Nº 229

FORECASTING CRUDE OIL AND NATURAL GAS SPOT PRICES BY CLASSIFICATION METHODS

Viviana Fernández

DOCUMENTOS DE TRABAJO

Serie Economía

Forecasting crude oil and natural gas spot prices by classification methods

Viviana Fernandez[1]

Abstract

In this article, we forecast crude oil and natural gas spot prices at a daily frequency based on two classification techniques: artificial neural networks (ANN) and support vector machines (SVM). As a benchmark, we utilize an autoregressive integrated moving average (ARIMA) specification. We evaluate out-of-sample forecast based on encompassing tests and mean-squared prediction error (MSPE). We find that at short-time horizons (e.g., 2-4 days), ARIMA tends to outperform both ANN and SVM. However, at longer-time horizons (e.g., 10-20 days), we find that in general ARIMA is encompassed by these two methods, and linear combinations of ANN and SVM forecasts are more accurate than the corresponding individual forecasts. Based on MSPE calculations, we reach similar conclusions: the two classification methods under consideration outperform ARIMA at longer time horizons.

JEL classification: C22, E32
Keywords: autoregressive integrated moving average; artificial neural networks; support vector machines.

[1] Associate Professor, Center for Applied Economics (CEA) at the Department of Industrial Engineering of the University of Chile. Postal: Avenida Republica 701, Santiago-Chile. Email: vfernand@dii.uchile.cl; fax: (562) 689-7895. Financial support from an institutional grant of the Hewlett Foundation to CEA is greatly acknowledged. All remaining errors are the author's.

1 Introduction

Forecasting economic activity has received considerable attention over the past fifty years. An increasing number of statistical methods, which frequently differ in structure, has been developed in order to predict the evolution of various macroeconomic time series, such as consumption, production and investment (e.g., Diebold 1998; Clements and Hendry 1998, chapter 1). In the area of natural resources, commodity prices have been the focus of various studies (e.g., Roche 1995; Labys 1999; Morana 2001). Two recent articles by Dooley and Lenihan (2005) and Lanza, Manera and Giovannini (2005) deal with base metals and crude oil, respectively. Dooley and Lenihan consider a lagged forward price model and an autoregressive integrated moving average (ARIMA) model to test the cash price forecasting power. They conclude that ARIMA modeling provides marginally better forecast results. Lanza, Manera and Giovannini in turn utilize cointegration and an error correction model (ECM) to predict crude oil prices. They conclude that an ECM outperforms a naïve model that does not involve any cointegrating relationships.

In recent years, the forecasting literature has shown that the combination of multiple individual forecasts from different econometric specifications can be used as a vehicle to increase forecast accuracy (e.g., Clemen 1989). In particular, Fang (2003) illustrates that, for the case of U.K. consumption expenditure, forecast encompassing tests are a useful tool to determine whether a composite forecast can be superior to individual forecasts. In addition, Fang argues that forecast encompassing tests are potentially useful in model specification, as forecast combination implicitly assumes the possibility of model misspecification.

Our study focuses on forecasting spot prices of crude oil and natural gas at a daily frequency for the sample period 1994-2005. The contribution of our work is twofold. First, we utilize one novel non-linear forecasting technique, which is based on support vector machines (SVM). SVM is a relatively new data classification technique, which has arisen as a more user-friendly tool than artificial neural networks (e.g., Burges 1998; Cristianini and Shawe-Taylor 2000). Applications of SVM to forecasting are fairly recent and have dealt primarily with financial and energy issues (e.g., Tay and Kao 2001, Kim 2003; Dong, Cao, and Lee 2005; Huang, Nakamori, and Wang 2005; Lu and Wang 2005).

The second contribution of this article is to perform encompassing tests for various time horizons by resorting to three non-linear models: ARIMA, artificial neural networks (ANN) and SVM. Our computations show that the time horizon is a key element to decide which model or combination of models can be preferable in terms of forecast accuracy.

This article is organized as follows. Section 2 briefly discusses the SVM technique, which is relatively recent in the forecasting literature, and it presents forecast accuracy and encompassing tests. Section 3 describes the data and discusses our estimation results. Section 4 concludes.

2 Methodology

2.1 An overview of Support Vector Machines (SVM)

SVM is a relatively recent technique within classification methods (e.g., Venables and Ripley 2002, chapter 12; Chang and Lin 2005). It consists of mapping a vector of attributes (i.e., regressors), **x**, into a higher dimensional space by a function ϕ, and finding a linear maximum-margin hyperplane.[2] That is, we seek a classifying hyperplane of the form $f(\mathbf{x})=w'\phi(\mathbf{x})+b=0$.

We penalize $f(x_i)$ when it is far off y_i by means of an ε-insensitive loss function:

$$L_\varepsilon(y)=\begin{cases}0 & \text{if } |f(x)-y|<\varepsilon\\ |f(x)-y|-\varepsilon & \text{otherwise}\end{cases} \quad (1)$$

where ε is arbitrary.

- The smallest distance to the hyperplane is called the margin distance. The hyperplane is called an optimal separating hyperplane if the margin is maximized. The data points that are located exactly the margin distance away from the hyperplane are denominated the support vectors.[3]

Specifically, the ε-Support Vector Regression (ε-SVR) solves the following quadratic programming problem:

$$\min_{\omega,b,\xi_i^-,\xi_i^+} \frac{1}{2}\mathbf{?}\,'\mathbf{?} + C\sum_{i=1}^{n}(\xi_i^- + \xi_i^+) \quad (2)$$

subject to

$$\begin{aligned} &y_i-(\mathbf{?}\,'\phi(\mathbf{x}_i)+b)\le\varepsilon+\xi_i^- && \forall i\\ &(\mathbf{?}\,'\phi(\mathbf{x}_i)+b)-y_i\le\varepsilon+\xi_i^+ &&\\ &\xi_i^-\ge 0,\xi_i^+\ge 0 && \end{aligned}$$

where $C>0$ is a penalty parameter and b is a constant term.

The function $K(\mathbf{x}_i,\mathbf{x}_j)=\phi(\mathbf{x}_i)'\phi(\mathbf{x}_j)$ represents a kernel. Well-known kernel functions are $K(\mathbf{x}_i,\mathbf{x}_j)=\mathbf{x}_i'\mathbf{x}_j$ (linear), $K(\mathbf{x}_i,\mathbf{x}_j)=(\gamma\mathbf{x}_i'\mathbf{x}_j+r)^d$, $\gamma>0$ (polynomial),

---

[2] A maximum-margin hyperplane separates two clouds of points, and it is at equal distance from the two. The smallest distance from the hyperplane is called the margin of separation.

[3] The distance of a point x_i to the hyperplane is given by $|w'\phi(\mathbf{x})+b|/\|\mathbf{?}\|^2$. The margin distance is given by $2/\|\mathbf{?}\|$.

$K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma \| \mathbf{x}_i - \mathbf{x}_j \|^2)$, $\gamma>0$ (radial basis function), and $K(\mathbf{x}_i, \mathbf{x}_j) = \tanh(\gamma \mathbf{x}_i' \mathbf{x}_j + r)$ (sigmoid). For the linear kernel case, the graphical representation of the SVM technique is given in Figure 1. As we see, we seek to minimize ξ_i^- when y_i is above $f(\mathbf{x})$, and to minimize ξ_i^+ when y_i is below $f(\mathbf{x})$. The data points lying on the ε-tube are denominated the support vectors. In general, the larger ε the fewer the number of support vectors and, consequently, the sparser the representation of the solution. Nevertheless, a large ε is detrimental to the accuracy provided by the training data (i.e., the observations used to calibrate the model).

2.2 Forecast evaluation

Granger y Newbold proposed the following statistic (see Enders 2004, page 85) which assumes that under the null hypothesis models 1 and 2 have the same mean-squared prediction error (MSPE), i.e., $E(e_{1t}^2 - e_{2t}^2)=0$:

$$\frac{r_{xz}}{\sqrt{(1-r_{xz}^2)/(H-1)}} \sim t(H-1) \tag{3}$$

where r_{xz} is the sample correlation coefficient between $x_t=e_{1t}+e_{2t}$ and $z_t=e_{1t}-e_{2t}$, and H is the length of the forecast error series. If r_{xz} is positive and statistically different from zero, model 1 has a larger MSPE than model 2. Otherwise, if r_{xz} is negative and statistically different from zero, model 2 has a larger MSPE. [4]

2.3 Forecasting encompassing

We also resort to a forecasting evaluation technique in Fang (2003), denominated forecasting encompassing. In particular, one of the specifications utilized by Fang is the following:

$$\Delta_h y_{t+h} = \beta_0 + \beta_1(\hat{y}_{t,t+h}^{(1)} - y_t) + \beta_2(\hat{y}_{t,t+h}^{(2)} - y_t) + u_{t+h} \tag{4}$$

where $\hat{y}_{t,t+h}$ is the forecast of y_{t+h} based on information available at time t, and $\Delta_h y_{t+h} = y_{t+h} - y_t$. (The difference operator is used due to non-stationarity of the time series).[5] When $\beta_1=0$ and $\beta_2\neq0$, the second model forecast encompasses the first. Conversely, if $\beta_1\neq0$ and $\beta_2=0$, the first model forecast encompasses the second. In the case that both forecasts contain independent information for h-period ahead forecasting of y_t, both β_1 and β_2 should be different from zero. It is worth noticing that no constraint is imposed on the sum $\beta_1+\beta_2$.

[4] We also utilized Diebold and Mariano (1995) test but, except for very short-time forecast horizons, our results were inconclusive as to the performance of one model relative to another.

[5] Given that we utilize the natural logarithm of the time series, $\Delta_h y_{t+h}=y_{t+h}-y_t$ represents the return on y between times t and t+h.

Equation (4) can be estimated in principle by ordinary least squares, utilizing standard errors robust to the presence of both heteroskedasticity and serial correlation. Nevertheless, if the two forecasts are highly collinear, Fang advises to resort to ridge regression.

3 Data description and estimation

The estimation results reported in this section were carried out with routines written by the author in S-Plus 7.0. In addition, the libsvm and nnet S-Plus library were utilized for implementing the SVM and the ANN techniques, respectively[6].

Our data set comprises daily observations of oil and natural gas spot prices (Crude Oil-Arab Gulf Dubai FOB U$/BBL and Henry Hub $/MMBTU, respectively), and of the Dow Jones AIG commodity index (DJAIG) and AMEX oil and gas index for the sample period 1994-2005. The data source is DataStream. Descriptive statistics of daily returns are shown in Table 1 and the variables in levels are depicted in Figure 2. As we see, natural gas experienced sharp fluctuations over the sample period, and the all four series show an increasing trend from 2002 onwards.

The autocorrelation function (ACF) of crude oil and natural gas decay very slowly, suggesting the presence of a unit root (Figure 3). Indeed, the Elliott-Rothenberg-Stock, augmented Dickey-Fuller (ADF), and modified Phillips-Perron tests do not reject the presence of a unit root in either series. Therefore, an ARIMA specification is considered as a benchmark to assess the forecast performance of ANN and SVM. Specifically, an ARIMA (2, 1, 0) appeared as satisfactory to both price series. In order to fit the ANN and SVM specifications, we use as predictors the DJAIG and AMEX oil & gas indices. The ANN model comprises 1 hidden layer and 2 units in the hidden layer. The SVM specification in turn is based on a radial kernel.

Our estimation strategy consists of leaving five months of data approximately for forecast evaluation. Specifically, we take a rolling window of about 2,900 observations, which allows us to obtain a series of 150 forecast errors for a time horizon that ranges between 1 and 20 days ahead. Figures 4 and 5 depict the evolution of the forecast errors yielded by the three estimation methods for 15- and 20-day ahead forecasts for oil and natural gas, respectively.

Table 2 and 3 provide more insight on how the forecast performance of the three model specifications evolves over time. Table 2 reports the Granger-Newbold statistic and its corresponding p-value for all three possible paired combinations of models. For oil, ARIMA has a smaller MSPE than ANN within 10-day ahead. However, for a longer time horizon, ANN outperforms ARIMA. SVM is the specification with the poorest MSPE performance, as both ARIMA and ANN have consistently smaller MSPE. For natural gas, the findings are slightly different. ARIMA always outperforms ANN, and it outperforms

[6] Examples on the use of the libsvm library are given in the textbook by Venables and Ripley (2002). Documentation on the SVM technique can be found at Chih-Jen Lin´s website, www.csie.ntu.edu.tw/~cjlin/papers/.

SVM for forecasts between 1 and 15 days ahead. In contrast, this time SVM has always a better performance than ANN in terms of MSPE.

Table 3 in turn reports forecast encompassing tests based on the discussion of Section 2.3. As we see, at short-time horizons (e.g., 2-4 days), ARIMA tends to outperform both ANN and SVM. However, at longer-time horizons (e.g., 10-20 days), ARIMA is in general encompassed by the two, and linear combinations of ANN and SVM forecasts are more accurate than corresponding individual forecasts in most cases. These findings corroborate what we concluded from Table 2, in that ARIMA is best for short-time horizons.

In sum, ARIMA in general provides with more accurate step-ahead forecasts than SVM and ANN at short-time horizons. However, its performance gets poorer relative to these two classification methods as we move further away in time.

4 Concluding remarks

In this article, we have resorted to two classification techniques to forecast future spot prices of two commodities: artificial neural networks (ANN) and support vector machines (SVM). Whereas the former is already well-known in the forecasting literature, the latter has gained ground in economic and financial applications very recently.

The forecast performance of the two above techniques is contrasted with that of a standard one, namely, ARIMA. Our computations, based on forecast encompassing and MSPE, show that ARIMA can be preferable to forecasting spot prices at very short-term horizons. However, at longer-time horizons, ANN and SVM outperform it, and, in addition, combined forecasts of these two techniques are more accurate than individual forecasts.

References

Burges, C. (1998). "A tutorial on support vector machines for pattern recognition." Data Mining and Knowledge Discovery 2(2), 955-974.

Chang, C.C., and C.J. Lin (2005), "LIBSVM: a library for support vector machines." http://www.csie.ntu.edu.tw/~cjlin

Clemen, R. (1989). "Combining forecasts: A review and annotated bibliography." International Journal of Forecasting 5, 559-583.

Clements, M., and D. Hendry (1998). Forecasting Economic Time Series. Cambridge: Cambridge University Press.

Christianini, N., and J. Shawe-Taylor (2000). An introduction to support vector machines and other kernel-based learning methods. Cambridge University Press.

Diebold, F., and R. Mariano (1995). "Comparing Predictive Accuracy." Journal of Business and Economic Statistics 13, 253-263.

Diebold, F. (1998). “The past, present, and future of macroeconomic forecasting.” Journal of Economic Perspectives 12, 175-192.

Dong, B., C. Cao, and S.E. Lee (2005), “Applying support vector machines to predict building energy consumption in tropical region.” Energy and Buildings 37(5), 545-553.

Dooley, G., and H. Lenihan (2005). “An assessment of time series methods in metal price forecasting.” Resources Policy 30, 208-217.

Enders, W. (2004). Applied Econometric Time Series. Second edition. Wiley Series in Probability and Statistics.

Fang, Y. (2003). “Forecasting combination and encompassing tests.” International Journal of Forecasting 19(1), 87-94.

Huang, W., Y. Nakamori, and S.Y. Wang (2005), “Forecasting stock market movement direction with support vector machine.” Computers & Operations Research 32(10), 2513-2522

Kim, K. (2003). “Financial time series forecasting using support vector machines.” Neurocomputing 55 (1-2), 307-319.
Labys, W. (1999). Modeling mineral and energy markets. Kluwer, USA.

Lanza, A., M. Manera, and M. Giovannini (2005). “Modeling and forecasting cointegrated relationships among heavy oil and product prices.” Energy Economics 27(6), 831-848.

Lu, W.Z., and W.J. Wang (2005), “Potential assessment of the “support vector machine” method in forecasting ambient air pollutant trends.” Chemosphere 59(5), 693-701.

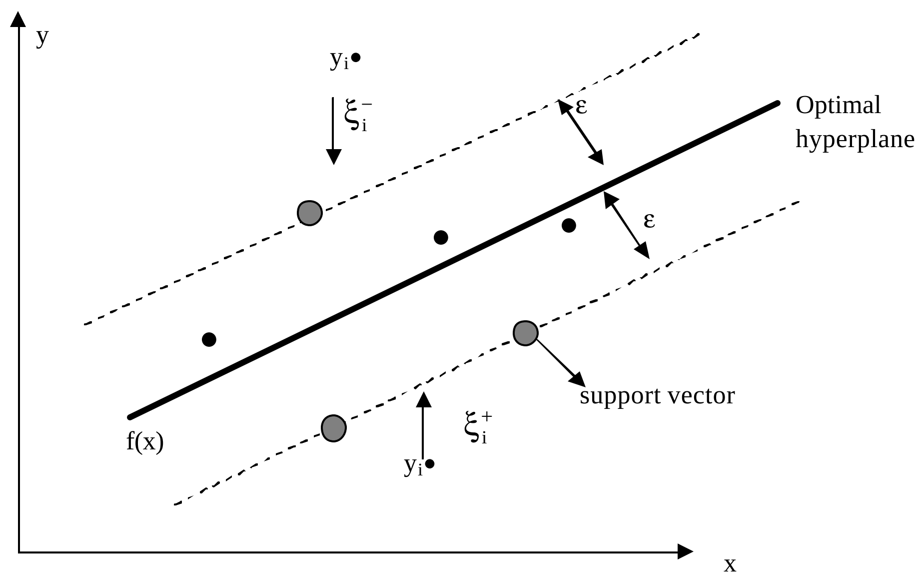
Morana, C. (2001). “A semiparametric approach to short-term oil price forecasting.” Energy Economics 23(3), 325-338.

Roche, J. (1995). Forecasting commodity markets. Probus Publishing Company, London.

Tay, F., and L. Cao (2001). “Application of support vector machines in financial time series forecasting.” Omega 29(4), 309-317.

Venables, W. and Ripley, B. (2002). Modern Applied Statistics with S. Forth edition. Springer-Verlag New York, Inc.

Figure 1 Graphical representation of the SVM technique for a linear kernel



<u>Note</u>: f(**x**) represents the forecasting function, with f(**x**)=**x**′w+b, where w is the normal vector to f(**x**).

Figure 2 Evolution of fuel prices and related indices

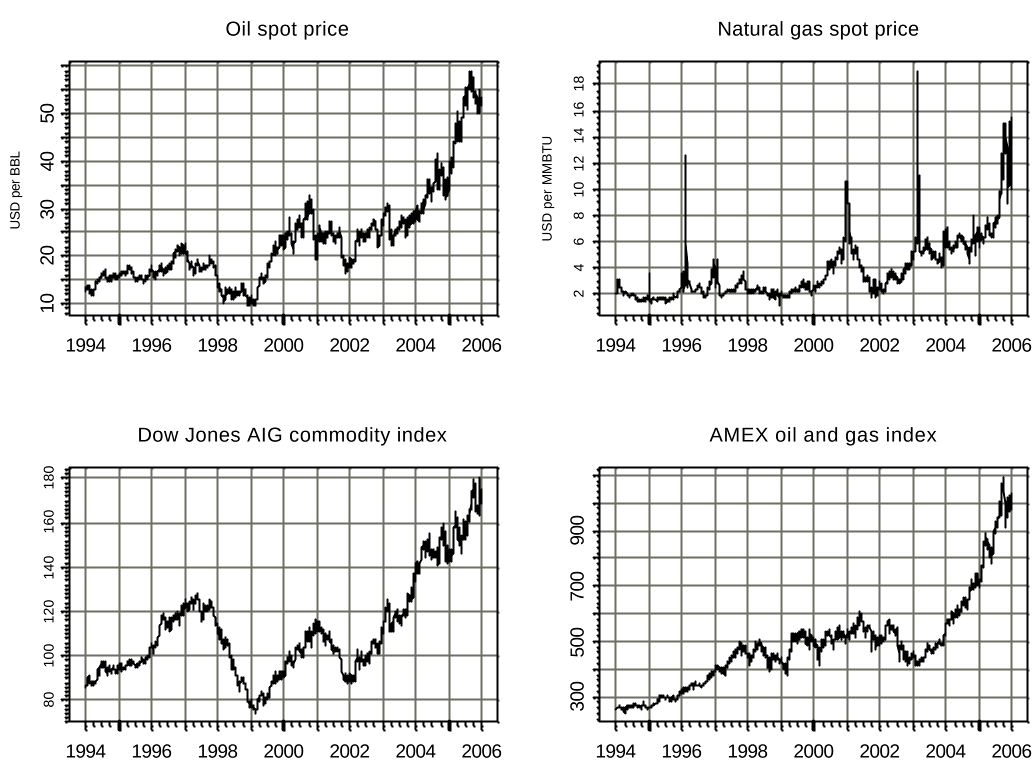


Figure 3 Autocorrelation functions of daily prices

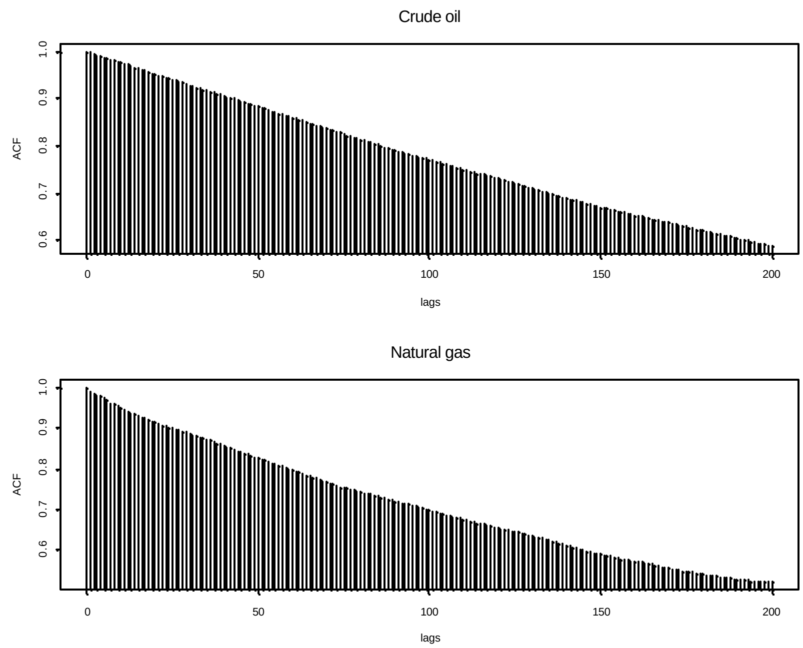


Figure 4 Rolling-estimates of out-of-sample forecast errors for crude oil

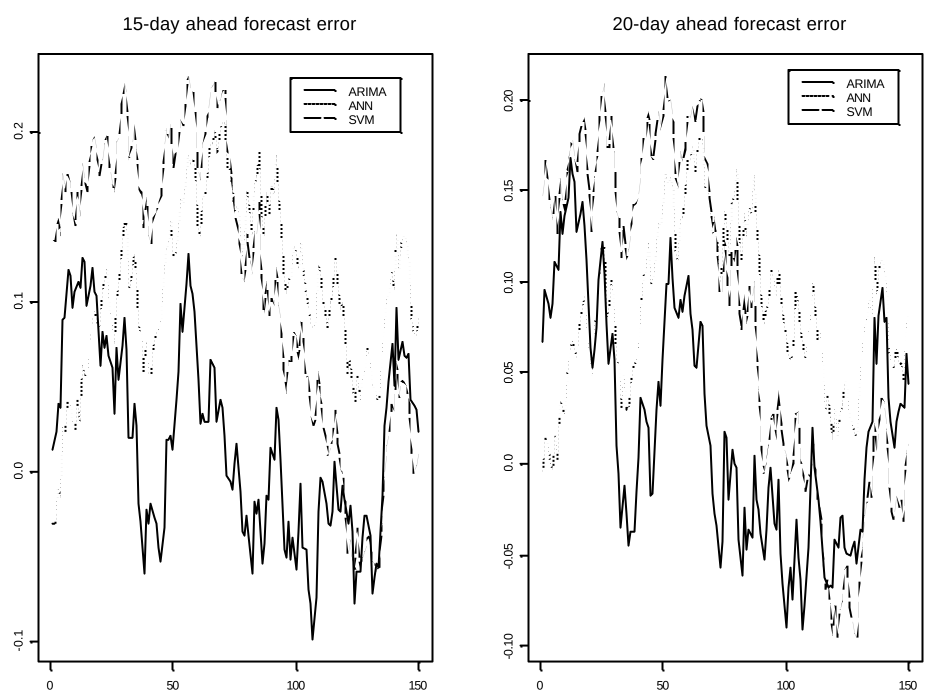


Figure 5 Rolling-estimates of out-of-sample forecast errors for natural gas

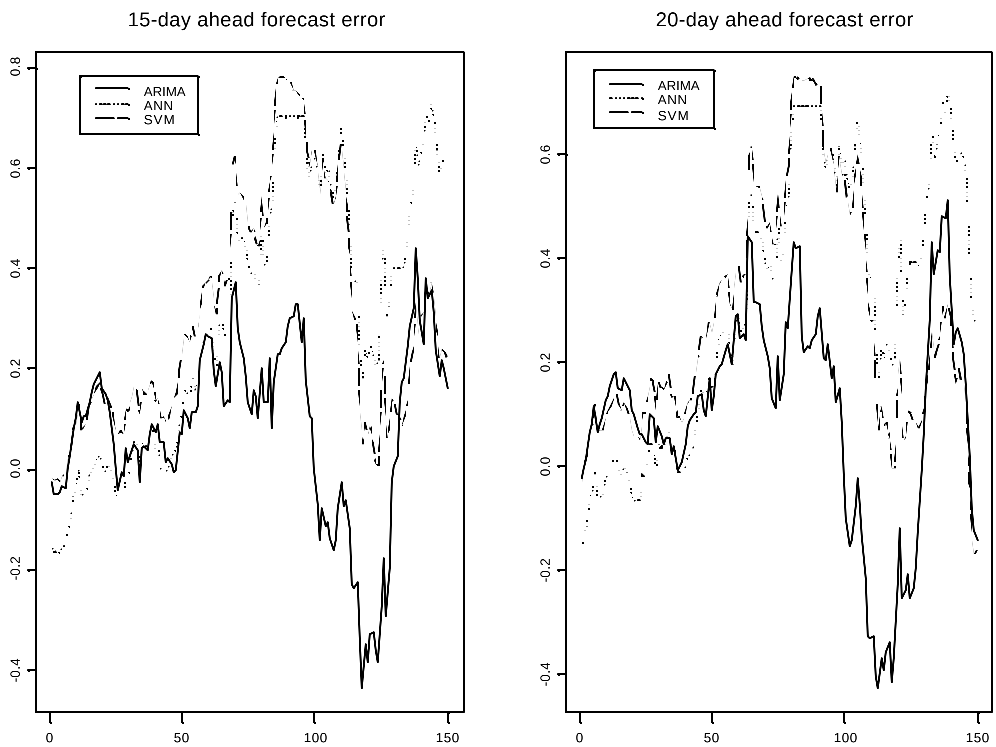


Table 1 Statistics of daily returns: January 1994-December 2005

Statistic	Natural gas	DJAIG	AMEX oil & gas	Crude oil
Minimum	–1.273	–0.043	–0.061	–0.129
1st Qu.	–0.018	–0.005	–0.006	–0.012
Median	0.000	0.000	0.000	0.001
Mean	0.001	0.000	0.000	0.000
3rd Qu.	0.018	0.005	0.008	0.013
Maximum	0.876	0.048	0.069	0.147
Std. deviation	0.062	0.008	0.012	0.021
Skewness	–1.422	0.028	–0.129	–0.224
Excess Kurtosis	103.29	1.78	1.96	3.27
Observations	3,077	3,077	3,077	3,077

Table 2 Granger-Newbold test for out-of-sample forecast evaluation

Crude oil

	ARIMA-ANN		ARIMA-SVM		SVM-ANN	
horizon (days)	statistic	p-value	statistic	p-value	statistic	p-value
5	–8.80	0.00	–11.82	0.00	1.97	0.03
10	–2.76	0.00	–7.27	0.00	3.93	0.00
12	–0.91	0.18	–6.72	0.00	5.32	0.00
15	1.49	0.07	–6.44	0.00	7.60	0.00
18	3.41	0.00	–6.25	0.00	9.84	0.00
20	4.66	0.00	–5.96	0.00	11.02	0.00

Natural gas

	ARIMA-ANN		ARIMA-SVM		SVM-ANN	
horizon (days)	statistic	p-value	statistic	p-value	statistic	p-value
5	–13.45	0.00	–10.81	0.00	–4.04	0.00
10	–7.87	0.00	–6.14	0.00	–3.21	0.00
12	–6.69	0.00	–4.73	0.00	–3.52	0.00
15	–5.51	0.00	–3.27	0.00	–3.53	0.00
18	–3.93	0.00	–1.94	0.03	–3.08	0.00
20	–2.89	0.00	–1.34	0.09	–2.17	0.02

Note: The ARIMA-ANN pair notation implies that ARIMA is model 1 and ANN is model 2, etcetera.

Table 3 Forecast encompassing

Oil						Natural gas					
h=2						h=2					
ARIMA		ANN		SVM		ARIMA		ANN		SVM	
slope	prob	slope	prob	slope	prob	slope	prob	slope	prob	slope	prob
0.47	0.00	0.05	0.02	--	--	0.45	0.00	0.02	0.23	--	--
0.50	0.00	--	--	–0.01	0.63	0.46	0.00	--	--	0.01	0.60
--	--	0.07	0.01	–0.02	0.55	--	--	0.03	0.25	0.00	0.97
h=4						h=4					
ARIMA		ANN		SVM		ARIMA		ANN		SVM	
slope	prob	slope	prob	slope	prob	slope	prob	slope	prob	slope	prob
0.43	0.00	0.13	0.00			0.41	0.00	0.05	0.08		
0.48	0.00	--	--	0.01	0.77	0.41	0.00	--	--	0.05	0.15
--	--	0.15	0.00	–0.02	0.53	--	--	0.05	0.28	0.02	0.76
h=10						h=10					
ARIMA		ANN		SVM		ARIMA		ANN		SVM	
slope	prob	slope	prob	slope	prob	slope	prob	slope	prob	slope	prob
0.35	0.02	0.37	0.00	--	--	0.34	0.14	0.14	0.00		
0.45	0.01	--	--	0.10	0.06	0.34	0.14	--	--	0.18	0.00
--	--	0.40	0.00	–0.05	0.29	--	--	0.03	0.78	0.16	0.12
h=15						h=15					
ARIMA		ANN		SVM		ARIMA		ANN		SVM	
slope	prob	slope	prob	slope	prob	slope	prob	slope	prob	slope	prob
0.19	0.19	0.56	0.00	--	--	0.35	0.15	0.22	0.00		
0.46	0.03	--	--	0.07	0.27	0.31	0.18	--	--	0.30	0.00
--	--	0.62	0.00	–0.14	0.00	--	--	0.06	0.48	0.25	0.01
h=20						h=20					
ARIMA		ANN		SVM		ARIMA		ANN		SVM	
slope	prob	slope	prob	slope	prob	slope	prob	slope	prob	slope	prob
0.06	0.68	0.70	0.00	--	--	0.29	0.29	0.33	0.00		
0.50	0.05	--	--	0.03	0.66	0.18	0.50	--	--	0.40	0.00
--	--	0.78	0.00	–0.23	0.00	--	--	0.20	0.01	0.23	0.02

Notes: Parameter estimates are obtained from expression (4). The slopes correspond with β_1 and β_2, whereas "prob" denotes the p -value of the t-statistic of each parameter estimate.

Centro de Economía Aplicada
Departamento de Ingeniería Industrial
Universidad de Chile

Serie Economía

Nota : Copias individuales pueden pedirse a CEA c/o Lina Canales, Av. República 701, Santiago, Chile, Fono: +562/678 4072, Fax: +562/689 7895, email: lcanales@dii.uchile.cl.

Los documentos también están disponibles en la página Web del CEA, en la dirección http://www.cea-uchile.cl/.

Note: CEA's working papers are available upon request from CEA c/o Lina Canales, Av. República 701, Santiago, Chile, Phone: +562/678 4072, Fax: +562/689 7895, email: lcanales@dii.uchile.cl.

CEA's working papers are also available at CEA's Web page, under the address http://www.cea-uchile.cl/.

2006

229. Forecasting crude oil and natural gas spot prices by classification methods
Viviana Fernández

228. Copula-based measures of dependence structure in assets returns
Viviana Fernández

227. Un Análisis Econométrico del Consumo Mundial de Celulosa
José Ignacio Sémbler, Patricio Meller y Joaquín Vial

226. The Old and the New Reform of Chile's Power Industry. (Por aparecer en el International Journal of Global Energy Issues (forthcoming 2007)).
M. Soledad Arellano

225. Socioeconomic status or noise? Tradeoffs in the generation of school quality information. (Por aparecer en el Journal of Development Economics).
Alejandra Mizala, Pilar Romaguera y Miguel Urquiola.

224. Mergers and CEO power
Felipe Balmaceda

123. Task-Specific Training and Job Design.
Felipe Balmaceda

122. Performance of an economy with credit constraints, bankruptcy and labor inflexibility
Felipe Balmaceda y Ronald Fischer

121. Renegotiation without Holdup: Anticipating spending and infrastructure concessions
Eduardo Engel, Ronald Fischer y Alexander Galetovic

220. Using School Scholarships to Estimate the Effect of Government Subsidized Private Education on Academic Achievement in Chile
Priyanka Anand, Alejandra Mizala y Andrea Repetto

219. Portfolio management implications of volatility shifts: Evidence from simulated data
Viviana Fernandez y Brian M Lucey

218. Micro Efficiency and Aggregate Growth in Chile
Raphael Bergoeing y Andrea Repetto

2005

217. Asimetrías en la Respuesta de los Precios de la Gasolina en Chile
Felipe Balmaceda y Paula Soruco

216. Sunk Prices and Salesforce Competition
Alejandro Corvalán y Pablo Serra

215. Stock Markets Turmoil: Worldwide Effects of Middle East Conflicts
Viviana Fernández

214. The Competitive Role of the Transmission System in Price-regulated Power Industries
M. Soledad Arellano y Pablo Serra

213. La Productividad Científica de Economía y Administración en Chile. Un Análisis Comparativo (Documento de Trabajo Nº 301. Instituto de Economía, Pontificia Universidad Católica de Chile)
Claudia Contreras, Gonzalo Edwards y Alejandra Mizala

212. Urban Air Quality and Human Health in Latin America and the Caribbean
Luis A. Cifuentes, Alan J. Krupnick, Raúl O'Ryan y Michael A. Toman

211. A Cge Model for Environmental and Trade Policy Analysis in Chile: Case Study for Fuel Tax Increases
Raúl O'Ryan, Carlos J. de Miguel y Sebastian Millar

210. El Mercado Laboral en Chile Nuevos Temas y Desafíos
Jaime Gatica y Pilar Romaguera

209. Privatizing Highways in The United States
Eduardo Engel, Ronald Fischer y Alexander Galetovic

208. Market Power in Price-Regulated Power Industries
M. Soledad Arellano y Pablo Serra

207. Market Reforms and Efficiency Gains in Chile
Raphael Bergoeing, Andrés Hernando y Andrea Repetto

206. The Effects on Firm Borrowing Costs of Bank M&As
Fabián Duarte, Andrea Repetto y Rodrigo O. Valdés

205. Cooperation and Network Formation
Felipe Balmaceda

204. Patrones de Desarrollo Urbano: ¿Es Santiago Anómalo?
Raphael Bergoeing y Facundo Piguillem

203. The International CAPM and a Wavelet-based Decomposition of Value at Risk
Viviana Fernández

202. Do Regional Integration Agreements Increase Business-Cycle Convergence? Evidence from Apec and Nafta
Viviana Fernández y Ali M. Kutan

201. La dinámica industrial y el financiamiento de las pyme. (Por aparecer en El Trimestre Económico)
José Miguel Benavente, Alexander Galetovic y Ricardo Sanhueza

200. What Drives Capital Structure? Evidence from Chilean Panel Data
Viviana Fernández

2004

199. Spatial Peak-load Pricing
M. Soledad Arellano y Pablo Serra

198. Gas y Electricidad: ¿qué hacer ahora?. (Estudios Públicos 96, primavera 2004, 49-106)
Alexander Galetovic, Juan Ricardo Inostroza y Cristian Marcelo Muñoz

197. Reformando el sector eléctrico chileno: Diga NO a la liberalización del mercado spot
M. Soledad Arellano

196. Risk, Pay for Performance and Adverse Selection in a Competitive Labor Market
Felipe Balmaceda

195. Vertical Integration and Shared Facilities in Unregulated Industries
Felipe Balmaceda y Eduardo Saavedra

194. Detection of Breakpoints in Volatility
Viviana Fernández

193. Teachers' Salary Structure and Incentives in Chile
Alejandra Mizala y Pilar Romaguera

192. Estimando la demanda residencial por electricidad en Chile: a doña Juanita le importa el precio
José Miguel Benavente, Alexander Galetovic, Ricardo Sanhueza y Pablo Serra

191. Análisis y Recomendaciones para una Reforma de la Ley de Quiebras
Claudio Bonilla, Ronald Fischer, Rolf Lüders, Rafael Mery, José Tagle

190. Trade Liberalization in Latin America: The Case of Chile
Ronald Fischer

189. Time-Scale Decomposition of Price Transmission in International Markets
Viviana Fernández

188. Slow Recoveries. (Por aparecer en Journal of Development Economics)
Raphael Bergoeing, Norman Loayza y Andrea Repetto

187. Market Power in Mixed Hydro-Thermal Electric Systems
M. Soledad Arellano

186. Efectos de la privatización de servicios públicos en Chile: Casos sanitario, electricidad y telecomunicaciones
Ronald Fischer y Pablo Serra

185. A Hierarchical Model for Studying Equity and Achievement in the Chilean School Choice System
Alejandra Mizala, Pilar Romaguera y Carolina Ostoic

184. Innovaciones en Productividad y Dinámica de Plantas. (Revista de Análisis Económico, 18(2), pp. 3-32, 2003)
Raphael Bergoeing y Facundo Piguillem

183. The Dynamics of Earnings in Chile
Cristóbal Huneeus y Andrea Repetto

182. Monopoly Regulation, Chilean Style: The Efficient-Firm Standard in Theory and Practice
Álvaro Bustos y Alexander Galetovic

181. Vertical Mergers and Competition with a Regulated Bottleneck Monopoly
Alexander Galetovic y Ricardo Sanhueza

180. Crecimiento Económico Regional en Chile: ¿Convergencia?
Rodrigo Díaz y Patricio Meller

179. Incentives versus Synergies in Markets for Talent
Bharat N. Anand, Alexander Galetovic y Alvaro Stein

178. Why is Manufacturing Trade Rising Even as Manufacturing Output is Falling?. (Por Aparecer en American Economic Review, Papers and Proceedings)
Raphael Bergoeing, Tim Kehoe, Vanessa Strauss-Kahn and Kei-Mu Yi

177. Transmisión eléctrica y la "ley corta": por qué licitar es (mucho) mejor que regular
Alexander Galetovic y Juan Ricardo Inostroza

176. Soft Budgets and Highway Franchising
Eduardo Engel, Ronald Fischer and Alexander Galetovic

* Para ver listado de números anteriores ir a http://www.cea-uchile.cl/.