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SHORT-TERM AND LONG-TERM RELATIONSHIPS BETWEEN PRICES OF IMPORTED OIL AND FUEL PRODUCTS IN THE U. S.

Václav Adamec[1]

[1] Department of Statistics and Operations Research, School of Business and Economics, Mendel University in Brno, Zemědělská 1, 613 00 Brno, Czech Republic

Abstract

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In this study, we analyzed a system of five monthly time series integrated *I(1)*: average price of crude oil imported to the U.S. from OPEC countries (*Opec*), imported oil price from other than OPEC countries (*NonOpec*) in USD per barrel, average price of regular gasoline in the U.S. (*Regular*), premium quality gasoline price (*Premium*) and kerosene price (*Kerosene*) in U.S. cents per gallon. Cointegration was established by EG test and the series were analyzed by VECM model with lag selected via BIC criterion. Cointegration rank was determined by the Johansen procedure. According to VECM coefficients, prices of oil from OPEC countries and beyond OPEC exert influence upon all commodity prices in the system, but in a contradictory manner. Responses to innovation shocks in *Opec* and *NonOpec* stabilized within 8 to 10 months upon a nonzero shift and further became permanent. Innovation shock in both types of gasoline and *Kerosene* had only short-term significant impact upon the system. Forecast error variance in all variables is explained mainly by variation in oil prices, especially *Opec*, which persists with increased horizon. For a short horizon $h = 1$, FEVDs in gasoline and kerosene prices are primarily made of variation in the respective fuel prices.

Keywords: oil price, cointegration, vector error correction model, impulse-response function, forecast error variance decomposition, R-software.

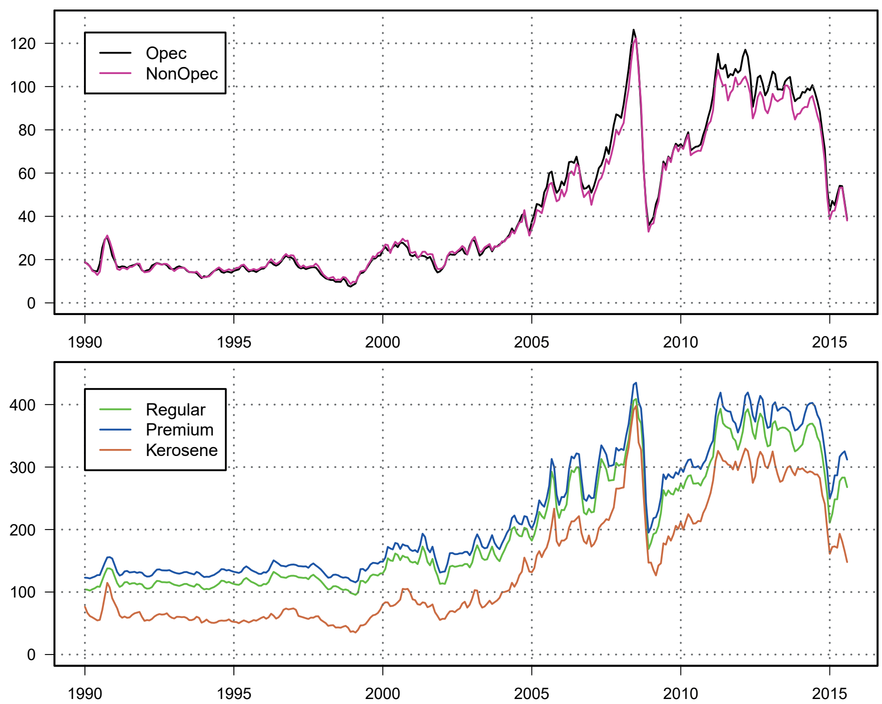
INTRODUCTION

It is widely acknowledged that securing an adequate supply of energy ranks among the most significant factors of economic growth. Availability and price of energy influence all sectors of the modern economy with unavoidable impact upon size of the economic output, unemployment and inflation. Price of both domestic and imported oil predetermines prices of most petrochemical products, primarily gasoline, diesel fuel, kerosene and heating oil that have use specially in the areas of transportation and generation of heat. In the economy, fuel prices thus contribute towards costs and inflation on the producer as well as on the consumer level, because increments in producer prices are transmitted whole or in part to the final consumer. Monitoring prices of crude oil or products made of oil therefore naturally attracts attention of the consumers, corporate companies as well as the central government.

A primary motivation for exploring relationships among prices of oil and oil products was the appearance of the energy crisis during 2006-2007 leading to extreme upturn in price of crude oil in the world and subsequently causing a record hike in fuel prices for the aviation sector as well as the ground transportation. Elevated costs of energy added to lower rates of economic growth and contributed to the lengthy recovery of the world economy in the period that followed. Understanding the principles of price formation and transmission through the product chain may hence potentially assist with limiting the consequences of adverse volatility and predict the price of strategic commodities and derivatives thereof for vital sectors of the economy.

It is often asserted, (see Borenstein *et al.*, 1997, for example) that prices of fuel in the U.S. are dependent upon the costs of purchasing oil (44 %), costs of production and profits (15 %), storage, distribution and marketing (14 %) and sizeable tax component constituted by the federal excise tax and sales tax imposed by states of the union (27 %). The important component is the vendor margin rate ranging from 5 to 15 percent. Oscillations in the profit margin can affect the resulting price, when change in price of crude oil is reflected in the price of the final product only to a limited extent, because fluctuations in oil price can be absorbed to some degree by the trader margins. Strength of the dependencies between fuel prices and price of oil can therefore vary. Several authors postulate that gasoline price responds to increase in oil price more quickly than to its decrease within four weeks from the change of crude oil price (Borenstein, Cameron, and Gilbert, 1997). Other research, Bumpass *et al.* (2015), for example, failed to validate hypothesis of asymmetric response claiming dependency of the results upon the cointegration model. Al-Gudhea *et al.* (2007) report evidence of asymmetric response in retail gasoline price from bivariate models of gasoline and crude oil price only. They also posit that asymmetry in price adjustment may depend on market power of the local retailers, consumer search costs or size of inventories. Studies that often report asymmetric response in gasoline price to oil price change do not agree about whether the price adjustment is asymmetric in the upward or downward direction (Chen *et al.*, 2005). Moreover, the research results generally appear to be varying with data definitions, frequency of data collection or the time period covered.

Dynamic correlations can be nonetheless expected among the price of inputs and the fuel products as well as price of oil from domestic production, imports from OPEC countries or other sources. Objective of this study is to characterize the long-term equilibrium, temporal (dynamic) and stochastic residual components of the vector error correction model (VECM) applied to a multivariate cointegrated system of five monthly time series of crude oil and fuel prices in the U.S. The econometric model shall bring added insight into the nature of dependencies among the energy prices. Specifically, it is expected to reveal, whether short-term causal relationships occur between the examined prices and, if detected, allow in detail explorations into the quantitative nature of these relationships with respect to direction and magnitude. Additionally, it is our focus, whether some variables, for example, prices of imported crude oil act upon the U.S. fuel price system externally without themselves being affected by the U.S. prices. In short, we propose to examine, whether some variables exert exogenous influence upon the remaining prices in the U.S. The VECM model shall be further used to predict prices of oil and fuel for the horizon of up to 3 years and assess tendencies in these predictions. Next, VAR(p) representation of VECM shall be retrieved to obtain function of the impulse and response (IRF) to illustrate impact of a sudden positive residual



1: *Trace diagrams of the monthly time series.*

innovation shock in one variable upon others and, as a concluding point, decompose variance of the prediction error (forecast error variance decomposition, FEVD) to relative contributions attributed to individual variables of the system.

MATERIALS AND METHODS

The prior assumption of the proposed exploration is that time series of the multivariate system have endogenous character; they are stochastic but mutually dependent with invariable time lag. It is further expected that prices of oil products be correlated with price of the raw material; that the period of interim fuel storage and transportation is not significant and volume of strategic reserves of oil and fuel products do not strongly influence the current price. The price is believed to be an outcome of supply and demand and that sensitivity of price to demand is limited. Crude oil price is thought to be affected by political stability in the main regions of production and shipping, climate, available production and transport capacity and it is subject to the phase of the economic cycle in the important countries of consumption. Price of oil products, on the other hand, is influenced by the price of oil and it is formed especially by market forces in the region of final consumption.

The data system of five time series (see Fig. 1) includes mean price of crude oil imported to the United States from the OPEC states (*Opec*), average price of oil imported from other than OPEC countries (*NonOpec*). The oil prices [USD per barrel] were weighted by the estimated volume of purchased oil and reflect costs of shipping and insurance, so called F.O.B. origin. Next, average monthly prices of oil-based fuel products were considered: regular quality gasoline (*Regular*), premium quality gasoline (*Premium*) and airliner fuel kerosene (*Kerosene*). The fuel prices were in cents per gallon; U.S. gallon = 3.84 l. Time series were available from 01:1990 to 08:2015 ($T = 308$). Data source was the economic information web page of Economagic (www.economagic.com), an information gateway of the Energy Information Administration (EIA) affiliated with the U.S. Department of Energy.

Consider a multivariate set of $m = 5$ time series in a natural, non-transformed state. Presence of possible seasonal oscillations occurring regularly in the commodity prices was checked by spectral decomposition analysis implemented in the Fisher test (Brockwell and Davis, 1991). Significance tests of the largest periodogram ordinates indicate absence of recurring seasonal movements in prices with period 12 months ($p > 0.05$). Literature reviewed does not mention handling seasonal patterns in similar or even identical data.

Early exploration of data diagrams reveals that variables of the system are likely non-stationary with a stochastic trend (unit root) common to several time series. Presence of common stochastic trend, so called cointegration, implies long-run equilibrium among variables that has permanent nature. It is therefore proposed that incidence of unit root is checked by augmented Dickey-Fuller (ADF) test with level constant and order of autocorrelation k selected by AIC criterion (Dickey and Fuller, 1981). General form of the auxiliary equation used in ADF test for a single variable is given in (1)

$$\Delta y_t = \beta_0 + \beta_1 y_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta y_{t-i} + \varepsilon_t \tag{1}$$

Since cointegration requires that all price variables are integrated *I(1)*, ADF tests with no constant were run again on the differenced data with *I(0)* outcome ($p < 0.05$). Furthermore, KPSS unit-root tests (Kwiatkowski *et al.*, 1992) were run to confirm the ADF tests.

Engle and Granger (1987) procedure is available to ascertain cointegration relationship among variables of the system and attest existence of common stochastic trends. For this purpose, a special procedure was programmed in the *R*-language (www.r-project.org) to produce a summary table. Rank of the assumed cointegration was determined via methods founded upon the canonical correlation analysis of Johansen (1991). The method of maximum eigenvalue (max λ_i) uses test statistic (2) and it sequentially tests, whether number of cointegration vectors is at most $r_0 + 1$ for $r_0 = 0,1,2,\ldots,m - 1$. The trace statistic approach follows formula (3). Specific critical quantiles are available for these variants.

$$-2\ln(Q; r \mid r+1) = -(T-p)\ln(1-\hat{\lambda}_{r+1}) \tag{2}$$

$$-2\ln(Q; r) = -(T-p)\sum_{i=r+1}^{m} \ln(1-\hat{\lambda}_i) \tag{3}$$

Omission of the cointegration relationships in the time series model is considered an error of specification (Hušek, 2007). For time series with cointegration, vector error-correction model (VECM) is proposed. The model in matrix form can be written

$$\Delta Y_t = \mu_0 + \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + \ldots + \Gamma_{p-1} \Delta Y_{t-p+1} + \varepsilon_t \tag{4}$$

In this formula, ΔY_t is a vector of differenced variables, μ_0 is a vector of level constants, $\Pi = \alpha\beta^T$ is a square $m \times m$ matrix of long-run impact coefficients obtained as a product of matrix α (matrix of weights of the ECM model, $m \times r$) and $m \times r$ matrix β storing the cointegration vectors. Lag of the VECM model is symbolized by p. Γ_i symbolize matrices of the short-time impact coefficients and ε_t denotes vector of errors. Rank of the matrix $r(\Pi) = r$ is equal to the number of linearly independent cointegration vectors and simultaneously $m - r$ is the number of common stochastic trends, the unit roots. It is acknowledged, that the long-run impact

I: *Engle-Granger test of cointegration.*

Variable	*Lag k*	*Estimate* β_1	Std. error	Test statistic	Critical quantiles for α 0.01	0.05	0.10	P-value
Opec	10	−0.009	0.006	−1.541	−3.44	−2.87	−2.57	0.513
NonOpec	6	−0.010	0.007	−1.478	−3.44	−2.87	−2.57	0.545
Regular	12	−0.008	0.007	−1.091	−3.44	−2.87	−2.57	0.722
Premium	12	−0.007	0.007	−0.968	−3.44	−2.87	−2.57	0.767
Kerosene	9	−0.010	0.007	−1.398	−3.44	−2.87	−2.57	0.585
Residuals	5	−0.346	0.065	−5.322	−3.44	−2.87	−2.57	0.000

matrix $\Pi = \alpha\beta^T$ may not be unique. For this reason, the vectors in β are a linear combination of the cointegration relationships. As long as $r(\Pi) = m$, Y_t is *I(0)* and use of the VECM model is inappropriate. On the other hand, if $r(\Pi) = 0$, then Y_t is not cointegrated and VAR(*p*) in differences is suggested (Tsay, 2005).

VECM model was applied with restricted constant and estimated by Maximum Likelihood (Zivot and Wang, 2006). Statistical analyses and diagrams were prepared with R-software and add-on libraries *urca* (Pfaff, 2013a) and *vars* (Pfaff, 2013b).

RESULTS AND DISCUSSION

Visual examination of the data diagrams suggests that we deal with I(1) time series with a non-seasonal unit root, because the variables may increase together with the economy, inflation or even currency exchange rates. KPSS tests point to non-stationarity. Engle and Granger (1987) procedure gives statistical evidence that cointegration relationship holds, since individual ADF tests failed to reject the null of unit root. Subsequent rejection of this hypothesis in residuals hints that there exists a linear combination of non-stationary variables that is stationary (see Tab. I). Deterministic component in the unit root tests was level constant. P-values of the ADF tests were asymptotic following MacKinnon (1996). Test of Phillips and Ouliaris (1990) with drift led to the same conclusion (not shown).

Subsequently, rank of cointegration was detected by the method of Johansen (1991), because it is less prone to bias and it allows testing for correct cointegration form (Bumpass *et al.*, 2015). Sequence of chi-square tests for the hypothetical rank ranging from 0 to 4 is shown in Tab. II for the maximum eigenvalue variant (left) and the trace test (right). All eigenvalues of Π matrix were $\lambda_i < 1$ (see Tab. II), which indicates that the VECM model is stationary, but Π matrix is less than full rank.

The variants of Johansen test failed to reject $H_0: r \leq 3$or technically $H_0: \lambda_4 = 0$. It implies that three largest eigenvalues of Π matrix are nonzero and rank of the cointegration is $r = 3$, which equals to the number of cointegrating relations. The finding that some $\lambda_i = 0$ supports the assumption that variables of the system are integrated *I(1)*, but there is a linear combination of the data $\beta^T Y_t$ that is stationary *I(0)*. The rank *r* generally determines the number of cointegration vectors and error correction (EC) terms to be estimated by the VECM model. Evidence of cointegration among the energy prices was in agreement with historical research, which arrived at the same conclusion, for example, Al-Gudhea *et al.* (2007).

Order of the short memory terms in the VECM model was determined by information criteria from VAR(*p*) plotted against lags 1 through 12 (Pfaff, 2008b). The minimums were found for lags 10 (AIC), 2 (BIC), 2 (HQC) and 10 (FPE). Conservative lag of $p = 2$ was finally chosen to avoid model overfitting and problematic interpretation discussed in Hušek (2007). The actual lag in the VECM model is nonetheless shorter by one due to simple differencing applied in all variables. The VECM model contained restricted constant, however, without seasonal dummies, which did not worsen the fit nor caused seasonal auto correlations. Coefficients of the VECM model were estimated by the OLS method (see Tab. III). The individual VECM equations explained between 41 % and 65 % variability. Errors showed absence of low-order serial correlations or cross-correlations, but

2: *Johansen procedure of determining rank of cointegration with restricted constant.*

i	H0	Eigen-value	Test statistic[1]	Critical quantiles for α 0.10	0.05	0.01	Test statistic[2]	Critical quantiles for α 0.10	0.05	0.01
1	$r \leq 0$	0.189	64.12	31.66	34.40	39.79	171.86	71.86	76.07	84.45
2	$r \leq 1$	0.172	57.84	25.56	28.14	33.24	107.74	49.65	53.12	60.16
3	$r \leq 2$	0.100	32.23	19.77	22.00	26.81	49.90	32.00	34.91	41.07
4	$r \leq 3$	0.050	15.57	13.75	15.67	20.20	17.67	17.85	19.96	24.60
5	$r \leq 4$	0.007	2.10	7.52	9.24	12.97	2.10	7.52	9.24	12.97

[1]Method of maximum eigenvalue
[2]Method of trace statistic

II: *Coefficients of the restricted VECM and indicators of model fit quality.*

Term	*d.Opec*	*d.NonOpec*	*d.Regular*	*d.Premium*	*d.Kerosene*
EC1	0.583**	0.795**	1.151**	1.133**	1.567**
EC2	–0.498**	–0.708**	–1.037**	–1.054**	–1.101**
EC3	0.030	0.024	–0.499**	–0.488**	0.325**
d.Opec (t – 1)	1.043 **	1.327 **	3.666**	3.601**	4.123**
d.NonOpec (t – 1)	–0.290	–0.516**	–0.939*	–0.953*	–1.498**
d.Regular (t – 1)	–0.038	–0.160	1.491*	1.653*	0.321
d.Premium (t – 1)	–0.012	0.122	–1.452*	–1.581*	–0.350
d.Kerosene (t – 1)	–0.090**	–0.121**	–0.267**	–0.262**	–0.409**
R^2	0.411	0.519	0.637	0.642	0.573
Residual scale	3.253	2.997	8.542	8.421	8.408
ρ_1	–0.010	–0.027	0.009	0.018	–0.032
DW	2.021	2.053	1.980	1.961	2.069
k_3	–0.533	–0.261	0.395	0.426	0.179
k_4	3.363	2.897	1.826	1.792	2.963

III: *Likelihood ratio tests of weak exogeneity for the VECM model (df = 3).*

Indicator	*Opec*	*NonOpec*	*Regular*	*Premium*	*Kerosene*
χ^2 *statistic*	20.028	38.678	25.896	25.536	23.557
P-value	0.000	0.000	0.000	0.000	0.000

ARCH(q) effect and lack of normality were noticed in residual terms of some equations.

It can be inferred from coefficients of the VECM model (Tab. III) that change in lagged oil price from OPEC countries has tendency to increase other prices in the system, while variable *NonOpec* tends to act upon the prices in the opposite direction. This finding confirms the well-publicized role of the OPEC cartel that is aimed primarily at driving higher prices of crude oil in the world market, if sufficient market share is maintained by OPEC. This is mostly happening through controlling the volume of crude oil supplied to the market. The prices are then set by market brokers and speculators who assume actions taken by OPEC (Ghassan and Banerjee, 2015). Further, we found evidence that lagged prices of kerosene act upon the other time series in the reverse direction, including the current *Kerosene* price. *Kerosene* price is thus determined mainly by the oil prices and negative coefficient of its own lagged price. This could be explained by the fact that oil refineries may tend to produce greater proportion of kerosene for storage and a different pricing scheme for kerosene is likely used. *Kerosene* is often sold in large volumes to a small number of airfield customers and it is not suitable to be used as a substitute for automobile fuel.

Lagged prices of regular and premium gasoline have zero impact upon current prices of imported oil. This finding is in agreement with sensible economic expectations, since oil price is mainly determined by oil supply and demand (EIA, 1999). In comparison with both types of gasoline, the relative impact of oil price upon the price of kerosene appears higher in our study. In general, average costs of distribution for kerosene are lower compared to gasoline and it is reflected in reduced final price of kerosene. Current gasoline price is causally correlated with lagged prices of oil, although lagged price of premium gasoline tends to negatively influence the current price of both types of gasoline.

In this analysis, it was also valuable to check the assumption, whether some variables absent from the cointegration relationships by Likelihood Ratio (LR) test. It applies consecutively restrictions on

IV: *Standardized beta cointegrating vectors (t–statistic).*

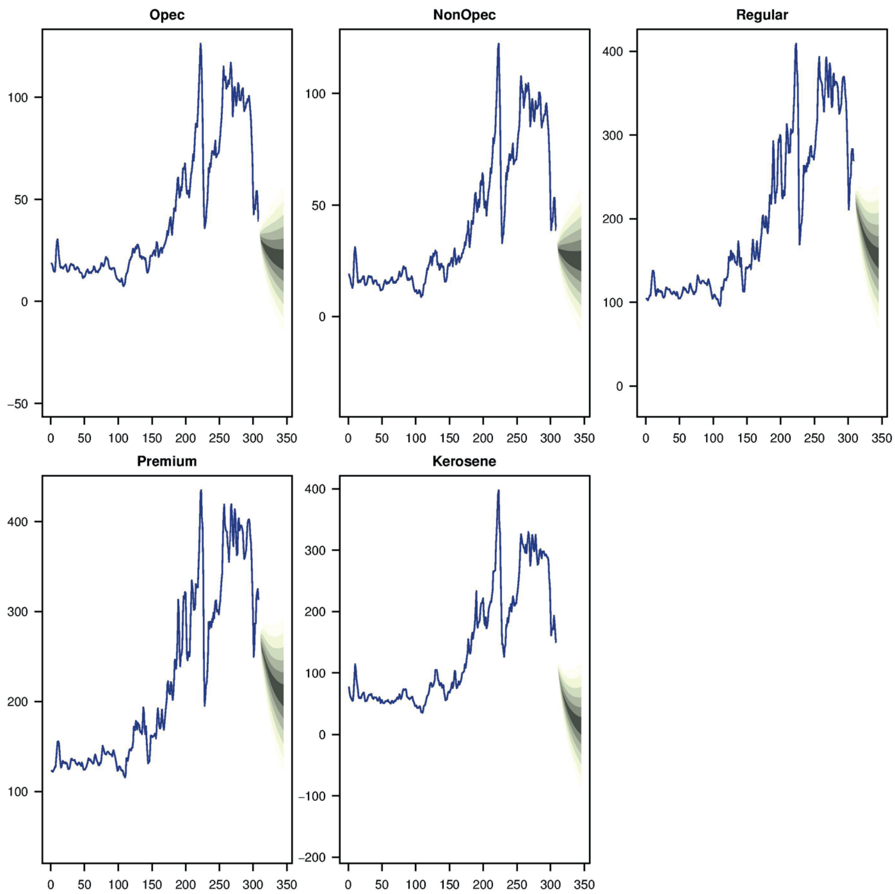
Term	*EC1*	*EC2*	*EC3*
Opec	1.000	0.000	0.000
NonOpec	0.000	1.000	0.000
Regular	0.000	0.000	1.000
Premium	–0.212 (–3.934)	–0.233 (–4.138)	–0.664 (–15.803)
Kerosene	–0.152 (–2.774)	–0.101 (–1.755)	–0.293 (–6.841)
Constant	23.235 (5.153)	22.203 (4.712)	–11.005 (–3.130)

rows of the α matrix of loadings, a part of the long-run impact matrix Π that is liable for reaction in the endogeneous variables to divergence from equilibrium in the previous period. Variables that absent from cointegration behave as exogenous and can be treated as fixed; those participating in cointegration have endogenous and stochastic character. Simplification of the system would be possible by conditioning it upon the exogenous variable(s) without losing accuracy of predictions (Lütkepohl, 2006). In this study, nevertheless, the assumption of exogeneity in was disproved and the weak form of endogeneity was shown to exist (see Tab. IV). This result can be simply explained by a competitive character of the energy market suggesting market efficiency and also by strong position of the U. S. as a major consumer of oil in the world.

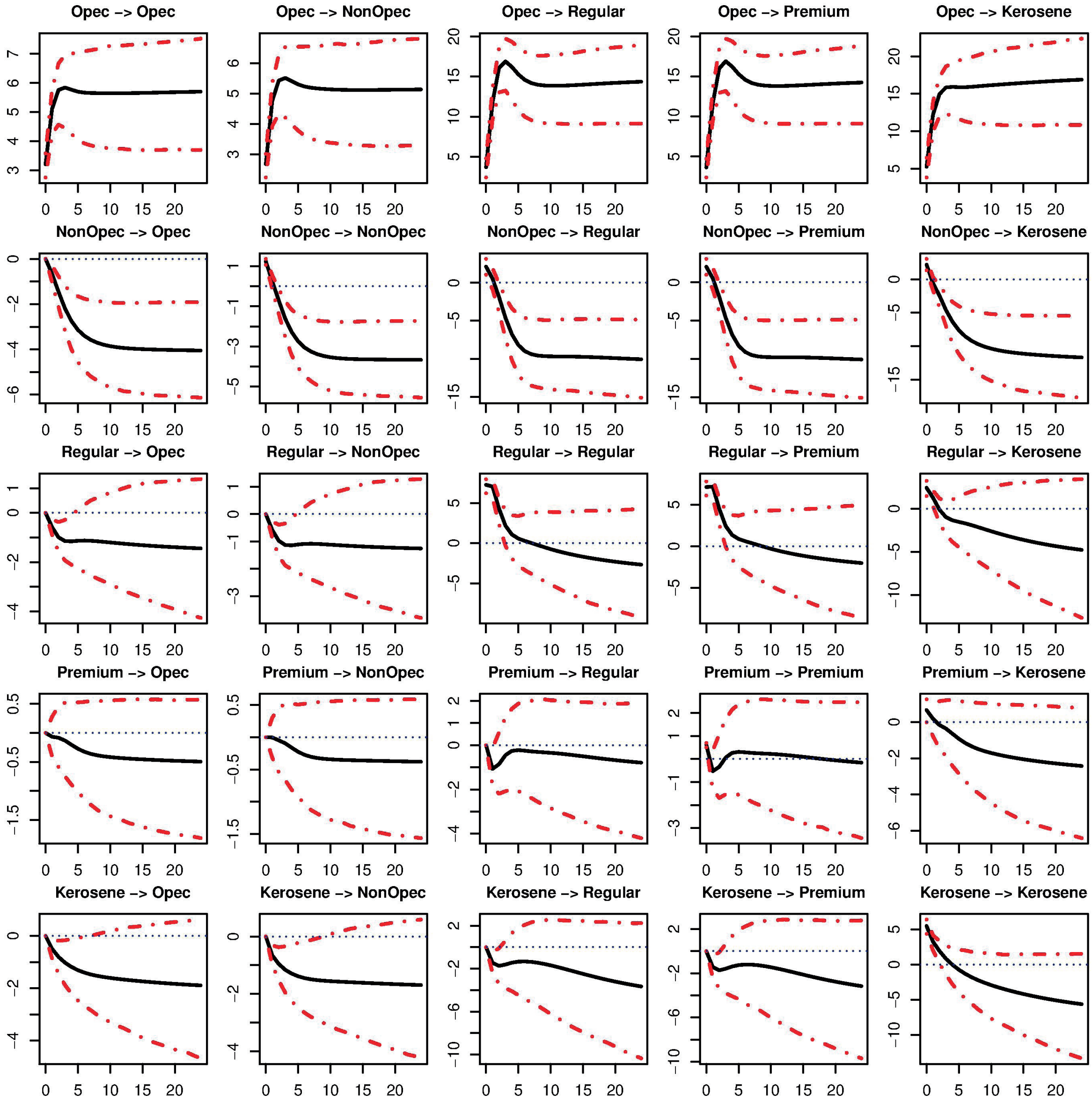
Important aspect of VECM analysis is to estimate matrix $\Pi = \alpha\beta^T$, where β stores the cointegration vectors and α the adjustment vectors (loading coefficients). Setting a diagonal coefficient per column to 1 is a simple method to induce identifiability of the remaining coefficients, parameters of the equilibrium relationships. Calculation of the *t*-statistics was secured with special function in *R*-language following Pfaff (2008a). Resulting cointegration vectors are given in Tab. V.

Coefficients of VECM model can be used to construct sequential forward predictions after transformation of the VECM model to VAR(*p*) representation following Lütkepohl (2006). Predictions for the *h* horizon 1 to 36 months are accompanied with symmetric 95 % confidence limits, as shown in Fig. 2. 95 % confidence boundaries are delimited by outer limits of the shadowed confidence region. The VECM model predicted sizeable fall in prices of airline and automobile fuel for years 2015 through 2018, a favorable phenomenon that is currently taking place.

VAR(*p*) representation of the VECM model was also used to receive orthogonal impulse-response function (IRF) for the prediction horizon from 1 to 24 months. At time $t + h$ for $h = 1,2,\ldots,24$, IRF can be interpreted as a reaction in variable $Y_{j,t,+h}$ to an innovation shock, i.e. impulse, of the magnitude $\hat{\sigma}$ occurring in variable Y_i. 95 % limits of the IRF confidence band were obtained by the method of bootstrap with 1500 simulated replications. Confidence limits of significant reactions to innovation impulse at period $t + h$ do not include



3: *Forward predictions from the VECM model for h from 1 to 36 months with 95% confidence limits.*

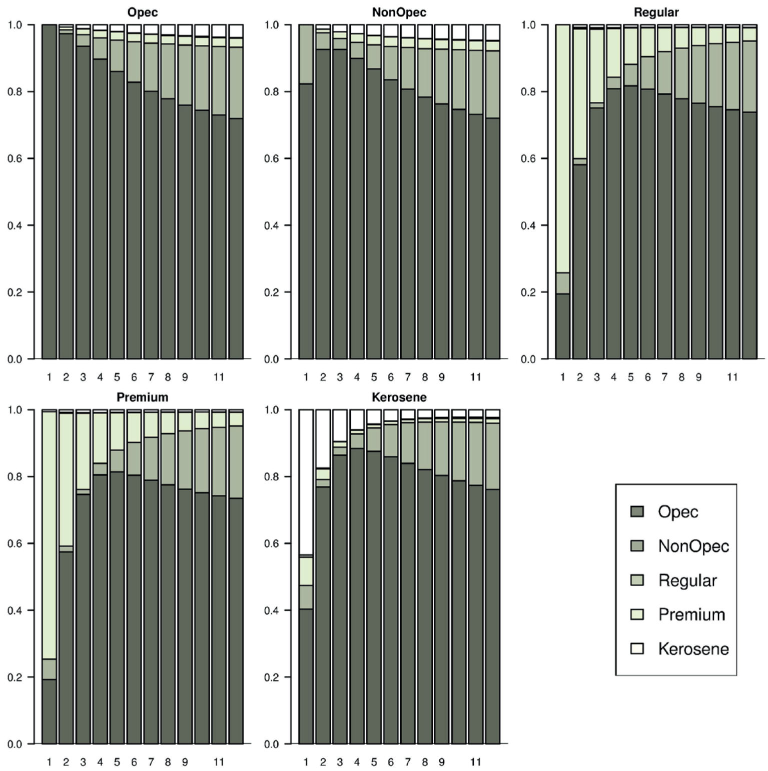


4: *Orthogonal IRF and 95% CI for prediction horizon 1 to 24 months. Impulse variable is placed first.*

zero (dotted line). Diagrams of the pair-wise IRFs are provided in Fig. 3

In general, nature of the pair-wise IRFs corresponds to size and sign of the VECM coefficients stored in Tab. III. A positive innovation shock of a single standard deviation in variable *Opec* changes all prices in the system in the same direction. On the other hand, a positive outer impulse in *NonOpec* leads to change in prices in the opposite direction. For all variables in the system, response to an innovation shock in prices of imported oil is consequently significant and becomes permanent. This discovery supports the idea of competitive behavior of *Opec* and *NonOpec* price (Ghassan and Banerjee, 2015). A similar pattern in response in gasoline price to a positive innovation shock in oil prices were noticed by Borenstein et al. (1997) and Al-Gudhea et al. (2007). In contrast, innovation shock in gasoline and kerosene has only short-term significant impact upon the other variables. In the long perspective, it is nonsignificant and can be treated as zero. For all variables in the VECM model, a response to a unit impulse stabilizes with time upon a nonzero shift and after becomes permanent. This observation is simply explained by *I(1)* property of the variables in level and existence of long-run cointegration ties in the multivariate system. For a comparison, in *I(0)* stationary system, IRF response to a residual shock always converges to zero, as prediction horizon increases.

Construction of the IRF matrix from VECM allowed for decomposition of the contributions individual variables have towards variance of the prediction error (FEVD) in the time series at



5: *Forecast error variance decomposition from the VECM for the horizon of up to 12 months.*

time $t + h$. Variance of prediction error in variable j and horizon h is then accounted for by relative contributions of all variables in the system (see Fig. 4). Apparently, variance of prediction error for the variables is mainly determined by variation in oil prices, especially *Opec*. Its share gradually increases with forecasting horizon h. For a short horizon $h = 1$, however, FEVD in forecasted gasoline and kerosene prices is made primarily of variation in automobile and airline fuel prices. For a distant horizon, FEVD is accounted for mainly by variation in oil prices, confirming thus the leading role of *Opec* price.

CONCLUSIONS

In this study, we analyzed the permanent cointegration ties and temporary dynamic relationships among prices of oil imported from OPEC and non-OPEC countries, two types of gasoline and kerosene with the VECM model. There is evidence, that variation in price of automobile and airline fuel is determined mainly by oil prices and price of regular gasoline, which is normally distributed through an intricate web of retailers and consumed in the largest quantities. Impact of oil price *Opec* and *NonOpec* upon variables of the multivariate system is significant, but exerted in opposing directions, because crude oil imported from different producer groups competes with each other. In OPEC and non-OPEC supplier groups this clearly suggests use of different profit and pricing strategies. Impact upon the system stabilized within 8 to 10 months and resulted in a significant long-run shift that is evident in all variables, as a result of a positive innovation impulse occurring in oil prices. The shift however has opposing direction when impulse occurs in *Opec* or *NonOpec* oil price. This finding provides firm evidence of long-run equilibrium ties among the nonstationary variables of the system. As expected, impact of reversed innovation shock in prices of automobile or airline fuel upon the prices of crude oil was small, short-term and mostly insignificant for high h. Further, this study found no statistical evidence that some variables behave in exogenous way upon other prices of the U.S. system and determine externally their movements.

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Contact information

Václav Adamec: vadamec@mendelu.cz