of new methods to capture either market structure or data properties, and by improved computers and software that facilitate the computational aspects of modeling. However, recent studies still find that fairly simple time-series models, with a limited basis in economic theory, can outperform SEMs forecasts and simulation results (Stock and Watson, 1999). How can this be explained? Is there a way to combine SEMs and time-series models to capitalize on the advantages of each? The Traditional Structural Approach: The quantitative analysis of commodity models has been mainly conducted using econometrics procedures. Econometric analyses of commodity market models can provide market participants and policy makers with a clearer vision of the economic environment in which they operate, by systematically identifying the characteristics of demand and supply. Thus, econometric commodities models help quantify the relationships that explain economic behavior of a market or system of markets (Holt and Aradhyula, 1990). Econometric structural commodity models are predominantly found in the literature, which are used to represent and quantify the relationships and factors that influence the market (Stock and Watson, 1998). In practice, these relationships and factors are specified as a set of equations, following the simultaneous equations models (SEM) approach developed during the late 1940s and early 1950s at the Cowles Commission, University of Chicago (Stock and Watson, 1998). The econometricians at the Cowles Commission recognized early that the error terms in a SEM specification are correlated with some of the endogenous variables, and showed that the ordinary least squares parameter estimates are inconsistent. The estimated parameters from SEMs can be used to solve for equilibrium price and quantity values, given the values of the exogenous variables and the error processes.

It is also known that markets often depart from the supply-demand equilibrium suggested by the theory of pure competition. From a time-series perspective, the deviations from equilibrium as revealed by available empirical data, particularly of the nonstationary type, have been more complex to model than initially suspected. It has been proven that when variables are nonstationary, such as in the "random walk" behavior, it is still possible to observe long-run market equilibrium. Also, some theoretical efforts that deal with nonstationary data in SEMs may be found in the literature (Hatanaka 1975).

MATERIAL AND METHODS

In this section a model is presented to investigate the behaviour of commodity prices which are affected by both production and storage choices.We try to focus our attention on the dynamics that characterize the metal markets. Under the assumption of competitive markets, we may obtain equations for the spot price and the marginal storage value.The latter includes the convenience yield considered as the economic benefits released by stockholding choices [36]. The estimates for the spot price and the marginal convenience yield are involved in the calculation of the marginal storage value which in turn enters the numerator of Tobin's q. In our model, this function represents the driver of the stockholding choices. It is worth noticing that the equilibrium of the model is here achieved under the representative agent assumption (Hatanaka 1975).

Model formulation

A general framework that links dynamic simultaneous equations models (DSEM) and time series models,and the implications of cointegration and seasonal cointegration for structural equation modeling are resented in this subsection. The econometric scope of the methods selected to conduct this research.This provides a broad overview of the main econometric and time seriescontributions to date since the time tested works of the Cowles Commission in the 1940s. The selectedmodels are highlighted as shaded boxes, and include the vector error correction model (VECM), theseasonal ECM (SVECM), the cointegration dynamic simultaneous equation model (CDSEM), and theseasonal cointegration DSEM (SCDSEM). the SCDSEM –a new modeldeveloped in this research, is constructed on the basis of the CDSEM of Hsiao and theSVECM of Johansen and Schaumburg. The CDSEM, in turn, blends the concepts of the VECMand the DSEM (Phillips and Durlof, 1990). while the DSEM of Zellner and Palm(bold box) represents the first serious attempt for combining the simultaneous equation modelingapproach advocated by the Cowles Commission with the ARIMA time series modeling approach of Boxand Jenkins. The major frame entitled “nonstationary conditions” contains methods that are ableto account for the presence of unit roots in the data. In this sense, the ARIMA models of Box and Jenkins, the works on spurious regressions, on unit roots [39]. Onerror correction models(Hsiao 1997a), and on seasonal unit roots,are framing the modeling strategy adopted in this study.The analysis of simultaneous equation models (SEM) using multiple time series (MTS) hasreceived limited empirical investigation. Most MTS models found in the empirical literature have used vector autoregressive (VAR) specifications, introduced, in forecasting and dynamic multiplier analyses. Despite their popularity, VAR-type models have the limitation of treating all variables as jointly dependent, ignoring, therefore, prior information prescribed by economic theory. The first modern treatment of combining time series with simultaneous equation models (SEM) was introduced by (Hsiao 1997b). They derived associated reduced form and transfer function equation systems similar to the single-equation models and to the widely known autoregressive integrated-moving average (ARIMA) models of Box and Jenkins. Structural equation modeling in economics, on the other hand, dates back to Haavelmo and the various works of the Cowles Commission since ending the 1930s (Hsiao 1997a). Zellner and Palm’s analysis went to the core of what today still is an area of much needed research, how to best combine economic theory models with time series data. Their idea was to formulate models that provided a blend between economic theory, that is, models that incorporate structural characteristics (endogenous-exogenous relationships) of simultaneous equation models (SEM) and that are also coherent with nonstationaryproperties of economic data. In this framework, dynamics are driven by the data since economic theory provides little guidance. The analysis generated a new class of hybrid models that transformed ARIMA structures into a dynamic SEM (DSEM) in reduced form. In previous econometric work, these reduced form specifications were known as final equations or transfer functions (Hylleberg,1995).

A unique feature of DSEMs is the accounting for prior information derived from economic theory in the structure of the parameter matrices of ARIMA models. This re-specification of economic-theory consistent ARIMA models resulted in the Zellner and Palm form of a dynamic simultaneous equation model (Hylleberg S, Engle, 1990),

$$\Gamma(\mathrm{L})\Delta \mathbf{y}\mathrm{t} + \mathrm{B}(\mathrm{L})\Delta \mathbf{x}\mathrm{t} = \theta 11(\mathrm{L})\mathbf{e}1\mathrm{t} \quad (1)$$

$$\mathrm{V}22(\mathrm{L})\Delta \mathbf{x}\mathrm{t} = \theta 11(\mathrm{L})\mathbf{e}2\mathrm{t} \quad (2)$$

where$\mathbf{y}\mathrm{t}$ and $\mathbf{x}\mathrm{t}$ are the endogenous and the exogenous variables of dimension G and K , Γ((L) and B(L) are lag polynomial matrices, respectively. Equation (2) describes an independent process for theexogenous variables. In the terminology of modern time series econometrics, if $\mathbf{y}\mathrm{t}$and$\mathbf{x}\mathrm{t}$are not cointegrated, then they could be modeled by a process such as (1). This was an improvement over traditional vector autoregressive models (VAR) because model (1) maintains the endogenous exogenous characteristics of SEM and has a separate process (2) explaining the exogenous variables. The adequacy of model (1)-(2) as a general specification for economic modeling with variables that may be integrated and possibly cointegrated was not resolved until cointegration theory appeared(Phillips and Durlof, 1986).. In a cointegration framework, (1) would represent a misspecified model because of the omission of long-run relationships of the variables. Additionally, conditions for identification of SEM were settled by the Cowles Commission, but in the context of structural-time series models, questions remained regarding identification when data are nonstationary and the relationship between short and long run dynamics for identification. Similarly, distributional results for estimators and test statistics were the subject of much inquiry. The works of Hsiao provide answers to the above questions by blending cointegration and dynamic SEM. As will be discussed below, Zellner and Palm’s model is one possible model in the more general specification approach of Hsiao.

Hsiao begins the analysis by assuming that endogenous and exogenous variables of SEM, ytand , of dimension $G´1$ and $K´1$, respectively, are generated by an autoregressive model of the form:

$$\phi(L)\mathbf{w}t = \varepsilon t, (3)$$

where $w't = (\mathbf{y}'t, \mathbf{x}'t)$is a (G +K)*1 vector of I(1) random variables, $\phi (L)$ is $(G + K)´ (G + K)$ matrix of polynomials in the lag operator L , $\phi(L) = \sum \phi j\, Lj$, and $\varepsilon t$is a $(G + K) \times 1$ vector of independently, identically distributed random variables with mean zero and covariance matrix Ω^* . This representation can be reparameterized by imposing a normalization that M(L) is diagonal in the factoring of Φ (L) =M(L)V(L) , where the roots of |M(L)|=0 and |V(L)|=0 are equal to one or lying outside the unit-circle, respectively. By diagonalization, |M(L) |=(1-L)d where d is the number of linearly independent I(1) processes in **w**t and G+K-d denotes the number of linearly independent cointegration processes.

Error-correction models

These models assume that the data are nonstationary and integrated of order one. Thus, multi-equation error-correction representation is possible. Two are the models in this class, introduced as models 1 and 2 in what follows.

Model 1

Nonseasonal vector error-correction model (VECM). VECMs were introduced in Engle and Granger (1987) and formulated as a system. This model is the most frequently used in applied economics and economics. It assumes the existence of a structural model but used in reduced form arguments in its specification. Under certain conditions, model 1 reduces to a classical vector autoregression (VAR) which was used in economics in the early 1980s.

Model 2

Vector error-correction with seasonal cointegration (SVECM). This model extends the cointegration technique in model 1 to the case where market data have unit roots at both the zero and seasonal frequencies. This model requires knowledge of prior information on which unit roots are present in order to filter out seasonal unit root components and to test for cointegration in the filtered series. This literature is due to (Phillips and Durlof, 1988). With a “top-down” simplification, for instance, assuming that seasonality is deterministic and that there is cointegration, model 2 reduces to model 1.

RESULT AND DISCUSSION

The main focus of this section is in presenting the results of the evaluation of the forecast and impulse responses performance of the four selected econometric models for the commodity market. Dynamics in multiple time series models are generally identified from the data. In forecasting and impulse response analyses, this often requires the use of statistical selection criteria to identify how many lags to include in the system

Among the various statistical selection criteria available in the literature, the Bayesian statistical criteria (BIC) proposed is used, since it is a criteria that does not assume a true, but unknown, data-generating process, and is given by

$$BIC(p) = \ln \left| \sum_{u}^{-}(p) \right| + \frac{2\ln\ln T}{T}\, pG^2$$

Wherep is the number of lags of the endogenous variables $|\sum_{u}^{-}(p)|$is de determinant of the matrix of variance and covariances of the residuals of the model of interest when estimated with p, T is the sample size, and G represents the number of endogenous variables. The estimated ˆp for p is chosen so that the BIC is minimized.
0 presents the BIC for the four selected models. The minimum BIC for the vector error correction model (VECM) of –16.9418 is observed when the model uses 5 lags and for the seasonal vector errorcorrection model (SVECM) the minimum BIC of –11.2347. For the cointegration dynamic simultaneous equation model (DSEM) the minimum BIC is of -22.9287, when calculated using 6 lags. For the seasonal cointegration dynamic simultaneous equation model (SDSEM) the minimum BIC of–22.5577 is also observed for 6 lags.

Table 1. BIC values for the selected models for a sample commodity market.

Models	Lags 2	3	4	5	6	7
VECM	-12.9536	-12.9564	-12.9348	**-16.9418**	◆	◆
SVECM	*	*	-6.5028	**-11.2347**	-10.9762	◆
CDSEM	•	•	-20.4404	-21.3266	**-22.9287**	•
SCDSEM	*	*	-21.320	-22.1523	**-22.5577**	•

[a] BICs in bold indicates a minimum. Some characteristics in the models avoid the calculation of the BIC: A * indicates the model specification assumes four or more lags, • indicates that some instrumental variables are linearly independent over the regression range, and ◆ indicates a non-invertible matrix in the reduced-rank regression.

In synthesis, the BIC identifies a vector autoregressive model of order 5 as the underlying model for the VECM and the SVECM models, while it identifies that the variables must enter with 6 lags for the DSEM specification and with 5 lags for the SDSEM

CONCLUSION

The general conclusions that emerge from this dissertation research may be summarized in the following areas: integration properties of the commodity market data, vector-error correction modeling results, and structural-time series findings. The conclusions are drawn from a forecasting experiment andfrom an analysis of the impulse response functions.

Unit-Root Properties quarterly data in the commodity market (1981:01-1999:04) have seasonal unit roots, requiring, therefore, that a VECM or a DSEM should be specified in the framework of seasonal cointegration. This finding is consistent with the often reported use of seasonal dummy variables in the specification of error-correction models in previous research. The finding is far reaching in the sense that it alerts practitioners to be more cautious in the formulation of dynamic models. Seasonal unit-root tests should become part of the tool kit of applied commodity modelers in order to avoid biases specifications and less than optimum forecasts.

Vector Error Correction Modeling. It is found that only in few instances, for example in the two-stepahead forecasts for commodity disappearance, did a vector error correction model (VECM) perform better than the alternative models. However, the same model (VECM) expanded to allow for seasonal cointegration (SVECM) improved forecasting performance compared to the VECM. This finding should again serve to alert practitioners that mechanical use of deterministic seasonal elements in forecasting serve little purpose. In fact, the attractiveness of the SVECM lies in the fact that seasonal error-correction terms improve forecasting at longer horizons.

Structural Time Series.The comparisons of typical VECMs and DSEM without and with seasonal cointegration in a forecasting context suggest that seasonally cointegrated VECMs perform better that their nonseasonal counterpart, particularly at forecast horizons longer that two quarters ahead. DSEM with seasonal cointegration, however, perform better at longer forecast horizons for production, disappearance, inventories, exports, and prices but not uniformly. Lastly, the impulse response analysis and dynamic multiplier comparisons lead to one salient conclusion, omission of seasonal cointegration components, when significant, generates much different response functions and dynamic multipliers. A typical pattern observed in the commodity data is that impulse responses may not die out when they should.

The research also introduced procedures for evaluating forecasting performance using tests of differences in mean-squared errors (MSE). It is concluded that minor differences in MSEs may not warrant the adoption of a new forecasting model, thus, applied forecasters should carefully assess the reliability of simple structures with these testing procedures.

The empirical comparisons generated from this study are based on the use of tests of forecasting performance and impulse response functions. Of much interest to structural analysts may be the estimation of elasticities and/or flexibilities using structural-time series models. Such an area of research is waiting to be addressed.

Of particular interest for immediate future research is an assessment of the small sample properties of impulse response functions for structural-time series models with seasonal cointegration.

Preliminary Monte Carlo evidence has been introduced on this issue in this study but a more comprehensive evaluation is needed. The effect of modeling yearly production as a quarterly variable, by assigning the realized production to quarter 3, and setting the other quarters to zero, must also be considered in the Monte Carlo experiment. This may be implemented by adding a forth endogenous variable to the DGP used in this dissertation, with data in quarter 3 and zeros elsewhere.

The focus of the study was on forecasting and impulse response properties of various multivariate models. Perhaps of more immediate empirical relevance may be a more extensive evaluation of various commodity market models using a structural-time series approach similar to the one used in this research.

To conclude, the development of a practical guide for specifying, estimating, forecasting, and impulse responses of the four models considered in this dissertation is in progress.

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