Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

MASTER THESIS

Impact of Oil Price Shocks on Automobile Stock Prices, An Impulse Response Analysis

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Academic Year: **2012/2013**

Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

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Prague, May 13, 2013

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Acknowledgments

I am grateful to my supervisor, PhDr. Ivo Jánský, for his help, valuable suggestions and comments.

Abstract

The goal of this master thesis is to analyze impact of shocks in oil prices to automobile industry stock prices and returns. We decompose oil price shocks on oil supply shocks, aggregate demand shocks and oil-specific demand shocks and assess their individual impacts on these stock prices/returns. This is done using the vector autoregression (VAR) methodology which allows us to compute impulse responses, that is the reaction paths on the individual shocks. In addition to linear VARs we also employ threshold VAR models in order to capture nonlinearities in impulse responses and besides the aggregate automobile stock price index we compute these nonlinear impulse responses also for some selected individual car producers. We think that this analysis have two different uses. First, it can be beneficial to stock market investors. Second, it can be used by policymakers in countries such as Slovakia and the Czech Republic, which are relatively heavily dependent on automotive industry.

JEL Classification	C32, C34, G10, G15, Q41, Q43
Keywords	Stocks Prices, Crude Oil Prices, Oil Shocks, VAR

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Abstrakt

Cieľom tejto diplomovej práce je analyzovať dopad šokov v cenách ropy na akcie automobilových firiem. V práci rozkladáme šoky v cenách ropy na ponukové ropné šoky, šoky agregátneho dopytu a špecifické ropné dopytové šoky a skúmame ich vplyv na ceny spomínaných akcií. Našim hlavným nástrojom je metóda známa ako vektorová autoregresia (VAR), ktorá nám umožňuje vypočítať reakčné krivky (impulse responses) cien automobilových akcií na jednotlivé šoky. Okrem lineárnych VAR modelov používame aj nelineárne VAR modely, ktoré nám umožňujú zachytiť asymetrie v reakčných krivkách. Naviac, tieto asymetrické reakčné krivky počítame okrem agregátneho indexu cien automobilovýh akcií aj pre ceny akcií niekoľkých jednotlivých autovýrobcov. Myslíme si, že takáto analýza má význam pre dve skupiny ekonomických aktérov. Po prvé, pre investorov na akciových trhoch, po druhé, pre navrhovateľov hospodárskej politiky v krajinách ako Slovensko a Česká republika, ktorých priemysel je relatívne úzko napojený na automobilových výrobcov.

Klasifikace JEL	C32, C34, G10, G15, Q41, Q43
Klíčová slova	Ceny akcií, Ceny ropy, Ropné šoky, VAR

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Acronyms

ADF Augmented Dickey-Fuller

GARCH Generalized autoregressive conditional heteroskedasticity

KPSS Kwiatkovski-Phillips-Schmidt-Schin

TVAR Threshold VAR

VAR Vector autoregression

VECM Vector error correction model

WTI West Texas Intermediate

Master Thesis Proposal

Author	Bc. Lukáš Malárik
Supervisor	PhDr. Ivo Jánský
Proposed topic	Impact of Oil Price Shocks on Automobile Stock Prices, An Impulse Response Analysis

Topic characteristics The goal of this master thesis is to analyze impact of particular shocks on stock prices of automobile companies. To my best knowledge there is only a few works dealing with effects of changes in oil prices on stock prices and none of them is aimed at the automobile industry only. In the past also many authors dealt with oil prices as with exogenous variables, that is the oil prices were independent of shocks that caused changes in real economic activities (e.g. demand shocks, supply shocks, political shocks). In my thesis I will include the oil prices as an endogenous variable, further I will decompose the shocks and then assess their individual effect on stock prices of selected industry. To perform this analysis I will use following data:

- Stock prices of automobile companies
- Global oil production
- Oil prices
- Time series representing global economic activity to simulate demand shocks

Because economies of our region (Czech Republic, Slovak Republic) are strongly linked to automobile industry, the master thesis could also provide insight on changes in these or similar countries connected with changes in automobile industry stock prices.

Hypotheses

1. Do the unit shocks (in context of impulse response analysis) to oil supply affect the prices of automobile industry stocks?
2. Do the unit shocks to global aggregate demand affect the automobile stock prices?
3. Do the prices of automobile industry stocks respond to negative and positive shocks in oil prices equally?

Methodology The main econometric method used in this master thesis will be the vector autoregression (VAR). This method allows model effects of time series of independent variables on multiple dependent variables (the vector autoregressive models can be considered as an alternative to simultaneous equations models). Because the main theme of the thesis are effects of shocks on stock prices I will use the method of impulse responses. I will employ this econometric approach to analyse impact of particular shocks in oil prices on automobile industry stock prices. The results of such analysis will then show to what degree does the particular shock affect the stock prices as well as how long does the shock persist.

Outline The expected structure of the master thesis is as follows:

1. Introduction
2. Summary of literature
3. Methodology
4. Description of data
5. Results
    a) Verification of the first hypothesis
    b) Verification of the second hypothesis
    c) Verification of the third hypothesis
6. Conclusion

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Author Supervisor

Chapter 1

Introduction

In this master thesis we aim to provide analysis of impact of oil price shocks on stock prices of automotive firms. The relationship between oil price changes and automotive stock prices is very often limited to statement of a kind that increase in oil price have to cause decrease in price of these stocks as oil is a main component of automobile fuel, hence driving a car is more expensive and therefore demand for automobiles decreases. Also, oil supply or oil production shocks (including political shocks or shocks encompassed by political and terrorist risk) are most often identified as the main oil price-driving factor. We chose, however, quite different approach in this master thesis. We will decompose shocks to oil price into three main shocks, that is supply shocks, demands shocks, and oil price specific shocks. Subsequently will analyze impact of each of these particular shocks to stock prices of automotive companies using a vector autoregression and impulse response econometric methods. The main value added of this thesis, however, rests on the use of a threshold VAR model. Employing this kind of a non-linear model in our analysis we will examine possible asymmetric effects of the mentioned shocks in oil prices on automotive stock prices.

We think that the close study of this phenomenon can be beneficial to two different groups of economic agents. First, dependencies between movements of crude oil price and automobile stock prices (and hence also returns) can be important for investors in these stocks. Second group consists of policymakers of small open economies, whose industry is relatively heavily oriented on car production. Typical representatives of these countries are Slovakia and the Czech Republic. We think that conclusions of this thesis can be helpful for policy-setting in case of oil price shocks.

The structure of this master thesis is as follows; Chapter 2 summarizes existing literature on the given topic, Chapter 3 describes a theoretical framework used in the thesis, Chapter 4 describes dataset used for the VAR analysis, Chapter 5 provides results of econometric analysis, Chapter 6 proposes ideas for further research, and finally Chapter 7 concludes.

Chapter 2

Review of literature

To my best knowledge there is none paper or study that deals solely with impact of oil price shocks on stock prices of automobile firms in a way which is discussed in this thesis. However, there are several studies which analyze impact of oil price shocks on stock market (both stock prices and dividends) and other variables (especially macro-variables such as GDP or inflation).

The idea to decompose shocks in oil prices on supply shocks, demand shocks and oil-specific demand shocks come was already used in a paper by Kilian (2009). He analyzes the impact of these shocks on the U.S. real GDP growth and CPI inflation. The main tool for purposes of their analysis is a VAR-like model (or a *"near-VAR model"*, (Kilian 2009, p. 12)), which is based on estimation of a fourvariate VAR model and regressing stock prices on estimated residuals from this model to obtain coefficients for impulse responses. To simulate the three types of shocks on the U.S. economy Kilian used oil production (proxy of oil supply shocks), oil prices (proxy of oil-specific demand shocks), index of global real economic activity (proxy of aggregate demand shocks), and a series describing *"exogenous shocks to crude oil production driven by political events in OPEC countries"* (Kilian 2009, p. 5). The last variable summarizes events such as Persian Gulf War, Iranian Revolution or terrorist attacks on tanker ships in Persian Gulf area. Quite interesting is also composition of the index of global real economic activity which acts as a proxy of demand shocks. Kilian in his paper dismissed use of traditional proxies of global real economic activity based on the global GDP or a global index of industrial production (such as published by IMF). As the main reasons he gives problems with frequency and availability of these time series on one hand (especially for emerging and small economies), and problems with construction of these time series on the other hand (e.g. not constant contribution of particular countries to global real economic activity). Therefore he introduced his own measure based on a global index of dry cargo single voyage freight rates.[1] The results presented in the paper indicate that especially political oil price shocks and oil-specific demand shocks negatively influence U.S. real GDP growth. The evidence for U.S. CPI inflation is more ambiguous, however, also in this case the oil-specific demand shocks show significant (in this case positive) influence. Kilian calls these shocks also precautionary demand shocks.

In the paper Kilian & Park (2009) authors examined impact of similar shocks as were described in the previous paper on U.S. stock market, that is on real stock prices (or rather real stock returns) of various industrial sectors and aggregate stock prices as well as on dividend growth. Similar VAR-like model is used as in Kilian (2009). The only difference is that authors omitted political supply shocks variable, so oil production supply now comprises of both political and non-political supply shocks. Also this study shows significant impact of oil prices on the U.S. economy. Again, most significant impact show oil-specific demand shocks (shocks in precautionary demand for oil) followed by aggregate demand shocks. According to the provided evidence, aggregate demand shocks tend to increase stock returns for 11 months while oil-specific demand shocks lower stock returns for more than 12 months. On the other hand, impulse responses show that oil supply shocks have very little influence on the stock returns (and this influence is not even statistically significant). Kilian and Park interpret this in a following way: *"the apparent lack of a systematic relationship between oil production disruptions and real U.S. stock returns is consistent with the view that much of the systematic effect of exogenous political events in the Middle East operates not through physical cutbacks of crude oil production but rather through shifts in precautionary demand driven by concerns about the future availability of oil supplies"* (Kilian & Park 2009, p. 11). The examined industry sectors include energy sector, automobile sector, retail sector, transportation sector, chemical sector and many others (*"industries that a priori are most likely to respond to disturbances in the crude oil market"*, p. 18). The impulse response analysis of automobile sector shows similar patterns as impulse responses of aggregate stock returns. Oil supply shocks seem to have no significant effect on stock returns, aggregate demand shocks tend to increase stock returns for 10 months and precautionary demand shocks tend to decrease stock returns for more than 12 months (also this impulse response is statisti-

[1] Single voyage freight rates of various commodities including grain, oilseeds and iron ore.

cally significant on 10% level for the whole 12 months unlike the response to aggregate demand shock which is significant only for first 5 months).

Sadorsky (1999) in his journal article uses a "quasi-nonlinear" VAR model to analyze asymmetric effects of oil prices on real stock returns (S&P 500 index returns deflated by U.S. consumer price index). He also estimated volatility of oil prices using a GARCH model and incorporated this volatility to the VAR model. First, Sadorsky reports impulse responses obtained from a linear VAR model. Response of real stock market returns to a 1 standard deviation shock in oil prices show quite different results compared to Kilian & Park (2009). An oil price shock is negative for first 14 months, but statistically significant only for first two months. However the difference is most likely caused by a different dataset and also by the different methodology (Kilian & Park (2009) reports accumulated impulse responses with bootstrapped confidence intervals while Sadorsky (1999) reports normal impulse responses with confidence intervals obtained by Monte Carlo simulation). Further in his paper Sadorsky continues with analysis of asymmetric shocks. His quasi-nonlinear VAR model is composed as follows. All variables are used exactly as in the linear VAR model except oil prices. This variable is divided into two variables, first containing positive values and zeros (represents positive oil price shocks), second containing negative values and zeros (represents negative oil price shocks). As an inference tool for this analysis Sadorsky used variance decomposition of forecast errors. He found out that *"positive shocks explain more of the forecast error variance...than do negative shocks"* (Sadorsky 1999, p. 17). The model which uses oil price volatility instead of oil prices shows that the volatility significantly affect stock returns. Nonlinear model for oil price volatility is constructed similarly as for the oil prices. In this case positive volatility shocks explain a larger part of the forecast error variance in stock returns than do the negative oil price volatility shocks. Sadorsky therefore proved that oil price shocks and oil price volatility shocks do indeed have asymmetric impact on real stock returns.

Lee & Ni (2002) in their paper also examine an impact of oil price shocks on the U.S. economy throughout the period 1959-1997. Their variables of interest are U.S. macro-variables such as industrial production, aggregate price level and various interest rates as well as industry-level data. Industry-level data comprise of production and price. Among others (e.g. petroleum refinery industry, chemical industry) they include automobile industry data. Lee and Ni use a block-recursively identified structural VAR model in a way that the U.S. macroeconomic variables are not contemporaneously affected by the industry-level data (so the block of macro-variables is identical for all industrial sectors). Using the impulse response analysis for inference authors show that a one standard deviation shock to oil price negatively affect the U.S. industrial production with a peak after about 16 months. Yet, this result have to be considered as ambiguous because Lee and Ni do not provide any confidence intervals for the impulse responses. Output of automobile industry also decreases immediately after an oil price shock. After about 19 months the output increases. Price in automobile industry also reacts negatively to an oil price shock, however after about 12 months the price is again increasing. Confidence intervals are already provided for this part, therefore it can be seen that parts of responses where industry-level variables start to increase are not significant.

Nonlinear relationships of (real) oil price shocks are examined in the study Kilian & Vigfusson (2011a).[2] Although this paper does not directly deal with impact of oil price shocks on stock market, it introduces powerful techniques and tools of nonlinear VAR methodology, therefore the procedures described in this paper will be widely followed in the subsequent chapters of this thesis which deal with nonlinear VAR. In fact, the main purpose of this paper is not to examine nonlinear effects but rather comment procedures of construction of impulse responses from nonlinear VAR models (aimed at capturing nonlinear effects of oil price shocks on U.S. macroeconomic variables, such as real output or unemployment) in contemporaneous economic literature and propose a correct solution for this problem. Kilian and Vigfusson first argue against a use of censored VAR models, that is against using only positive oil price shocks for estimation (because of contemporaneous opinion that only positive oil price shocks are relevant for the U.S. economy). They show that if a real data generating process of oil price shocks on the U.S. macro-variables is not symmetric than linear VAR models yield spurious estimates. Such results can be also obtained using censored, seemingly nonlinear, VAR models.[3] Further, authors criticize implementation of linear impulse response methodology on nonlinear

[2]Kilian and Vigfusson strongly recommend use of real oil prices: *"…we follow [an earlier paper of Kilian] in specifying the net increase in the real price of oil rather than the nominal price… because the real price is the economically relevant measure of the price of oil"* (Kilian & Vigfusson 2011a, p. 32)

[3]Net oil price increases as a measure of oil price were developed by Hamilton. If we consider monthly data, then net oil price increase is defined as *"the maximum of (a) zero and (b) the difference between the log-level of the crude oil price for the current month and the maximum value of the logged crude oil price achieved in the previous 12 (or alternatively 36) moths"* (Kilian & Vigfusson 2011a, p. 3).

VAR models, which is observable in several papers. Using simple examples they show that impulse responses computed in such way tend to overestimate impact of the oil price shocks on the macro-variables of interest. Finally, Kilian and Vigfusson describe technique of nonlinear impulse response calculation and also introduce tests for asymmetries.

Chapter 3

Methodology

3.1 Linear model

For the first part of our analysis we will use a classic linear VAR model.[1] Three basic steps can be identified in a VAR estimation procedure: model selection, model estimation and model diagnostics.

There are two most imperative issues regarding the selection of a VAR model. First, it is a concern in what form to use chosen time series in the estimation process. In other words, one has to check if a VAR in levels, VAR in differences or a *Vector Error Correction Model (VECM, VEC model)* should be used. In general, we can say that latter two processes are just extensions of a VAR in levels process. However, checking for cointegrating relationships in a dataset is very important because by differencing, in case of non-stability, we may lose some important information about a long term relationship between time series.[2] The second issue is about the lag length (order) of a model.

Before we will describe how to deal with these issues, let us first define the three VAR models subtypes in order to introduce notation for further reasoning. Let $\mathbf{y}_t$ be vector of dependent (endogenous) variables, then in our case this

[1]Linear VAR methodology follows econometric textbooks Brooks (2008), Hamilton (1994), Lütkepohl (2005), and Tsay (2010). In addition to these classical textbooks we also use documentation for R software Pfaff (2008).

[2]*"Note that simply taking first differences of all variables eliminates the cointegration term which may well contain relations of great importance for a particular analysis. Moreover, in general, a VAR process with cointegrated variables does not admit a pure VAR representation in first differences"* (Lütkepohl 2005, p. 248).

vector has a form:

$$\mathbf{y}_t = \begin{pmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \\ y_{4,t} \end{pmatrix} = \begin{pmatrix} \text{oil supply} \\ \text{real economic activity} \\ \text{oil price} \\ \text{stock price} \end{pmatrix}. \tag{3.1}$$

Then the reduced forms of the models are defined as follows:

$$y_t = \nu + \sum_{i=1}^{p} A_i y_{t-i} + u_t \tag{3.2}$$

$$\Delta y_t = \sum_{i=1}^{p} A_i \Delta y_{t-i} + u_t \tag{3.3}$$

$$\Delta y_t = \nu_t + \Pi y_{t-1} + \sum_{i=1}^{p-1} A_i \Delta y_{t-i} + u_t \tag{3.4}$$

where (3.2) is VAR in levels of order p, (3.3) is VAR in differences of order p and (3.4) is a VECM corresponding to a VAR(p) process, μ_0 is a vector of intercept terms, A_i, $i = 1, \ldots, p$ are matrices of coefficients, Π is a matrix of cointegrating relationships and u_t are vectors of reduced error terms or reduced white noise innovations with following properties: $E(u_t) = 0$, $E(u_t u_t') = \Sigma_u$ is a variance-covariance matrix and for all $s \neq t$, $E(u_t u_s') = 0$. Further, ν_t is deterministic term that may take form of an intercept ($\nu_t = \nu_0$) or of an linear trend $\nu_t = \nu_0 + \nu_1 t$. This intercept and linear trend can be both restricted and unrestricted, so there are five modifications of a VECM: no deterministic term, restricted intercept, unrestricted intercept (causing linear drift), restricted trend and unrestricted trend (can cause quadratic trend).[3]

The procedure of determination of order of a VAR process is same for stable and unstable processes.[4] Throughout the VAR literature there are two methods of order determination used: information criteria minimization method and likelihood ratio test method. Regarding the former method, we will use the Akaike criterion, the Hannan-Quinn criterion and the Schwarz criterion (also

[3]See e.g. Lütkepohl (2005) for further information on deterministic terms in a cointegrated VAR process

[4]Here by stable processes we mean VAR in levels processes and by unstable processes we mean VAR in differences and VECM processes. The issue of stability will be discussed more closely later in this chapter.

called Bayesian criterion) given by the following equations, respectively:

$$\mathrm{AIC}(m) = \ln|\hat{\Sigma}_{j,u}(m)| + \frac{2k'}{T} \tag{3.5}$$

$$\mathrm{HQ}(m) = \ln|\hat{\Sigma}_{j,u}(m)| + \frac{2\ln\ln T}{T}k' \tag{3.6}$$

$$\mathrm{SC}(m) = \ln|\hat{\Sigma}_{j,u}(m)| + \frac{\ln T}{T}k' \tag{3.7}$$

where m is the lag order for which we are evaluating the information criteria, $|\hat{\Sigma}_u(m)|$ is a determinant of a variance-covariance matrix of reduced form innovations u_t estimated via OLS equation-by-equation method (which is the commonly used method for reduced VAR estimation), $k' = K + K^2m$ is total number of parameters to be estimated (we have K equations in the system and in each equation there are m lags of K endogenous variables) and T is total number of observations. The information criteria work in a way that with the increasing number of lags in a system the first term decreases while the second term increases, so there is a penalization for using too many lags. In order to find the proper number of lags we have to minimize the criteria, in other words, we choose such number of lags for which a value of a particular information criterion is minimal. A proper number of lags also depends on a frequency of data. Also note that if we want to determine a lag order of a VECM and the criteria select a VAR of order p as a right model, we should use a VECM with $p-1$ differenced terms for each endogenous variable as this VECM corresponds to a VAR(p) process (Lütkepohl 2005, p. 327). The lag order determination using the likelihood ratio test is the second possible approach for lag order determination. Rationale behind likelihood ratio test is that it tests the joint hypothesis that some number of lags in all equations (of some unrestricted model) is jointly equal to zero (so we can use the restricted model). Likelihood ratio test is specified by the following equation:

$$\mathrm{LR} = T(\ln|\hat{\Sigma}_r| - \ln|\hat{\Sigma}_{\mathrm{ur}}|), \tag{3.8}$$

where T is the total number of observations adjusted for first p observations, $|\hat{\Sigma}_r|$ is determinant of estimated variance-covariance matrix of reduced form innovations of a restricted model and $|\hat{\Sigma}_{\mathrm{ur}}|$ is determinant of estimated variance-covariance matrix of reduced form innovations of an unrestricted model. In this test the null hypothesis says that we can restrict the coefficients to zero. The LR test statistic is asymptotically distributed as χ^2 with degrees of freedom equal to the total number of restrictions. Therefore, if we have K equations and we have want to restrict last q parameters (in other words, lags) to zero, then the test statistic from equation (3.8) is asymptotically distributed as $\chi^2(K^2q)$. The definition of the likelihood ratio test statistic alone indicates main disadvantage of this approach, which allows only pairwise comparison across models with different orders. A strategy when using this test is, therefore, start with the upper bound of lag order, let us denote it M, and continue to lower orders. Because we are dealing with monthly data and we have total observations of 223, we set $M = 12$, so in the marginal case we will have to estimate a VAR model with $K + K^2M = 4 + 4^2 12 = 196$ parameters. Also, model of order 12 should be sufficiently long to capture any seasonal patterns in the data. In our opinion these two facts imply that in our case any higher upper bound of maximum lag order would be contra-productive and also dangerous that it would cause we will end up with more parameters to estimate than is the number of observations.

To decide whether the individual time series are cointegrated and whether we should use VECM, we have to first test if the time series are non-stationary, in other words if they have a unit root. In order to test for stationarity we use two tests, the Augmented Dickey Fuller (ADF) test and Kwiatkowski-Phillips-Schmidt-Schin (KPSS) test. Let us have time series x_t, $t = 1, \ldots, T$ we want to test for a unit root. Then ADF equation with an optional intercept and an optional time trend is specified as follows:

$$\Delta x_t = a_0 + a_1 t + \psi x_{t-1} + \sum_{i=1}^{k} \alpha_i \Delta x_{t-i} + e_t. \tag{3.9}$$

Under the null hypothesis $\psi = 0$, which means that there is a unit root in the time series (so it is non-stationary). However, the t-statistic is not compared to the classical Student distribution tables but to Dickey-Fuller distribution tables. The latter unit root test, KPSS test, is a Lagrange multiplier type test. Consider following decomposition of a time series:

$$x_t = \xi + r_t + e_t, \tag{3.10}$$

where again x_t is a time series we want to test for unit roots, ξ is a deterministic term and $r_t = r_{t-1} + v_t$ is a random walk. Test statistic of the KPSS test is given as:

$$\mathrm{LM} = \sum_{t=1}^{T} \frac{S_t^2}{\hat{\sigma}_e^2}, \tag{3.11}$$

where $S_t = \sum_{i=1}^{t} \hat{e}_i^2$, $t = 1, \ldots, T$, $\hat{e}_t$ being residuals from the regression given by (3.10), and $\hat{\sigma}_e^2$ is the estimate of the error variance from the same regression. Contrary to the ADF test, the null hypothesis is now no unit root (i.e. stationarity) and we use critical values published in Kwiatkowski *et al.* (1992) to evaluate the test.

Now, let us recall the vector $y_t = (y_{1,t}, y_{2,t}, y_{3,t}, y_{4,t})'$. Assume that $y_{i,t} \sim I(1)$ for $i = 1, 2, 3, 4$, that is the time series $y_{i,t}$ are integrated of order 1. Further, assume that there is a nonzero vector $\beta = (\beta_1, \beta_2, \beta_3, \beta_4)'$, such that:

$$\beta' y_t = \beta_1 y_{1,t} + \beta_2 y_{2,t} + \beta_3 y_{3,t} + \beta_4 y_{4,t} = v_t, \tag{3.12}$$

where for the disturbances v_t holds $v_t \sim I(0)$, thus they are stationary. Then we say that time series $y_{i,t}$, are cointegrated of order $C(1, 1, 1, 1)$ and the vector β is called cointegrating vector. The definition of cointegration implies that this vector is not uniquely given as the property specified by (3.12) holds even if the vector β is multiplied by any nonzero constant. Interpretation of cointegration follows from properties of v_t and (3.12). Because of stationarity the disturbances v_t are required to have a constant mean around which they are permitted to oscillate with a time invariant variance. Therefore, the long-term relationship between variables $y_{i,t}$ is given by the mean of v_t. The variables can, for a short period, left this equilibrium, but they will inevitably return to it (in order the cointegration relationship to be preserved). This property is known as the error correction. In a system of variables there can arise more situations, that is more cointegration relationships, than it is described by (3.12). In this case the cointegration vector β becomes matrix of cointegration vector (let us still keep the notation β) and thus cointegration relationships have following form:

$$\beta' y_t = \begin{pmatrix} \beta_1^1 & \beta_2^1 & \beta_3^1 & \beta_4^1 \\ \beta_1^2 & \beta_2^2 & \beta_3^2 & \beta_4^2 \\ \beta_1^3 & \beta_2^3 & \beta_3^3 & \beta_4^3 \end{pmatrix} \begin{pmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \\ y_{4,t} \end{pmatrix} = \begin{pmatrix} v_{1,t} \\ v_{2,t} \\ v_{3,t} \\ v_{4,t} \end{pmatrix} = v_t, \tag{3.13}$$

where $v_t \sim I(0)$. Simple matrix multiplication then yields:

$$\beta_1^1 y_{1,t} + \beta_2^1 y_{2,t} + \beta_3^1 y_{3,t} + \beta_4^1 y_{4,t} = v_{1,t} \tag{3.14}$$

$$\beta_1^2 y_{1,t} + \beta_2^2 y_{2,t} + \beta_3^2 y_{3,t} + \beta_4^2 y_{4,t} = v_{2,t} \tag{3.15}$$

$$\beta_1^3 y_{1,t} + \beta_2^3 y_{2,t} + \beta_3^3 y_{3,t} + \beta_4^3 y_{4,t} = v_{3,t} \tag{3.16}$$

Equations (3.14) to (3.16) imply that, in our case, for 4 variables there can be totally up to 3 cointegration relationships and thus equally as many cointegrating vectors. In the cointegration literature the two most widely used procedures to test variables for cointegration are Engle-Granger procedure and Johansen procedure. For purposes of VECM estimation we need to determine the number of cointegrating vectors. Johansen procedure is designed exactly in this way therefore we will use this approach for purpose of this master thesis. To explain the mechanism of Johansen procedure let us recall the specification of a VEC model given by (3.4). In this equation we can rewrite the matrix Π in a following way:

$$\Pi = \alpha\beta'. \tag{3.17}$$

We call the Πy_t an error-correction term (or a matrix of adjustment coefficients and cointegrating vectors) and α a vector of adjustment coefficients which govern the speed of adjustment to a long term equilibrium. Now, let r be rank of matrix β, so $r = rk(\beta)$. Then also $rk(\alpha) = r$, and $rk(\Pi) = r$, for r holds condition $0 \leq r \leq K-1$. The Johansen procedure determines the number of cointegrating vectors by testing the rank of matrix Π by employing the so called trace and maximum eigenvalue test statistics given by following equations

$$\lambda_{\text{trace}}(r) = -T \sum_{i=r+1}^{K} \ln(1 - \hat{\lambda}_i) \tag{3.18}$$

$$\lambda_{\max}(r+1) = -T \ln(1 - \hat{\lambda}_{r+1}) \tag{3.19}$$

where $\hat{\lambda}_i$ is the i-th largest eigenvalue of the matrix Π. Under the null hypothesis $rk(\Pi) \leq r$, $r = 1, \dots, K-1$. The Johansen procedure starts with $r = K-1$ and continues until we are able to reject the null hypothesis for r cointegrating vectors. Rejecting the null hypothesis for $K-1$ cointegrating vectors in favor of K cointegrating vectors corresponds to stationarity of original data and thus VAR in levels can be used. On the other hand, not rejecting the null hypothesis for $r = 0$ corresponds to no cointegration relationship in the data and thus

VAR in differences can be used. In order to evaluate the test critical values from Engle & Yoo (1987) are used.

Next step after establishing lag order and cointegration order is estimation. As it was mentioned before, reduced form of both the VAR in levels and VAR in differences can be estimated via OLS equation-by-equation method. This is, however, not true for the VECM, which will be estimated by Johansen maximum likelihood method.[5] In order to achieve that the shocks in a VAR process will not be explosionary, the process has to be stable.[6] A VAR(p) process is stable if roots of a reverse characteristic polynomial

$$\det(I_{Kp} - \Phi z) = \det(I_K - \Phi_1 z - \cdots - \Phi_p z^p) \tag{3.20}$$

do not lie inside and on the complex unit circle. Further, Granger causality will be tested using reduced form models.[7] Assume a VAR(p) process given by (3.2), then

$$\begin{aligned} y_{1,t} =& \phi_{1,0} + \Phi_{11,1} y_{1,t-1} + \Phi_{12,1} y_{2,t-1} + \Phi_{13,1} y_{3,t-1} + \Phi_{14,1} y_{4,t-1} + \cdots \\ &+ \Phi_{11,p} y_{1,t-p} + \Phi_{12,p} y_{2,t-p} + \Phi_{13,p} y_{3,t-p} + \Phi_{14,p} y_{4,t-p} + u_{1,t} \end{aligned} \tag{3.21}$$

is the first equation of this system. The variable $y_{2,t}$ does not Granger-cause $y_{1,t}$ if coefficients at all lags of $y_{2,t}$ are equal to zero, formally if $\Phi_{12,1} = \cdots = \Phi_{12,p} = 0$. Granger causality is tested using simple F-test. If the data are cointegrated and estimated by a VEC model corresponding to a VAR(p) model, then a $var(p+1)$ model is fitted and used for Granger causality tests; this approach is called *lag-augmented test*.

Similarly to univariate models, after we fit a VAR or VEC model, we are interested if the residuals are a white noise process. As Lütkepohl (2005, p. 157) states, the procedures of VAR or VECM estimation *"may be interpreted as methods for determining a filter that transforms the given data into a white noise series"*. The innovations u_t were defined as $u_{j,t}$ $N(0, \Sigma_u$, $E(u_t u_s') = 0$ for all $s \neq t$, which implies that we have to check the residuals of a fitted model for autocorrelations and normality in order to evaluate their whiteness. For the former issue we will use a multivariate version of Portmanteau test. The Port-

[5] For its complexity the method is not discussed here. For more information on VAR and VECM estimation see e.g. Lütkepohl (2005).

[6] Condition similar to stationarity condition in univariate models. Integrated and cointegrated processes are unstable by definition.

[7] Granger causality is used in the "oil shocks context" e.g. in Hamilton (1983).

manteau test statistic for the joined significance of the residual autocorrelations up to lag h is as follows:

$$Q_h = T \sum_{i=1}^{h} \operatorname{tr}(\hat{C}_i' \hat{C}_0^{-1} \hat{C}_i \hat{C}_0^{-1}), \tag{3.22}$$

where $\hat{C}_i = \frac{1}{T}\hat{U}F_i\hat{U}'$, $\hat{U} = (\hat{u}_1, dots, \hat{u}_T)$ and $F_i = [I_i : 0]$ is $i \times T$ matrix for $i = 1, \ldots, h$. Under the null hypothesis the autocorrelations are equal to zero and the test statistic is asymptotically distributed as $\chi^2(K^2(h-p))$ for a VAR(p) model and as $\chi^2(hK^2 - K^2(p-1) - Kr)$ for a VECM corresponding to a VAR(p) model, where r is number of cointegrating vectors. Normality of residuals is tested using multivariate Jarque-Bera test, which compares skewness and kurtosis of residuals to the theoretical moments of normal distribution. Consider $\hat{u}_t$, $\hat{P}\hat{P}' = \hat{\Sigma}_u$, and

$$\hat{w}_t = (\hat{w}_{1t}, \ldots, \hat{w}_{Kt})' = \hat{P}^{-1}\hat{u}_t \tag{3.23}$$

$$\hat{b}_1 = (\hat{b}_{11}, \ldots, \hat{b}_{K1})' \tag{3.24}$$

$$\hat{b}_2 = (\hat{b}_{21}, \ldots, \hat{b}_{K2})' \tag{3.25}$$

where $\hat{b}_{k1} = \frac{1}{T}\sum_t \hat{w}_{kt}^3$, $\hat{b}_{k2} = \frac{1}{T}\sum_t \hat{w}_{kt}^4$, for $k = 1, dots, K$. Then Jarque-Bera test statistics are

$$\hat{\lambda}_s = T\hat{b}_1'\hat{b}_1/6 \sim \chi^2(K) \tag{3.26}$$

$$\hat{\lambda}_k = T(\hat{b}_2 - 3_K)'(\hat{b}_2 - 3_K)/24 \sim \chi^2(K) \tag{3.27}$$

$$\hat{\lambda}_{sk} = \hat{\lambda}_s + \hat{\lambda}_k \sim \chi^2(2N) \tag{3.28}$$

The null hypotheses of these tests are normality. These test statistics and their asymptotic distributions are same for VAR as well as for VEC models. Also, as Choleski decomposition is used in this test, the variables ordering matters for this test.[8] In this point we have to emphasize that we expect the null hypothesis to be strongly rejected. One reason is the typical heavy-tailed nature of the financial data, which should be reflected especially by the kurtosis test.

An estimated VAR or VEC model includes many parameters, of which many is often insignificant, therefore we will draw our inference from impulse responses. For a VAR in level models to allow for instantaneous interactions between variables we will use orthogonalized impulse responses. Consider de-

[8]The issue of variables ordering will be discussed in following paragraphs.

composition $\Sigma_u = W\Sigma_\varepsilon W'$, where Σ_ε is a diagonal matrix with positive elements and W is a lower triangular matrix with unit diagonal. These matrices can be computed using Choleski decomposition $\Sigma_u = PP'$, further by defining $W = PD^{-1}$, $\Sigma_\varepsilon = DD'$, $\text{diag}(D) = \text{diag}(P)$. Let $\mathsf{A} = W_{-1}$, then after premultiplying (3.2) by A yields after some adjustments:

$$y_t = A_0^* y_t + A_1^* y_{t-1} + \cdots + A_p^* y_{t-p} + \varepsilon_t, \tag{3.29}$$

$$y_t = (I_K - A_0^*)^{-1} A_1^* y_{t-1} + \cdots + (I_K - A_0^*)^{-1} A_p^* y_{t-p} + (I_K - A_0^*)^{-1} \varepsilon_t, \tag{3.30}$$

where $A_0^* = (I_K - \mathsf{A})$ with $\text{diag}(A_0^*) = 0$, $A_i^* = \mathsf{A}\, A_i$, $i = 1, dots, p$ and $\varepsilon_t = \mathsf{A}\, u_t$ with $E(\varepsilon_t\, \varepsilon_t') = \Sigma_\varepsilon$. Equation (3.30) shows that a one standard deviation shock in ε_{it} is represented by an instantaneous effect $(I_K - A_0^*)^{-1} D = P$, as $\text{diag}(D)$ elements are standard deviations of ε_t. This can be related to a moving average (MA) representation of a VAR(p) process defined as:

$$y_t = \mu + \sum_{i=0}^{\infty} \Theta_i w_{t-i}, \tag{3.31}$$

where $\Theta_i = \Phi_i P$, Φ_i are impulse response matrices from a canonical MA representation, $w_t = P^{-1} u_t$ and the variance-covariance matrix $\Sigma_w = I_K$.[9] Coefficients Θ_i are orthogonal impulse responses and $\Theta_0 = P$ is a matrix of instantaneous effects. The Choleski decomposition used in orthogonal impulse responses construction causes that the variables ordering is important. Recall, A is a lower triangular matrix with unit main diagonal. Therefore, assuming ordering of the vector y_t given by (3.1), such structure of this matrix imposes following restrictions on instantaneous effects among the dependent variables:

(i) global oil production is independent of shocks in any other endogenous variable within a month,

(ii) global real economic activity responds only to shocks in global oil production within a month,

(iii) oil price responds only to shocks in global oil production and global real economic activity within a month,

[9] Canonical MA representation of a VAR(p) process is defined as

$$y_t = \mu + \sum_{i=0}^{\infty} \Phi_i u_{t-i}, \ \Phi_0 = I_K,$$

and can be derived using backshift polynomials (see e.g. Lütkepohl (2005)).

(iv) automobile stock prices respond to shocks in any of the previous variables within a month.

The rationale behind this ordering is that, first, oil supply is considered as the most sticky variable as the adjustments of oil production are quite time consuming and costly process. Second, similarly as in Kilian & Park (2009), we assume that the global real economic activity will not be affected by oil-specific demand shocks and shocks in automobile stock prices within a month.[10] Third, oil price is not significantly affected by automobile stock prices shocks within a month as the oil price is determined by development in many other industrial sectors. Finally, automobile stock prices respond to shocks in all variables instantaneously as the automobile industry is sensitive to oil market changes and the demand for automobiles is also sensitive to current and expected economic activity.

Although integrated and cointegrated VAR processes do not have so straightforward MA representation as stable VAR processes, we are able to derive impulse responses for them. Both (3.3) and (3.4) are nothing else than adjusted and rearranged (3.2). Consider therefore this form. Each VAR(p) process can be written as a VAR(1) process, assume that this form is defined in a following way:

$$Y_t = AY_{t-1} + U_t. \tag{3.32}$$

Suppose that the h-step forecast in time t and actual value in time $t+h$ are defined by following expressions, respectively:

$$Y_t(h) = A^h Y_t, \tag{3.33}$$

$$Y_{t+h} = A^h Y_t + U_{t+h} + AU_{t+h-1} + \cdots + A^{h-1}U_{t+1}. \tag{3.34}$$

The forecast error is hence defined as:

$$Y_{t+h} - Y_t(h) = U_{t+h} + AU_{t+h-1} + \cdots + A^{h-1}U_{t+1}. \tag{3.35}$$

Now consider matrix $J = [I_K : 0 : \cdots : 0]$ of dimensions $K \times Kp$. If we

[10]Kilian (2009, p. 13) argues the restriction on oil-specific demand shocks for global real economic activity *"...is consistent with the sluggish behavior of global real economic activity..."*. Further, we assume that the automobile industry and thus shocks in automobile stock prices do not have such ability (in the sense of importance of automobile industry for the global economic activity) to significantly affect this variable within a month.

premultiply (3.35) by the matrix J we get:

$$y_{t+h} - y(h) = u_{t+h} + \Phi_1 u_{t+h-1} + \cdots + \Phi_{h-1} u_{t+1}, \tag{3.36}$$

where $\Phi_i = JA^i J'$, for which a relation $\Phi_i = \sum_{j=1}^{i} \Phi_{i-j} A_j$, $i = 1, 2, \ldots$ holds. As Lütkepohl (2005, p. 263) states, *"the elements of the $\Phi_i = (\phi_{jk,i})$ matrices may represent impulse responses just as in the stable case, more precisely, $\phi_{jk,i}$ represents the response of variable j to a unit forecast error in variable k, i periods ago"*. In the same way as it was done for stable VAR processes can be derived also orthogonal impulse responses for integrated and cointegrated processes.

3.2 Nonlinear model

In this Section we will use a nonlinear (threshold) VAR model to capture possible asymmetric response of car producers stock prices to positive and negative shocks.

In related literature authors distinguish between two major sources of asymmetries in responses of macroeconomic variables such as consumption of energy-intensive durables. First, there are several direct channels to this phenomenon. Edelstein & Kilian (2009) as well as Kilian & Vigfusson (2011b) identify four direct channels. As the oil price increases real income of consumers decreases which is translated into diminishing demand for energy-intensive durables. *"Second, changing energy prices may create uncertainty about the future path of the price of energy, causing consumers to postpone irreversible purchases of durables"* (Edelstein & Kilian 2009, p. 2). The third channel is related to precautionary savings as consumers tend to smooth their consumption and save in "good times" for cases of possible future adverse development (Edelstein and Vigfusson mention especially fear from unemployment). Finally, consumption of durables that are complementary to other durables in energy use decline more rapidly than of other durables. Although Edelstein and Kilian, and Kilian and Vigfusson applied this rationale on durable goods, it is relatively trivial to adjust their reasoning for automobile sector. First, in terms of price elasticity of demand, cars can be regarded for a luxury good whose demand (and thus also related stock price) is very sensitive to gasoline price (hence also to oil price). However, we presume that a response to a positive oil price shock[11] is of much

[11] Here by positive oil price shocks we mean shocks that cause positive response of oil price,

larger magnitude than a response to the same shock, just with an opposite sign. This can be explained by the consumption smoothing of non-luxury goods and the existence of uncertainty. Because consumers tend to increase savings, they will not immediately increase consumption of luxury (energy-intensive) goods by the same amount as was the cut of consumption. Uncertainty about future oil prices contributes to this gradual increase of consumption. Further, Edelstein & Kilian (2009), and Kilian & Vigfusson (2011b) identify also "indirect" causes of asymmetries in durables consumption. The rationale of this second channel lies in production adjustment across different industrial sectors. More preciously, as an increase in energy prices causes decrease of demand of energy-intensive durables, production of these durables is also reduced and respective sources, that is capital and labor, are transferred to more profitable uses. Moreover, Edelstein and Kilian, and Kilian and Vigfusson stress that similarly to the reallocation of sources between industrial sectors the reallocation can also take place within one industrial sector. In this case capital and labor are reallocated from production of goods that is relatively more energy-intensive to goods that is relatively less energy-intensive. Edelstein & Kilian (2009, p. 2) then sum up that *"the uncertainty effect and the reallocation effect necessarily generate asymmetric responses of macroeconomic aggregates to energy price increases and decreases, they amplify the response to unexpected price increases but dampen the response to unexpected energy price decreases"*. These conclusions can be important especially to small open economics such as Slovakia or the Czech Republic whose industry is, especially in case of Slovakia, heavily oriented on car production and hence even little downswings in car demand can cause substantial problems in these countries. On the other hand, the oil price downswing and hence the car demand upswings do not bring comparable positive effects. Even an intra-sectoral reallocation limited to automobile industry can be potentially dangerous if a countries' car production facilities are oriented on production of the relatively more fuel-intensive, or in other word luxury, cars. For this very reason we will analyze impact of oil price shocks (that is supply, demand and oil-specific demand shocks) on the aggregate index of stock prices of car producers as well as on stock price of individual car producers. Using the individual approach we will try to show differences in impacts of the three oil price shocks between luxury car producers (producers of relatively more fuel-intensive cars) and producers of what can be called as

that is negative oil supply shocks, positive aggregate demand shocks and positive oil-specific shocks.

people's cars (relatively less energy-intensive cars).

As we mentioned before many studies, for example Hamilton (2010), Edelstein & Kilian (2009), Kilian & Vigfusson (2011b), Kilian & Vigfusson (2011a) or Park & Ratti (2008), employ net oil price increases as a measure of positive oil price shocks. In case of monthly data a (three-year) net oil price increase is defined as

$$\dot{x}_t = \max\{0, x_t - max\{x_{t-1}, \dots, x_{t-36}\}\}, \tag{3.37}$$

where x_t is price of oil. These studies further use censored-like models in order to compute impulse responses. Kilian & Vigfusson (2011a) uses following model

$$\begin{aligned} x_t &= b_{10} + \sum_{i=1}^{p} b_{11,i} x_{t-i} + \sum_{i=1}^{p} b_{12,i} y_{t-i} + \varepsilon_{1t} \\ y_t &= b_{20} + \sum_{i=0}^{p} b_{21,i} x_{t-1} + \sum_{i=1}^{p} b_{22,i} y_{t-i} + \sum_{i=0}^{p} g_{21,i} \dot{y}_{t-1} + \varepsilon_{2,t} \end{aligned} \tag{3.38}$$

where x_t is oil price, $\hat{x}_t$ is net oil price increase and y_t is a macroeconomic variable of interest. They stress that residuals of this bivariate model are uncorrelated, hence it can be estimated via traditional OLS method (Kilian & Vigfusson 2011a, pp. 17-18).

Different model for nonlinear VAR modeling proposes paper Lo & Zivot (2001) and Tsay (1998), where the authors use threshold VAR and VECM processes for their analysis.[12] We can apply their methodology on our case in a following way. Let us consider a following model

$$\Delta y_t = \begin{cases} \alpha^1 + \Phi_1^1 \Delta y_{t-1} + \dots + \Phi_p^1 \Delta y_{t-p} + \varepsilon_t^1 & \text{if } \Delta y_{3,t-1} \leq 0 \\ \alpha^2 + \Phi_1^2 \Delta y_{t-1} + \dots + \Phi_p^2 \Delta y_{t-p} + \varepsilon_t^2 & \text{if } \Delta y_{3,t-1} > 0 \end{cases} \tag{3.39}$$

where ε_t are serially uncorrelated normal innovations with zero mean and a variance-covariance matrix Σ. According to Tsay (1998), if threshold value is known for Σ holds following

$$\hat{\Sigma} = \frac{\varepsilon' \, \varepsilon}{T - (np + 1)}. \tag{3.40}$$

Notice that in a setting as presented in (3.39) the model is self-exciting, that is the state determining variable is the variable y_3 and the decisive value of the

[12] In addition to these two references, more theory on nonlinear VAR models can be found in Granger *et al.* (2011).

state determining variable is that in the previous period. Finally, an advantage of this model is that it is integrated in the *tsdyn package* for R statistical software.[13] Note that while the model is written with difference operators for the all elements of the vector y_t, we will use variable real_ea in levels, that is we will treat it as stationary.

Similarly as for the linear analysis, also in nonlinear analysis we will draw our inference from impulse responses. Because of the nonlinear nature of model (3.39) the computation of impulse responses is not so straightforward as in the case of linear VAR models. For nonlinear models the MA representation is also of nonlinear nature, therefore it cannot be used for computation of impulse responses (see Equation (3.31) for the orthogonalized MA representation and the related footnote for the canonical MA representation). Because of this inconvenience the impulse response function for the nonlinear model have to be computed from the definition. Koop *et al.* (1996) defines impulse response function in a following way. Let $y_t = F(t_{t-1}, \dots, y_{t-p}) + H_t \, \varepsilon_t$ where F is a known function (in our case nonlinear VAR process), H_t is a random matrix and function of $\{y_{t-1}, \dots, y_{t-p}$ and let Ω_{t-1} be a set containing information necessary to compute the forecast of y_t (these are $y_{t-1}, \dots, y_{t-p}$ in our case). Further, let ω_{t-1} be a representation of Ω_{t-1} and let y_{t+n} be a forecast of y_t for time $t+n$. Now, assume that an expectation of y_{t+n} conditional on ε_t and Ω_{t-1} exist. Then an impulse response function for n periods ahead, which considers that a shock of magnitude δ occurred at time t in ε_t is given as

$$\begin{aligned} I(n, \delta, \omega_{t-1}) =& E[y_{t+n} | \, \varepsilon_t = \delta, \varepsilon_{t+1} = 0, \dots, \varepsilon_{t+n} = 0, \omega_{t-1}] - \\ & - E[y_{t+n} || \, \varepsilon_t = \delta, \varepsilon_{t+1} = 0, \dots, \varepsilon_{t+n} = 0, \omega_{t-1}] \end{aligned} \tag{3.41}$$

Contrary to the linear impulse responses, we will compute nonlinear impulse responses for a maximum horizon of one year, hence $n = 1, \dots, 12$. Rather atheoretical approach to this methodology is presented and utilized most notably in Edelstein & Kilian (2009), Kilian & Vigfusson (2011a) and Kilian & Vigfusson (2011b).[14] Especially Kilian & Vigfusson (2011a) describes in detail the whole process and thereafter summarizes it into few simple steps, which we will use also in our thesis. Thus, the necessary steps to obtain asymmetric impulse responses are as follows (Kilian & Vigfusson 2011a, pp. 18-19):

[13] In addition to already mentioned literature, we also used documentation of the *tsdyn package*, Di Narzo *et al.* (2011), in order to compose the threshold VAR model.

[14] In addition to these "energy" VARs, this approach is also employed in fiscal VARs, for example in Afonso *et al.* (2011).

(i) Estimate a nonlinear VAR(p) model. Take p consecutive values of y_t (note that y_t is a 4×1 vector so in fact take p consecutive values of y_j, $j = 1, 2, 3, 4$). These values are nothing else than a one particular representation of Ω_{t-1}, let us denote it ω^i_{t-1}.

(ii) Take the estimated coefficients from the estimated VAR model and fix them. Further, based on ω^i_{t-1} simulate (forecast) values $y_{j,t+n}$ for $j = 1, 2, 3, 4$ and $n = 1, \ldots, 12$. Without loss of generality let us assume that we want to compute response to an impulse of magnitude δ in time t in oil supply, that is $\varepsilon_{1t} = \delta$. Then the values are simulated in a following way. First, values y_{t+n} are simulated with ε_t and ε_{t+n} drawn from their empirical distributions. Second, another set of values y_{t+n} is computed setting $\varepsilon_{1t} = \delta$ while ε_{2t}, ε_{3t} and ε_{4t} as well as all later innovations, that is ε_{t+n}, are drawn from their marginal distributions.

(iii) Compute differences between these two paths, as Kilian & Vigfusson (2011a) puts it, for the automobile stock returns variable, that is compute $y^{\delta}_{4,t+n} - y_{4,t+n}$, for $n = 1, \ldots, 12$ where $y^{\delta}_{4,t+n}$ is a realization with a shock while $y_{4,t+n}$ is a realization without the shock.

(iv) Repeat steps (ii) and (iii) a sufficient number of times, let us denote it m as Kilian and Vigfusson, and compute average across this m. Result of the averaging is the response of $y_{4,t+n}$ for n periods ahead to an impulse of magnitude δ. This response is, however, conditional on chosen ω_{t-1}.

To make the responses more robust, that is not conditional on the chosen history represented by ω_{t-1}, we will use also unconditional responses in addition to the conditional ones. According to Kilian & Vigfusson (2011a) unconditional impulse response function, denoted $I(n, \delta)$, can be obtained by averaging the conditional impulse response function across all ω_{t-1}, which can be written as

$$I(n, \delta) = \int I(n, \delta, \omega_{t-1})\, \mathrm{d}\omega_{t-1} \tag{3.42}$$

To prove that the automobile stock prices (or returns) indeed exhibit an asymmetric behavior with respect to oil price shocks we have to test for the symmetry in the model. For the censored-like model a simple slope test based on Mork (1989) or Kilian & Vigfusson (2011a) can be used. For the model described by Equation (3.38) we would use an F-test for the null hypothesis

$$\mathrm{H}_0 : g_{21,i} = 0, \tag{3.43}$$

for $i = 0, \ldots, p$. For our two-state threshold model we will use an asymmetry test proposed in Hansen (1999) for univariate models and further adjusted for multivariate models in Lo & Zivot (2001). Null hypothesis in this test is linearity, that is we test a linear VAR model against an alternative of a TVAR model, in our case with two regimes. The test statistic of this test is classical likelihood ratio test statistic

$$\mathrm{LR} = T(\ln(|\hat{\Sigma}|) - \ln(|\hat{\Sigma}_{\mathrm{th}}|) \tag{3.44}$$

where $|\hat{\Sigma}|$ and $|\hat{\Sigma}_{\mathrm{th}}|$ are determinants of the estimated variance-covariance matrices of the linear and the two regimes threshold VAR models, respectively. On the other hand the distribution of the test statistic is not so trivial and has to be bootstrapped as proposed in Hansen (1997).

Chapter 4

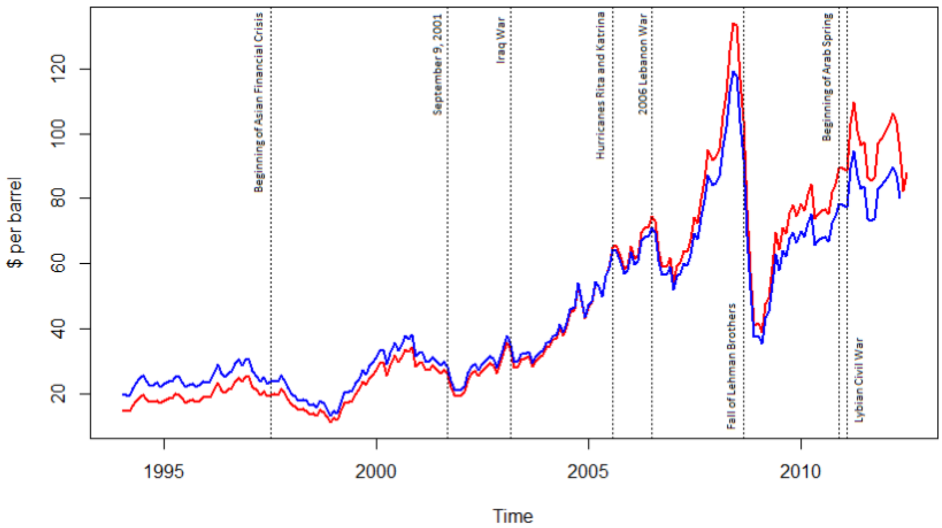
Description of data

Employing the VAR model we will decompose oil price shocks on three components. This implies that in addition to stock prices automotive firms we will use following time series; crude oil price as a measurement of oil price specific shocks (or shocks to precautionary demand of crude oil), global crude oil production as a proxy of supply shocks, and finally a global real economic activity index which should introduce demand shocks into the model. In addition to these main time series, an aggregate price index is used for the purpose of deflating nominal stock prices as well as nominal crude oil prices. All time series are used in the monthly frequency and cover the period January 1994-July 2012.

4.1 Crude oil prices

Examining the literature that deals with oil price shocks effects on macroeconomic variables or on stock market one can find various measures of oil prices. One common feature of all these measures throughout the literature is that the authors use real prices. For example, Hamilton (1988) utilizes PPI of fuels, on the other hand, Mork (1989) emphasizes a use of refiners acquisition cost because of misleading properties of PPI measure during 1970s caused by regulation issues. Also Kilian (2009) and Kilian & Park (2009) use oil price measured as refiners acquisition cost of imported crude oil, which is subsequently deflated by the U.S. CPI. From this point of view is very interesting the study Ramey & Vine (2010), which uses oil prices (measured as PPI and refiners acquisition cost) as well as gasoline prices (measured as CPI of gasoline). However, because of availability of the data the nominal global crude oil prices could be preferred compared to some local real representations of oil prices (as is the price measured as PPI). Further, because the scope of our study are real shocks, the nominal prices can be deflated using some price index. According to this reasoning three measures of crude oil prices can be used for our purposes, being West Texas intermediate light crude oil, Brent sweet light crude oil and U.S. refiner acquisition cost of crude oil. West Texas intermediate light crude oil price (WTI) is quoted on the New York Mercantile Exchange (NYMEX). Brent sweet light crude oil price can be regarded for a "European counterpart" to WTI, which is quoted on the IntercontinentalExchange (ICE).

Figure 4.1: WTI crude oil price. Nominal price (red line) is measured in U.S. dollars per barrel, real price (blue line) is measured in June 2005 U.S. dollars per barrel.

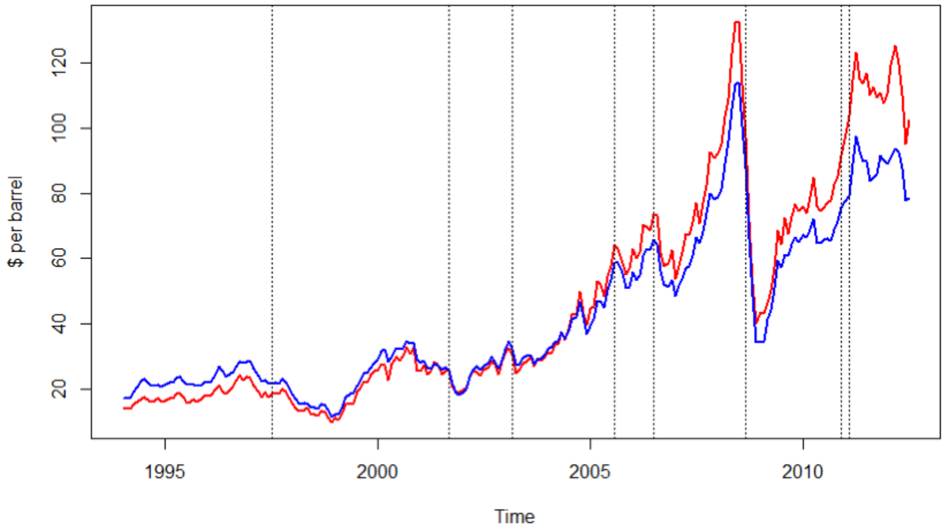


Source: U.S. Energy Information Administration and author's computations.

Figures Figure 4.1, 4.2 and 4.3 show the nominal as well as the real crude oil prices measured as WTI, Brent and refiners acquisition cost, respectively. All crude oil price time series were originally downloaded as nominal. Because all of the prices are originally measured in U.S. dollars, we decided to deflate them using the U.S. consumer price index for all urban areas.[1] As a base period is chosen June 2005, so the real prices are reported in June 2005 U.S. dollars per barrel.

[1]WTI, Brent and refiners acquisition crude oil prices can be found on the website of the U.S. Energy Information Administration, `http://www.eia.gov/petroleum/data.cfm#prices`. The U.S. CPI time series for all urban areas is downloadable from the website of the Federal Reserve Bank of St. Louis, `http://research.stlouisfed.org`.

Figure 4.2: Brent crude oil price. Nominal price (red line) is measured in U.S. dollars per barrel, real price (blue line) is measured in June 2005 U.S. dollars per barrel.

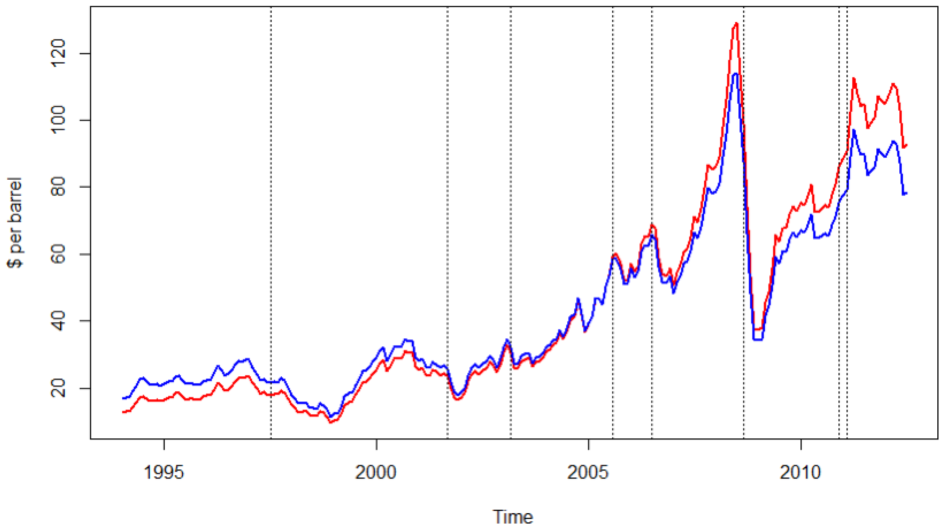


Source: U.S. Energy Information Administration and author's computations.

Auxiliary lines in the figures enable us look at the behavior of oil prices during the most important events that could be called by the abstract notion (oil price) *shocks*, or in other words they show timing of events that are generally known to have some impact on oil prices. All three price measure begin with a relatively calm period. The prices were stable until 1996 when all three plots show a significant downturn, which hits its trough in 1998 M8. As emphasized by Kilian (2009, p. 4) the 1996 (or 1998) oil price shocks, can be assigned to the Asian financial crisis (1997 M7-1999/2000[2]) and they are realizations of demand shocks. With the end of the crisis prices return to pre-crisis level and also surpassed them. The next significant events that affected oil prices was recession in the early 2000s and also political grievances marked by 9/11 in the plots. Further, a small hike in oil price can be seen in the beginning of 2003. This price increase can be understood as a reaction to the worsening political situation in Iraq and as an anticipation of Iraq War which began three months later. In 2005 two events can be identified that could have an impact on the crude oil price. First, Hurricane Katrina struck the Gulf of Mexico in August, followed by Hurricane Rita in September. Kilian (2009, p. 4) points out that while the reduction in the U.S. crude oil production was relatively minor in

[2]Dating based on R.J. Barro. *Economic growth in East Asia before and after the financial crisis.* NBER working paper, no. 8330, 2001.

Figure 4.3: Crude oil prices measured as refiners acquisition cost. Nominal price (red line) is measured in U.S. dollars per barrel, real price (blue line) is measured in June 2005 U.S. dollars per barrel.



Source: U.S. Energy Information Administration and author's computations.

terms of the global production, these events cause decrease in U.S. refining capacity (from 17.150 million barrels per day in July 2005 to 15.747 million barrels per day in October 2005 as documented by the U.S. Energy Information Administration). Such a decrease in demand for crude oil caused decrease in the price of crude oil. A minor instability in oil price could have been also introduced by the Lebanon War (Israel-Hezbollah War) in 2006. However, by far the greatest fluctuations in oil price were caused by the events related to the global Financial Crisis of 2007. The highest spike in June 2008 shows inflation of the bubble, while the subsequent trough in December 2008 signify its burst. Finally, fluctuations in crude oil price which began in 2010 represent events known as Arab Spring, that is a chain of revolutions in several Arab countries. Especially, the Libyan Civil War, which began in February 2011, could have had a significant impact on global oil prices as Lybia was listed as the 29th largest oil producer in the World by the U.S. Energy Information Administration. Also, an uncertainty about Israeli reaction concerning the Iranian nuclear program surely contributed to fluctuations in the crude oil price.

4.2 Index of global real economic activity

A global real economic activity time series will introduce a measure of global demand shocks into a VAR model. Various economic indicators can be used as a measure of the real economic activity, especially the global real GDP or a global index of industrial production. However, we decided to follow the papers Kilian (2009) and Kilian & Park (2009) in this matter and use the index of global real economic activity as designed in the former paper.

The main reason for implementing this measure of the real economic activity is that it is, in addition to the fact that it was used in several papers for similar purposes as is the goal of this thesis, publicly accessible and free of charge.[3] However, as it is emphasized in Kilian (2009), there are also several imperfections of the above mentioned conventional economic activity proxies, which makes this index preferable. On the account of global GDP method, Kilian sees the main problem in the data availability. He also argues against other indexes based on value added methodology. Along with the mentioned data availability problem, Kilian challenges aggregation methods, or in other words, weights used to compose such indexes.[4] Further, his last argument about the value added measures is their problematic relationship to global activity on commodity markets. An increase in the global economic activity as documented by the value added measure can be caused, for example, both by industrial sector or services sector. It is straightforward that the services sector use commodities in much lower quantities than industrial sector. Consecutively, the value added measure would indicate a positive demand shock, while demand of commodities would in fact remain unchanged. On the other hand, the industrial production method suffers with similar problems.

The index of global real economic activity is composed of single voyage freight rates for various commodities (e.g. grain, coal, iron). The freight rates are also measured for different trade routes in U.S. dollars per metric ton. The composed time series is finally deflated using U.S. CPI and linearly detrended.[5] Figure 4.4 shows the plot of the index with highlighted main events that affected

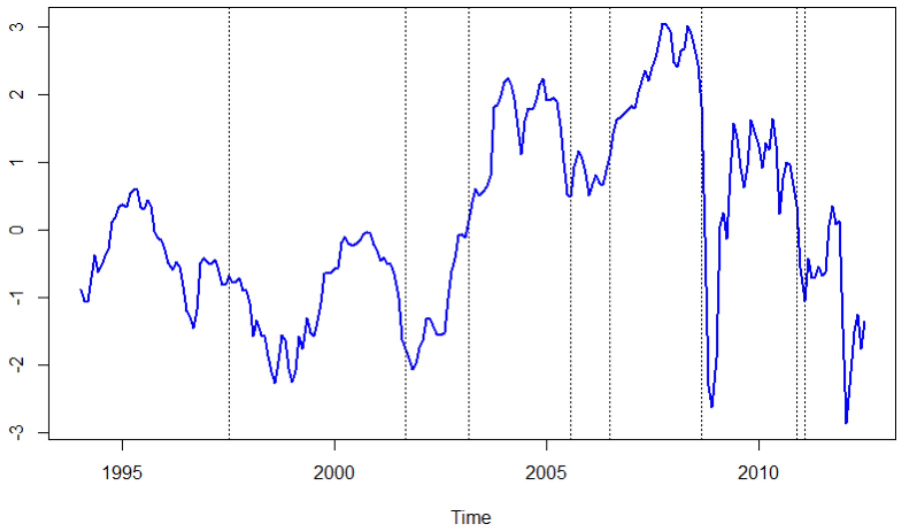
[3]The index of global real economic activity time series can be downloaded on the personal website of professor Lutz Kilian, `http://www-personal.umich.edu/~lkilian/paperlinks.html`. The whole time series covers the period 1968 M1-2012 M8.

[4]*"... it is not straightforward to properly weight each country's contribution to global, real economic activity ... To make matters worse, the relative importance of individual countries for global economic activity is shifting over time"* (Kilian 2009, p. 6).

[5]More on construction and rationale behind the index of global real economic activity in Kilian (2009).

crude oil price throughout the monitored period. As it can be seen, (political) events which are believed to bear main impact on the supply of crude oil, have almost none or only very limited effect on global economic activity. On the contrary, events which heavily affected the global economic activity caused also significant distortions in the crude oil price. Relatively stable business cycle is present in the data until 1995, when the economic activity peaked. Another major disruption coincides with the Asian financial crisis. The global economic activity hit its trough in 1998. Subsequently, a short period of prosperity followed peaking in 2000, followed by a recession that hit several developed countries and, as Kilian (2009, p. 11) states, whose trough coincides with 9/11. However, the heaviest disruptions caused the Financial Crisis of 2007 and the subsequent prolonged global recession or economic stagnation.

Figure 4.4: Index of global real economic activity, deflated using U.S. CPI and linearly detrended, 2005 M6=1.

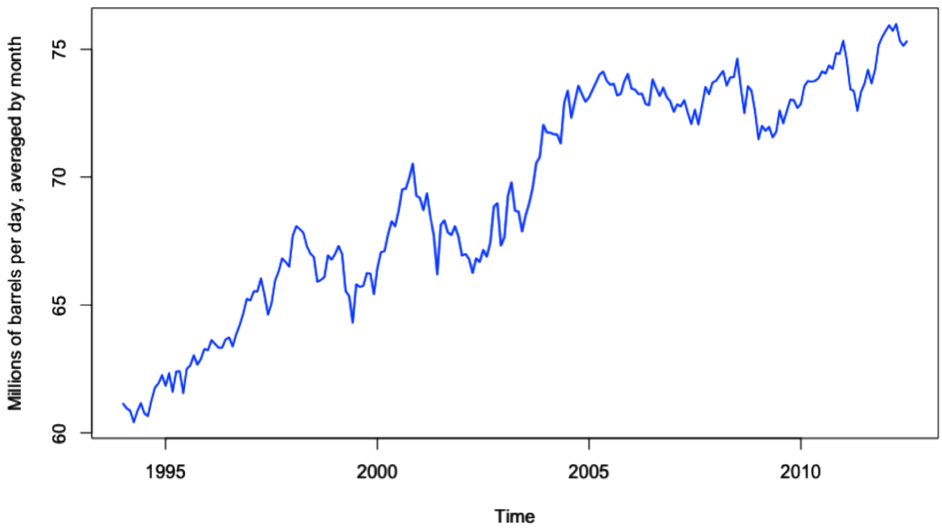


Source: Personal website of professor Kilian and author's computations.

4.3 Global crude oil production

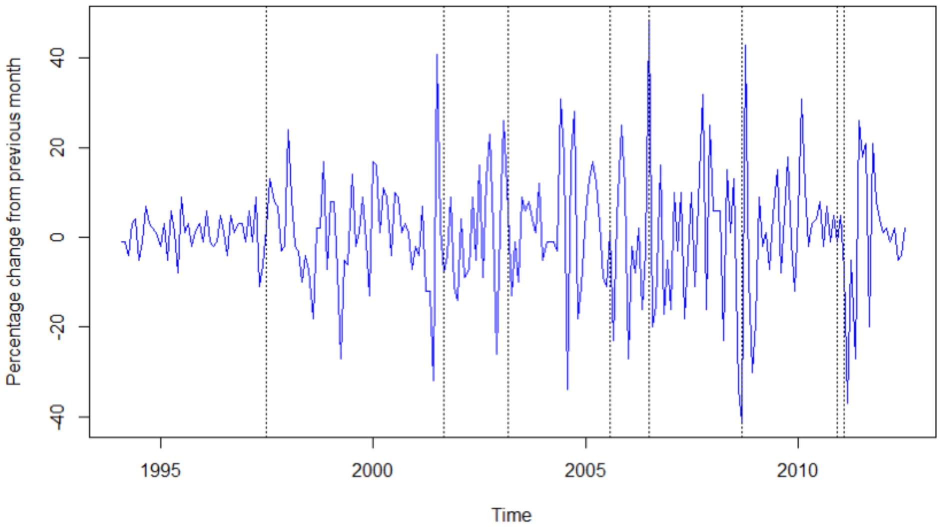
Above we introduced crude oil prices and index of global real economic activity, which will simulate specific price demand shocks and global demand shocks, respectively. In addition to these, global oil production will simulate supply shocks in our VAR model, including supply shocks caused by natural disasters as well as by political supply shocks (e.g. decreased in production due political events in Middle East). Figure 4.5 shows the global crude oil production measured in millions of barrels pumped per day, averaged by month and Figure 4.6 shows monthly changes in global crude oil production. We can see that oil supply reductions coincide in fact with all highlighted events. However, it is questionable if these reductions occurred as a direct cause of these events or as a cause of oil price hikes. As it was indicated in Chapter 2, Kilian (2009) suggests that the precautionary demand shocks precede supply shocks, in other words the political uncertainty and tension preceding the actual political event affects the oil price before the actual event takes place. Even if this is true for the oil price-supply relationship, we could conclude that at least the falls of production due to the hurricanes Katrina and Rita could be perceived as "direct" supply shocks. The graphs suggest that by far the most significant reductions in oil production occurred during the Financial Crisis of 2007 and Libyan civil unrest of 2011.

Figure 4.5: Global crude oil supply production in millions of barrels pumped per day, averaged by month.



Source: U.S. Energy Information Administration and authors's computations.

Figure 4.6: Monthly changes in global crude oil production.



Source: U.S. Energy Information Administration and authors's computations.

4.4 Automobile industry stock prices

The automobile industry stock prices time series act as the time series of main interest. The VAR analysis should reveal how shocks in all preceding time series influence the behavior of these prices. In our analysis we will study impacts of shocks on an aggregate time series as well as on its determinants. These determinants will represent individual automobile manufacturers. We expect that oil price shocks will have different effect on individual manufacturers because of differences in fuel consumption by their products.

As an aggregate time series representing automobile industry we composed an equal weighted portfolio (or rather an equal weighted index) composed of stock prices of major global car manufacturers. Totally there are 18 car manufacturers included in the index.[6] The index is constructed as follows: first, time series of individuals car manufacturers, which we downloaded using Reuters Wealth Manager database, are converted to U.S. dollars using correspondent exchange rate time series. Similarly as the oil prices, also stock price time series of all car manufacturers are deflated by CPI for all urban areas. Subsequently,

[6]See Appendix A for the list of included car producers and for more detailed information on its construction. The index prices will also be called automobile stock prices, interchangeably.

the first value of the equal weighted index is computed using a following formula

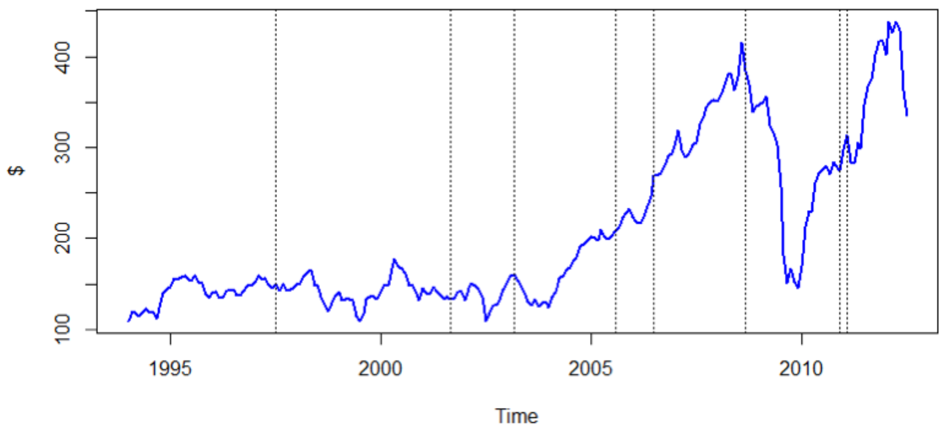
$$\text{real\_asp}_1 = \frac{100}{18} \sum_{i=1}^{18} \frac{\text{series}_{i,2}}{\text{series}_{i,1}}, \tag{4.1}$$

where real_asp stands for real automobile stock prices, $\text{series}_{i,1}$ is the first value in time of stock prices of i-th car manufacturer, hence the 0th value of the index is is assumed to be 100. Next, all further index values are calculated using equation

$$\text{real\_asp}_t = \frac{\text{real\_asp}_{t-1}}{18} \sum_{i=1}^{18} \frac{\text{series}_{i,t+1}}{\text{series}_{i,t}}, \tag{4.2}$$

for $t = 2, \ldots, 223$. After correspondent number of repetitions an equal weighted index of real automobile stock prices is obtained. The resulting index is plotted in Figure 4.7. Similarly as for the previous time series, the graph of the index

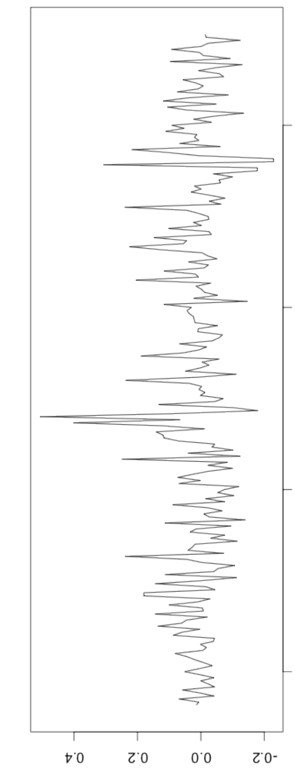
Figure 4.7: Prices of equal weighted stock index composed of major car producers. Deflated to U.S. dollars of June 2005.



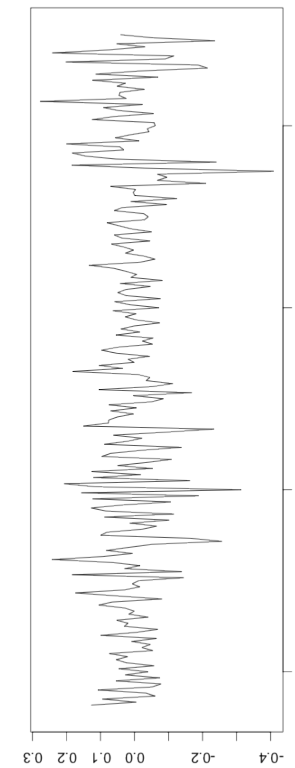
Source: Reuters Wealth Manager and authors's computations.

exhibits largest fluctuations shortly after the beginning of Asian financial crisis, in the early 2000s and during the global Financial Crisis of 2007.

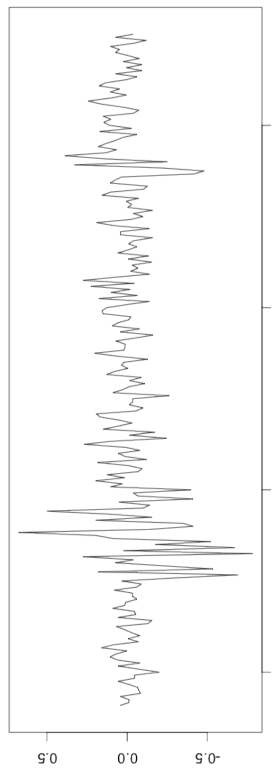
For the analysis of individual time series we will use real stock returns of car producers Audi, BMW, KIA, and Hyundai (similarly as before, the nominal prices are deflated to June 2005 U.S. dollars). Plots of these stock returns are depicted in Figure 4.8.



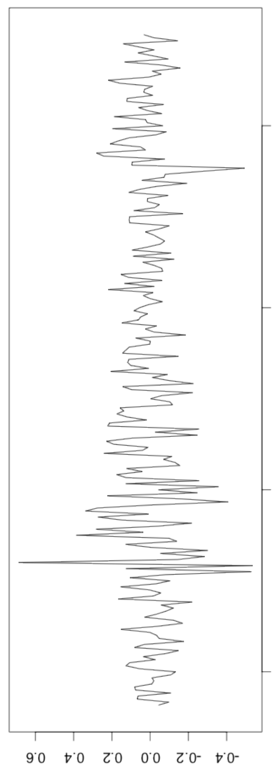
(a) Audi real stock returns.



(b) BMW real stock returns.



(c) KIA real stock returns.



(d) Hyundai real stock returns.

Figure 4.8: Real stock returns of individual car producers.

Source: Reuters Wealth Manager and authors's computations.

Chapter 5

Empirical results

5.1 Results of linear analysis

Following the methodology outlined in the previous chapter, our first task is to examine the time series for unit roots. Even before that, we transform all variables except the global real economic activity (because of the fact that it includes negative values) into natural logarithms. Nonstationarity of all time series in our dataset is suggested already by their plots, which shows clear trends (Figures 4.1, 4.4, 4.5, and 4.7). These graphical tests are further supported by ADF and KPSS tests, which also indicated unit roots present in the data.

Table 5.1: Unit root tests for levels. Notation l_oil_sup, real_ea, l_real_wti, and l_real_auto stand for (logarithms) oil supply, real economic activity, real WTI prices, and real automobile stock prices, respectively.

Variable	ADF	KPSS	
	p-value	LM_{KPSS}	5% crit. value
l_oil_sup	0.377	4.116	0.463
real_ea	0.044	1.31	0.463
l_real_wti	0.656	3.823	0.463
l_real_auto	0.652	3.339	0.463

Source: author's computations.

Recall that the null hypothesis of the ADF test is presence of a unit root while the opposite is true for the KPSS test. Table 5.1 shows some very interesting results. While the KPSS test suggest that all time series are nonstationary at the 5% level of significance, according to ADF test the global real economic activity is slightly stationary on the same level of significance. This finding does not at all corresponds to the construction of this variable which is, as

Table 5.2: Unit root tests for variables in first differences. Note that all variables except the real global economic activity are in logarithms.

Variable	ADF	KPSS	
	p-value	LM_{KPSS}	5% crit. value
Δl_oil_sup	< 0.01	0.076	0.463
Δreal_ea	< 0.01	0.078	0.463
Δl_real_wti	< 0.01	0.031	0.463
Δl_real_asp	< 0.01	0.037	0.463

Source: author's computations.

Kilian (2009) states, already detrended. On the other hand, unit root tests for differenced variables indicate that all of them are stationary at the 5% level. Because the of unit roots test for the global real economic activity is peculiar we will treat it first as nonstationary and subsequently we will use it as a stationary variable and compare the two results.

If the global real economic activity is nonstationary, we have all endogenous variables nonstationary, what implies that one or more cointegrating relationships can be present in the data. However, we have to determine a VAR lag order before employing the Johansen procedure. First, information criteria are used with the maximum lag order set to $m = 12$ lags. Table 5.3 summarizes the results yielded by the criteria. As we can see the result is ambiguous because

Table 5.3: VAR order selection using information criteria method.

IC	suggested order
AIC	4
HQ	2
SC	1

Source: author's computations.

of different performance of different criteria. Therefore, we continue with likelihood ratio test. Initially, the orders of unrestricted and restricted models are set to 4 and 3, respectively. The likelihood ratio fails to reject null hypothesis about simpler model, so the testing procedure have to continue. In our case the test rejects null hypothesis for a restricted model with 1 lag of endogenous variables (p-value $= 1.087 \times 10^{-6}$). We believe, however, that one lag is too few to capture all the dependencies in the data, therefore we will continue our analysis for a VAR(4) model (as it is suggested by the AIC), while the final model will depend on performance of the given model with respect to the whiteness of residuals.[1] Finally, with determined lag order we can approach to cointegration tests. Table 5.4 shows that, according to the both tests of

Table 5.4: Johansen test for rank of cointegration.

Hypothesis	λ_{trace}	5% crit. value	$\lambda_{\max}$	5% crit. value
$r \leq 3$	4.27	9.24	4.27	9.24
$r \leq 2$	11.55	19.96	7.28	15.67
$r \leq 1$	23.02	34.91	11.47	22.00
$r = 0$	59.16	53.12	36.14	28.14

Source: author's computations.

Johansen procedure, there is one cointegration relationship among the time series. In maximum eigenvalue and trace test we included an intercept term into cointegration relationship, which corresponds to a VECM with restricted constant (no constant term in VAR process and constant term in cointegration term), which we think corresponds best to the nature of our data. To summarize the lag order selection procedure and the Johansen procedure, the results suggest the use of a VECM with one cointegrating vector and 3 lags of first-differenced endogenous variables. Checking the whiteness of residuals should show the adequacy of a given model. For the above outlined VEC model we are unable to reject hypothesis about serially correlated residuals and their normality (for example the p-value for the joint test for residuals autocorrelation at lag 20 is 0.0244 so we reject the null hypothesis about no serial correlation in residuals at the 5% level). We stated earlier in the text that we expect normality to be rejected given the nature of financial data (distributed according to heavy-tailed distributions). Although we also think that no serial correlation in residuals is not so important for model which should assess impact of oil price shocks on car manufacturers stock, prices rather than provide explanation of variance in these stock prices (hence residual autocorrelations in such a model would suggest existence of some important variable that is not included in the model), we decide to augment our model with additional lags. Thus, instead of VECM with three lags of variables in first differences we will use a model with 5 lags; a VEC model of this lag length corresponds to a VAR(6) process and thus it should cover all seasonal effects during the year. In compliance with results of the Johansen procedure we keep the number of cointegration vectors fixed to 1. The estimated model can be found in Appendix B. Even using the augmented model we are unable to achieve normality of residuals. P-values for

[1] Although, the VAR(1) model could be very convenient for predictions for which more parsimonious models are used.

skewness, kurtosis and the combined Jarque-Bera test statistics are as follows: p-value($\hat{\lambda}_s$) = 0.0002, p-value($\hat{\lambda}_k$) = 2.2×10^{-16}, and p-value($\hat{\lambda}_{sk}$) = 2.2×10^{-16}. However results for serial correlations tests are much improved by the augmentation; they are summarized in Table 5.5. From this table we can see that at

Table 5.5: Test for autocorrelation in VECM residuals.

	Lag			
	20	25	30	35
p-value	0.0798	0.1455	0.1252	0.2605

Source: author's computations.

a given lags we are unable to reject the null hypothesis about autocorrelations equal to zero at the 5% level of significance. As we emphasized before, the estimated matrices Γ_i include a lot of insignificant coefficients, also the whole model comprises of so much coefficients that their interpretation would be very confusing, hence we will continue with the interpretation of the cointegration relation, Granger-causality and impulse responses.

The cointegration relation, i.e. the long-run co-behavior, estimated by the model is depicted in Figure 5.1. Most evident extremes on the graph correspond to Asian financial crisis and to Financial crisis of 2007 with the preceding growth and the succeeding recovery period. Equations (5.1) and (5.2) represent estimated cointegrating relation normalized to the first and the fourth variable (that is oil supply and automobile stock prices), respectively.

$$y_{1t} - 0.001y_{2t} - 0.371y_{3t} + 0.383y_{4t} - 4.901 = 0 \tag{5.1}$$

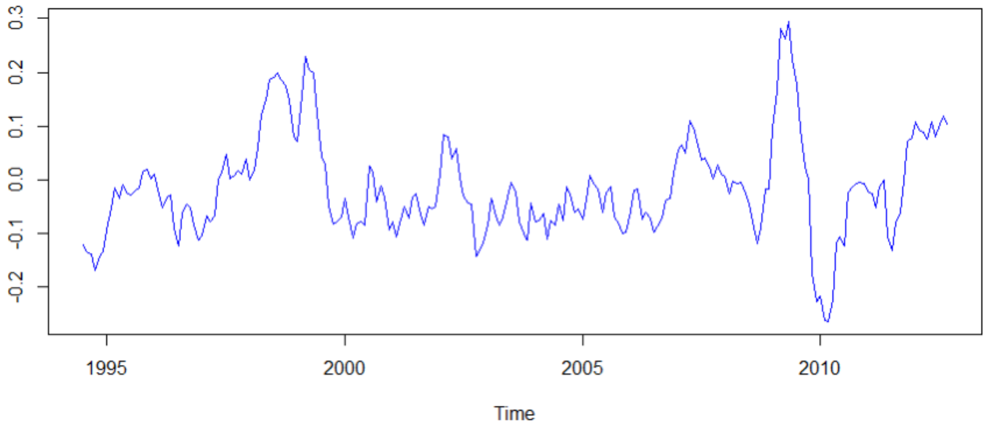
$$y_{4t} + 2.609y_{1t} - 0.004y_{2t} - 0.969y_{3t} - 12.786 = 0 \tag{5.2}$$

Looking at Equation (5.2) we could conclude that e.g. a 1 percentage point increase in the WTI price per barrel of crude oil, all things being equal, results in an increase of 0.969 percentage points of automobile stock price. This, however, may not be true because of the presence of differenced terms in the model. The true effects will be shown by impulse responses.

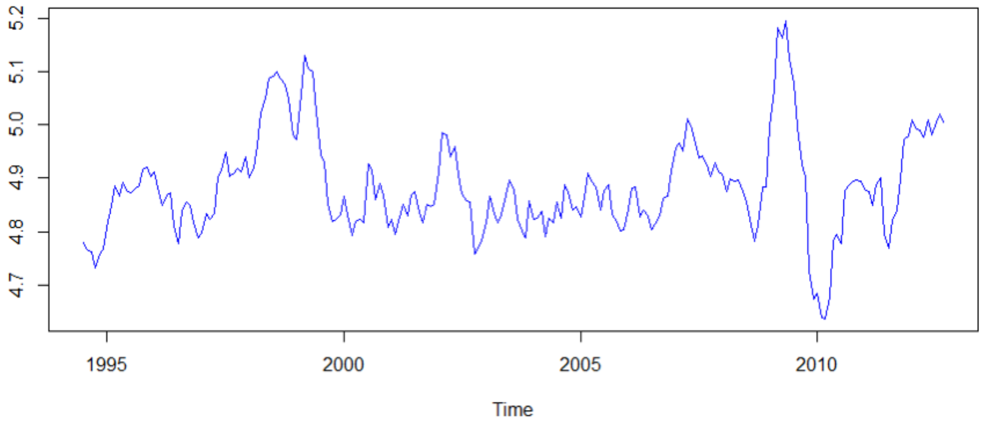
Because the corresponding VAR process to our VEC model is a VAR(6) process, we use a VAR(7) process to test the Granger-causality. First, we are interested if the first three variables, that is the global oil production, the global real economic activity, and the real WTI crude oil price, do Granger-cause the real automobile stock price. Using an F-test we get p-value = 1.572×10^{-5} for this test. Such result allows us to strongly reject the null hypothesis about no

Figure 5.1: Cointegration relation.

(a) Cointegration relation including the constant term.



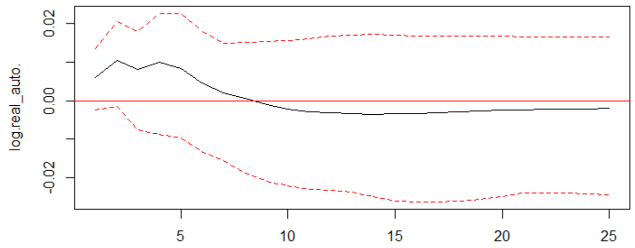
(b) Cointegration relation without the constant term.



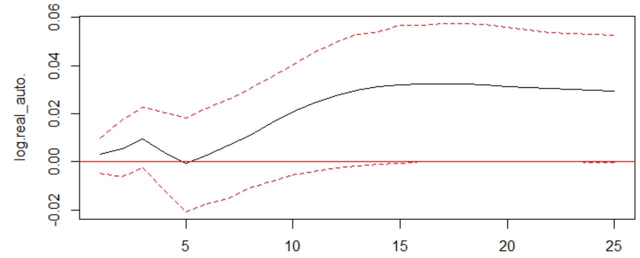
Source: author's computations.

Granger-causality between the given variables on the 5% level of significance. In other words, we determined that oil supply, global demand, and oil price indeed affect, in some way which we do not know yet, behavior of automobile stock prices and, therefore, using these variables we are able to explain some portion of variation in these stock prices. Let us now test the Granger-causality in the opposite way, that is if the automobile stock prices Granger-cause the other three variables. This time we obtained p-value = 0.6281. Such result shows that the automobile stock price alone does not have, according to our model, a significant effect on the block of variables consisting of global oil production, global real economic activity and real oil price. This seems only logical as the automobile industry, despite its unquestionably high importance for particular economies, does not have have a sufficient strength to exert significant impact on global price or supply of oil given the wide spectrum of use of oil.

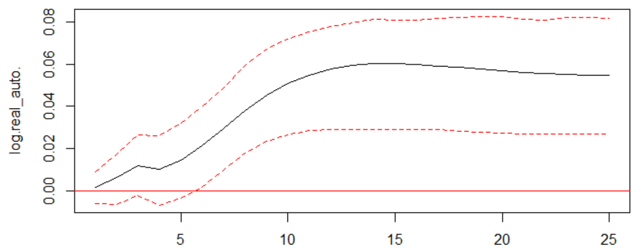
Finally, we compute orthogonalized impulse responses, which allow for instantaneous effects between variables. Figure 5.2 shows estimated impulse responses. Also 95% confidence interval is depicted on all graphs in order to evaluate significance of responses. In Figure 5.2(a) we can see response to a one standard deviation shock in global oil supply. Real automobile stock price reacts immediately by upward movement and positive response persists with little fluctuations until the 4th month, since when the response starts to decline. After that the response is negative. However, we can see that the 95% confidence interval covers both negative and positive values on the graph, implying that the response to oil supply shock is statistically not different from zero at the 5% level of significance. Reaction to an aggregate demand shock, plotted in Figure 5.2(b), also shows instantaneous positive effect on automobile stock prices followed by a decrease almost to negative values. The automobile stock price starts to increase again in the 5th month since the impulse. The response to an aggregate demand shock is also not significant on the 5% level for the whole 24 months. Most striking result brings the response to an oil-specific demand shock. As Figure 5.2(c) shows, oil-specific demand shock of magnitude one standard deviation causes large positive response in automobile stock price. The response is not instantaneous and not even significant for the first 6 months, but since the first month after the shock the automobile stock price starts to rise at a quite rapidly increasing pace (convex curvature for at least first 7 months). This increase is stopped in the 12th month after which the automobile stock price is still increasing, although with a decreasing pace. The response to an oil-specific demand shock is significant between 6th and 16th



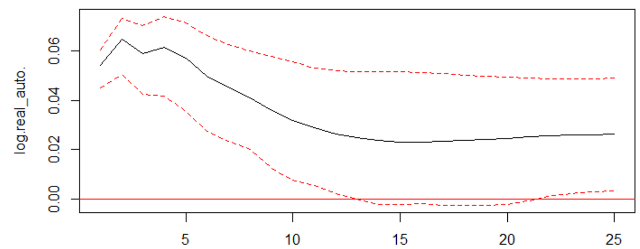
(a) Impulse from oil_sup.



(b) Impulse from real_ea.



(c) Impulse from real_wti.



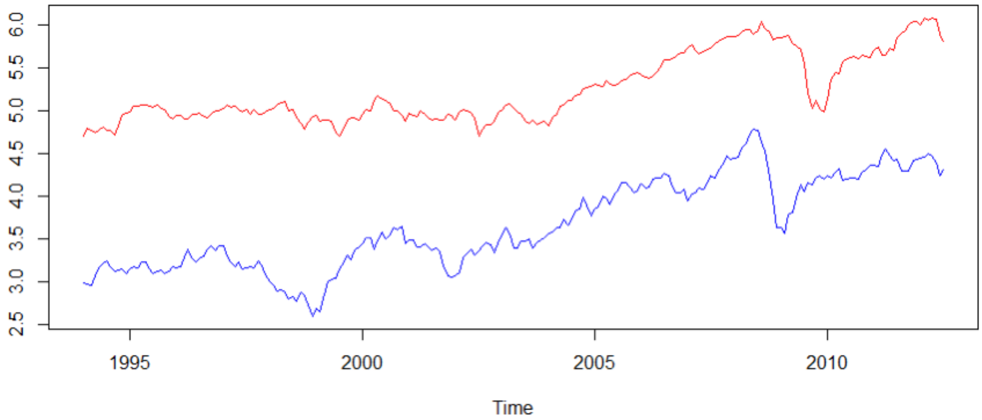
(d) Impulse from real_auto.

Figure 5.2: Impulse responses of real automobile stock prices (real_auto) to 1 standard deviation shocks for 24 months ahead. Red dashed lines mark boundaries of 95% confidence intervals. Confidence intervals are computed by bootstrapping method using 200 repetitions.

Source: author's computations.

month. Obtained result is completely different from that presented by Kilian & Park (2009), where automobile oil price reacted with a significant decrease to an oil-specific demand shock. We believe the main reason of this crucial difference between findings presented in the study from Kilian and Park and our own findings lies in selection of different time periods. Authors Kilian and Park analyze the data covering period 1975 M1-2005 M9.[2] Notice the movement of real automobile stock price and real WTI price in Figure 5.3.

Figure 5.3: Development of real automobile stock price (red line) and real WTI crude oil price (blue line). Both variables are in logarithms.

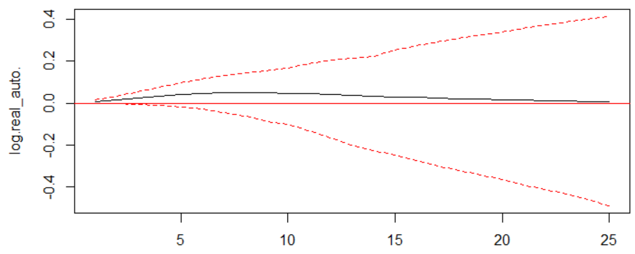


Source: U.S. Energy Information Administration, Reuters Wealth Terminal and author's computations.

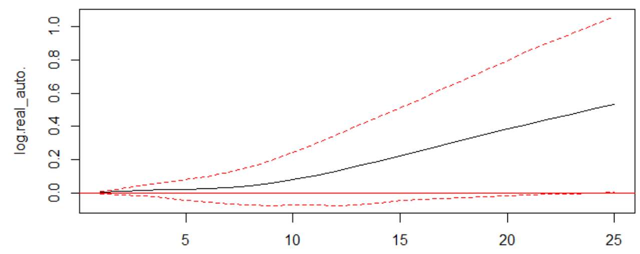
While the first part of the plot, that is approximately until 2004 M1, shows plenty of examples of counter-movement of the two time series, in the second part of the plot covering the pre-Crisis economic growth, Financial Crisis and the subsequent recovery period, the oil price and the automobile stock price exhibit strong positive co-movement, driven by increasing (during the pre-Crisis boom and post-Crisis recovery) as well as decreasing (after the bust) aggregate demand. To not isolate this co-movement only on the "second period", the co-movement is also present in the "first period" as well. Recall that this co-movement is also supported by cointegration relation represented by Equation

[2]They also use CPI-deflated refiners acquisition cost of crude oil as a measure of real oil price and real stock returns used by Fama and Frech publicly accessible at `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html` as a measure of automobile stock prices. However, as we also showed in Section 4.1, there are almost none differences between various measures of oil price and we think that a different measure of automobile stock prices should not bias results is such substantial way. Therefore, we believe that different measures of oil price and automobile stock price could not substantially change results of the VAR analysis.

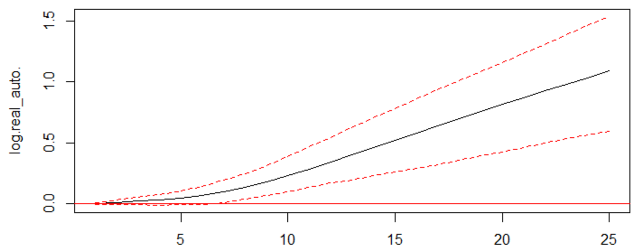
5.2. Also the fact that we employed the VEC model which utilize the cointegration relationships in the data contributed to the difference between this thesis and the paper Kilian & Park (2009). Finally, Figure 5.2(d) depicts plot of impulse response function to a shock in automobile stock price. Although this is not an oil price-affecting shock and hence not a scope of this thesis, we can see that the shock is positive and strongly significant. Subsequently, we compute also cumulative impulse responses, plotted in Figure 5.4, to assess cumulative impact of different shocks. Similarly as for the normal impulse responses also cumulative impulse response for a one standard deviation oil supply shock is not significant on the 5% level of significance (Figure 5.4(a)). The same is also true for the one standard deviation shock in global aggregate demand (Figure 5.4(b)). Figure 5.4(c) shows the gradual increase in the automobile stock price after an oil price shock of magnitude one standard deviation. As we argued before, the automobile stock price increases first with an increasing pace, hence the cumulative impulse response function is convex on this interval. After the 7th month the increase is approximately constant or slightly decreasing.



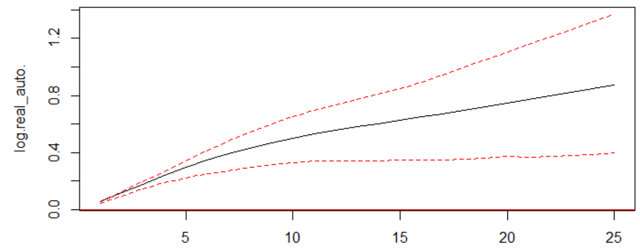
(a) Impulse from oil_sup.



(b) Impulse from real_ea.



(c) Impulse from real_wti.



(d) Impulse from real_auto.

Source: author's computations.

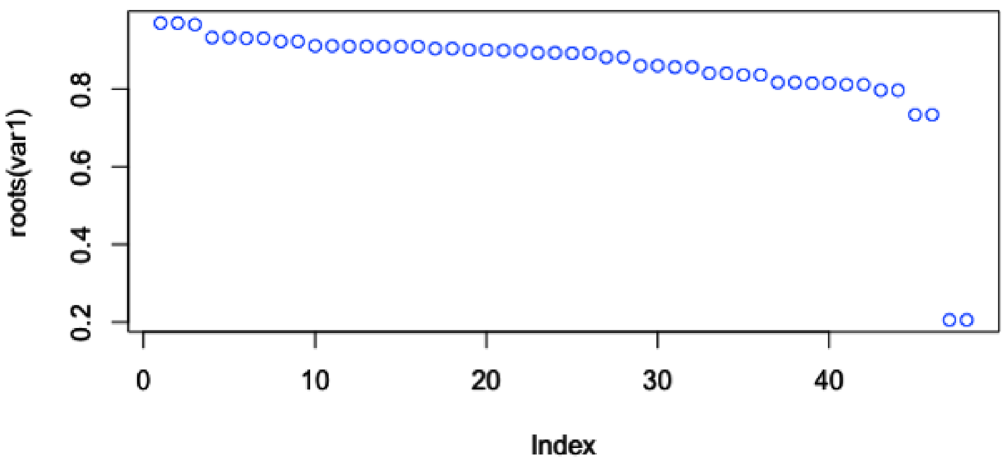
Figure 5.4: Cumulative impulse responses of real automobile stock prices (real_auto) to 1 standard deviation shocks for 24 months ahead. Red dashed lines mark boundaries of 95% confidence intervals. Confidence intervals are computed by bootstrapping method using 200 repetitions.

Source: author's computations.

Let us now treat the real economic activity variable as stationary, that is $I(0)$. In this case we will transform all remaining variables into first log-differences and fit a VAR(12) model. This will be done for two reasons: a) the twelve lags will allow us to cover all dependencies throughout a year, b) it will allow us a direct comparison with the model of Kilian & Park (2009) so we will be able to assess if the positive effect of real oil price shock on automobile stock prices is restricted only to model which allows for cointegration or it is also present in shorter-term relations (as the cointegration describes long-term relations) between these variables.

After estimating this VAR(12) with variable suspicious for a unit root it is imperative to test the stability of the VAR process.[3] In our case the stability condition is not violated as all of the eigenvalues of matrix A lie inside the unit circle which is equivalent to roots of the reverse characteristic polynomial larger than 1 in modulus (see Figure 5.5). Further, we have to test the adequacy of

Figure 5.5: Stability test.



Source: author's computations.

the VAR(12) model by testing normality and serial correlation of residuals. Similarly as for the VEC model, normality is strongly rejected with p-values for skewness, kurtosis and Jarque-Bera test statistics being p-value$_s = 0.0005$, p-value$_k = 2.2 \times 10^{-16}$ and p-value$_{JB} = 2.2 \times 10^{-16}$, respectively. On the other hand, autocorrelation test are quite favourable for our model; they are

[3]Earlier we emphasized that the integrated VAR process is assumed to be originally unstable by definition. However, now we seemingly ignore that the variables are already in differences and we seemingly treat the VAR model as in levels. Thus, if the stability analysis indicated that the system is unstable, we would be forced to transform the variables further, into the second differences and thus ensure the stability.

summarized in Table 5.6. The table shows that for the first two lags the

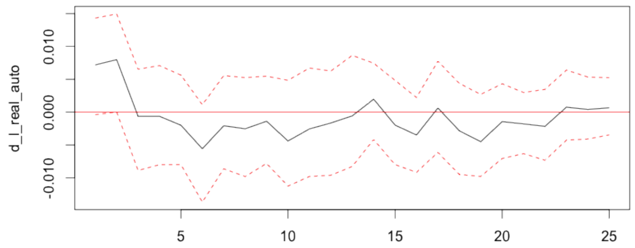
Table 5.6: Test for autocorrelation in VAR residuals

	Lag			
	25	30	35	40
p-value	0.043	0.032	0.147	0.21

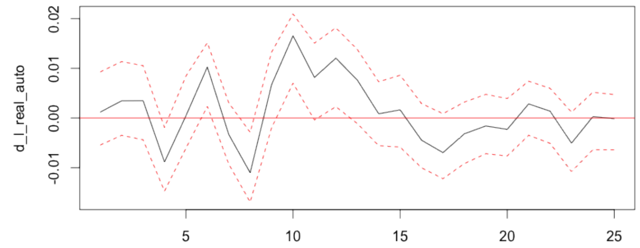
Source: author's computations.

autocorrelations are only marginally significant, while for the other two lags we cannot reject the null hypothesis about no serial correlation in residuals at the 5% level of significance. Taking into consideration these results and the earlier stated fact that for the purpose of our analysis we do not need perfectly uncorrelated residuals, we can use this model further on. Hence, we can continue with testing the Granger-causality. Especially, we want to know if oil production, global real economic activity and real oil price do Granger-cause automobile stock returns variable. For this setting the test returns p-value = 1.837×10^{-5} so the null hypothesis about no Granger-causality between the given set of variables and automobile stock returns is strongly rejected on the 5% level. Finally, Figures 5.6 and 5.7 show orthogonalized and cumulative impulse responses to one standard deviation shocks.

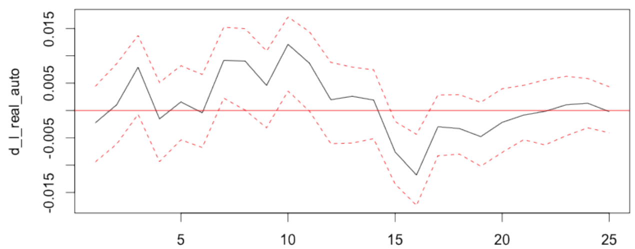
Regarding the oil supply shock, we can see approximately the same pattern as before, that is the nonsignificant response. Different behavior exhibits a response to an aggregate demand shock. For, approximately, the first 9 months is the orthogonalized response quite volatile. In this period there are significant decreases of the automobile stock returns in the 4th and 7th month after the shock interrupted by a significant increase in the 6th month. Between the 9th and 13th month is the response significantly positive on the 5% level. Thereafter it oscillates around the zero line and is statistically not different from zero on the 5% level. The initial oscillation and later significant increase in the automobile stock returns is reflected also by the cumulative response. According to it the automobile stock returns can respond to an aggregate demand shock by an increase of almost 6% for the first 15 months. While these conclusions are still in line with those of Kilian & Park (2009) results given by response to an oil-specific demand shock are completely opposite. The orthogonalized impulse response shows only two regions with significant automobile stock returns increases, around the 8th and 10th month, and even a significant decrease starting in the 15th month. However the cumulative response shows us much better the positive effect of an oil-specific demand shock on the automobile



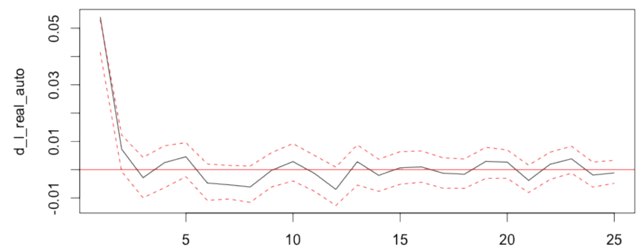
(a) Impulse from d_l_oil_sup.



(b) Impulse from real_ea.



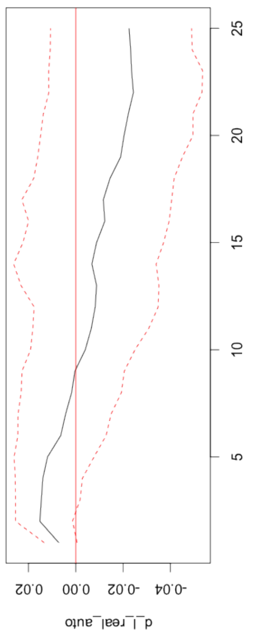
(c) Impulse from d_l_real_wti.



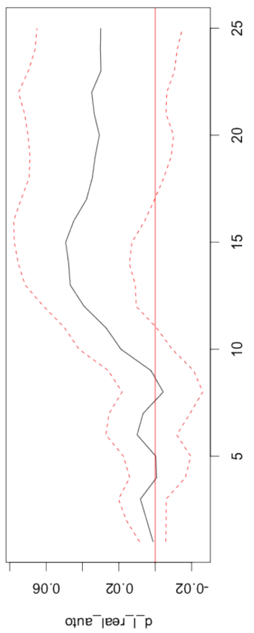
(d) Impulse from d_l_real_auto.

Figure 5.6: Impulse responses of real automobile stock returns (real_auto) to 1 standard deviation shocks for 24 months ahead. Red dashed lines mark boundaries of 95% confidence intervals, d_l stands for log-differences. Confidence intervals are computed by bootstrapping method using 200 repetitions.

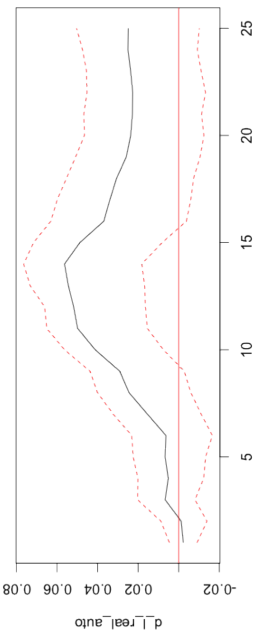
Source: author's computations.



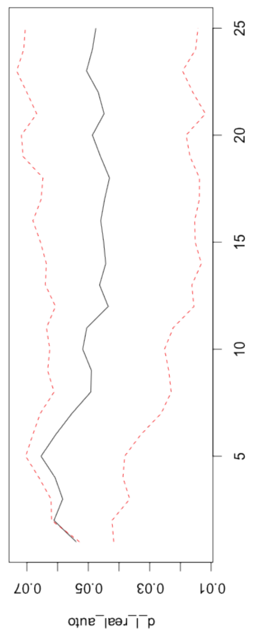
(a) Impulse from d_l_oil_sup.



(b) Impulse from real_ea.



(c) Impulse from d_l_real_wti.



(d) Impulse from d_l_real_auto.

Figure 5.7: Cumulative impulse responses of real automobile stock returns (real_auto) to 1 standard deviation shocks for 24 months ahead. Red dashed lines mark boundaries of 95% confidence intervals. Confidence intervals are computed by bootstrapping method using 200 repetitions.

Source: author's computations.

stock returns. From the 2nd month on the response is positive and showing quite rapid increase in the returns. Between the 7th and 16th month is the increase in returns significant on the 5% level of significance. The response also shows that for the first 15th months after the shock, the automobile stock returns can increase by approximately 6%.

To summarize this section, we were able to prove the proposition of Kilian & Park (2009) that oil price shocks are transferred to macroeconomic variables through the oil-specific demand shocks. However, we found that during the period we analyzed there is a reverse relationship between these shocks and the automobile stock prices/returns compared to that of Kilian and Park. This reverse relationship is confirmed by two models out of which the first describes long-term behavior of variables while the second describes rather cyclical behavior of used variables. We believe that the strong positive co-development of oil price and automobile stock price/returns, which seems to be in contradiction with the common sense (as the rising oil prices should mean a fall of car demand and hence a decrease of automobile stock price/returns) is a specific property of examined time period. Unlike any other period before, this period is characteristic by high economic activity (which proved to be a bubble) driven by low interest rates and excessive monetary expansions followed by bust and deep recessions with subsequent recovery attempts, during which the oil price as well as automobile stock price/returns exhibit similar behavior.

5.2 Results of non-linear analysis

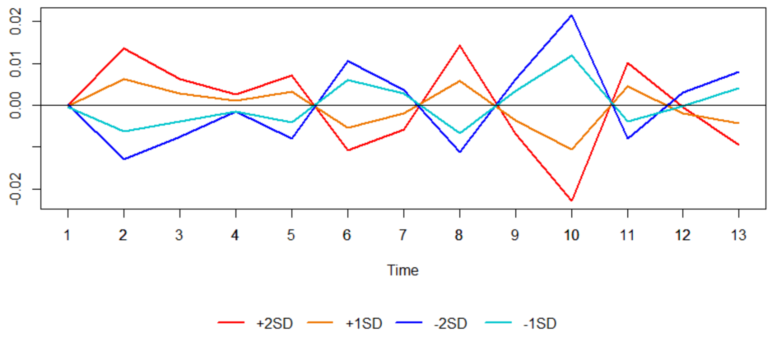
For the nonlinear analysis we use a threshold model described by Equation (3.39) with $p = 12$, that is with 12 lags. We use this model in order to allow direct comparison with results of linear analysis as well as with results published in Kilian & Park (2009). Also, the number of lags is chosen to account for cyclical effects throughout a whole year. Using the estimated model we are able to compute the Hansen's threshold test.[4] Because of complexion of the test we first find the data-generating VAR process for our variables using the information criteria method. According to Akaike information criterion, the data-generating process is a VAR(3) process. Finally, using this result the Hansen's test returns p-value for the LR test statistic lower than 0.01, so the null hypothesis about linearity is strongly rejected at the 5% level of significance.

After the proof of a presence of non-linearity in the VAR process we can approach to simulations of impulse responses using the procedure outlined in Chapter 3.2. As it was already stated earlier, we compute impulse responses for 12 months ahead. Further we set the number of simulations (repetitions) for each history $m = 200$, thus for each history we simulate 200 paths of length 12. Then by averaging across all histories, whose total number is 210 in our case, we can compute the unconditional impulse responses (Figure 5.8).[5] In Figure 5.8(a) we can see responses of automobile stock returns on oil supply shocks of magnitude +1SD, +2SD, -1SD and -2SD. The plot shows that responses to positive oil supply shocks are approximately mirror image of negative oil supply shocks. Therefore, the response can be considered for symmetric in sign. Situation is more complicated if we consider "symmetry in magnitude". Notice that e.g. in month 7 we can see that +2SD response is more than twice the +1SD response, hence the positive responses are not symmetric in magnitude.

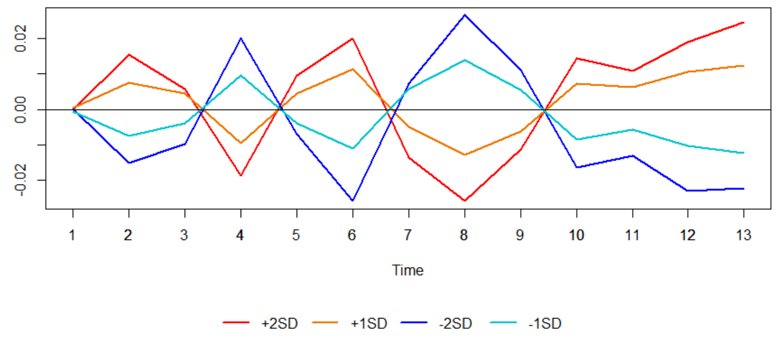
Similar reasoning can be also applied on the negative responses. For example in the 1st month since the shock the -2SD response is more than twice the -1SD response and there is even an intersection of the -2SD and -1SD responses in month 1. Thus the responses to oil supply shocks are symmetric in sign but not in magnitude, if we account for different intercepts and slope coefficients for negative and positive oil price growth. In the case of aggregate demand shocks are the results very similar. Figure 5.8(b) shows that responses to positive and negative shocks are approximately symmetric in sign but not in magnitude.

[4]Estimated model can be found in Appendix D.

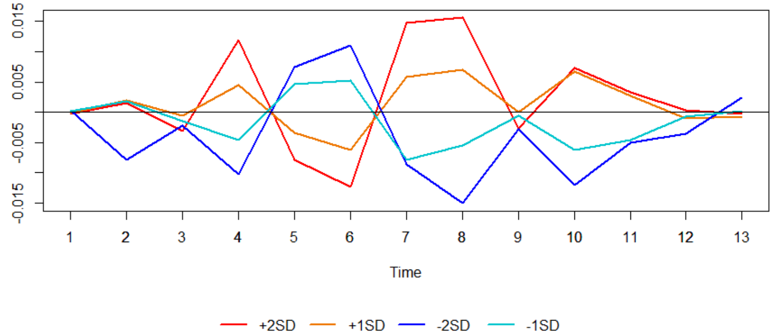
[5]For all nonlinear impulse response plots we use template inspired by impulse response plots in Afonso *et al.* (2011).



(a) Impulse from d_l_oil_sup.



(b) Impulse from real_ea.



(c) Impulse from d_l_real_wti.

Figure 5.8: Unconditional impulse responses of real automobile stock returns to shocks of various magnitude and size for 12 months ahead (SD means standard deviation). Note that the x-axis label is shifted by 1, i.e. the 1st month corresponds in fact to the 0th month. This holds also for all further nonlinear impulse response plots.

Source: author's computations.

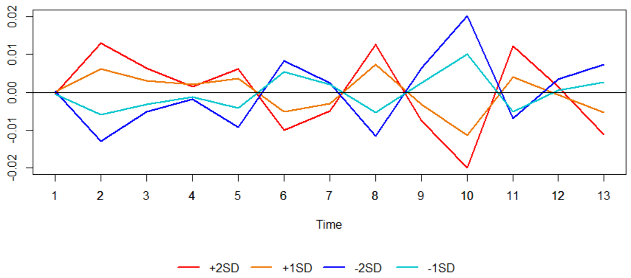
For example in the 5th month since the shock is the -2SD response much more than twice the -1SD response. In the same month the +2SD response is less than twice the +1SD response, although the differences are quite small.

On the other hand, results for oil-specific demand shocks, shown in Figure 5.8(c), are much more different compared to the two previous shocks. Now we can clearly see that the responses are not symmetric in sign nor in magnitude. Most interesting parts of the plot are first 2 months, where +2SD, +1SD and -1SD shocks seem to have very similar impact on the automobile stock returns, and the last 5 months, where similar reasoning can be applied especially for the +2SD and +1SD responses (these seem to have almost identical paths in this period). Notice also the whole paths of +2SD and +1SD responses. They, again, show that automobile stock returns react positively to positive oil-specific demand shocks, especially after the 5th month after the shock.

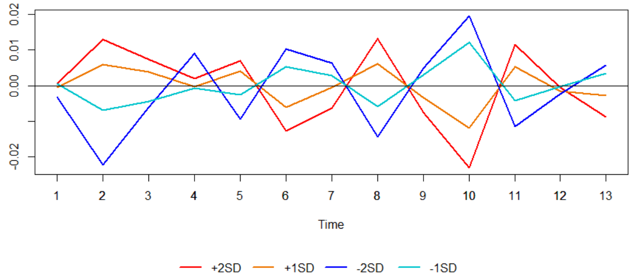
Using slightly adjusted procedure for unconditional impulse responses we can easily compute impulse responses in state of decreasing oil prices or in state of increasing oil prices. Construction of the model (3.39) implies that by state of decreasing (increasing) oil prices we mean all histories for which holds condition $\Delta y_{3,t-1} < 0$ ($\Delta y_{3,t-1} > 0$), therefore we call these histories negative (positive). Similarly as for the unconditional impulse responses, we simulated 200 paths for each history. Figure 5.9 shows computed impulse responses for both the positive and the negative histories for all three oil price shocks. A closer look at Figures 5.9(a) and 5.9(b) reveals only slight differences between the responses to oil supply shocks in the two different states. Most notable is the much deeper decrease of automobile stock returns in case of positive oil price changes. Results are similar also for the aggregate demand shocks. Again, we can see only minor differences between responses of automobile stock returns in both states (Figures 5.9(c) and 5.9(d)). Finally, Figures 5.9(e) and 5.9(f) shows responses to oil-specific demand shocks for the two kinds of histories.

As we emphasized before, we estimate also impulse responses of individual car producers in order to asses existence of differences between producers of luxury cars and less luxury cars. As representatives of the first group we choose stock returns of companies BMW and Audi. This selection is connected to the goal of our thesis, which is to assess impacts of oil price shocks on countries heavily involved in automobile production, especially on Slovakia and the Czech Republic. Production of Audi Q7 is located in Bratislava's Volkswagen factory.[6] Concerning the BMW, this car producer plans to open a new factory

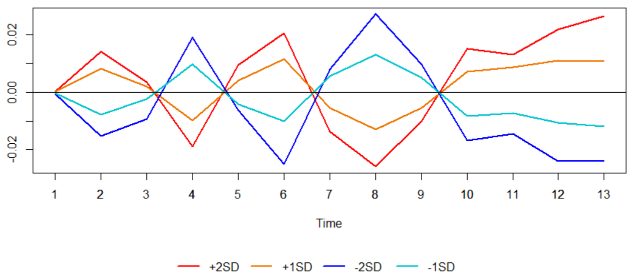
[6] According to `http://sk.volkswagen.sk/sk.html`.



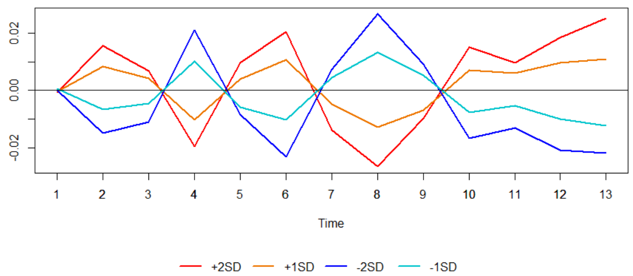
(a) Impulse from d_l_oil_sup for negative histories.



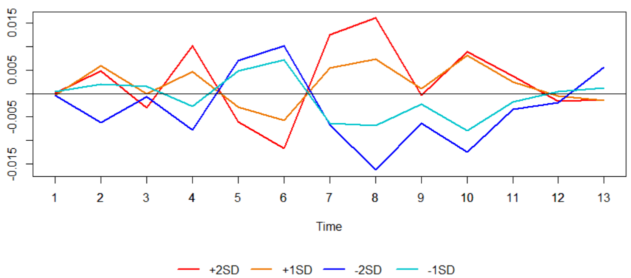
(b) Impulse from d_l_oil_sup for positive histories.



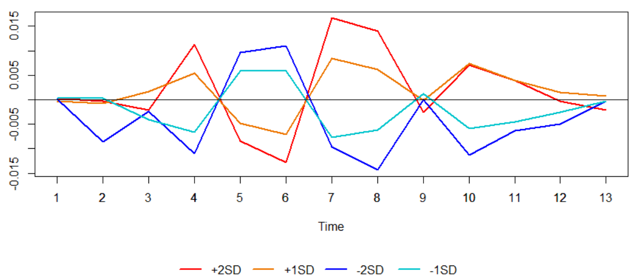
(c) Impulse from d_l_real_ea for negative histories.



(d) Impulse from d_l_real_ea for positive histories.



(e) Impulse from d_l_real_wti for negative histories.



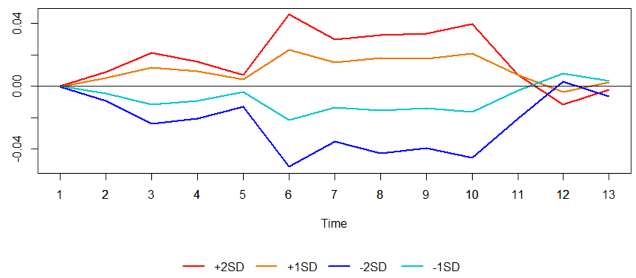
(f) Impulse from d_l_real_wti for positive histories.

Figure 5.9: Conditional impulse responses from TVAR for decreasing (negative histories, right column) and increasing (positive histories, left column) oil prices.

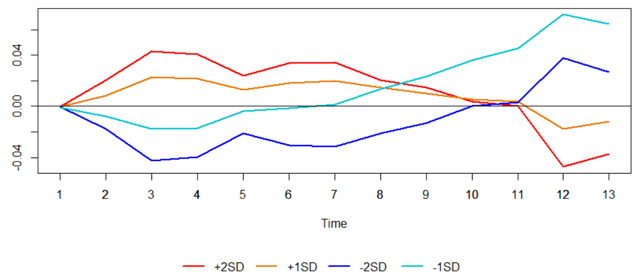
Source: author's computations.

in the Central Europe and potential candidates are exactly Slovakia and the Czech Republic.[7] The latter group includes stock returns of KIA (produced in Slovakia) and Hyundai (produced in the Czech Republic). For all these series we use exactly the same methodology as for the aggregate automobile stock returns, that is a threshold VAR(12) model from which unconditional impulse responses are computed with 200 repetitions for each history. The initial shocks again set to +2SD, +1SD, -2SD and -1SD. Results are summarized in Figures 5.10 and 5.11. In this case we use cumulative impulse responses in order to more easily resolve differences between the two groups. Comparing the results for oil supply shocks we can see that for the first 6 months are the responses for luxury car producers quite similar; positive oil supply shock causes increase in stock returns and vice versa. There is no similar patter between KIA and Hyundai stock returns; in this case responses of KIA stock returns much more resemble responses of stock returns of producers from the first group. In case of aggregate demand shocks is the situation almost opposite. Stock returns of both KIA and Hyundai react positively on positive aggregate demand shocks and negatively on negative demand shocks. For BMW and Audi stock returns are the responses much more volatile. The only common reaction takes place between the 4th and 6th month when stock returns of both firms react positively to positive aggregate demand shocks (opposite is true for negative aggregate demand shocks). However, if we notice vertical axis for these two shocks we can see that oil supply shocks and aggregate demand shocks have much greater influence on stock returns of the second group (with values reaching even $\pm 15\%$) than on the first group (maximum effects around $\pm 4\%$). Of utmost interest are the responses to oil-specific demand shocks (Figures 5.10(e), 5.10(f), 5.11(e) and 5.11(f)). First of all, they do not confirm our earlier conclusions about positive responses to positive precautionary demand shocks. Second, they do not even show specific patterns for each group; both for the stock returns of luxury car producers and car producers of less luxury cars respond stock returns negatively to positive precautionary demand shocks. Yet, from the plots we can see that in all four plots the responses are not "symmetric in sign".

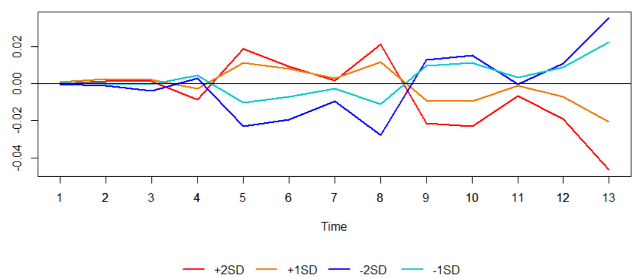
[7] Sources: http://de.auto.de/magazin/showArticle/article/102303/BMW-denkt-ueber-neues-Werk-nach, http://www.nachrichten.at/nachrichten/wirtschaft/BMW-will-Werk-in-Osteuropa-bauen-Slowakei-im-Rennen-um-Standort;art15,1087291#ref=rss, http://hnonline.sk/ekonomika/c1-59537540-slovensko-je-v-hre-o-zavod-bmw.



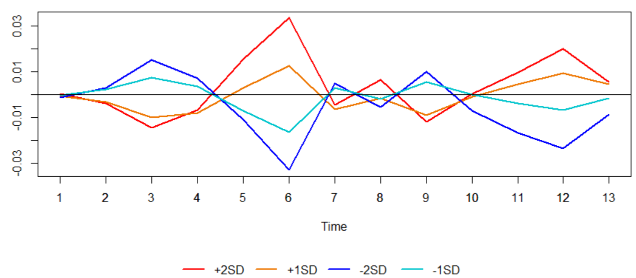
(a) Impulse response of BMW stock returns to oil supply shocks.



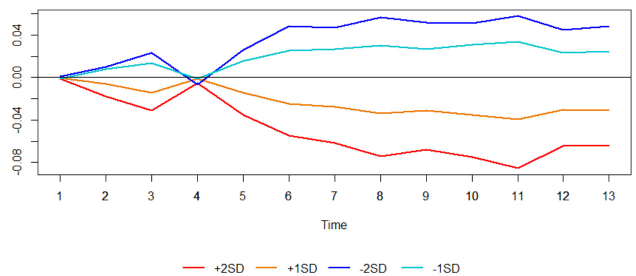
(b) Impulse response of Audi stock returns to oil supply shocks.



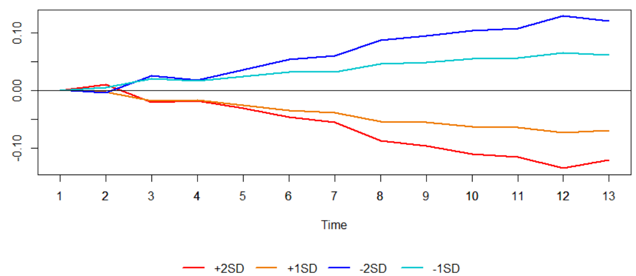
(c) Impulse response of BMW stock returns to aggregate demand shocks.



(d) Impulse response of Audi stock returns to aggregate demand shocks.



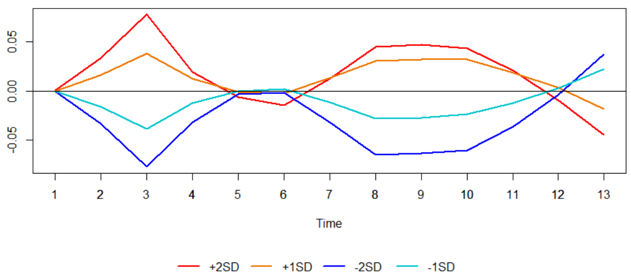
(e) Impulse response of BMW stock returns to oil-specific demand shocks.



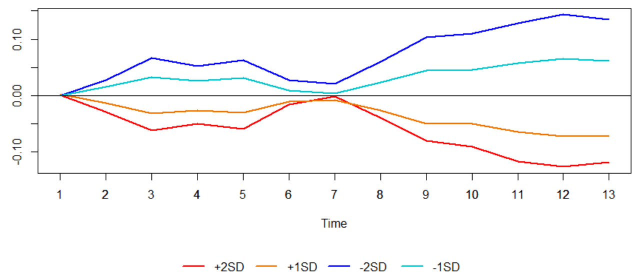
(f) Impulse response of Audi stock returns to oil-specific demand shocks.

Figure 5.10: Impulse responses of luxury cars producers.

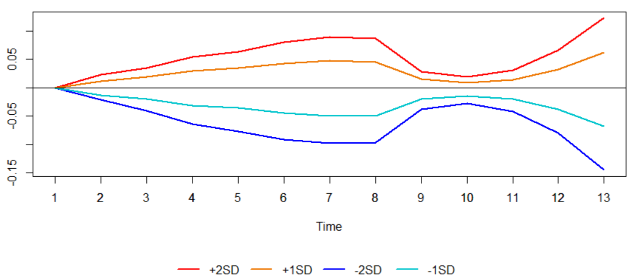
Source: author's computations.



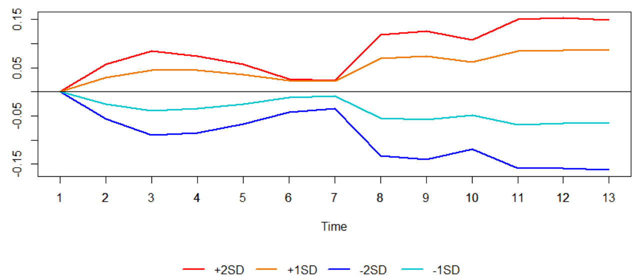
(a) Impulse responses of KIA stock returns to oil supply shocks.



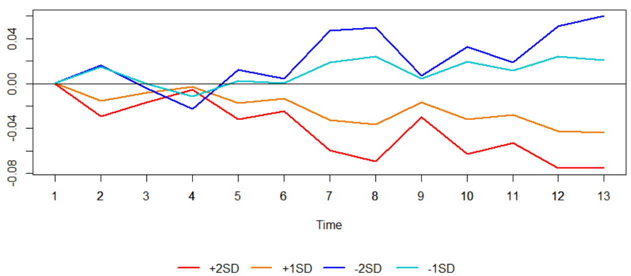
(b) Impulse responses of Hyundai stock returns to oil supply shocks.



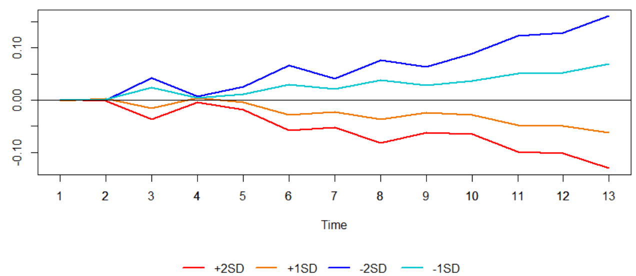
(c) Impulse responses of KIA stock returns to aggregate demand shocks.



(d) Impulse responses of Hyundai stock returns to aggregate demand shocks.



(e) Impulse responses of KIA stock returns to oil-specific demand shocks.



(f) Impulse responses of Hyundai stock returns to oil-specific demand shocks.

Figure 5.11: Impulse responses of producers of less luxury cars.
Source: author's computations.

Chapter 6

Possible extensions

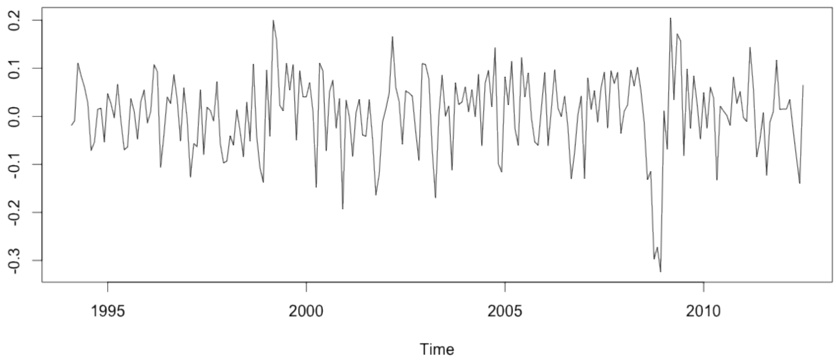
Given the nature of data we use in our analysis, probably the most interesting extension or correction applicable to our models is to incorporate non constant variance of our variables into the models. First inspiration for such an extension comes directly from plots of financial time series used in our models, that is real WTI price changes and real automobile stock returns, plotted in Figure 6.1. In these two graphs we can clearly see areas with clustered high volatility, for example in periods of crises (early 2000s or 2007 and subsequent years), as well as periods of clustered low volatility, for example around the year 2005.[1] Second inspiration is in residuals from our models, e.g. in case of residuals from the VAR(12) model in differences depicted in Figure 6.2, we can see that the volatility clustering problem is still present in these residuals. In other words, the residuals still include some information which we were unable to extract using our models. As it is known, this is caused by the fact that the VAR models work with innovations with variance constant in time.

The first option how to account for non constant volatility is to incorporate the volatility in form of a variable directly into a VAR model. Such approach is already used in the study Sadorsky (1999) as well as in Lee *et al.* (1995). It uses volatility of oil prices estimated using GARCH methodology. This volatility is then censored and only the positive values are then incorporated into the VAR model, which should analyze impact of volatility increases on macro variables of choice. However, the study Kilian & Vigfusson (2011b) concludes that there are several problems with censored models. Therefore, we would emphasize not to censor the estimated GARCH volatility, but to include it, uncensored, into a nonlinear (threshold) model and thus allow for nonlinear effects. The

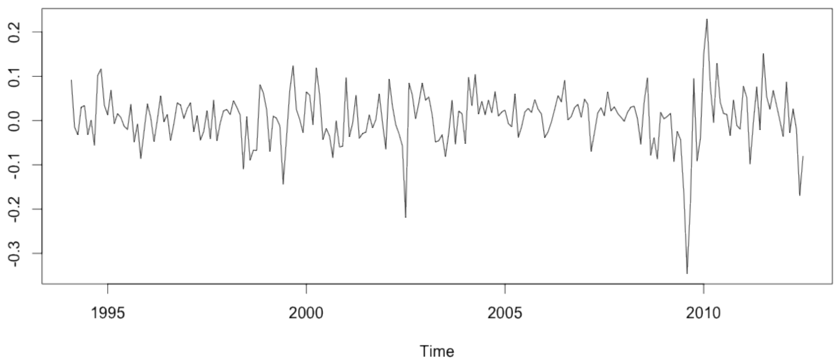
[1] Similar patterns of volatility clustering can be also seen on time series plots of individual car makers' stock returns in Chapter 4, Figure 4.8.

Figure 6.1: Real WTI price changes and real automobile stock returns.

(a) Real WTI price changes.



(b) Real automobile stock price changes.



Source: Reuters Wealth Manager, U.S. Energy Information Administration and author's computations.

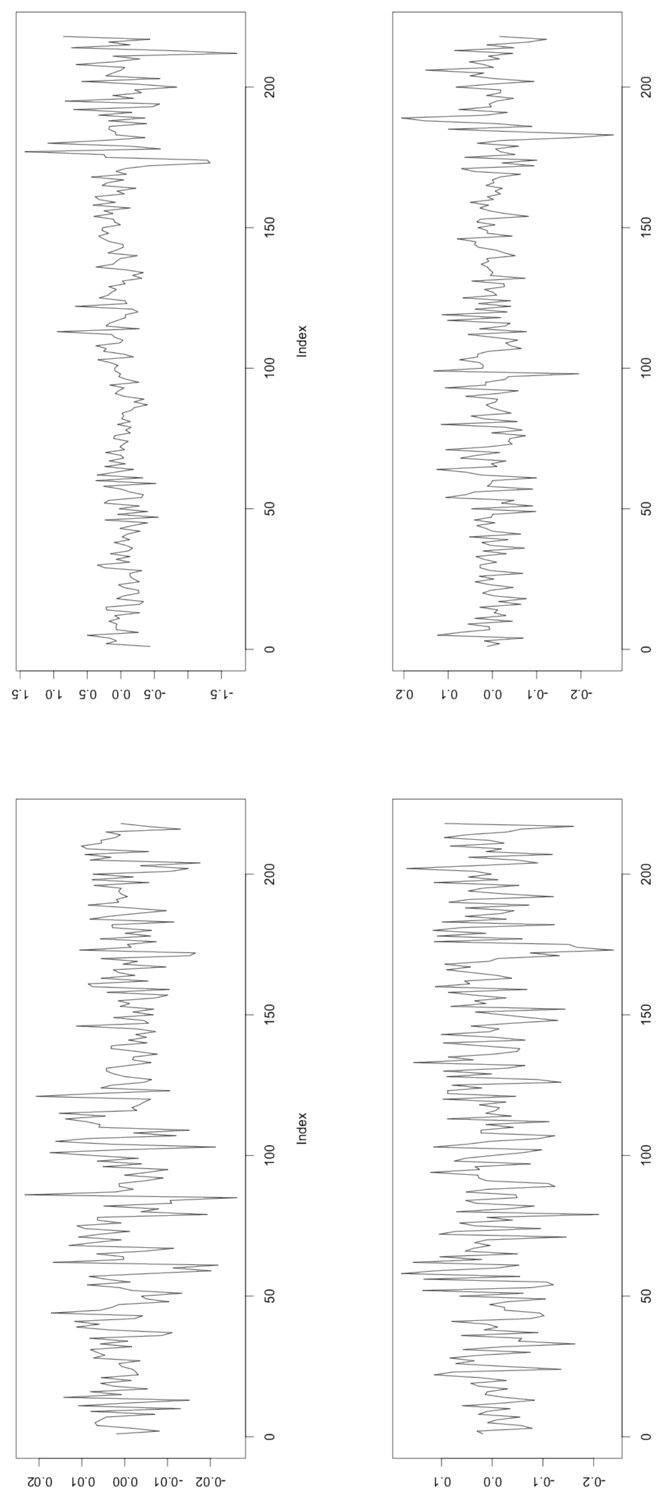


Figure 6.2: Residuals from the VAR(12) model.
Source: author's computations.

previous approach would allow us to study impact of oil price volatility shocks on automobile stock returns. We think that interesting can be also studying impact of classical oil price shocks on volatility of automobile stock returns. In a most simple way this can be done by estimating the volatility of automobile stock returns by an appropriate GARCH model and use it in a VAR model in place of automobile stock returns.

To model the non constant volatility preserved in residuals one should use a multivariate GARCH (MGARCH) model. To sketch this approach, suppose that $u_t = (u_{1t}, u_{2t}, u_{3t}, u_{4t})'$ are our residuals from a VAR model. Then we assume that they follow a process

$$u_t = \Sigma_{t|t-1}^{\frac{1}{2}} \varepsilon_t, \tag{6.1}$$

where $\varepsilon_t \sim (0, I_4)$ is independent and identically distributed white noise and $\Sigma_{t|t-1}^{\frac{1}{2}}$ is the conditional variance-covariance matrix of u_t. Then, according to Lütkepohl (2005), an MGARCH(p,q) model for u_t can be defined as follows

$$\mathrm{vech}(\Sigma_{t|t-1}^{\frac{1}{2}}) = \gamma_0 + \sum_{j=1}^{q} \Gamma_j \mathrm{vech}(u_{t-j}u'_{t-j}) + \sum_{j=1}^{m} G_m \mathrm{vech}(\Sigma_{t-j|t-j-1}^{\frac{1}{2}}), \tag{6.2}$$

where Γ_j and G_j are coefficient matrices and *vech* is half-vectorization operator.

Also another approach, not so closely related to the methodology we used in our thesis, would be to analyze the co-movement of oil prices and automobile stock prices using wavelet analysis. This method would include designing a wavelet and subsequently, using continuous wavelet transform, computing wavelet coherence. Similarly as it is done in the study Vacha & Barunik (2012) for crude oil prices, heating oil prices, gasoline prices and natural gas prices, such approach should reveal if and on which frequencies are the oil prices and automobile stock prices "correlated".

Chapter 7

Conclusion

In this master thesis we studied impact of oil price shocks on automobile stock prices and returns. We used decomposition of oil price shocks on oil supply shocks, aggregate demand shocks and oil-specific demand shocks and employing the vector autoregression methodology we computed impulse response functions, which acted as our main tool of inference. First, we used classical linear VAR approach, in which we used a VECM and a VAR in differences models. Both of these models confirmed findings of previous studied, that is that oil supply shocks are translated especially via oil-specific demand shocks into the macro variables. However, in our case the direction of impulse responses was totally different compared to other studies, as a positive oil-specific demand shock caused a significant increase in automobile stock prices and returns. We think that this is caused by strong co-movement of oil prices and automobile stock prices during the chosen period and especially during periods closely linked to the recent Financial Crisis. By these closely linked periods we have in mind the unhealthy growth period preceding the Crisis, the period of Crisis itself, and period of stagnation which followed the Crisis.

In the second part of the thesis we employed nonlinear (threshold) VAR model. Using impulse response functions computed from definition (because of nonexistence of Wold's decomposition for nonlinear VAR models) we searched for asymmetries in impulse response functions. Indeed, we found that especially responses to oil-specific demand shocks show signs of asymmetries in sign as well as in magnitude. Subsequently, we also analyzed impulse response functions of individual car producers. We used two criteria for selecting the car producers; first, we used stock returns of car producers with factories in Slovakia and the Czech Republic in order to show possible impacts on economies of these two countries in case of oil price shocks, second we selected two producers of relatively luxury cars and two producers of relatively less luxury cars in order to find some patterns characteristic for these two groups. The most interesting finding is that the individual car producers' stock returns do not respond positively to positive oil-specific demand shocks. Although, we found asymmetries also in responses of stock returns of individual car producers, the only indication of difference in responses of the two groups we found is in case of responses to aggregate demand shocks; for luxury car producers the responses to these shocks are much more erratic or volatile than it is for the responses of less luxury car producers.

In the last chapter we also outlined possible future extensions for our methodology as well as completely new methodology, which we think is very suitable for further analysis of co-movement of oil prices and automobile stock prices.

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Appendix A

Index of car manufacturers

Index of car manufacturers' stock prices is composed of stock of following car produders (in alphabetical order):

Audi
BMW
Daihatsu
Daimler
FIAT
Honda
Hyundai
Isuzu
KIA
Mazda
Mitsubishi
Nissan
Peugeot
Suzuki
Toyota
Volkswagen
Volvo
Yamaha

Appendix B

Estimated VEC model

	ECT	log(oil_sup) -1	real_ea -1	log(real_wti) -1
Equation log(oil_sup)	-0.0151(0.0082).	-0.0782(0.0704)	0.0001(0.0017)	-0.0106(0.0079)
Equation real_ea	-0.1490(0.3647)	1.5484(3.1180)	0.3987(0.0745)***	0.6768(0.3496).
Equation log(real_wti)	0.1273(0.0790)	0.5701(0.6758)	0.0458(0.0162)**	0.1928(0.0758)*
Equation log(real_auto)	-0.2688(0.0551)***	0.9495(0.4714)*	0.0046(0.0113)	-0.0452(0.0529)
	log(real_auto) -1	log(oil_sup) -2	real_ea -2	log(real_wti) -2
Equation log(oil_sup)	0.0041(0.0100)	-0.1448(0.0713)*	0.0048(0.0018)**	0.0097(0.0080)
Equation real_ea	0.3908(0.4419)	5.6473(3.1570).	-0.2865(0.0799)***	0.4286(0.3556)
Equation log(real_wti)	0.0608(0.0958)	-0.6624(0.6843)	-0.0089(0.0173)	0.0921(0.0771)
Equation log(real_auto)	0.2867(0.0668)***	-0.0166(0.4773)	0.0033(0.0121)	-0.0276(0.0538)
	log(real_auto) -2	log(oil_sup) -3	real_ea -3	log(real_wti) -3
Equation log(oil_sup)	0.0083(0.0104)	-0.0548(0.0710)	-0.0022(0.0019)	-0.0053(0.0080)
Equation real_ea	-0.3215(0.4607)	-0.2846(3.1410)	-0.0072(0.0841)	-0.8274(0.3524)*
Equation log(real_wti)	-0.1372(0.0999)	0.4699(0.6808)	0.0155(0.0182)	-0.0436(0.0764)
Equation log(real_auto)	-0.0142(0.0697)	0.5059(0.4749)	-0.0380(0.0127)**	-0.1515(0.0533)**
	log(real_auto) -3	log(oil_sup) -4	real_ea -4	log(real_wti) -4
Equation log(oil_sup)	-0.0115(0.0104)	0.0654(0.0712)	0.0047(0.0019)*	-0.0047(0.0081)
Equation real_ea	-0.5755(0.4586)	0.4099(3.1512)	-0.0823(0.0854)	-0.1875(0.3604)
Equation log(real_wti)	-0.0116(0.0994)	1.6259(0.6830)*	0.0351(0.0185).	0.0348(0.0781)
Equation log(real_auto)	0.1231(0.0693).	-0.0322(0.4764)	0.0181(0.0129)	-0.0127(0.0545)
	log(real_auto) -4	log(oil_sup) -5	real_ea -5	log(real_wti) -5
Equation log(oil_sup)	0.0040(0.0103)	0.0121(0.0702)	0.0006(0.0019)	0.0002(0.0080)
Equation real_ea	0.0526(0.4544)	-5.6003(3.1081).	0.0645(0.0859)	-0.0048(0.3548)
Equation log(real_wti)	-0.0145(0.0985)	-0.1686(0.6737)	-0.0292(0.0186)	0.0352(0.0769)
Equation log(real_auto)	0.1316(0.0687).	-0.5435(0.4699)	0.0013(0.0130)	-0.0656(0.0536)
	log(real_auto) -5	log(oil_sup) -6	real_ea -6	log(real_wti) -6
Equation log(oil_sup)	-0.0089(0.0103)	-0.0818(0.0705)	-0.0017(0.0019)	0.0115(0.0079)
Equation real_ea	0.2865(0.4556)	-4.5391(3.1193)	-0.0829(0.0823)	-0.4253(0.3505)
Equation log(real_wti)	0.1032(0.0987)	-0.0858(0.6761)	0.0096(0.0178)	-0.0791(0.0760)
Equation log(real_auto)	-0.0935(0.0689)	0.4284(0.4716)	-0.0336(0.0124)**	0.0095(0.0530)
	log(real_auto) -6			
Equation log(oil_sup)	0.0246(0.0100)*			
Equation real_ea	-0.4822(0.4406)			
Equation log(real_wti)	-0.0642(0.0955)			
Equation log(real_auto)	-0.0580(0.0666)			

Figure B.1: Estimated linear VEC model, output from R. Standard errors are in parentheses, parameter estimates marked by *, **, *** are significant on the 90%, 95% or 99% level of significance, respectively.

Appendix C

Estimated VAR in differences model

	Estimate	Std. Error	t value	Pr(>|t|)	
d_l_oil_sup.l1	-9.766e-02	7.103e-02	-1.375	0.1707	
real_ea_s.l1	4.122e-05	1.714e-03	0.024	0.9808	
d_l_real_wti.l1	-2.067e-03	7.526e-03	-0.275	0.7838	
d_l_real_auto.l1	-2.187e-03	9.863e-03	-0.222	0.8247	
d_l_oil_sup.l2	-1.482e-01	7.070e-02	-2.097	0.0373	*
real_ea_s.l2	3.290e-03	2.856e-03	1.152	0.2506	
d_l_real_wti.l2	1.251e-02	7.713e-03	1.622	0.1064	
d_l_real_auto.l2	5.635e-03	1.022e-02	0.552	0.5818	
d_l_oil_sup.l3	-3.494e-02	7.079e-02	-0.494	0.6222	
real_ea_s.l3	-4.284e-03	2.849e-03	-1.504	0.1343	
d_l_real_wti.l3	1.637e-03	7.628e-03	0.215	0.8303	
d_l_real_auto.l3	-9.875e-03	1.026e-02	-0.962	0.3371	
d_l_oil_sup.l4	8.135e-02	7.057e-02	1.153	0.2504	
real_ea_s.l4	1.203e-03	1.695e-03	0.710	0.4788	
d_l_real_wti.l4	5.037e-03	7.575e-03	0.665	0.5069	
d_l_real_auto.l4	-2.120e-03	9.955e-03	-0.213	0.8316	
const	1.076e-03	6.010e-04	1.790	0.0750	.

(a) Equation 1.

	Estimate	Std. Error	t value	Pr(>|t|)	
d_l_oil_sup.l1	-9.766e-02	7.103e-02	-1.375	0.1707	
real_ea_s.l1	4.122e-05	1.714e-03	0.024	0.9808	
d_l_real_wti.l1	-2.067e-03	7.526e-03	-0.275	0.7838	
d_l_real_auto.l1	-2.187e-03	9.863e-03	-0.222	0.8247	
d_l_oil_sup.l2	-1.482e-01	7.070e-02	-2.097	0.0373	*
real_ea_s.l2	3.290e-03	2.856e-03	1.152	0.2506	
d_l_real_wti.l2	1.251e-02	7.713e-03	1.622	0.1064	
d_l_real_auto.l2	5.635e-03	1.022e-02	0.552	0.5818	
d_l_oil_sup.l3	-3.494e-02	7.079e-02	-0.494	0.6222	
real_ea_s.l3	-4.284e-03	2.849e-03	-1.504	0.1343	
d_l_real_wti.l3	1.637e-03	7.628e-03	0.215	0.8303	
d_l_real_auto.l3	-9.875e-03	1.026e-02	-0.962	0.3371	
d_l_oil_sup.l4	8.135e-02	7.057e-02	1.153	0.2504	
real_ea_s.l4	1.203e-03	1.695e-03	0.710	0.4788	
d_l_real_wti.l4	5.037e-03	7.575e-03	0.665	0.5069	
d_l_real_auto.l4	-2.120e-03	9.955e-03	-0.213	0.8316	
const	1.076e-03	6.010e-04	1.790	0.0750	.

(b) Equation 2.

	Estimate	Std. Error	t value	Pr(>|t|)	
d_l_oil_sup.l1	-9.766e-02	7.103e-02	-1.375	0.1707	
real_ea_s.l1	4.122e-05	1.714e-03	0.024	0.9808	
d_l_real_wti.l1	-2.067e-03	7.526e-03	-0.275	0.7838	
d_l_real_auto.l1	-2.187e-03	9.863e-03	-0.222	0.8247	
d_l_oil_sup.l2	-1.482e-01	7.070e-02	-2.097	0.0373	*
real_ea_s.l2	3.290e-03	2.856e-03	1.152	0.2506	
d_l_real_wti.l2	1.251e-02	7.713e-03	1.622	0.1064	
d_l_real_auto.l2	5.635e-03	1.022e-02	0.552	0.5818	
d_l_oil_sup.l3	-3.494e-02	7.079e-02	-0.494	0.6222	
real_ea_s.l3	-4.284e-03	2.849e-03	-1.504	0.1343	
d_l_real_wti.l3	1.637e-03	7.628e-03	0.215	0.8303	
d_l_real_auto.l3	-9.875e-03	1.026e-02	-0.962	0.3371	
d_l_oil_sup.l4	8.135e-02	7.057e-02	1.153	0.2504	
real_ea_s.l4	1.203e-03	1.695e-03	0.710	0.4788	
d_l_real_wti.l4	5.037e-03	7.575e-03	0.665	0.5069	
d_l_real_auto.l4	-2.120e-03	9.955e-03	-0.213	0.8316	
const	1.076e-03	6.010e-04	1.790	0.0750	.

(c) Equation 3.

	Estimate	Std. Error	t value	Pr(>|t|)	
d_l_oil_sup.l1	-9.766e-02	7.103e-02	-1.375	0.1707	
real_ea_s.l1	4.122e-05	1.714e-03	0.024	0.9808	
d_l_real_wti.l1	-2.067e-03	7.526e-03	-0.275	0.7838	
d_l_real_auto.l1	-2.187e-03	9.863e-03	-0.222	0.8247	
d_l_oil_sup.l2	-1.482e-01	7.070e-02	-2.097	0.0373	*
real_ea_s.l2	3.290e-03	2.856e-03	1.152	0.2506	
d_l_real_wti.l2	1.251e-02	7.713e-03	1.622	0.1064	
d_l_real_auto.l2	5.635e-03	1.022e-02	0.552	0.5818	
d_l_oil_sup.l3	-3.494e-02	7.079e-02	-0.494	0.6222	
real_ea_s.l3	-4.284e-03	2.849e-03	-1.504	0.1343	
d_l_real_wti.l3	1.637e-03	7.628e-03	0.215	0.8303	
d_l_real_auto.l3	-9.875e-03	1.026e-02	-0.962	0.3371	
d_l_oil_sup.l4	8.135e-02	7.057e-02	1.153	0.2504	
real_ea_s.l4	1.203e-03	1.695e-03	0.710	0.4788	
d_l_real_wti.l4	5.037e-03	7.575e-03	0.665	0.5069	
d_l_real_auto.l4	-2.120e-03	9.955e-03	-0.213	0.8316	
const	1.076e-03	6.010e-04	1.790	0.0750	.

(d) Equation 4.

Figure C.1: Estimated linear VAR in differences model, output from R. Standard errors are in parentheses, parameter estimates marked by *, **, *** are significant on the 90%, 95% or 99% level of significance, respectively.

Appendix D

Estimated TVAR model

	Intercept	d_l_oil_sup -1	real_ea_s -1	d_l_real_wti -1	d_l_real_auto -1
Equation d_l_oil_sup	0.0029(0.0023)	-0.1444(0.1429)	-0.0043(0.0052)	0.0223(0.0273)	0.0147(0.0276)
Equation real_ea_s	-0.0071(0.0865)	4.2716(5.2795)	1.6796(0.1924)***	0.3447(1.0103)	-1.2475(1.0197)
Equation d_l_real_wti	0.0108(0.0206)	2.2313(1.2551).	0.1570(0.0457)***	0.2650(0.2402)	-0.1367(0.2424)
Equation d_l_real_auto	0.0103(0.0151)	0.6116(0.9243)	0.0651(0.0337).	0.0984(0.1769)	0.0230(0.1785)
	d_l_oil_sup -2	real_ea_s -2	d_l_real_wti -2	d_l_real_auto -2	d_l_oil_sup -3
Equation d_l_oil_sup	-0.3724(0.1796)*	0.0082(0.0105)	0.0202(0.0187)	0.0083(0.0274)	-0.0885(0.1701)
Equation real_ea_s	10.9172(6.6356)	-1.1447(0.3874)**	0.6287(0.6899)	-0.7774(1.0143)	-2.1732(6.2844)
Equation d_l_real_wti	-4.0279(1.5775)*	-0.2189(0.0921)*	-0.1247(0.1640)	-0.1853(0.2411)	-0.4328(1.4940)
Equation d_l_real_auto	0.8657(1.1617)	-0.0705(0.0678)	-0.2257(0.1208).	-0.0117(0.1776)	-0.0179(1.1002)
	real_ea_s -3	d_l_real_wti -3	d_l_real_auto -3	d_l_oil_sup -4	real_ea_s -4
Equation d_l_oil_sup	-0.0054(0.0094)	0.0156(0.0189)	0.0072(0.0251)	-0.0311(0.1574)	0.0059(0.0090)
Equation real_ea_s	0.3611(0.3480)	-0.0670(0.6994)	0.1403(0.9280)	-6.5794(5.8158)	0.2451(0.3317)
Equation d_l_real_wti	0.0060(0.0827)	0.0583(0.1663)	0.0155(0.2206)	3.6516(1.3826)**	0.2082(0.0788)**
Equation d_l_real_auto	-0.0412(0.0609)	0.1901(0.1224)	-0.0383(0.1625)	0.8446(1.0182)	0.1217(0.0581)*
	d_l_real_wti -4	d_l_real_auto -4	d_l_oil_sup -5	real_ea_s -5	d_l_real_wti -5
Equation d_l_oil_sup	-0.0247(0.0188)	-0.0102(0.0232)	0.0735(0.1690)	-0.0048(0.0093)	-0.0082(0.0207)
Equation real_ea_s	-0.3367(0.6933)	0.7611(0.8569)	-3.2160(6.2449)	-0.2440(0.3421)	0.5402(0.7661)
Equation d_l_real_wti	0.0188(0.1648)	0.1755(0.2037)	0.0031(1.4846)	-0.2515(0.0813)**	-0.0695(0.1821)
Equation d_l_real_auto	-0.1634(0.1214)	-0.0248(0.1500)	0.8435(1.0933)	-0.0325(0.0599)	-0.1936(0.1341)
	d_l_real_auto -5	d_l_oil_sup -6	real_ea_s -6	d_l_real_wti -6	d_l_real_auto -6
Equation d_l_oil_sup	0.0073(0.0267)	-0.0451(0.1538)	-0.0006(0.0086)	0.0216(0.0199)	0.0019(0.0269)
Equation real_ea_s	1.8283(0.9867).	-5.8892(5.6845)	0.2113(0.3169)	-0.1513(0.7347)	-0.8937(0.9934)
Equation d_l_real_wti	-0.3179(0.2346)	0.5296(1.3514)	0.2111(0.0753)**	-0.4544(0.1747)*	-0.5117(0.2362)*
Equation d_l_real_auto	-0.5619(0.1727)**	-0.8689(0.9952)	-0.1013(0.0555).	0.0051(0.1286)	-0.1196(0.1739)
	d_l_oil_sup -7	real_ea_s -7	d_l_real_wti -7	d_l_real_auto -7	d_l_oil_sup -8
Equation d_l_oil_sup	0.0737(0.1530)	-0.0016(0.0077)	-0.0283(0.0186)	-0.0129(0.0255)	-0.1252(0.1555)
Equation real_ea_s	4.2030(5.6531)	-0.1208(0.2841)	0.2744(0.6886)	-1.6717(0.9414).	0.3831(5.7475)
Equation d_l_real_wti	4.1468(1.3440)**	-0.0440(0.0676)	-0.4850(0.1637)**	-0.7517(0.2238)**	-1.2472(1.3664)
Equation d_l_real_auto	1.1212(0.9897)	0.0100(0.0497)	0.1058(0.1206)	-0.1770(0.1648)	0.8827(1.0062)
	real_ea_s -8	d_l_real_wti -8	d_l_real_auto -8	d_l_oil_sup -9	real_ea_s -9
Equation d_l_oil_sup	0.0086(0.0087)	-0.0090(0.0187)	0.0161(0.0278)	0.0353(0.2040)	-0.0152(0.0105)
Equation real_ea_s	-0.1887(0.3201)	0.2469(0.6912)	0.8138(1.0265)	-2.1772(7.5394)	0.1999(0.3881)
Equation d_l_real_wti	-0.0694(0.0761)	-0.1010(0.1643)	0.6581(0.2440)**	-2.9120(1.7924)	0.0221(0.0923)
Equation d_l_real_auto	0.0435(0.0560)	0.1281(0.1210)	0.1079(0.1797)	-0.6091(1.3199)	0.0550(0.0680)
	d_l_real_wti -9	d_l_real_auto -9	d_l_oil_sup -10	real_ea_s -10	d_l_real_wti -10
Equation d_l_oil_sup	0.0052(0.0196)	0.0262(0.0244)	0.0166(0.1640)	0.0155(0.0107)	0.0084(0.0183)
Equation real_ea_s	-0.0015(0.7238)	0.3874(0.9018)	-4.7849(6.0592)	0.2301(0.3959)	0.6973(0.6764)
Equation d_l_real_wti	-0.1859(0.1721)	0.0564(0.2144)	-0.1566(1.4405)	0.0222(0.0941)	0.0112(0.1608)
Equation d_l_real_auto	-0.0707(0.1267)	-0.0862(0.1579)	1.7595(1.0608).	-0.0552(0.0693)	-0.0434(0.1184)
	d_l_real_auto -10	d_l_oil_sup -11	real_ea_s -11	d_l_real_wti -11	d_l_real_auto -11
Equation d_l_oil_sup	-0.0215(0.0206)	-0.0126(0.1774)	-0.0088(0.0074)	-0.0468(0.0186)*	0.0357(0.0243)
Equation real_ea_s	1.8759(0.7617)*	-9.7445(6.5553)	-0.1556(0.2752)	-1.1604(0.6855).	-0.2416(0.8983)
Equation d_l_real_wti	0.2260(0.1811)	-1.0667(1.5584)	-0.0513(0.0654)	0.2415(0.1630)	-0.0159(0.2136)
Equation d_l_real_auto	-0.1082(0.1333)	0.8095(1.1476)	0.0360(0.0482)	-0.0829(0.1200)	-0.3088(0.1573).
	d_l_oil_sup -12	real_ea_s -12	d_l_real_wti -12	d_l_real_auto -12	
Equation d_l_oil_sup	0.2964(0.1451)*	0.0019(0.0040)	0.0058(0.0161)	-0.0594(0.0291)*	
Equation real_ea_s	-7.1262(5.3603)	-0.1686(0.1469)	-0.9658(0.5944)	0.3146(1.0772)	
Equation d_l_real_wti	0.7566(1.2743)	0.0198(0.0349)	-0.1580(0.1413)	0.3567(0.2561)	
Equation d_l_real_auto	-0.0205(0.9384)	-0.0062(0.0257)	-0.0810(0.1041)	-0.0288(0.1886)	

Figure D.1: Estimated low regime coefficients of TVAR model for aggregate automobile stock prices, output from R. Standard errors are in parentheses, parameter estimates marked by *, **, *** are significant on the 90%, 95% or 99% level of significance, respectively.

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                       Intercept        d_l_oil_sup -1   real_ea_s -1       d_l_real_wti -1 d_l_real_auto -1
Equation d_l_oil_sup   0.0029(0.0023)   -0.1444(0.1429)  -0.0043(0.0052)    0.0223(0.0273)  0.0147(0.0276)
Equation real_ea_s     -0.0071(0.0865)  4.2716(5.2795)   1.6796(0.1924)***  0.3447(1.0103)  -1.2475(1.0197)
Equation d_l_real_wti  0.0108(0.0206)   2.2313(1.2551).  0.1570(0.0457)***  0.2650(0.2402)  -0.1367(0.2424)
Equation d_l_real_auto 0.0103(0.0151)   0.6116(0.9243)   0.0651(0.0337).    0.0984(0.1769)  0.0230(0.1785)
                       d_l_oil_sup -2   real_ea_s -2      d_l_real_wti -2   d_l_real_auto -2 d_l_oil_sup -3
Equation d_l_oil_sup   -0.3724(0.1796)* 0.0082(0.0105)    0.0202(0.0187)    0.0083(0.0274)   -0.0885(0.1701)
Equation real_ea_s     10.9172(6.6356)  -1.1447(0.3874)** 0.6287(0.6899)    -0.7774(1.0143)  -2.1732(6.2844)
Equation d_l_real_wti  -4.0279(1.5775)* -0.2189(0.0921)*  -0.1247(0.1640)   -0.1853(0.2411)  -0.4328(1.4940)
Equation d_l_real_auto 0.8657(1.1617)   -0.0705(0.0678)   -0.2257(0.1208).  -0.0117(0.1776)  -0.0179(1.1002)
                       real_ea_s -3     d_l_real_wti -3  d_l_real_auto -3 d_l_oil_sup -4     real_ea_s -4
Equation d_l_oil_sup   -0.0054(0.0094)  0.0156(0.0189)   0.0072(0.0251)   -0.0311(0.1574)    0.0059(0.0090)
Equation real_ea_s     0.3611(0.3480)   -0.0670(0.6994)  0.1403(0.9280)   -6.5794(5.8158)    0.2451(0.3317)
Equation d_l_real_wti  0.0060(0.0827)   0.0583(0.1663)   0.0155(0.2206)   3.6516(1.3826)**   0.2082(0.0788)**
Equation d_l_real_auto -0.0412(0.0609)  0.1901(0.1224)   -0.0383(0.1625)  0.8446(1.0182)     0.1217(0.0581)*
                       d_l_real_wti -4  d_l_real_auto -4 d_l_oil_sup -5   real_ea_s -5        d_l_real_wti -5
Equation d_l_oil_sup   -0.0247(0.0188)  -0.0102(0.0232)  0.0735(0.1690)   -0.0048(0.0093)     -0.0082(0.0207)
Equation real_ea_s     -0.3367(0.6933)  0.7611(0.8569)   -3.2160(6.2449)  -0.2440(0.3421)     0.5402(0.7661)
Equation d_l_real_wti  0.0188(0.1648)   0.1755(0.2037)   0.0031(1.4846)   -0.2515(0.0813)**   -0.0695(0.1821)
Equation d_l_real_auto -0.1634(0.1214)  -0.0248(0.1500)  0.8435(1.0933)   -0.0325(0.0599)     -0.1936(0.1341)
                       d_l_real_auto -5  d_l_oil_sup -6   real_ea_s -6       d_l_real_wti -6  d_l_real_auto -6
Equation d_l_oil_sup   0.0073(0.0267)     -0.0451(0.1538)  -0.0006(0.0086)   0.0216(0.0199)   0.0019(0.0269)
Equation real_ea_s     1.8283(0.9867).    -5.8892(5.6845)  0.2113(0.3169)    -0.1513(0.7347)  -0.8937(0.9934)
Equation d_l_real_wti  -0.3179(0.2346)    0.5296(1.3514)   0.2111(0.0753)**  -0.4544(0.1747)* -0.5117(0.2362)*
Equation d_l_real_auto -0.5619(0.1727)** -0.8689(0.9952)   -0.1013(0.0555).  0.0051(0.1286)   -0.1196(0.1739)
                       d_l_oil_sup -7   real_ea_s -7     d_l_real_wti -7    d_l_real_auto -7   d_l_oil_sup -8
Equation d_l_oil_sup   0.0737(0.1530)   -0.0016(0.0077)  -0.0283(0.0186)    -0.0129(0.0255)    -0.1252(0.1555)
Equation real_ea_s     4.2030(5.6531)   -0.1208(0.2841)  0.2744(0.6886)     -1.6717(0.9414).   0.3831(5.7475)
Equation d_l_real_wti  4.1468(1.3440)** -0.0440(0.0676)  -0.4850(0.1637)**  -0.7517(0.2238)**  -1.2472(1.3664)
Equation d_l_real_auto 1.1212(0.9897)   0.0100(0.0497)   0.1058(0.1206)     -0.1770(0.1648)    0.8827(1.0062)
                       real_ea_s -8     d_l_real_wti -8  d_l_real_auto -8   d_l_oil_sup -9   real_ea_s -9
Equation d_l_oil_sup   0.0086(0.0087)   -0.0090(0.0187)  0.0161(0.0278)     0.0353(0.2040)   -0.0152(0.0105)
Equation real_ea_s     -0.1887(0.3201)  0.2469(0.6912)   0.8138(1.0265)     -2.1772(7.5394)  0.1999(0.3881)
Equation d_l_real_wti  -0.0694(0.0761)  -0.1010(0.1643)  0.6581(0.2440)**   -2.9120(1.7924)  0.0221(0.0923)
Equation d_l_real_auto 0.0435(0.0560)   0.1281(0.1210)   0.1079(0.1797)     -0.6091(1.3199)  0.0550(0.0680)
                       d_l_real_wti -9  d_l_real_auto -9 d_l_oil_sup -10    real_ea_s -10    d_l_real_wti -10
Equation d_l_oil_sup   0.0052(0.0196)   0.0262(0.0244)   0.0166(0.1640)     0.0155(0.0107)   0.0084(0.0183)
Equation real_ea_s     -0.0015(0.7238)  0.3874(0.9018)   -4.7849(6.0592)    0.2301(0.3959)   0.6973(0.6764)
Equation d_l_real_wti  -0.1859(0.1721)  0.0564(0.2144)   -0.1566(1.4405)    0.0222(0.0941)   0.0112(0.1608)
Equation d_l_real_auto -0.0707(0.1267)  -0.0862(0.1579) 1.7595(1.0608).     -0.0552(0.0693)  -0.0434(0.1184)
                       d_l_real_auto -10 d_l_oil_sup -11  real_ea_s -11     d_l_real_wti -11  d_l_real_auto -11
Equation d_l_oil_sup   -0.0215(0.0206)    -0.0126(0.1774)  -0.0088(0.0074)  -0.0468(0.0186)*  0.0357(0.0243)
Equation real_ea_s     1.8759(0.7617)*    -9.7445(6.5553)  -0.1556(0.2752)  -1.1604(0.6855).  -0.2416(0.8983)
Equation d_l_real_wti  0.2260(0.1811)     -1.0667(1.5584)  -0.0513(0.0654)  0.2415(0.1630)    -0.0159(0.2136)
Equation d_l_real_auto -0.1082(0.1333)    0.8095(1.1476)   0.0360(0.0482)   -0.0829(0.1200)   -0.3088(0.1573).
                       d_l_oil_sup -12  real_ea_s -12    d_l_real_wti -12 d_l_real_auto -12
Equation d_l_oil_sup   0.2964(0.1451)*  0.0019(0.0040)   0.0058(0.0161)   -0.0594(0.0291)*
Equation real_ea_s     -7.1262(5.3603)  -0.1686(0.1469)  -0.9658(0.5944)  0.3146(1.0772)
Equation d_l_real_wti  0.7566(1.2743)   0.0198(0.0349)   -0.1580(0.1413)  0.3567(0.2561)
Equation d_l_real_auto -0.0205(0.9384)  -0.0062(0.0257)  -0.0810(0.1041)  -0.0288(0.1886)
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Figure D.2: Estimated high regime coefficients of TVAR model for aggregate automobile stock prices, output from R. Standard errors are in parentheses, parameter estimates marked by *, **, *** are significant on the 90%, 95% or 99% level of significance, respectively.