Determining oil price drivers with Dynamic Model Averaging

by

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Abstract

Modelling spot oil price is a hard but important task. Various researches has previously shown that oil price drivers can vary in time. In other words, it is hard to find one oil price model which would perform well in every period. On the other hand, usually the best performing model changes in time. From the econometric point of view such a situation requires building a model with two features. First, there is an uncertainty about the "true" model. Therefore, supposing there is initially given some set of models, the "true" model should be allowed to change with time. Secondly, suppose that the methodology is narrowed just to regression models arising from some set of initially given explanatory variables (drivers). Then, also the regression coefficients of these models should be allowed to vary in time. Such a construction is already known. It is Dynamic Model Averaging (DMA). This methodology arose as a certain extension and improvement of Bayesian Model Averaging (BMA). Indeed, this method comes from the Bayesian econometrics. As the initial set of oil price drivers the following factors have been chosen: stock market index, interest rates, economic activity index, exchange rates, supply and demand, import quotas, inventories level, and stress market index. The paper is organized as follows: First a brief overview about the oil price drivers is given. Next, a brief description of Dynamic Model Averaging is provided. Finally, the results are presented and conclusions are formulated.

1 Introduction: Oil Price Drivers

The literature review provides various oil price drivers. However, the most common are supply and demand quotas. Indeed, these factors are usually perceived as playing the fundamental role for oil market. Nevertheless, a few interesting observations should be formulated.

First of all, since 1980s it has been questioned whether supply and demand (e.g. OPEC quotas decisions) are the only important oil price drivers. For example, just recently, during the oil price surge of 2007/2008 "Master Hypothesis" was formulated. According to it, the index investments were the major spot oil price driver (Irwin and Sanders, 2012).

Secondly, many studies showed that in different time period, different factors can play the most important role as an oil price driver. Moreover, researchers found that time-varying parameters models usually describe markets better than fixed parameters models. In particular, this observations perfectly applies to oil market (Aastveit and Bjornland, 2015; Stefanski, 2014; Ji, 2012).

At least, it is interesting that there is no commonly accepted "oil price model". In other words, the oil market is very often found to be very complex and persistent to modelling. As a result, various

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organizations use different mathematical models (Yang et al., 2002). However, still the most common one is just to focus on futures contracts. But, unfortunately, such forecasts are quite poor (Alquist and Kilian, 2010).

Various factors can be found in literature as important spot oil price drivers. For example, long time ago a hypothesis was formulated by Hotelling, according to which the price of a non-renewable commodity should depend on the interest rate. Recent evidences support this statement (Arora and Tanner, 2013). Moreover, economic activity can impact oil price. This measure is actually hard to quantify, because the common index (i.e., GDP) is provided in quarterly frequency, which would significantly impact the analysis. On the other hand, a suitable proxy of global economic activity has been proposed by Kilian (Kilian, 2009; He et al., 2010). Many studies focused also on the relationship between oil markets and financial markets. Indeed, stock markets indices, volatility of stocks and exchange rates have been found as important oil price drivers, at least in certain time period (Du and He, 2015; Aloui et al., 2013; Basher et al., 2012; Li and Leung, 2011; Bernabe et al., 2004). Finally, within the context of the mentioned "Masters Hypothesis" speculative pressures are usually measured by oil inventories (Hamilton, 2009). The more thorough review can be found, for example, in a paper by Drachal (2016).

It should also be mentioned that for certain drivers usually it is hard to collect the global data. In such cases just U.S. data can be taken as satisfactory proxies (Kilian and Murphy, 2014).

Herein, the aim is to estimate a model for spot oil price, which would capture two important features. First, the strength of the relationship between oil price and its driver should be able to vary in time. Secondly, the model should capture the uncertainty about the inclusion of a driver in the model. This will be done within Dynamic Model Averaging framework (Raftery et al, 2010).

2 Data

According to the presented arguments 10 potential oil price drivers were selected (see Table 1). Strategic Petroleum Reserves were excluded from the level of inventories (Bu, 2014). Monthly data beginning on Jan, 1990 and ending on Dec, 2016 were taken, resulting in 324 observations for each time-series. The time period of the analysis was chosen according to data availability.

This research is similar to the one presented by Drachal (2016). However, certain modifications were applied. First of all, instead of widely used Killian index as an indicator of global economic activity, the world crude steel production was taken. Indeed, recently Ravazzolo and Vespignani (2015) provided arguments that world steel production is the best monthly indicator of global economic activity in term of selected econometric properties. The data about steel production were obtained from World Steel Association. This included data from countries which accounted for approximately at least 98% of total world crude steel production in the analyzed period.

Secondly, in previous paper by Drachal (2016) Chinese economy was taken as an indicator of emerging markets. Herein, directly EM MSCI index is taken.

All time-series were obtained directly in monthly frequency except IMP. In particular, average monthly value was taken for IMP with a help of Ryan and Ulrich (2014) xts R package. It should be noticed that VXO was chosen, because VIX was not computed before 2003. It values were taken as the month-end closing.

Of course, drivers should be lagged one period back. In other words, data from periods including *t-1* and before should be included to forecast oil price at time *t*.

Table 1: Description of variables used in models

variable	description
WTI	WTI spot price in USD per barrel
MSCI	MSCI World Index
EM	EM (Emerging Markets) MSCI Index
TB3MS	U.S. 3-month treasury bill secondary market rate in %
CSP	Crude steel production in thousand tonnes
TWEXM	Trade weighted U.S. dollar index (Mar, 1973 = 100)
PROD	U.S. product supplied for crude oil and petroleum products in thousands of barrels
CONS	Total consumption of petroleum products in OECD in quad BTU
IMP	Average U.S. imports of crude oil in thousands of barrels per day
INV	U.S. total stocks of crude oil and petroleum products in thousands of barrels
VXO	Implied volatility of S&P 100

Most time-series were log-differenced. Only TB3MS and VXO (i.e., rates) were taken in ordinary differences. This is in agreement with standard methodology and also for Dynamic Model Averaging such transformations were applied, for example, by Baur et al. (2014). As a result, assuming 5% significance level all considered time-series are stationary, according to augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests (see Table 2).

Table 2: Stationarity tests

	ADF statistic	ADF p-value	PP statistic	PP p-value	KPSS statistic	KPSS p-value
WTI	-7.7723	0.0100	-210.7704	0.0100	0.0643	0.1000
MSCI	-6.5991	0.0100	-300.5006	0.0100	0.0546	0.1000
EM	-6.7452	0.0100	-271.9554	0.0100	0.0649	0.1000
TB3MS	-3.8651	0.0161	-189.7133	0.0100	0.1294	0.1000
CSP	-6.4724	0.0100	-458.5101	0.0100	0.0792	0.1000
TWEXM	-7.6516	0.0100	-200.0467	0.0100	0.1304	0.1000
PROD	-7.6770	0.0100	-452.8701	0.0100	0.5389	0.0329
CONS	-9.3762	0.0100	-467.6868	0.0100	0.0389	0.1000
INV	-10.0362	0.0100	-225.0797	0.0100	0.1485	0.1000
IMP	-10.085	0.0100	-378.8406	0.0100	0.1067	0.1000
VXO	-9.2804	0.0100	-277.4125	0.0100	0.0208	0.1000

Finally, the time-series were normalized, i.e., rescaled to fit between 0 and 1. The purpose of such a transformation is explained in the Methodology section.
All calculations were done in R (2015) software.

3 Methodology

For the detailed description of Dynamic Model Averaging (DMA) the Reader should consult the original paper by Raftery et al. (2010). Herein, just a brief, technical description is given.

Let there be m determinants. Then, $K = 2^m$ different regression models can be constructed (including the one with constant solely). Let t denote the time index, and let y_t denote the dependent variable (herein, WTI). Let $x^{(k)}_t$ denote drivers (independent variables) in the k-th model ($k = \{1,...,K\}$). Finally, the state space model is given by the following equations:

$$y_t = x_t^{(k)}\theta_t^{(k)} + \varepsilon_t^{(k)}, \tag{1}$$

$$\theta_t^{(k)} = \theta_{t-1}^{(k)} + \delta_t^{(k)}, \tag{2}$$

where $k = \{1, ..., K\}$ and $\theta_t^{(k)}$ denotes regression parameters of the k-th model. It is assumed that errors are normally distributed, i.e., $\varepsilon_t^{(k)} \sim N(0,V_t^{(k)})$ and $\delta_t^{(k)} \sim N(0,W_t^{(k)})$. Starting at $t = 0$ the initial values have to be assigned to variance matrices $V_0^{(k)}$ and $W_0^{(k)}$. Further, inference of $V_t^{(k)}$ is estimated by a recursive method of moments estimator. This needs a certain forgetting factor $\lambda \in (0,1]$ to be specified (Raftery et al., 2010; Dedecius et al., 2012). The inference of $W_t^{(k)}$ is estimated by recursive use of the Kalman filter updating. In this paper, $W_0^{(k)}$ has been estimated following the procedure basing on the whole data sample given by Raftery et al. (2010). It is also necessary to set the initial value for $V_0^{(k)}$. However, if data are normalized, then it is reasonable to set $V_0^{(k)}$ to be the unit matrix.

In particular, let the variable Y_t be scaled. Then, the normalization is done with the formula

$$y_t = \left(Y_t - \min_{i=0,...,t,...} Y_i \right) \Big/ \left(\max_{i=0,...,t,...} Y_i - \min_{i=0,...,t,...} Y_i \right). \tag{3}$$

Now, an non-informative prior is defined for all models in the initial period $t = 0$, i.e.,

$$\pi_{0|0,k} = \frac{1}{K}. \tag{4}$$

Next, the recursive updating is performed according to the following two equations:

$$\pi_{t|t-1,k} = \left(\pi^{\alpha}_{t-1|t-1,k} + c \right) \Big/ \left(\sum_{i=1}^{K} \pi^{\alpha}_{t-1|t-1,i} + c \right), \tag{5}$$

$$\pi_{t|t,k} = \left[\pi_{t|t-1,k} f_k \left(y_t | Y^{t-1} \right) \right] \Big/ \left[\sum_{i=1}^{K} \pi_{t|t-1,i} f_i \left(y_t | Y^{t-1} \right) \right], \tag{6}$$

where $f_k(y_t \mid Y^{t-1})$ is the predictive density of the k-th model at y_t, given the data from previous periods, and α is a certain forgetting factor fixed from $(0,1]$. $\pi_{t/t,k}$ are called posteriori inclusion probabilities and $\pi_{t/t-1,k}$ are called posteriori predictive probabilities. Some small constant is added in Equation (5) in order to avoid reducing the probabilities to zero due to numerical approximations during computations. For example, following Raftery et al. (2010), $c = 0.001 / K$.
Then, the DMA forecast is formulated in the following way:

$$y_t^{DMA} = \widehat{\sum_{k=1}^{K} \pi_{t|t-1,k} y_t^{(k)}}, \tag{7}$$

where $\widehat{y_t^{(k)}}$ is the prediction given by the k-th regression model.

Now, let $\pi_{t|\widehat{t-1,k}} := \max_{i=\{1,\dots,K\}}\{\pi_{t|t-1,i}\}$, where $\pi_{t|t-1,i}$ are computed as in Equation (5). Also, let in the above computational scheme modify the Equation (7) to be:

$$y_t^{DMS} = \sum_{k=1}^{K} \widehat{\pi_{t|t-1,k}} \widehat{y_t^{(k)}}. \tag{8}$$

Then, Equation (8) gives the Dynamic Model Selection (DMS) forecast. The difference between DMA and DMS is that in DMA model averaging is performed, whereas DMS method selects in each period the model with the highest posteriori predictive probability.

Now, notice that in each time period t, posteriori predictive probabilities for each model which contains a given variable can be summed. This measure can be further used to describe the time-varying importance of a given variable as an oil price driver.

4 Results and Conclusions

Table 3 presents MSE (mean squared error) for various DMA and DMS models. In particular these models come from assuming various combinations of forgetting factors α and λ, i.e., $\alpha, \lambda = \{1, 0.99, 0.95, 0.90\}$.

Table 3: MSE

DMA		**α**			
		1	0.99	0.95	0.9
λ	1	0.0148	0.0147	0.0154	0.0163
	0.99	0.0146	0.0146	0.0152	0.0161
	0.95	0.0144	0.0143	0.0149	0.0159
	0.90	0.0143	**0.0142**	0.0147	0.0157
DMS		**α**			
		1	0.99	0.95	0.9
λ	1	0.0163	0.0170	0.0186	0.0200
	0.99	0.0163	0.0168	0.0176	0.0199
	0.95	**0.0156**	0.0160	0.0167	0.0178
	0.90	0.0158	0.0160	0.0169	0.0186

Minimum values of MSE are bolded. From Table 3 it can also be seen that for given α and λ DMS always produced higher MSE than respective DMA model. DMA model which minimizes MSE criterion is the one with $\alpha = 0.99$ and $\lambda = 0.90$. Because these values are not equal to *1* both specific model averaging procedure and time-varying parameters play an important role.

Table 4 presents MAE (mean absolute error). In particular, as previously, these models come from assuming various combinations of forgetting factors α and λ, i.e., $\alpha, \lambda = \{1, 0.99, 0.95, 0.90\}$. Minimum values of MAE are bolded. From Table 4 it can also be seen that for given α and λ DMS always produced higher MAE than respective DMA model. DMA model which minimizes MAE criterion is the one with $\alpha = 0.99$ and $\lambda = 0.90$. This is the same model which minimizes MSE. Because these values

are not equal to *1* there exists another argument favoring that both specific model averaging procedure and time-varying parameters play an important role. The conclusions are the same as that based on MSE criterion.

It is interesting to observe that according to the chosen criteria (i.e., MSE and MAE) the best model is the one with $\alpha = 0.99$. This is in agreement with previous studies of DMA method by different authors (Koop and Korobilis, 2012). However, it can be observed that generally lower values of λ are preferred. For clarity the MSE and MAE are presented in Figure 1.

Table 4: MAE

DMA		**α**			
		1	0.99	0.95	0.9
λ	1	0.0939	0.0932	0.0940	0.0950
	0.99	0.0931	0.0927	0.0938	0.0950
	0.95	0.0919	0.0919	0.0929	0.0945
	0.90	0.0914	**0.0913**	0.0923	0.0938
DMS		**α**			
		1	0.99	0.95	0.9
λ	1	0.0985	0.0989	0.1009	0.1034
	0.99	0.0988	0.0982	0.1000	0.1033
	0.95	0.0957	0.0965	0.0978	0.1013
	0.90	**0.0949**	0.0950	0.0986	0.1042

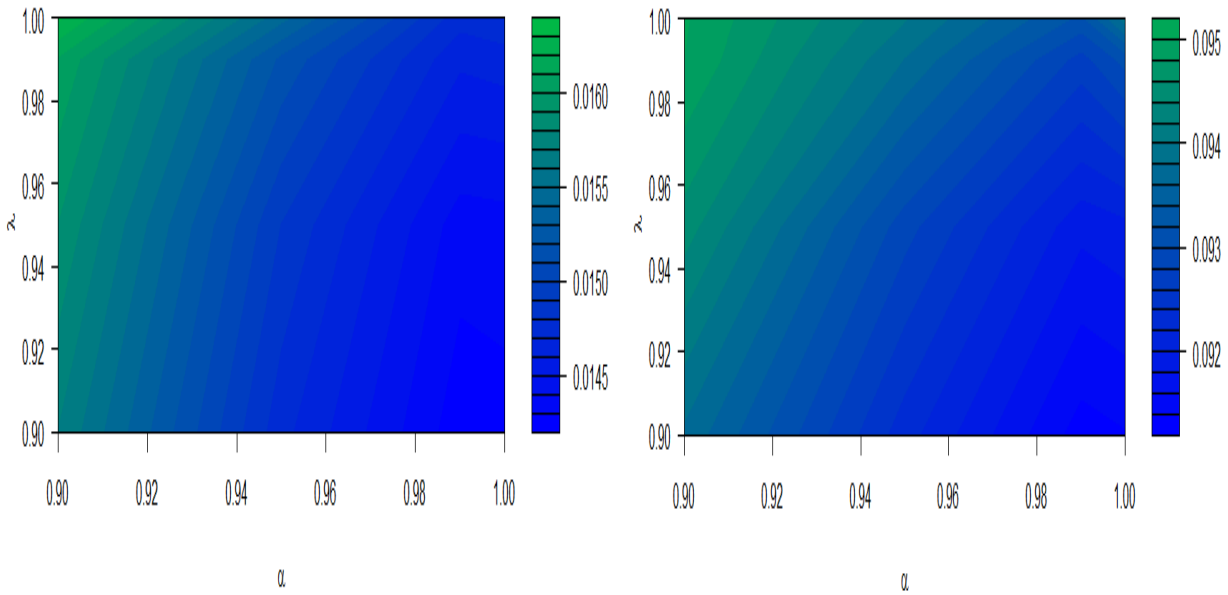
Finally, obtained forecast quality measures should be compared with some alternative forecasts. This is presented in Table 5. From Table 5 it can be seen that the selected DMA model is "better" than naïve forecast (according to minimizing both MSE and MAE). This model produces errors smaller than, also, time-varying parameter regression (TVP). In other words, the TVP model denoted in Table 5 is obtained with a help of the same regression coefficients updating as in DMA with the only exception that instead of estimating and averaging various models, just a one model is estimated, i.e., the one with all drivers indicated in Table 1. Comparison of DMA with TVP model once again strongly favors averaging procedure across several models. The results of this comparison show that, indeed, by incorporating into the time-varying parameters framework an averaging scheme the forecast of a better quality is obtained.

At the end of the Methodology section posteriori predictive probabilities were mentioned. In particular, it was stated that they can be summed for each model which contains a given variable. As a result this measure can be used to describe the time-varying importance of a given variable as an oil price driver. These probabilities for every estimated DMA model are shown in Figure 2. It should be noticed that for all 16 estimated models (4 possible values of α and 4 possible values of λ) these probabilities generally present the same time-varying behavior. This can serve as an argument favoring robustness of DMA to different initial parameters' setting.

However, making conclusions about which factors drive oil price, based just on these probabilities can be a bit misleading. Indeed, despite overall high posteriori inclusion probability of some variable, in one model this variable can have, for example, a positive coefficient, and simultaneously, in a second model – negative. Therefore, the overall impact can reduce to zero. Therefore, except analyzing the plots on Figure 2 (i.e., posteriori inclusion probabilities), it would be desirable to

analyze the expected values of regression coefficients for different potential oil price drivers. The expected values of these coefficients are computed with respect to posteriori inclusion probabilities (presented in Figure 2). These expected values of coefficients are presented in Figure 3.

Figure 1: MSE and MAE for DMA models

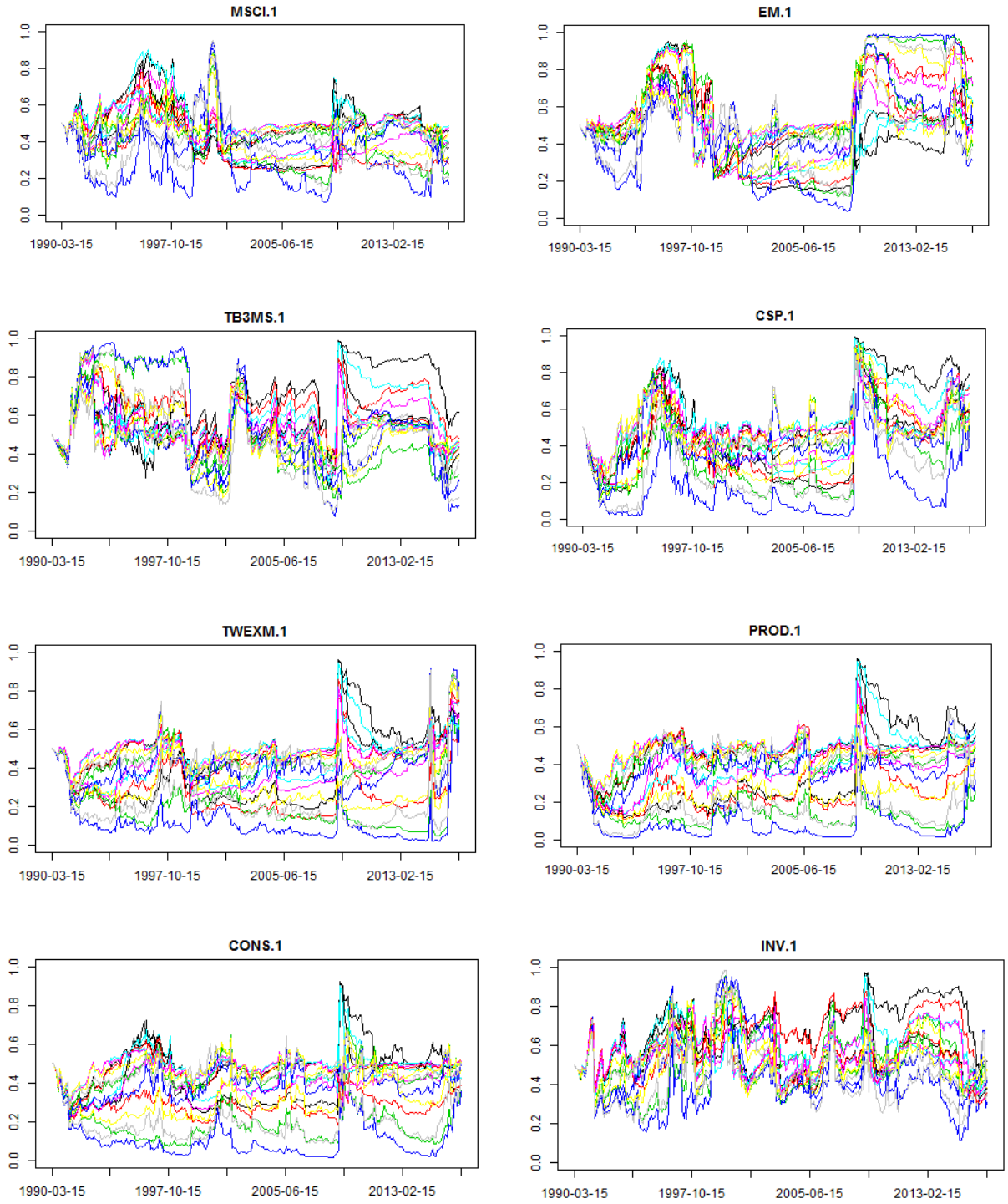


MSE MAE

Table 5: Alternative forecast

	MSE	MAE
Naive	0.0198	0.1112
TVP	0.0155	0.0978
DMA with $\alpha = 0.99$ and $\lambda = 0.90$	**0.0142**	**0.0913**

Figure 2: Posteriori inclusion probabilities



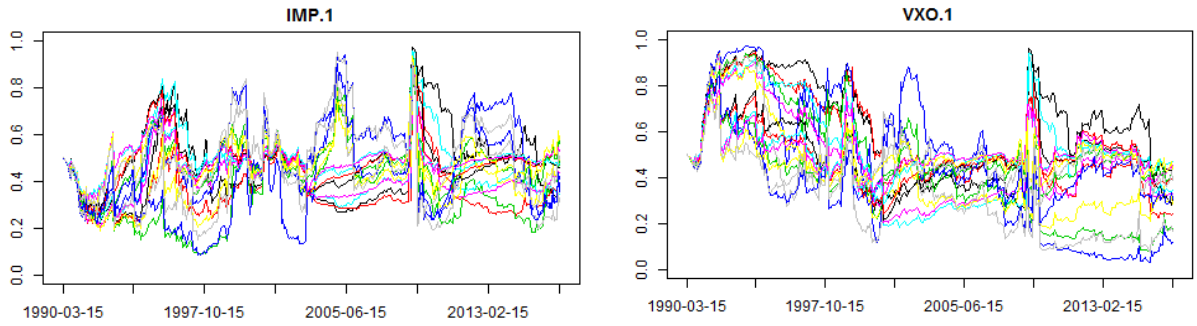
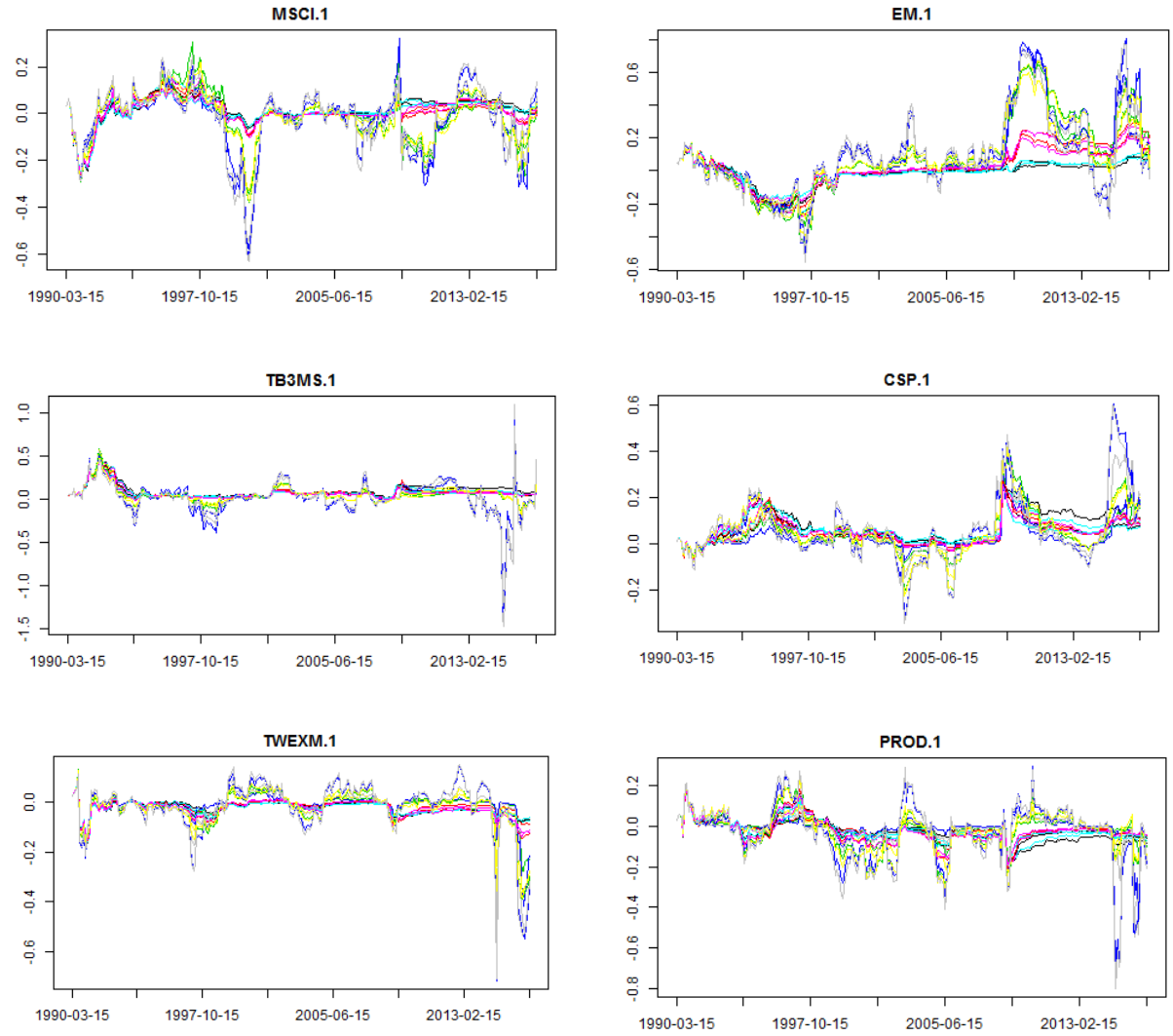
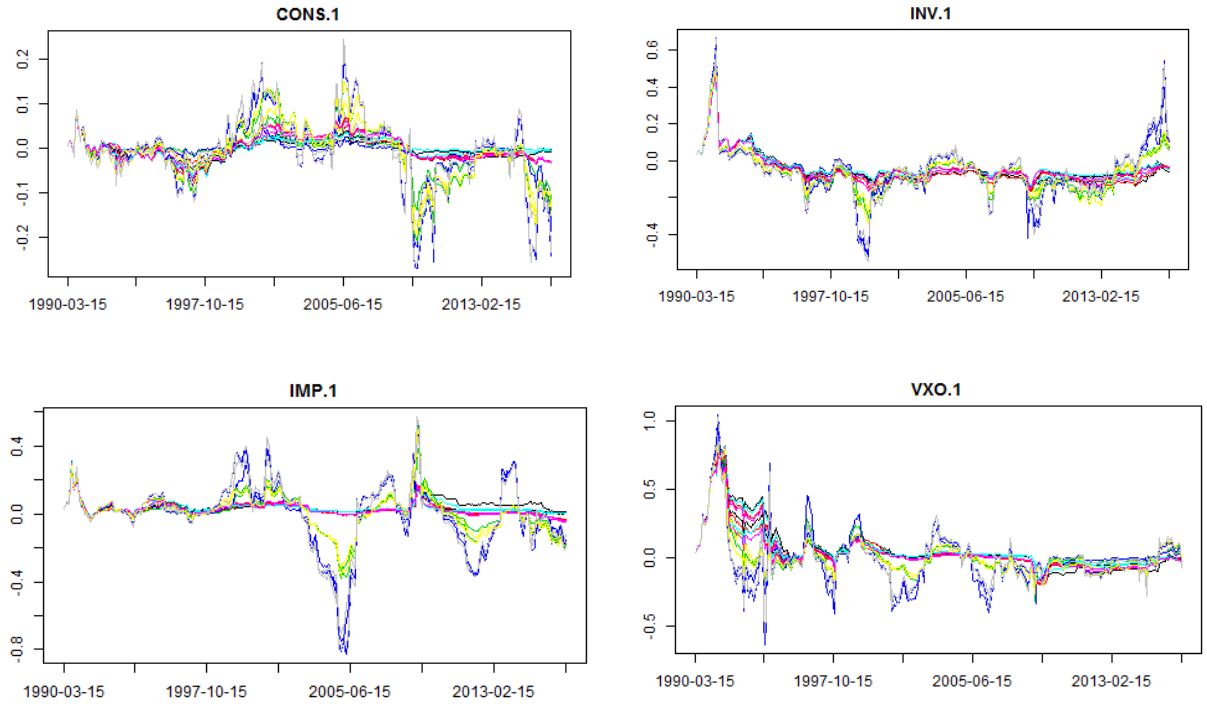


Figure 3: Expected values of regression coefficients





First of all, from Figure 3 it can be seen that chosen drivers can have different impact on oil price (in case of the direction of a change) in different time periods. For example, at the end of 1990s the relationship between oil price and developed stock markets was rather negative, whereas around 2008 – positive. It can also be seen that there was a high positive relationship between emerging stock markets and oil price at the beginning of the recent global financial crisis. Also, recently such a high and positive relationship is observed. Interestingly, there is no such an obvious relationship between stress market index and oil price. It can be observed that the relationship between import quotas and oil price was highly negative around 2005. Within the context of the mentioned "Masters Hypothesis", there is no sign of strong relationship between inventories levels and oil price during the recent oil price surge. In 1990s and in the beginning of 2000s the relationship between oil demand and oil price was positive, but afterwards it become rather negative. In case of supply, the outcomes clearly present that periods of positive relationship are followed by periods of negative relationship and vice versa. The relationship between oil price and exchange rates become strong (and negative) during recent few years. In case of interest rates, especially interesting is recent period. From strong negative relationship, a passage to strong positive one can be observed. Finally, global economic activity presented strong positive relationship around 2009. Later this relationship weakened, but recently it is again strong (and positive).

Finally, it can be interesting to see whether similar results would be obtained if instead of crude steel production, Kilian index is taken. MSE and MAE for a model with CSP replaced by Kilian index are presented in Table 6.

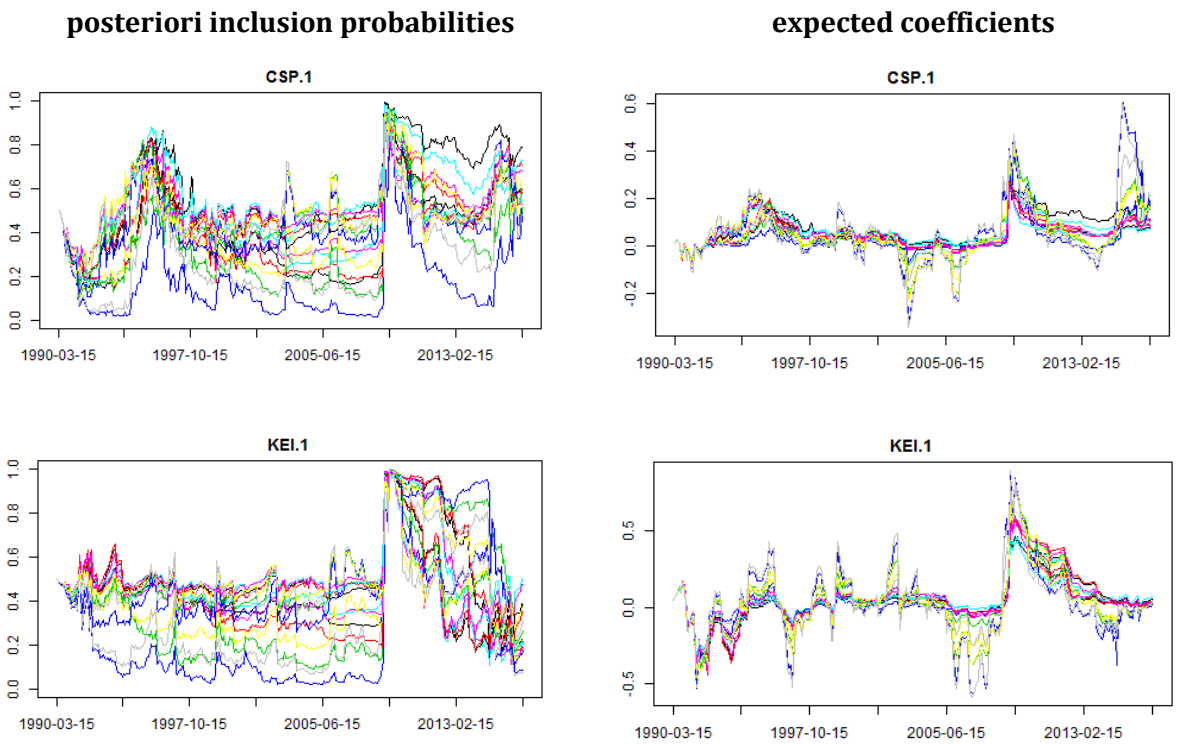
According to minimize MSE model with the same parameters α and λ would be chosen. The same conclusions are valid with respect to minimizing MAE. In some cases models with Kilian index can produce forecast of a better quality than models with CSP. However, the difference is not so high. Definitely, it would be interesting to compare the analogous plots as those presented in Figure 2 and Figure 3. These plots are not presented herein, because they are almost the same as for the models with CSP. However, interestingly, the plots for Kilian index itself differ slightly from those for CSP

(see Figure 4). By analyzing Figure 4 it can be seen that the robustness of DMA to choosing different variables should be taken with caution.

Table 6: MSE and MAE for models with Kilian index instead of CSP

MSE		**α**			
		1	0.99	0.95	0.9
λ	1	0.0149	0.0147	0.0152	0.0162
	0.99	0.0147	0.0146	0.0149	0.0156
	0.95	0.0145	0.0143	0.0147	0.0155
	0.90	0.0144	**0.0142**	0.0145	0.0154
MAE		**α**			
		1	0.99	0.95	0.9
λ	1	0.0943	0.0938	0.0947	0.0963
	0.99	0.0936	0.0931	0.0942	0.0953
	0.95	0.0923	0.0917	0.0932	0.0949
	0.90	0.0918	**0.0911**	0.0925	0.0944

Figure 4: Comparison of Kilian index and CSP



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