EXCHANGE RATE FORECASTING BASED ON OIL PRICE

A Thesis

Presented to

The Faculty of the Department

of Economics

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Master of Arts

By

Saif Ali

December, 2013

EXCHANGE RATE FORECASTING BASED ON OIL PRICE

An Abstract of a Thesis

Presented to

The Faculty of the Department

of Economics

University of Houston

In Partial Fulfillment

Of the Requirements for the Degree of

Master of Arts

By

Saif Ali

December, 2013

ABSTRACT

This paper is aimed at finding out how well nominal oil price can predict nominal exchange rates out-of-sample compared to the random walk benchmarks. The choice of country selection for the exchange rates is based on whether the country is an oil exporter or importer. Despite using two different models, we find that for only one country (Russia) oil price is able to perform better than the random walk benchmarks. In addition, the countries that have a higher share of oil export of the total export and are net exporters are able to show short-horizon predictability of the exchange rate but only for large sample sizes. Overall, the results of the most of the countries were not better than the random walk. The fact that a country is a big net exporter and has a high oil export/import share of total export/import might be the reason why oil price is able to predict exchange rate better than the random walk.

Table of Contents

Section	Page Number
Introduction	1
Data	5
Model	7
Empirical Results	11
Lagged Oil Price Model	11
Vector Autoregression (VAR) Model	16
Main Findings	18
Conclusion	19
References	22
Appendix	26
Tables	26
Figures	29

Introduction

The literature on exchange rate forecasting has been focused on finding a proper model which can provide reliable forecast for exchange rates. Researchers have used several models for this purpose but there has not been any significant evidence that the fundamental models are able to outperform the naïve or the random walk out-of-sample. Meese and Rogoff (1983a, b) have shown that fundamentals, both in the case of lagged and structural models, such as interest rates, output or inflation differentials have no predictive power for exchange rates. They show that none of the traditional fundamental models outperform the simple random walk benchmark for the out-of-sample exchange rate forecasting. Since then, several models have been used to predict exchange rates but there has not been much success. In argument with the Meese and Rogoff (1983a,b) paper, empirical research (Chinn and Meese, 1995 and Engel, Mark and West, 2007) has shown that the fundamental models have some explanatory and extrapolative ability. However, Giacomini and Rossi (2010) argue that the predictability is unstable over time.[1]

There is another strand of related literature that is moving away from the traditional fundamentals. For instance, papers by Wang and Wu (2008), Molodtsova and Papell (2009) show empirical evidence that the Taylor rule models can provide some forecasting ability of the exchange rates. While some research is focused on more complicated models, a number of papers actually tried to focus on the simple relationship between oil price and exchange rate. The use of oil price to explain exchange rate movement can be explained by simple

[1] The studies that found certain predictability at long-horizon have criticism regarding stationarity, robustness to sample period etc. (Kilian, 1999, Faust, Rogers and Wright, 2001).

economic fundamental reasoning[2]. Amano and van Norden (1998) show that the price of oil affects the Nordic countries' currency values.[3] Ozturk, Feridun and Kalyoncu (2008) using a VAR model analysis, show that for a small open economy like Turkey, an oil importer; the real crude oil price granger causes the real exchange rate. Englama (2010) used VAR and Vector Error Correction Model (VECM) to find the effect of oil price volatility on exchange rate volatility. In the simple oil price and exchange rate relationship, the oil export/import share of total export/import can also play a significant part. Obstfeld and Rogoff (1996) argue that a small open economy which is an oil exporter should have an exchange rate that is affected by the fluctuations of the oil price. Oil export/import is a major component of an economy's trade balance. In economies with a large fraction of oil trade, the oil price change will affect the terms of trade and thereby cause appreciation/depreciation to that currency vis-à-vis a trademark currency, say, US Dollar. But most of the research works mentioned above is done using real oil price and real exchange rates. There has not been much research work on the causality between nominal oil price and nominal exchange rate.

Ferraro, Rogoff and Rossi (2012) focus on short horizon nominal exchange rate forecasting ability of nominal oil price specifically for the Canadan Dollar. Previously, Cheung, Chinn and Pascual (2005) have found that no basic fundamental model has been able to outperform the random walk for forecasting the Canadian-US Dollar exchange rate. Ferraro et al. (2012) argue that short horizon predictability of oil prices has not been properly analyzed in the existing literature. They show that a contemporaneous fundamental model

[2] Chen, Rogoff and Rossi (2010) show that there is an effect of change of exchange rates on change of commodity prices. They argue that this effect for in-sample as well as for out-of-sample cases. However, reverse causality, oil price causing movements in exchange rate isn't as strong as shown in the out-of-sample forecast results.

[3] Studies conducted by Cooper (1994) and Brown (1986) show that in the case of OPEC countries and for large oil exporters exchange rates affect the oil price.

between oil price and exchange rate of Canadian Dollar vis-à-vis US Dollar is able to consistently outperform the random walk benchmark model out-of-sample. They also show that a lagged exchange rate model never successfully outperforms both the random walk with and without drift. They use high frequency of data (daily) for their model and reason that this high frequency of data captures the effect of oil price on exchange rate. This relation can very well be a short lived effect, hence not statistically significant in longer horizons as shown in other papers (Cheung et al. 2005). They use very short forecast horizon for rolling sample with different sample sizes. Their out-of-sample predictability for short horizon forecasts disappears in the longer horizon as concluded in the other papers.

In this paper, we focus on the ability of the nominal oil price to predict nominal exchange rates of several currencies. As mentioned earlier, Ferraro et al. (2012) are not able to find predictability when using that the lagged oil price model for Canadian Dollar (CAD). Our objective is two-folded. First, in addition to the CAD exchange rate, we take several other currencies (Mexico, Norway, Russia, UK, India, Singapore, Thailand, South Korea and Japan) against the US Dollar (USD) and we estimate the lagged oil price model to test the predictability against the random walk benchmarks. Second, in addition to the simple lagged oil price model, we use the Vector Autoregression (VAR) model to forecast exchange rates and compare them to the random walk benchmark. Besides these objectives, we try to find whether the predictability of the exchange rate based on the oil price is different depending on whether the country is an exporter or importer or oil. Also, the objective is to find whether the analysis provides different results for different size of net export figures of the economies.

We are not including other fundamentals (output gap, interest rate differential and inflation differential) in the oil price model due the fact that generally the data is not available at daily frequencies. Besides, Ferraro et al. (2012) show that using daily interest rates differentials for predicting exchange rates does not do a better job than the random walk. Including the interest rates differentials in the model is, therefore, unlikely to improve the forecasts. Also, as mentioned, the objective is to show the sole effect of oil price on exchange rate and whether that relation can be used to predict exchange rates.[4] They also argue that the relationship between oil price and exchange rate is ephemeral. One of the reasons behind the addition of the VAR model is to see whether after adding more lags into a system of equation, the predictability of exchange rate by oil price is consistent with the results of the lagged oil price model.

The analysis results show that the lagged oil price model is able to outperform the random walk with and without drift to some extent. But this result is only valid for Russia, an oil exporter and also a giant net exporter. Also, the model has been able to outperform random walk benchmarks but only for large sample sizes for countries such as Japan, Canada, South Korea and Norway. Oil price model that represented other currencies couldn't outdo the random walk out-of-sample forecast performance. From the analysis, it is found that oil price significantly affects the exchange rate for countries which are net exporters and also have a high share of oil export/import. As mentioned earlier, the relation between oil price and exchange rate is very transitory. The VAR model analysis shows that indeed the

[4] Ferraro, Rogoff and Rossi (2012) show that for Canadian Dollar, Norwegian Krone and Australian Dollar the contemporaneous oil price model is able to forecast significantly better than random walk benchmarks. However, only for the Krone, the lagged model is able to outperform the random walk. Since, the lagged oil price model exhibits different results; looking more into the lagged relation between may reveal new information.

relation between oil price and exchange rate is momentary and if more past information in the form of lag is introduced into the model, its ability to forecast exchange rate worsens.

This paper is organized in next four parts. Part 2 describes the data. Part 3 explains the models, benchmark models and measures used to compare results found in the analysis. Part 4 is the results section where the outputs are explained. Part 5 is the findings which is basically the explanations, inference and decisions reached from the analysis for both the lagged models and the VAR models. Part 6 draws a conclusion for all of the analysis made in the paper.

Data

The countries that we choose for this paper are divided into two parts: oil exporters and oil importers. Among the ten countries we choose for the analysis, four are oil exporters (Canada, Norway, Russia and Mexico) whereas six countries are oil importers (Japan, UK, India, Thailand, Singapore and South Korea). Notice that these countries have varying degree of the ratio of oil export/import to total export/import.[5] The data is taken from the databank of the International Trade Center website. Among the exporters, Mexico and Norway are the smaller open economies as opposed to Russia and Canada. Among Mexico and Norway, Norway has oil export share of total export bigger than that of Mexico (Panel A, Figure 1). Among Russia and Canada, which are the relatively two bigger economies here, Russia has a much higher share of oil export of its total export (Panel A, Figure 1). So, among these

[5] Ferraro et al. (2012) focus mainly on Canada as it is a small open economy, has a pretty large share of oil export of total export and has a long history of floating exchange rates. They couldn't find any superior predictability using the lagged oil price model. We want to see whether this effect is only due to the very selective reasons of choosing Canada to perform the analysis.

countries, all possible scenarios are taken into account. Among the six oil importing countries, Japan, UK and India are the big economies and Thailand, Singapore and South Korea are relatively small economies. Among these, UK has the lowest share of oil import of total import. Close to UK is Thailand. Although India, Japan and South Korea have a higher share of oil import in recent years, the share of total import is at maximum of about 40% for India (Panel B, Figure 1). Whereas, Russia and Norway has about 70% (Panel A, Figure 1).

It should be noted that among the oil exporters, Mexico is the only country which has been a consistent net importer. Although since 2008 Canada has been a net importer, pretty much from the year 2001 all other oil exporters have been net exporters (Panel A, Figure 2). For oil importing countries, from 2001 till 2012, UK and India have been the consistent net importer. Among all, Japan has been the highest net exporter till recent years. The rest of the countries were moderate net exporters throughout the years with some exceptions (Panel B, Figure 2). These countries are chosen to observe the effect of oil price changes on their currencies' relative value vis-à-vis a standard currency which is the US Dollar. Some of these countries are price takers while some are major players in the oil market. So, the interesting thing is to observe which exchange rates show such a valid association with crude oil price so that it helps predict the exchange rate out-of-sample and is superior to the classic the random walk benchmark.

All of the daily nominal exchange rate data are taken from the Bank of England's interactive database. For different currencies the available data range varies. This is mostly because not every country had floating exchange rate since beginning. Data at daily frequency are not available for each country for the same time period. The oil price series is the spot rate of West Texas Intermediate (WTI) crude oil which is pretty much the most standard crude oil. The data sample ranges for Canada, Japan, UK and Norway from January 2, 1986 to August 6, 2013; a total of 7,199 observations. For Mexico, the sample ranges from November 8, 1993 to August 6, 2013; a total of 5,152 observations. For Singapore, sample ranges from January 4, 2000 to August 6, 2013; a total of 3,546 observations. And for Russia, Thailand, India and South Korea, the sample ranges from April 1, 2005 to August 6, 2013; a total of 2,178 observations.

Model

The first model used to find the simple out-of-sample predictability is the simple lagged oil price model which is given below.

$$\Delta s_t = \alpha + \beta \Delta p_{t-1} + e_t, \quad t = 1,2,\dots\dots,T$$

Here, Δs_t and Δp_t are difference of the natural logarithm of respectively the spot exchange rates for relevant country and the oil price. e_t is the error term in the model and T is the total sample size. The lagged value of the change of the logarithm of the oil price is used for prediction. The number of lag is taken to be one.[6] The regression model is estimated using different sizes of rolling in-sample windows. Then the regression produces a one-step-ahead out-of-sample pseudo forecast for the change of exchange rate for all in-sample window sizes. This forecast for a certain period, as suggested by the model, is given by the realized value of the change of oil price in the period before.

[6] Our choice of lags is due to the fact that the effect of oil price on exchange rate is short-lived (perhaps even less than a day). We therefore choose the minimum number of lags (one).

In this model, if the forecast for certain period t+1 is Δs_{t+1}^{f}, which is the one step ahead pseudo out-of-sample forecast, then the model becomes: $\Delta s_{t+1}^{f} = \alpha + \beta \Delta p_{t}^{f}$, where t=R,R+1…..T-1. The α and β are the parameter estimates from the rolling sample regressions. Here, R is the number of rolling sample window size. This regression is estimated repeatedly for every rolling in-sample size and the parameters are then used to find the one-step-ahead pseudo forecast. Then all the forecasts are used in computing standard forecast error measurements to compare with that of random walk benchmark models as done in Meese and Rogoff (1983).

The second model used in this paper is the VAR model. A VAR model is used to actually observe how robust the lagged oil price model results are. A typical VAR model is given below.

$$X_t = C + \emptyset_1 X_{t-1} + \ldots\ldots + \emptyset_q X_{t-q} + e_t$$

Here, X_t is a matrix of variables, X_t = (x_{1t}, x_{2t},...x_{gt}), C is a matrix of constant coefficients, $\emptyset_i$ is a matrix of coefficients, q is the number of lag in the VAR system and g is the number of variables in the system. This is the setup of a typical VAR model. For a VAR in this analysis, we have two variables, namely, the change of oil price and change of exchange rates. The way VAR models work is that x_{1t} is explained by the past values of all other variables which in our case are only two. This works both ways which means that x_{2t} is also explained by the past values of both variables.

We know that there are two variables in the VAR model; which are the change of oil price and change of exchange rate. To properly estimate the VAR models we find the proper lag for the VAR model for each of the exchange rate. A model specification criterion is used to find the proper lag of the VAR model for each of the exchange rates. The well-known model selection criterion that we use is the Schwarz Information Criterion (SIC). Using this criterion, we find the proper number of lags by looking at the minimum value of the criterion. Using the number of lags selected by BIC, the VAR models are estimated to find the forecast of the exchange rates.

There are going to be two equations per each country's VAR model. In one equation, the change of exchange rate is estimated in-sample and predicted out-of-sample by both the 1-lag change of exchange rate data and change of oil price data. In the other equation, change of oil price is the dependent variable whereas the independent variables are the same two variables mentioned above. After the VAR model equations are estimated, the first equation is used to predict one-step-ahead out-of-sample forecast for different size of rolling in-sample window. The size of the sample windows is exactly the same as used in the previous simple lagged oil price model. These forecasts for each of the in-sample window sizes are restored for analysis, transformation and comparison.

The forecasts we get from these two kinds of models are used to compare to those of the random walk (RW) benchmarks. Since Meese and Rogoff (1983), RW has been the benchmark model in terms of exchange rate forecasting. Ferraro et al. (2012) use both kinds of RW as benchmarks to their own contemporary and lagged oil price model. The two kinds of RW benchmarks are the RW with drift and RW without drift. The RW benchmark models are shown below.

RW without drift: $\Delta s_t = \Delta S_{t-1} + e_t$ t=1, 2,….., T

RW with drift: $\Delta s_t = \delta + \Delta S_{t-1} + e_t$ t=1, 2,….., T

From these two kinds of RW benchmark models, using the same procedure we find the one-step-ahead out-of-sample forecasts for different rolling in-sample windows. After all the forecasts are found, the Diebold and Mariano (1995) test of equal predictive ability is used to find whether the oil price models forecasts significantly better than the RW benchmarks or not. Diebold-Mariano (DM) test compares the Mean Squared Errors (MSE) of the two different models and suggests which model performs better in a statistical significant manner. The null hypothesis of the DM test is equal predictive ability between two sets of forecasts coming from two different models. The alternative is set according to the preference of researcher. In this paper, the alternative is the premise that oil price model (simple lagged, VAR) forecasts significantly better than the RW benchmarks.

DM test is a popular test in the literature of forecasting as it compares forecasts in a same scale and also gives the statistical significance of a set of forecast performing better than the other one. But it has certain limitations as well. When it comes to nested models, the results of DM test breakdown. However, Giacomini and White (2006) show that we can use DM test for testing the alternative hypothesis that oil price model forecasts better than the RW benchmark models.

The interpretation and use of the Diebold-Mariano test statistic found from the model analysis is useful in helping us decide which one is the better forecasting model for exchange rates. The critical value of the DM test is set to be -1.96. This means that whenever the DM statistic is lower than -1.96 for a certain in-sample estimation window size, the forecast for the oil price model is better than the RW benchmark. In this paper, we use 19 different in-sample window sizes which are basically given by total size of sample T multiplied with fraction of sample size 1/k where k=2,3,…..,20. This is the same procedure of finding different in-sample estimation window sizes used in the Ferraro et al. (2012) paper.

Empirical Results

This section is divided in two parts. In the first part we discuss the simple lagged oil price model for different countries' exchange rates and its forecasting ability over that of the RW benchmark models. The second part consists of explanations of the outputs from the VAR oil price models. Also it explains how the VAR model is or isn't better than the RW benchmark using the DM test. The results are shown in line graphs where for different in sample sizes the ratio of the in-sample estimation window size and the total sample size (1/k) is given on the x-axis and the DM statistics are given in the y-axis. As noted before, if the DM statistic is lower than the critical value of -1.96 then by rejecting the null hypothesis of equal predictive ability, it is concluded that the oil price model (simple lagged/VAR) forecasts significantly better. For each model, we will go through each country's results separately.

Lagged oil price model

The estimated coefficients are given in table 1. We can see that Canada, Russia, Mexico and Norway all have slope coefficients which are significant at 10% significance level with Mexico just outside of 10%. Using the oil price regression model, we find the DM statistic for different in-sample estimation windows and using a scatter plot, we report them against the ratio of in-sample window size and total sample size. For Canada, Figure 3 shows that for the RW without drift, the DM statistic is lower than -1.96 but only for big sample size (1/2 of the total sample). For the RW with drift, also big sized samples produce forecasts which are better than those of the RW as the DM statistic is less than -1.96. However, all other different in-sample estimation window sizes produce forecasts which are not better than the RW benchmarks. This is in line with the findings of the Ferraro et al. (2012). Although, they did not, for any in-sample window size, find better predictability than the RW benchmarks. It might be that including the observations after November 2010 which is their last observation month played a role in the fact that using a large sample actually slightly improves the forecasts to the point that they are better than the RW forecasts. This suggests that the very short lived effect of oil price on exchange rates is useful when considering longer sample sizes.

Figure 4 shows the DM statistic for different in-sample sizes for Mexico. It can be seen that for none of the different sample sizes the oil price model is significantly better in forecasting the Mexican Peso-US Dollar exchange rate as no DM statistic is below the critical value of -1.96. For Mexico, we conclude that the RW benchmarks outperform the oil price model by failing to reject the null hypothesis.

Norway's DM statistics for different in-sample estimation window sizes are given in figure 5. We can see that for both the RW with and without drift, large sample sizes (1/2 and 1/3 of the total sample size) DM statistic is lower than -1.96. Therefore, we can conclude that for large sample estimation windows the oil price model forecasts better than the RW benchmarks for Norwegian Kroner-US Dollar. However, as all the other in-sample estimation window sizes produce forecasts which aren't better than those of the RW benchmarks; overall, the RW benchmarks do still have the upper hand over the forecasts of exchange rate.

In figure 6, Russia's DM test statistics are shown for both the RW with and without drift benchmarks. Here we see different results. For the RW without drift, about 6 of the 19 different in-sample estimation windows sizes produce a DM statistic which is lower than the -1.96 boundary which suggests that for those sample sizes the oil price model forecasts better than the RW. The result for the RW with drift model is even more robust. We can see that about 14 of the 19 different in-sample window sizes have a DM statistic lower than -1.96. Therefore, we conclude that for Russia, oil price model, with some restrictions and special cases, forecasts better than the RW benchmarks.

Figure 7, 8, 9 and 10 shows the DM statistics for the oil price model for the countries UK, India, Singapore and Thailand respectively. We see from figure 7 that for UK the oil price model never has a DM statistic which is less than -1.96 for both the RW benchmarks. Hence, it is concluded that the oil price model is never successful in forecasting the Great Britain Pound-US Dollar exchange rate better than the RW benchmarks. Figure 8 also shows that for India, the oil price model never produces a DM statistic which is lower than -1.96. Therefore, conclusion is that the null hypothesis can't be rejected at 5% significance level. Figure 9 represents Singapore's oil price model DM statistics. From the graph it can be seen that no matter what the in-sample window size is, the DM statistic is never below the critical value for both the RW with and without drift. Therefore, we again conclude that for Singapore Dollar-US Dollar exchange rate, the oil price model can't beat the benchmark. Figure 10 shows the Thai Baht's oil price model DM statistics for both the RW benchmarks. It can be seen that much like the previous three oil price models discussed, the DM statistics are never lower than -1.96 which leads us not to reject null hypothesis and conclude that the oil price model forecast for Thai Baht is never significantly better than that of the RW benchmarks.

The oil price model for South Korean Won (KRW) produces the DM statistics which are given in figure 11. We can see results that for large in-sample estimation window sizes (1/2 of the total) the DM statistics are actually lower than -1.96 for both the RW benchmarks. But for the rest of the different sample sizes it fails to achieve the same. Therefore, it is concluded that although the model maybe better in forecasting KRW-USD for large in-sample window, over the different sample sizes it is not better than the RW benchmarks' forecasts.

Figure 12 shows the DM statistics of the oil price model for the Japanese Yen-US Dollar exchange rates. It can be seen that for the RW without drift only for one specific sample size which is the largest of all (1/2 of total) the oil price model has produced a DM statistic which is lower than -1.96. The rest in-sample estimation window sizes exhibit DM statistics which aren't lower than the critical value. For the RW with drift, only two in-sample sizes (1/2 and 1/3 of the total) for the model produce DM statistics which are lower than -1.96. Therefore, although for large sample sizes oil price model forecasts better than the RW benchmarks; overall, the Yen-USD exchange rate oil price model does not perform better than the RW benchmarks. However, the information that the model show better results for large in-sample window size is a clue toward a bigger conclusion that will be discussed next.

We can see from Panel A, figure 1 that in midst of oil exporters Mexico is the country which has the least share of oil export of its total export. Also in the oil price models among the oil exporters, Mexico's model performs worst. It has positive DM statistics throughout the different sample sizes. Canada has a higher share of oil export and shows a little bit of better predictability over the RW benchmarks for large sample sizes. Norway has even higher share of oil export and also shares the similar results with Canada. Norway's oil price model produces a DM statistics lower than critical value only for certain large in-sample window sizes. Then the largest of the four exporters, Russia comes into picture. Russia has the highest share of oil export as a percentage of total export. Interesting fact is that for Russia the oil price model is able to perform better than the RW benchmarks in terms of forecasting Russian Ruble exchange rate as explained earlier and shown in figure 6. Next we look at the oil importing countries' results. From panel B, Figure 2 it is clear that India and UK are the net total importers throughout the years. Singapore and Thailand are just about net exporters over the years and so is South Korea. But South Korea has a higher percentage of oil import. However, Japan is the main net exporter country throughout majority of the years despite falling to a net importing stature in later years. Japan also has a higher share of oil import of total import. From the results explained above, we see that the oil price models for India, UK, Singapore and Thailand's exchange rates never outperform the RW benchmarks. But the oil price model performs better than the RW benchmarks for large in-sample estimation window sizes for South Korea and Japan. Both have high share of oil import as a percentage of total import. The oil price model does not outperform the RW benchmarks for on average over different samples sizes for all oil importing countries.

We infer from the above analysis that maybe for countries which are net exporters and have a high oil export/import share of total export/import the oil price model is able to forecast better than the RW benchmarks for generally large in-sample estimation window sizes. This gives us a new view on this literature. Maybe the fact that the countries that are dependent upon oil export/import and also are net exporters, have an effect on the terms-of-trade of that country which is a fundamental reasoning to begin with. Easily explained, maybe for a country which is a heavy oil exporter or importer, it has an exchange rate that is closely associated with the oil price so much that the predictability of the oil price model surpasses that of the RW benchmarks for generally large in-sample estimation window sizes. To test whether the results we are getting from the oil price model are robust, we use VAR models. Once the empirical results of the VAR model are discussed we can see whether this claim can be made also for those models.

Vector Autoregression (VAR) Model

This part of the paper discusses the results of the DM test analysis using BIC to find lags. To be noted, for most countries, BIC provides a lag of one (1). So, to actually compare the results properly on an apple-to-apple basis we use lag one for all the VAR models for all the ten exchange rates. Also, notice that a VAR model with a zero lag is essentially a RW without drift therefore just to compare with the RW with drift there is no point using lag zero. Figures 13 gives the DM test statistics for Canada VAR model against the RW benchmarks using lag one. A lag of zero is selected by BIC for this country model. After estimating the model and finding the forecasts, errors and subsequently the DM statistics, those are plotted against the denominator of the ratio of different in-sample window size to the total sample size. We see from the figures that for only the largest in-sample window size the VAR model is able to perform superiorly over the RW benchmarks. For the every other case of different sample sizes the models are not able to outperform the RW benchmarks. Therefore, it is concluded that the VAR model can't forecast better than the RW.

For Mexico, we see in figure 14 that in the case of lag 1, the DM statistic is never negative; let alone being lower than the critical value of -1.96. Thus we conclude for Mexico, the VAR model can never outperform the RW benchmarks.

The DM statistics of the Norwegian Krone VAR model are shown in figures 15. It can be seen that the one lag VAR model has a DM statistic lower than -1.96 for large in-sample window size (1/2 of the total). This suggests there might be some predictive ability in the VAR model for Krone-USD exchange rate. But since for all other in-sample sizes the model couldn't outperform the RW benchmarks it is safe to say that the model does not forecast better than the RW.

Russian Ruble DM statistics for the VAR model are given in figure 16. The number of lags chosen by BIC is 1. The 1-lag VAR model exhibits DM statistics lower than the critical value for relatively large sample sizes for the RW without drift and has DM statistics lower than or very close to critical value for about 10 out of 19 different sample sizes. We can say that the result for Russian Ruble is definitely robust, or at least when compared to other results so far. This means Ruble VAR(2,1) model is able to outperform the RW benchmarks for certain times if not all of them.

For all of the oil importing countries, figures 17, 18, 19, 20, 21 and 22 show the DM statistics for the VAR models (lag 1) of the currencies of UK, India, South Korea, Singapore, Thailand and Japan respectively. Throughout all of these 6 oil importing countries' VAR models, lags chosen by BIC, never experience DM statistics lower than the critical value of -1.96. In other words, none of the VAR models used to predict the exchange rates of respective countries mentioned above are able to outperform the RW benchmark models.

Main Findings

The results presented above from the lagged oil price model and the VAR model analysis reveal subtle hints about the relationship between the exchange rate and oil price. We concur with the fact that the relation of oil price and exchange rate is short-lived by looking at the number of lags chosen for VAR models. Throughout the 10 exchange rates that are observed, oil exporters and importers, BIC has continuously chosen low number of lags. This particular fact is an indication that including too many lags or including too much past information into the effort of predicting the future exchange rate distorts the entire process implying transitory relation.

Notice that from the discussion of oil price model outputs, we want to see how those results play up over here at the VAR model section. It is found that the lagged oil price model for countries with a large oil export/import share of the total export/import is able to perform better than the RW only for large in-sample estimation windows. Among all of them, Russian Ruble is able to perform in several cases by producing superior forecasts than the RW benchmarks. When we compare the results of the lagged oil price model with the VAR model we see that the only exchange rate that is able to perform in both of the models to some extent is the one mentioned above. The oil price models for the four countries (Canada, Norway, Japan and South Korea) which are able to beat the RW benchmarks for only one or two of the cases of very large in-sample estimation window, are not able to display similar results for the VAR models. Only Norway is able to perform in almost the same way as it does in the lagged oil price model.

Russia has a very high share of oil export in terms of total export compared to other countries. The sheer size of net export figures for Russia may have something to tell about the predictability of exchange rate by oil price. It maybe that those countries that are large net exporters and have oil trade occupying certain high portion of total trade are prone to a strong fundamental relationship between oil price and exchange rates. It maybe that it is a necessary condition for the significant oil price-exchange rate relation that the country has to be a big net exporter and then the secondary/sufficient condition is that the country has a high share of oil trade as of total trade. For such countries, a theory like this, if proven by further research can well and truly do wonders for those countries. The results are summarized in a matrix in table 2.

Conclusion

The results suggest that the lagged oil price model is able to outperform the RW with and without drift benchmarks on average for different sample sizes for Russia and is able to outperform the RW benchmarks only for large sample sizes for countries such as Japan, Canada, South Korea and Norway. The lagged oil price model fail to forecast better than the RW benchmarks for other countries. Among the ten countries chosen for this paper, Russia is biggest net exporter. Canada, Norway, South Korea and Japan are also net exporters but all of them have low levels of net export figures throughout the years observed. Also among the four, three have large oil export/import as a share of total export/import respectively. The above information suggests that there may be a missing link between the fundamental relationship of oil price & exchange rate and the country's status as a net exporter. Maybe oil price significantly affects the exchange rate for countries which are not only heavy on the oil trade side but also are net exporters. The results from the VAR model analysis also confirms this theory but also adds more hints. The VAR models show that in addition to the lagged oil price in the explanatory variables, lagged exchange rates, if included in model, the results are somewhat robust to the change. The VAR model for Russia still outperforms the RW benchmarks to some extent. But all other models for different other countries except for some with large sample sizes are not able to beat the forecasts of the RW benchmarks.

Also, the VAR model analyses show that the relation between oil price and exchange rate is in fact transitory and if past information in the form of lag is introduced into the model, its ability to forecast exchange rate deteriorates. The findings of this thesis can be of great importance if proper focus and effort is given into further looking into the matter. Maybe not always a fundamental model will be able to beat the RW benchmark in terms of forecasting but if it can provide a decent enough forecast for majority of the times that would be a tremendous improvement on the existing literature of exchange rate forecasting.

Previous research has tried to analyze the link between the exchange rate and fundamental variables. Some researchers have also tried to find the appropriate relation between oil price and exchange rates. Maybe the answer doesn't lie inside of what is the inherent rule for all cases. Just maybe this time, the relationship between this fundamental price and exchange rate is dependent upon certain pre-conditions. These pre-conditions may vary from different levels of oil trade involvement in the global economy to oil usage per day for the whole economy. Certainly from this paper's perspective, being a large net exporter and a heavy oil trader in the global market has affected the relation between the oil price and its currency's exchange rate such a way that models developed to predict exchange rate via oil price has actually shown promise to say the least.

References

Amano, R. and S. Van Norden (1998a), “Exchange Rates and Oil Prices,” *Review of International Economics*.

Amano, R. and S. Van Norden (1998b), “Oil Prices and the Rise and Fall of the U.S. Real Exchange Rate,” *Journal of International Money and Finance*.

Brown, Stephen P. A., (1986) “Exchange Rates and World Oil Prices” *Economic Review*, P. 1

Chinn, M.D., and R.A. Meese, (1995), “Banking on Currency Forecasts: How Predictable Is Change in Money?” *Journal of International Economics* 38, 161-178.

Chen, Y., K.S. Rogoff and B. Rossi (2010), “Can Exchange Rates Forecast Commodity Prices?” *Quarterly Journal of Economics*, forthcoming.

Cheung, Y.W., M.D. Chinn, and A.G. Pascual (2005), “Empirical Exchange Rate Models of the Nineties: Are Any Fit to Survive?” *Journal of International Money and Finance* 24, 1150-1175.

Cooper, R., (1994) “Changes in Exchange Rates and Oil Prices for Saudi Arabia and Other OPEC Members.” *The Journal of Energy and Development*, 20(1), p. 109

Dawson, J. (2006) “The Effect of Oil Prices on Exchange Rates: A Case Study of the Dominican Republic,” *The Park Place Economist*, XIV.

Englama, A. (2010) “Oil Prices and Exchange Rate Volatility in Nigeria: An Empirical Investigation,” *Central Bank of Nigeria Economic and Financial Review*, 48/3

Engel, C., N. Mark and K.D. West (2007), “Exchange Rate Models Are Not as Bad as You Think,” in: *NBER Macroeconomics Annual*, D. Acemoglu, K.S. Rogoff and M. Woodford, eds., Cambridge, MA: MIT Press.

Faust, J., J.H. Rogers and J.H. Wright (2003), “Exchange Rate Forecasting: The Errors We’ve Really Made,” *Journal of International Economics* 60(1), 35-59.

Faust, J., J.H. Rogers, S-Y.B. Wang and J.H. Wright (2007), “The High-Frequency Response of Exchange Rates and Interest Rates to Macroeconomic Announcements,” *Journal of Monetary Economics* 54, 1051-1068.

Ferraro, D., K.S. Rogoff, and B. Rossi (2012), “Can Oil Prices Forecast Exchange Rates,” *National Bureau of Economic Research W. P.* 17998.

Giacomini, R. and B. Rossi (2010), “Forecast Comparisons in Unstable Environments,” *Journal of Applied Econometrics* 25(4), 595-620.

Harri, A., L. Nalley, and D. Hudson (2009), “The Relationship between Oil, Exchange Rates, and Commodity Prices,” *Journal of Agricultural and Applied Economics*, 41(2), 501-510

Kilian, L. (1999), “Exchange Rates and Monetary Fundamentals: What Do We Learn From Long-Horizon Regressions?” *Journal of Applied Econometrics* 14, 491-510.

Kilian, L. (2008a), “The Economic Effects of Energy Price Shocks,” *Journal of Economic Literature* 46, 871-909.

Meese, R. and K.S. Rogoff (1983a), “Exchange Rate Models of the Seventies: Do They Fit Out of Sample?” *Journal of International Economics* 14, 3-24.

Meese, R. and K.S. Rogoff (1983b), “The Out of Sample Failure of Empirical Exchange Rate Models,” in: *Exchange Rates and International Macroeconomics*, J. Frankel, ed., University of Chicago Press.

Meese, R. and K.S. Rogoff (1988), “Was it Real? The Exchange Rate-Interest Differential Relation over the Modern Floating Rate Period,” *Journal of Finance* 43, 923-948.

Molodtsova, T. and D.H. Papell (2009), “Out-of-sample Exchange Rate Predictability with Taylor Rule Fundamentals,” *Journal of International Economics* 77(2), 167-180.

Neely, C. and L. Sarno (2002), "How well do monetary fundamentals forecast exchange rates?" *Review, Federal Reserve Bank of St. Louis* Sep, 51-74.

Obstfeld, M. and K.S. Rogoff (1996), *Foundations of International Macroeconomics,* MIT Press.

Ozturk, I., M. Feridun and H. Kalyoncu (2008), “Do Oil Prices Affect the USD/YTL Exchange Rate: Evidence from Turkey, *Economic Trends and Economic Policy* 115

Rogoff, K. S. and V. Stavrakeva (2008), “The Continuing Puzzle of Short-Horizon Exchange Rate Forecasting,” *National Bureau of Economic Research W.P.* 14071.

Rossi, B. (2005), “Testing Long-Horizon Predictive Ability with High Persistence, and the Meese-Rogoff Puzzle,” *International Economic Review* 46(1), 61-92.

Wang, J. and J. Wu (2008), “The Taylor Rule and Forecast Intervals for Exchange Rates,” *Federal Reserve Bank of Dallas W.P*. 22.

Appendix

Tables

Table 1 (coefficients and t-stats from the lagged oil price model for different countries)

Countries	Constant	Slope coefficient
Canada	-0.00003951 (0.70682)	-0.01179 (-5.28895)
Mexico	0.00026765 (2.02706)	-0.00905 (-1.63815)
Norway	-0.00003147 (-0.38092)	-0.01485 (-4.50809)
Russia	0.00008884 (0.70278)	-0.03763 (-7.06023)
UK*	-0.00000825 (-0.11622)	-0.0049 (-1.73094)
India*	0.00015412 (1.45651)	-0.00967 (-2.16784)
South Korea*	0.00005521 (0.31413)	-0.03942 (-5.31976)
Singapore*	-0.00007429 (-1.19953)	-0.00315 (-1.24871)

Thailand*	-0.00010475 (-0.93687)	-0.00651 (-1.38014)
Japan*	0.00010148 (-1.25397)	0.00094 (0.00323)

Note: Asterisk (*) indicates the country is an oil importer.

Table 2 (Classification of the sample countries)

Matrix for the countries based on attributes of trade balance and oil trade share		**Net oil exporters**		**Net oil importers**	
		Net exporter	*Net importer*	*Net exporter*	*Net importer*
Oil trade share of total export/import	*High*	Russia, Norway		Japan, South Korea	India
	Medium	Canada		Singapore, Thailand	
	Low		Mexico		UK

Note: since the oil trade share of total trade varies from year to year, this matrix is based on the average status of oil share and average idea of trade balance over the years observed (2001-2012).

Table 3

<table>
<tr><td colspan="2" rowspan="2">Matrix for the countries based on attributes of trade balance and oil trade share</td><td colspan="2">Net oil exporters</td><td colspan="2">Net oil importers</td></tr>
<tr><td>Net exporter</td><td>Net importer</td><td>Net exporter</td><td>Net importer</td></tr>
<tr><td rowspan="3">Oil trade share of total export/import</td><td>High</td><td>Russia, Norway*</td><td></td><td>Japan*, South Korea*</td><td>India**</td></tr>
<tr><td>Medium</td><td>Canada*</td><td></td><td>Singapore**, Thailand**</td><td></td></tr>
<tr><td>Low</td><td></td><td>Mexico**</td><td></td><td>UK**</td></tr>
</table>

Note: * indicates the oil price model outperforms the RW benchmarks only for large sample sizes. ** indicates the oil price model failed to outperform the RW benchmarks for all sample sizes. Bold font indicates the VAR model outperforms the RW benchmarks. Italic font indicates the VAR model outperforms the RW benchmarks only for large sample sizes

Figures

Figure 1 (Panel A)

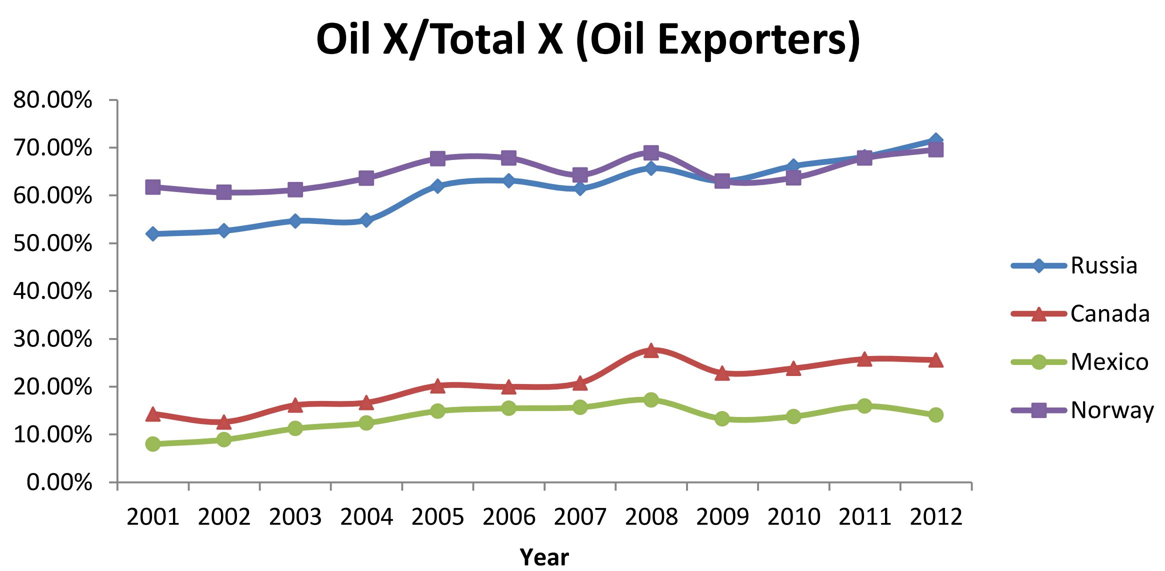

Figure 1 (Panel B)

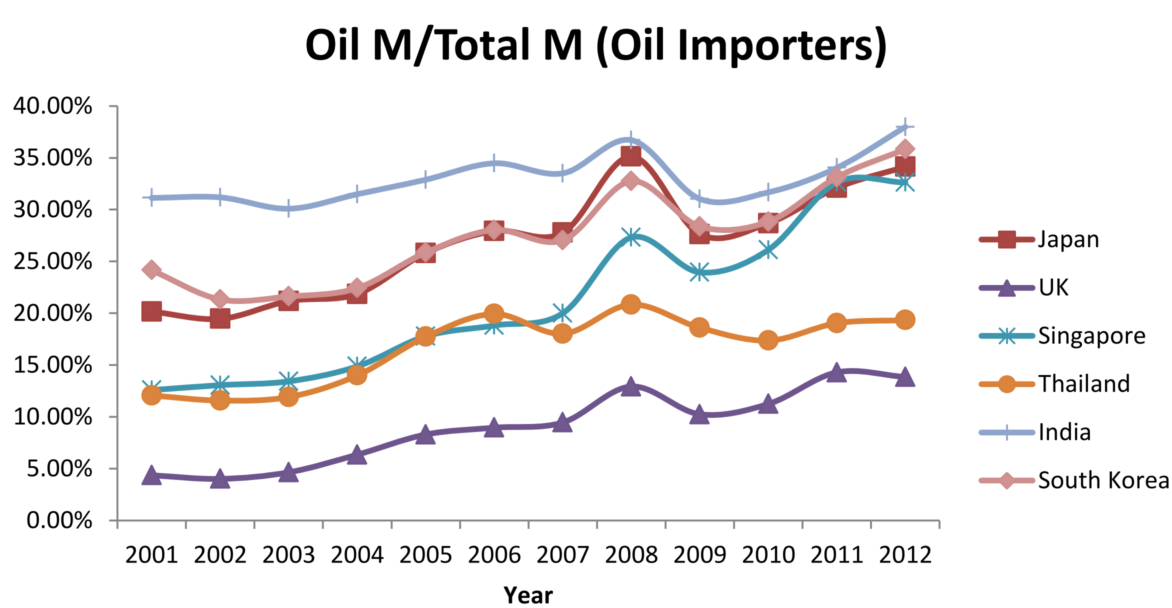

Figure 2 (Panel A)

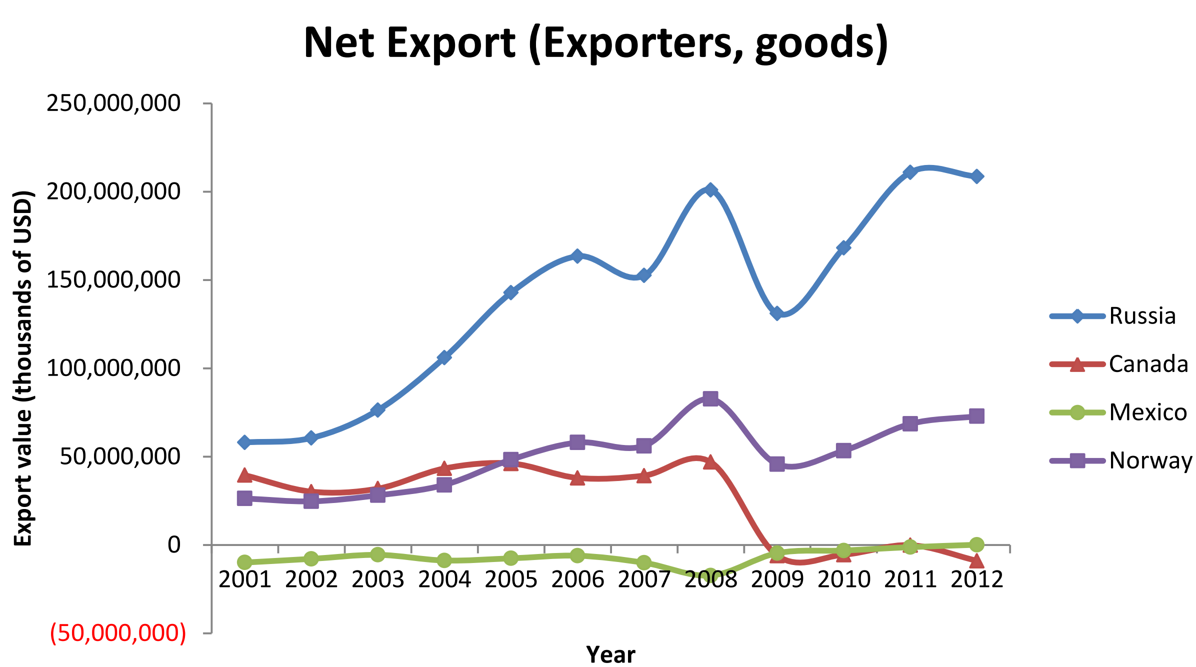

Figure 2 (Panel B)

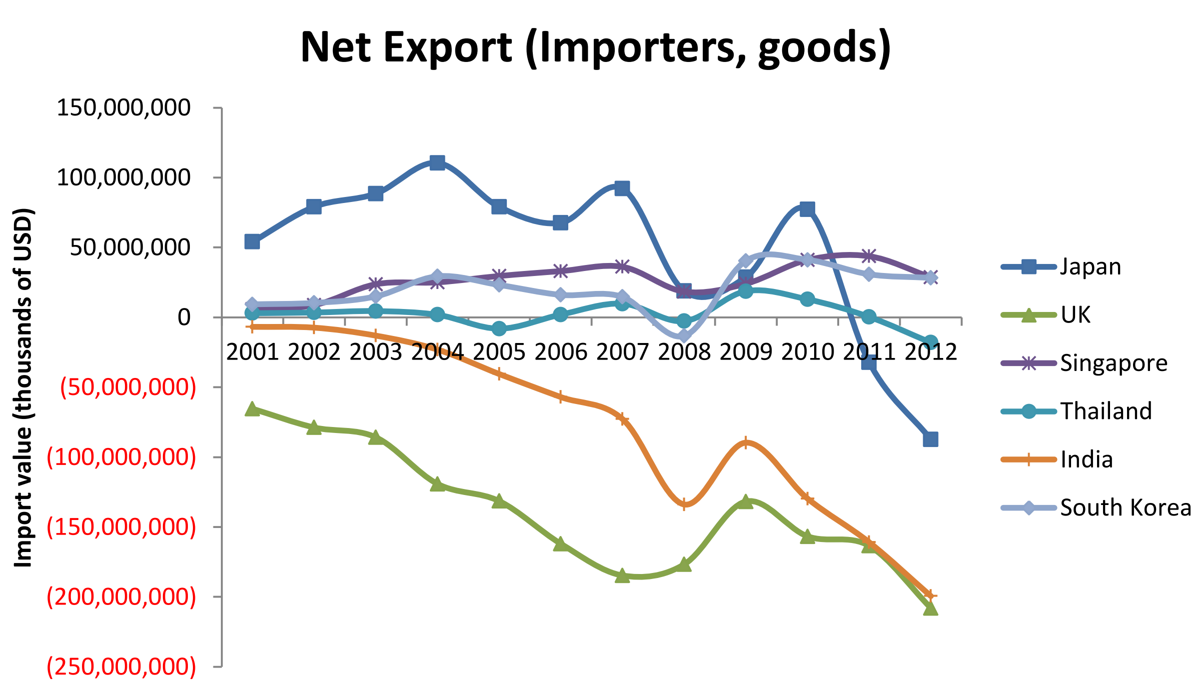

Figure 3 (lagged oil price model, Canada)

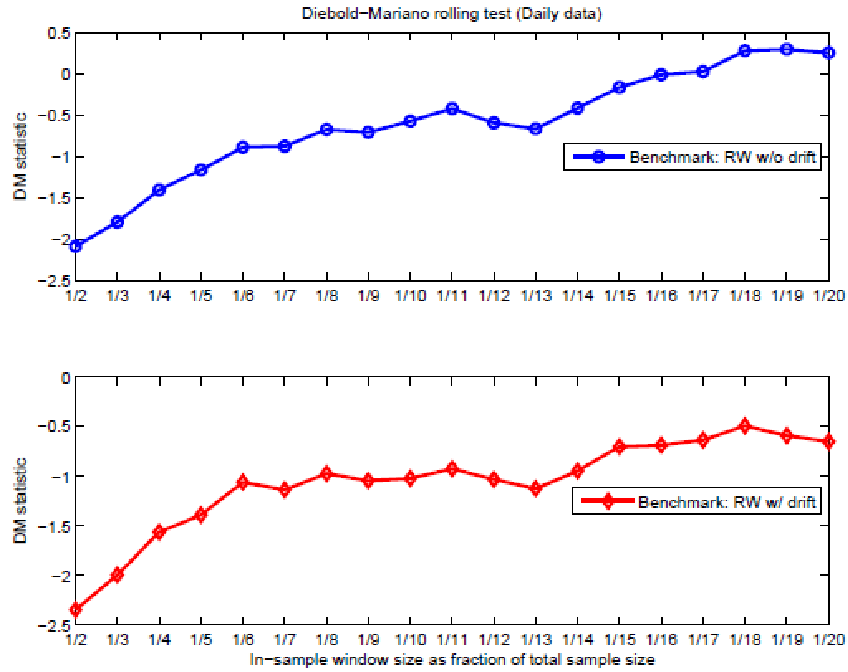

Figure 4 (lagged oil price model, Mexico)

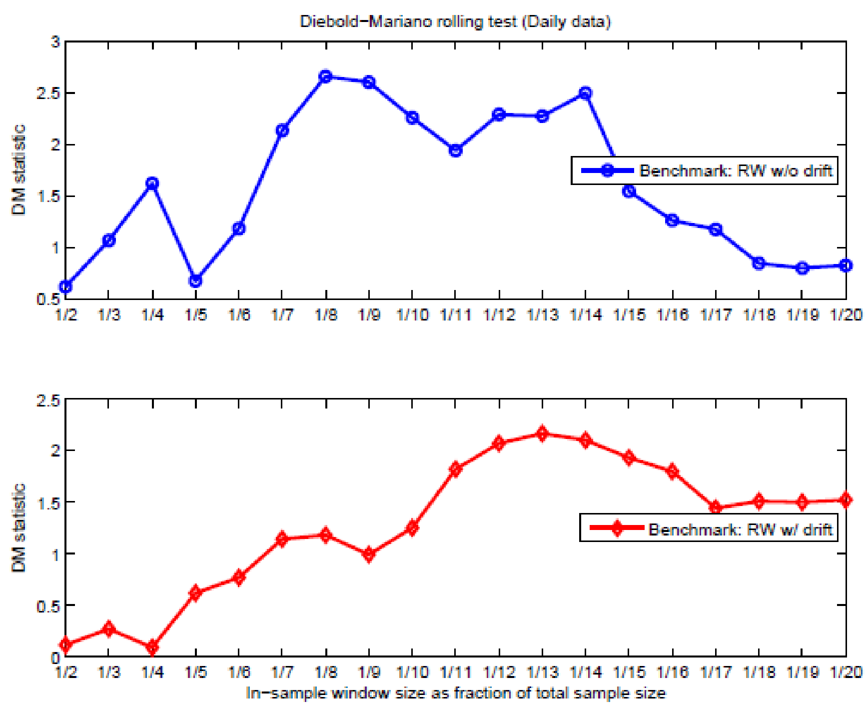

Figure 5 (lagged oil price model, Norway)

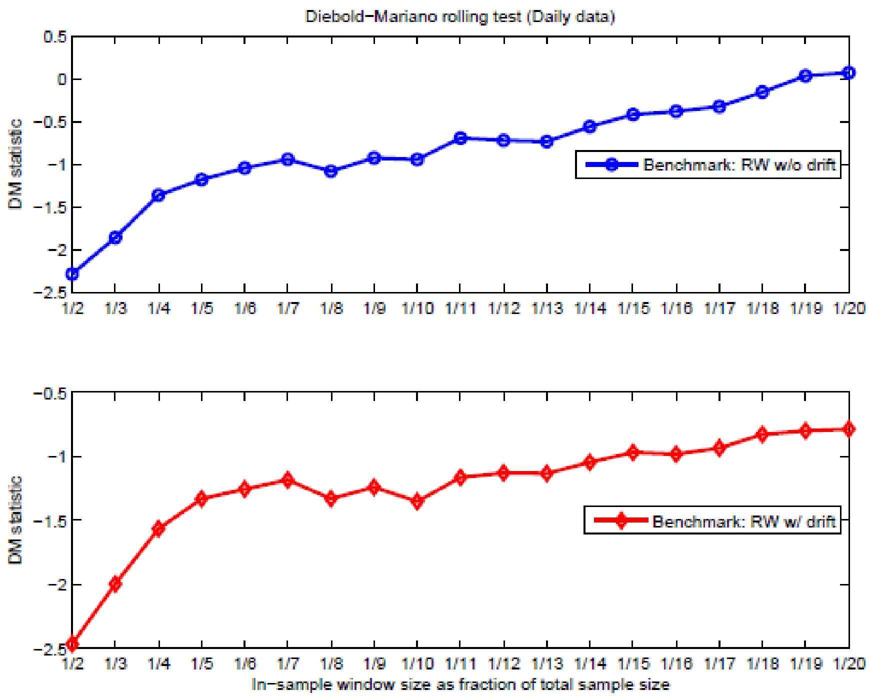

Figure 6 (lagged oil price model, Russia)

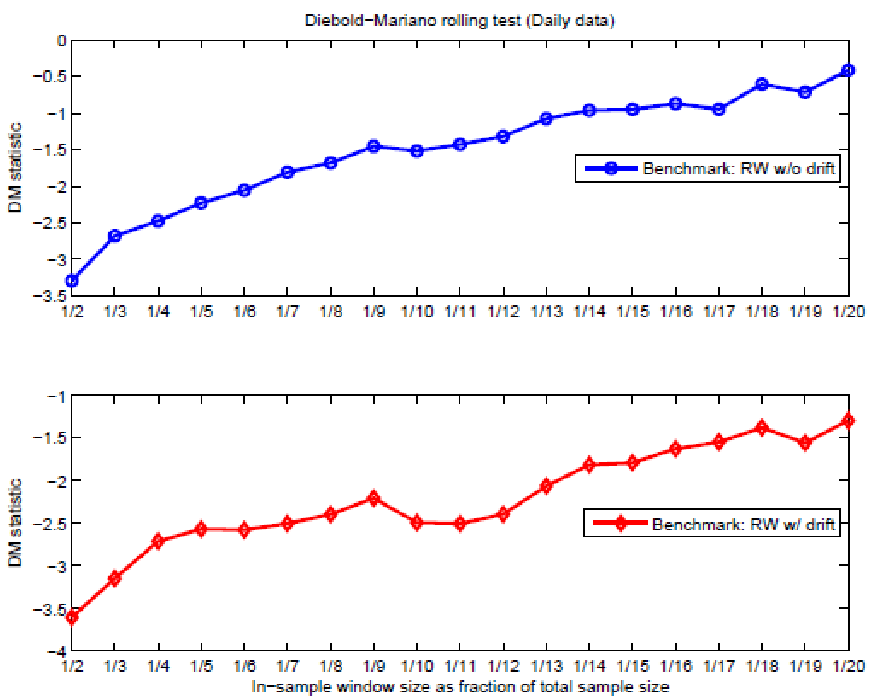

Figure 7 (lagged oil price model, UK)

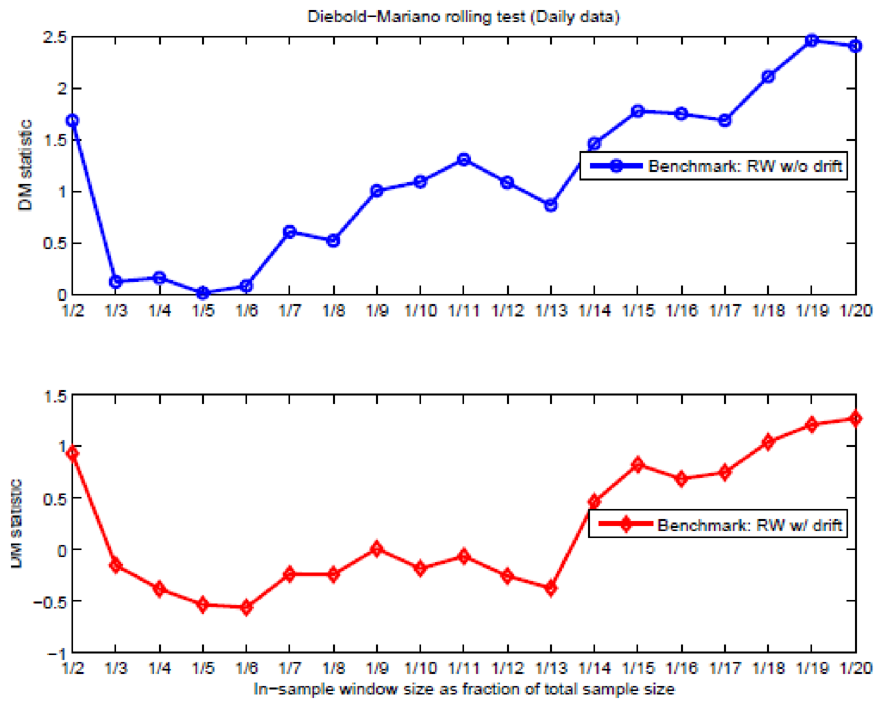

Figure 8 (lagged oil price model, India)

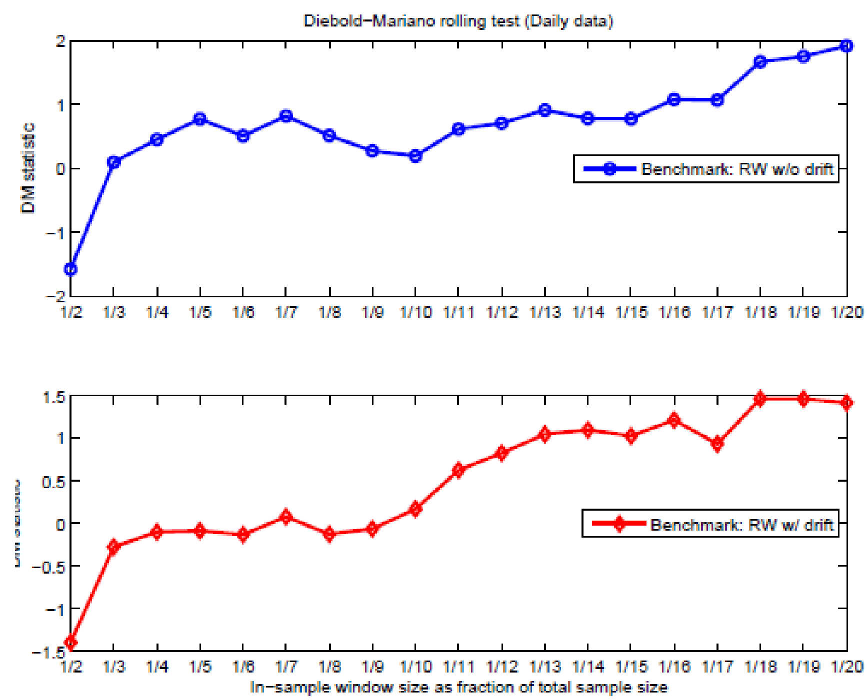

Figure 9 (lagged oil price model, Singapore)

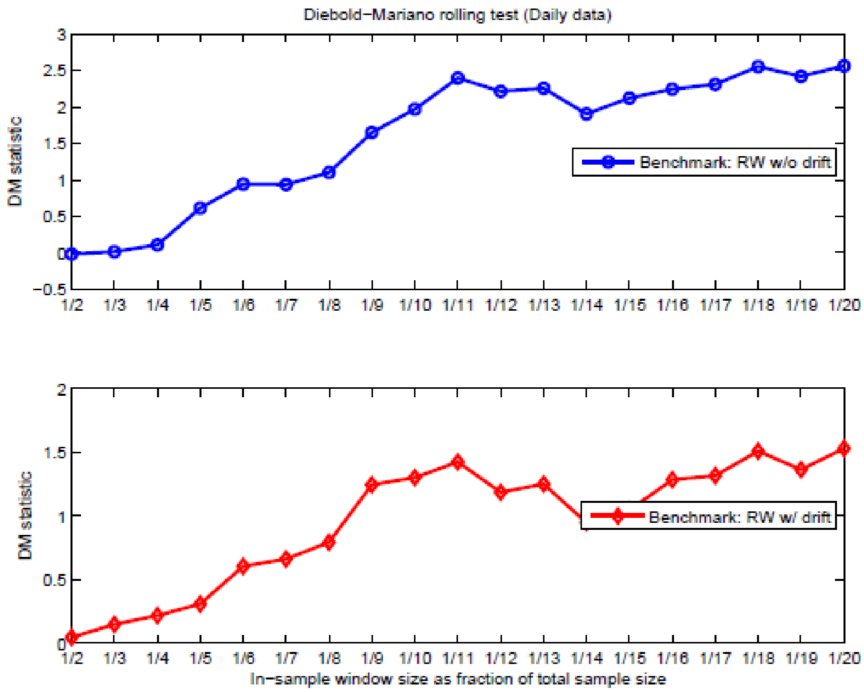

Figure 10 (lagged oil price model, Thailand)

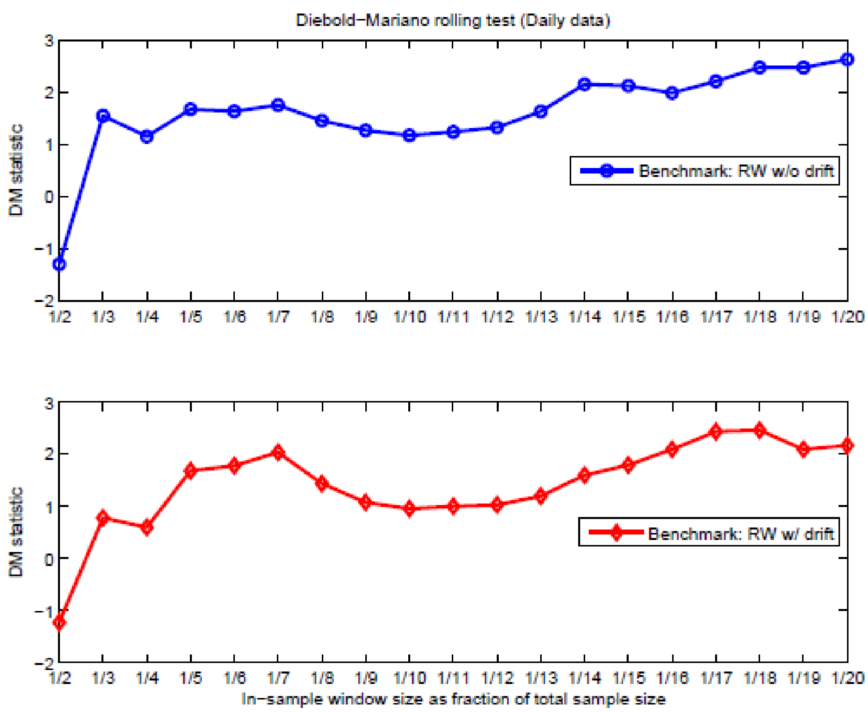

Figure 11 (lagged oil price model, South Korea)

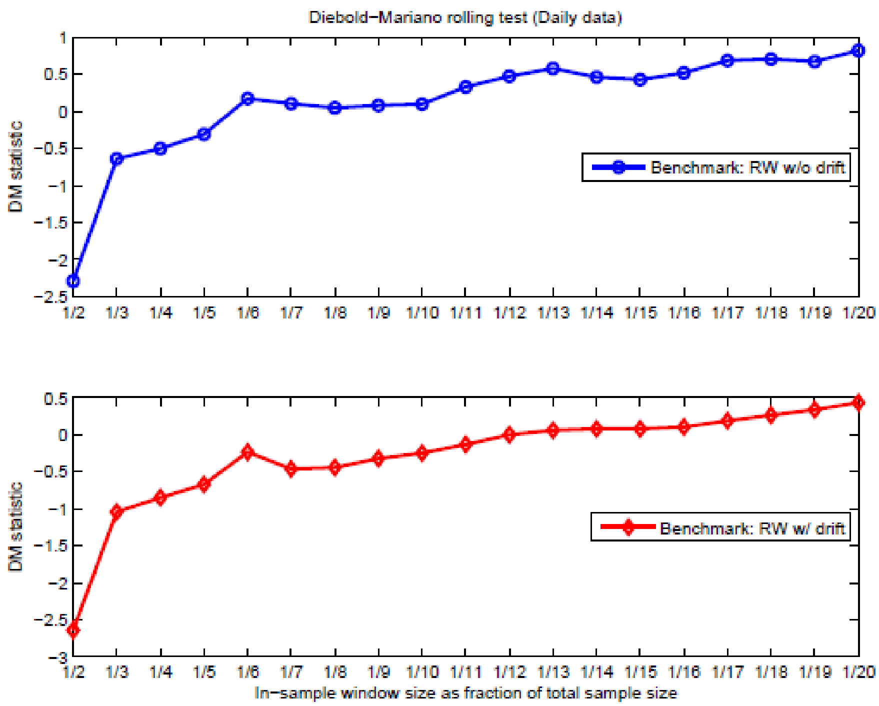

Figure 12 (lagged oil price model, Japan)

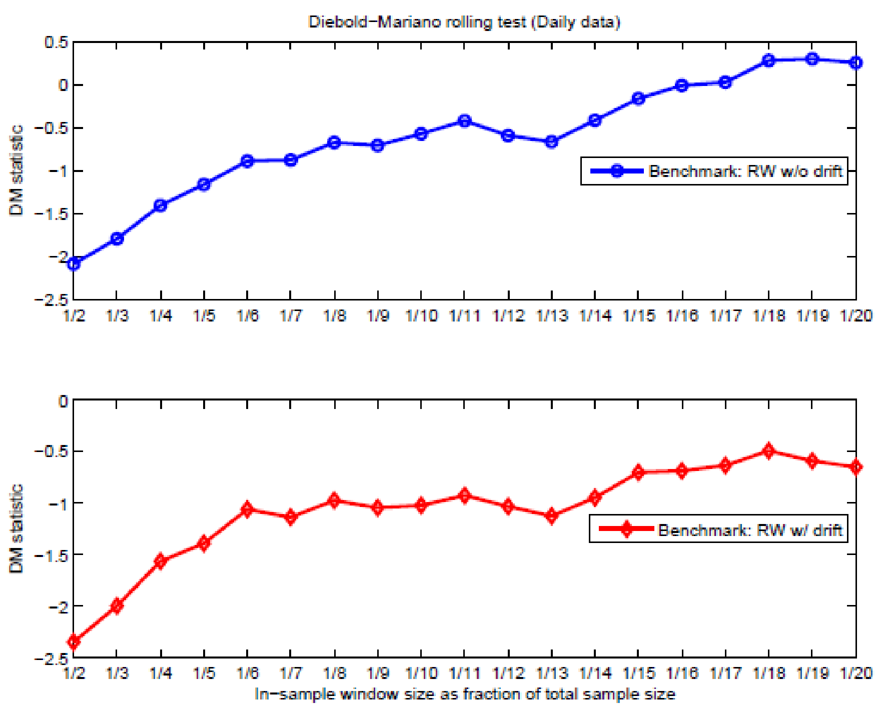

Figure 13 (VAR model, lag 1, Canada)

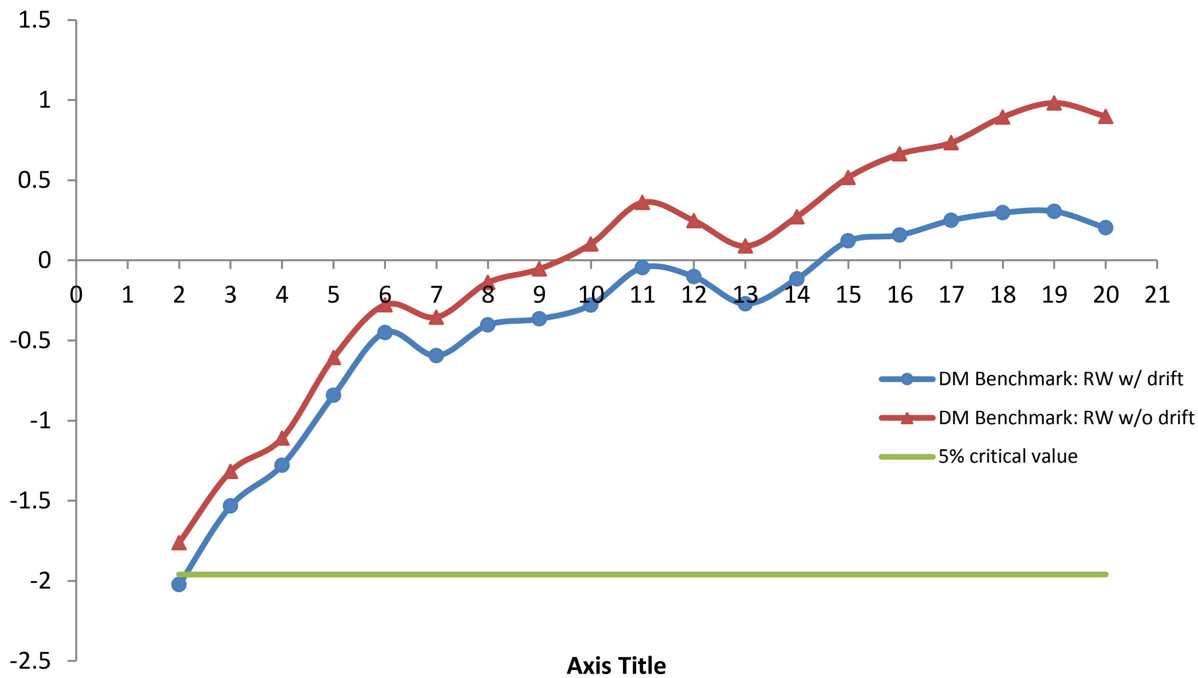

Figure 14 (VAR model, lag 1, Mexico)

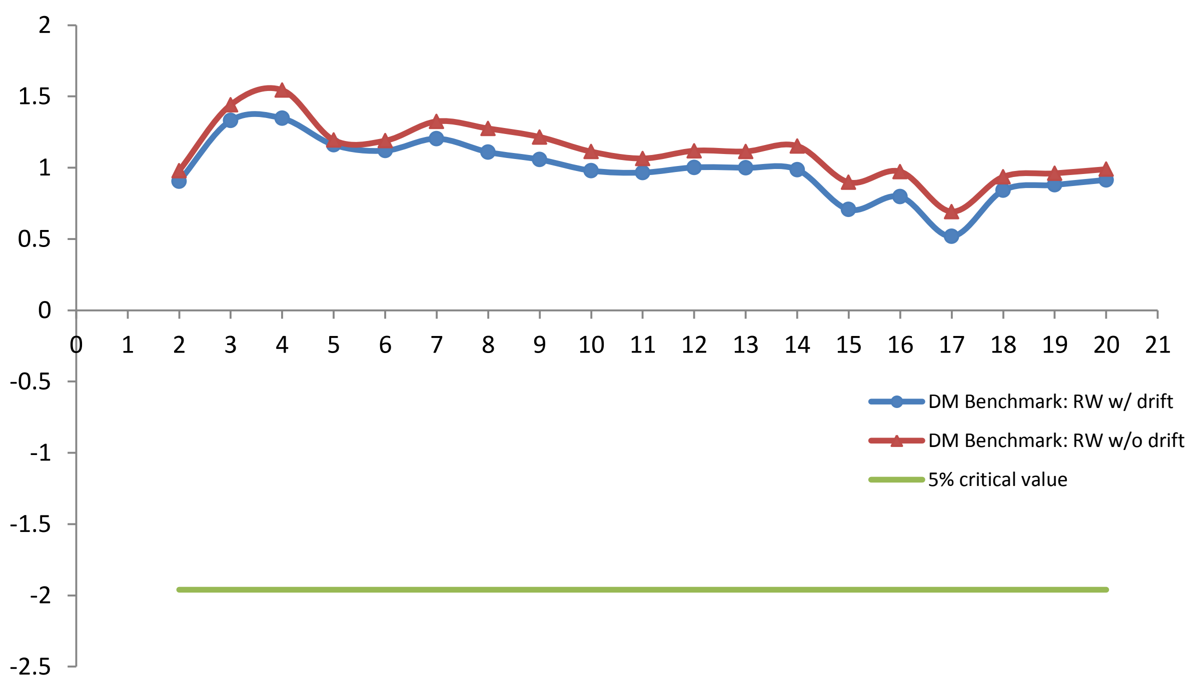

Figure 15 (VAR model, lag 1, Norway)

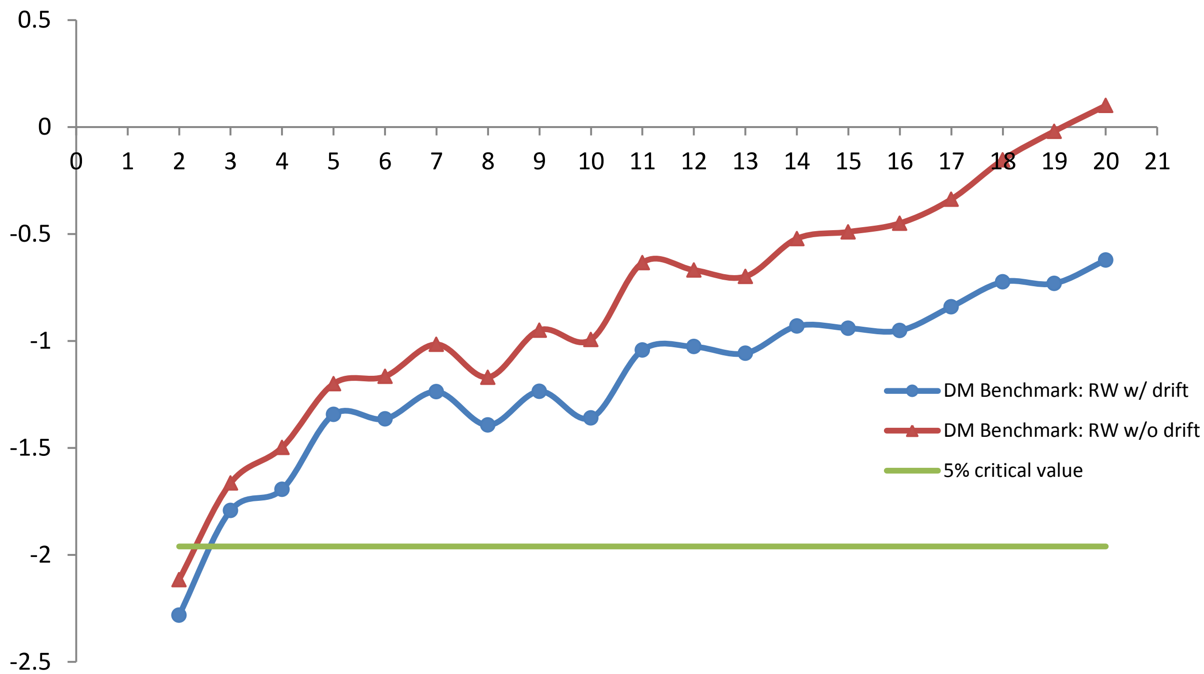

Figure 16 (VAR model, lag 1, Russia)

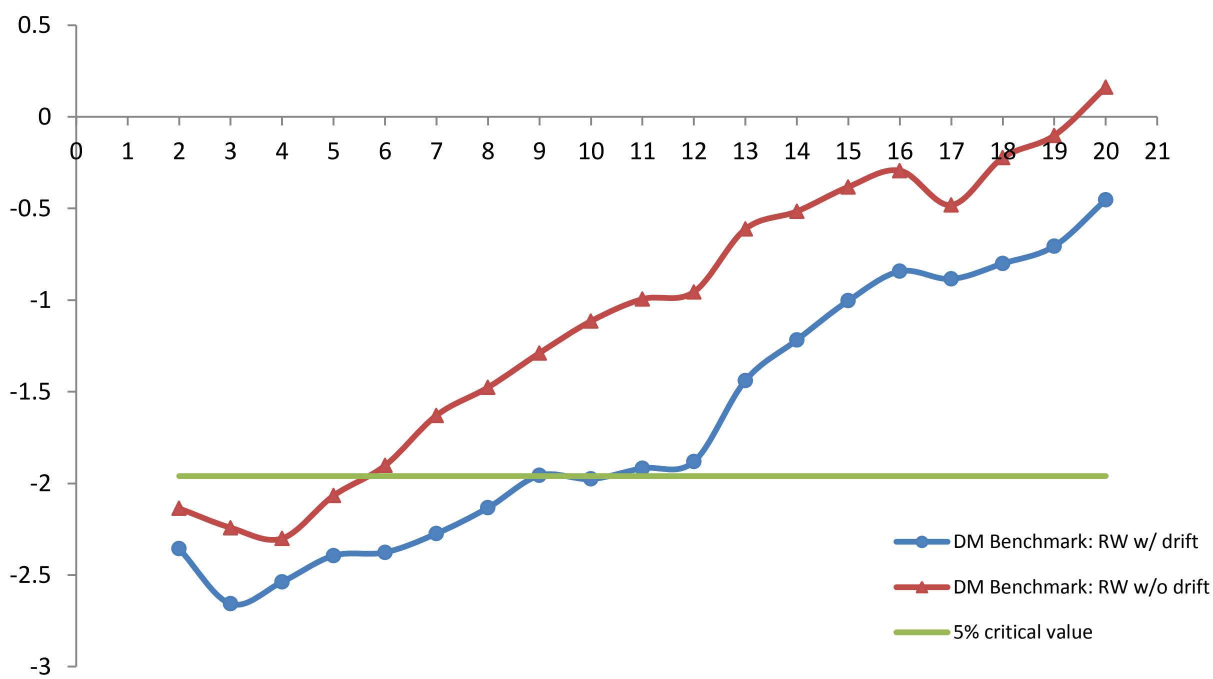

Figure 17 (VAR model, lag 1, UK)

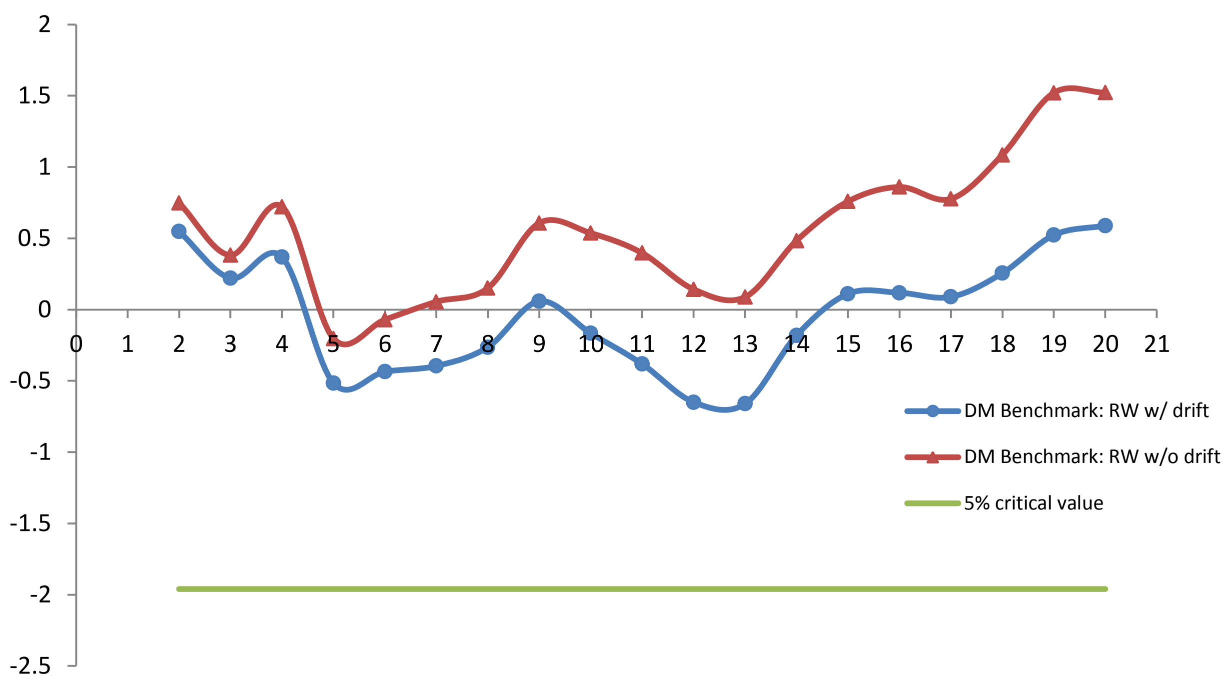

Figure 18 (VAR model, lag 1, India)

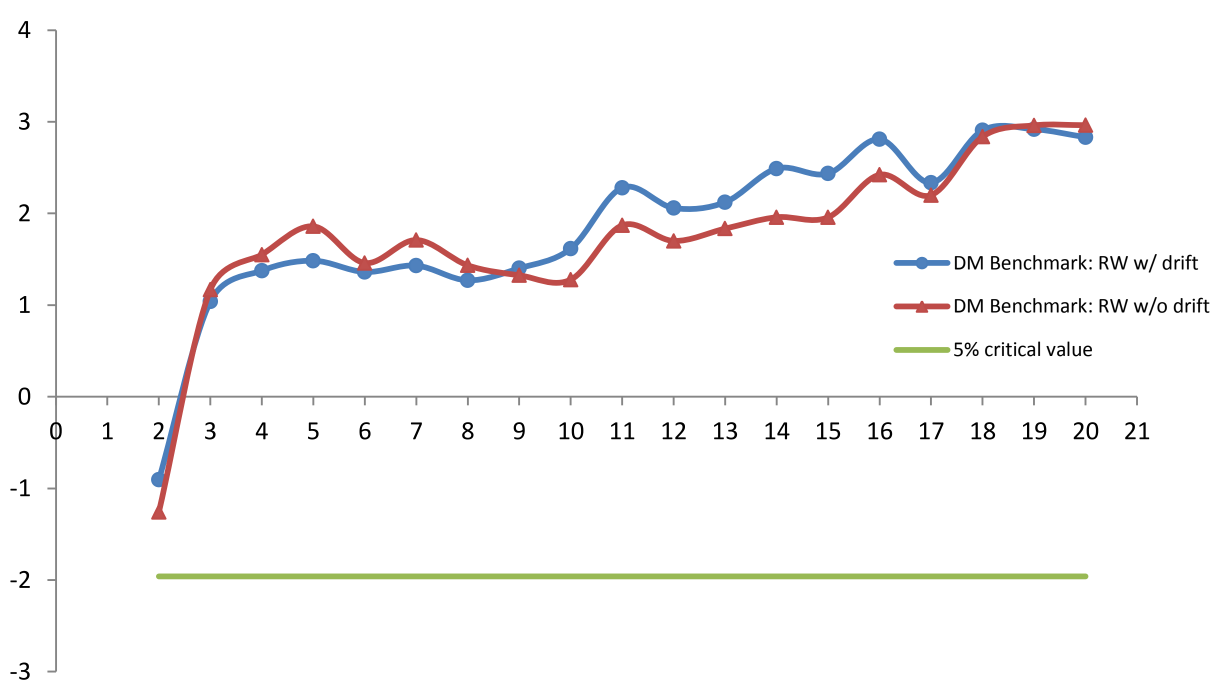

Figure 19 (VAR model, lag 1, South Korea)

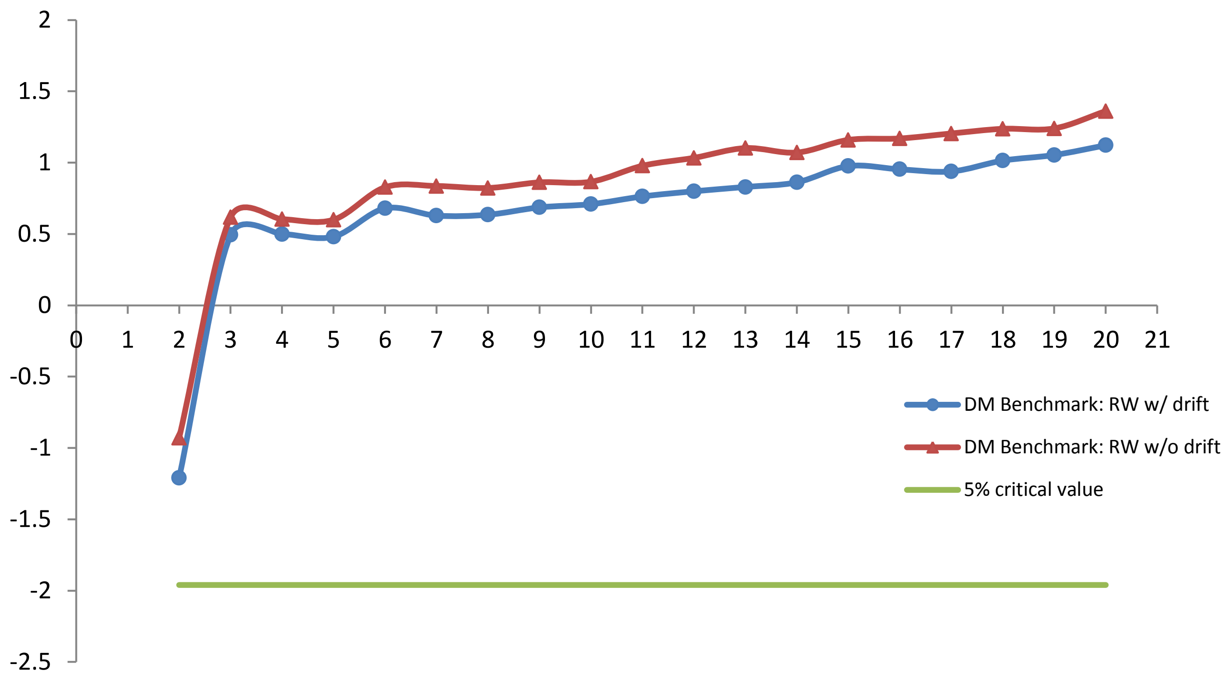

Figure 20 (VAR model, lag 1, Singapore)

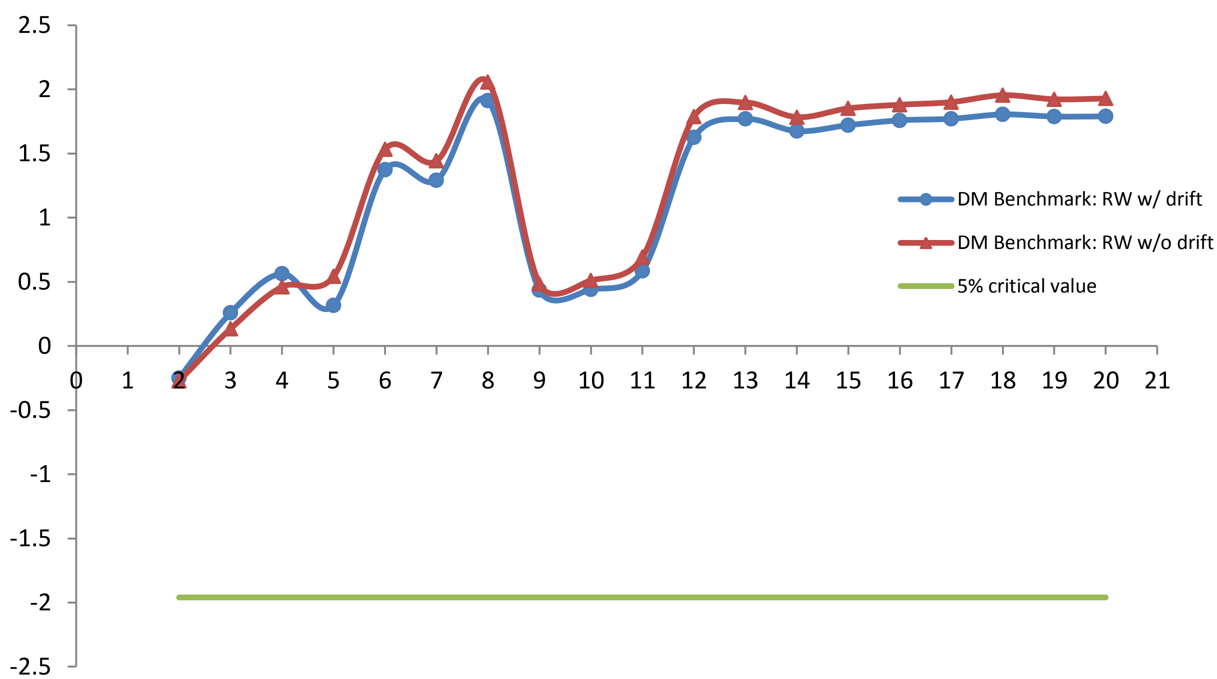

Figure 21 (VAR model, lag 1, Thailand)

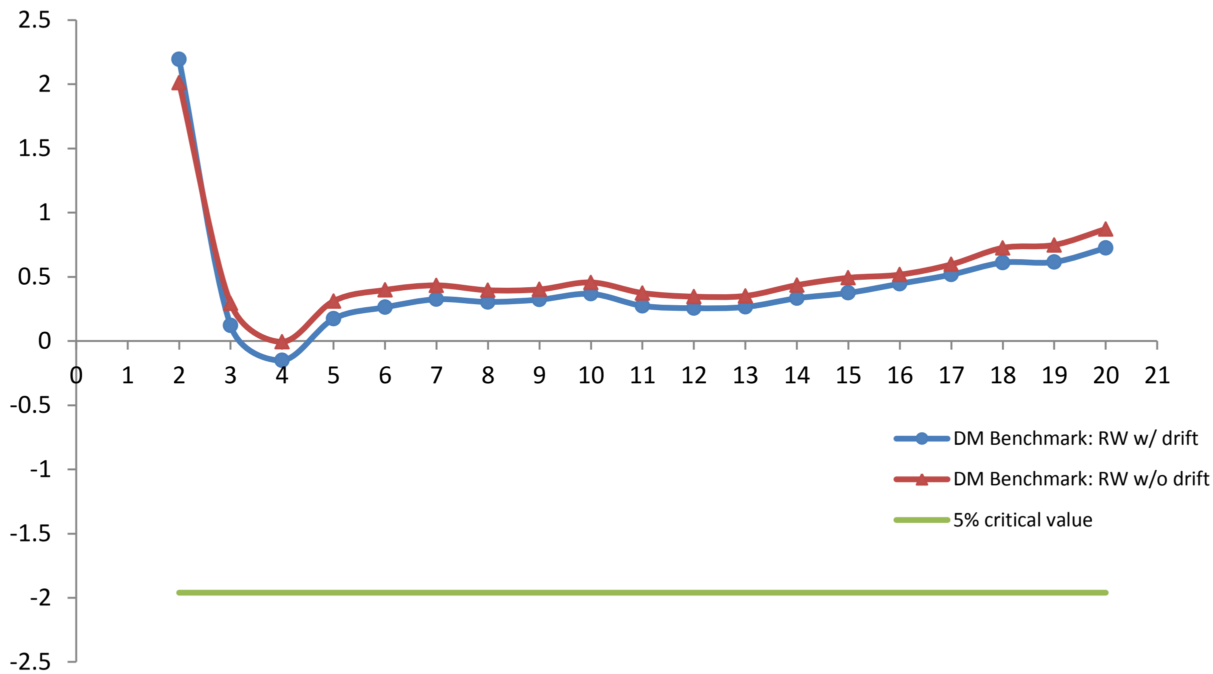

Figure 22 (VAR model, lag 1, Japan)