An Econometric Investigation of Forecasting GDP, Oil Prices, and Relationships among GDP and Energy Sources

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To the soul of my mother
To my husband and my children
for their endless and unconditional love and support

Abstract

In order for a policy to be effective, the links between the policy tools and the subsequent targets must be known, understandable, stable, and predictable. In this respect, this thesis is composed of three separate yet related empirical studies as summarised below, that target some important macroeconomic variables, which play a central role in the conduct of macroeconomic policies.

First, simple regression and factor-based estimates are utilized to produce forecasts for Bahrain quarterly GDP growth in Chapter 2. Using a quarterly dataset from 1995: Q1 to 2008: Q3. The simple regression model is estimated using a small dataset, that includes six explanatory variables. These variables are selected carefully on the basis of in-sample correlation with the target variable. Alternatively, a factor model based on 65 indicators is employed to forecast Bahrain's quarterly GDP growth. Using simulated out-of-sample experiments, the performance of both approaches are asses and compared. The main finding from this forecasting exercise is that the best forecasting performance can be reached using simple regression estimates with a handful of variables. In particular, results of point and density nowcasts show that the simple regression estimates, which uses industrial production as an indicator is more accurate than the static factor approach, which uses 65 variables in the case of Bahrain. Currently, the official flash estimates of Bahrain's quarterly GDP are published with a delay of 90 days after the end of the reference quarter. However, the single simple regression model reduces the lag to 54 days.

Second, as oil price fluctuations have important implications for future inflation and economic growth, the aim of the third chapter in this thesis is to forecast West Texas Intermediate (WTI) crude oil prices using a large monthly dataset, that covers the period from March 1983 to December 2011. To achieve this aim, forecasting with factor models offer a usual approach that utilizes large datasets, however; a forecasting model which simply includes all factors in state space equation and do not allow for time varying may be not suitable with a highly volatile market such as oil market. To overcome these limitations, an approach that accounts both for parameter and model uncertainty is employed. In particular, this chapter uses the Dynamic Model Averaging (DMA) approach suggested by Koop and Korobilis (2012). The key element of the DMA approach is that it allows both for model and parameter to vary at each point of time. By doing so, the DMA is robust to structural breaks. Empirical findings show that DMA approach outperforms any other alternative model used in the forecasting literature. Results also show that there is model but not parameter variation in this oil price forecasting exercise. Finally, the findings suggest that the DMA approach provides a better proxy of expected spot prices than future prices.

Third, Johansen cointegration technique is used to examine the long-run relationship between oil consumption, nuclear energy consumption, oil price and economic growth in Chapter 4. For this purpose, four industrialized countries including: the US, Canada, Japan and France, and four emerging economies: Russia, China, South Korea and India, over the period from 1965 - 2010. The results suggest that there is a long-run relationship between the four variables. Exclusion tests show that at least one energy source enter the cointegration space significantly, which implies that energy has a long-run impact on economic growth. The emerging economies are found to be heavily dependent on both oil and nuclear energy consumption. The causal linkage between the variables is examined through the exogeneity test. The results point that energy consumption (i.e., oil or nuclear) has either a predictive power for economic growth, or a feedback impact between with real GDP growth in all countries. Thus, energy conservation policies might have drawbacks or damaging repercussions on economic growth for this group of countries.

JEL classification: C11, C22, C32, C50, C53, E31, E37, Q40, Q43, Q47

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Chapter 1

Introduction

The study of macroeconomic variables is essential for understanding the function of any economy, especially issues regarding the behaviour of total income, output, employment, and the general price level. Since these variables are statistically measurable, they facilitate the analysis of their effects on economic performance and provide a bird's-eye view of the economic world as well as a strong foundation for formulating useful economic policies. Real macroeconomic policymaking, however, faces the problem of having to assess current economic states with incomplete statistical information. Though important economic indicators such as GDP are published quarterly and with considerable delay, significant uncertainty surrounds indicator estimation and thereby complicates the work of policymakers and business people who, if not in advance, must at least promptly adjust to changes in the underlying economic structure. Therefore, earlier realistic GDP estimates would substantially benefit these and other economic agents.

In this respect, policymakers, the general public, and academics have been interested in producing accurate GDP forecasts. Model builders have exploited recent developments in computation to develop models, both simple and complex, that simulate reality with high degrees of accuracy. Despite a growing need for information to mimic economic relationships, traditional economic (i.e., small-scale) models used for forecasting, such as univariate time series and multivariate models, cannot accommodate more than a few time series, since they typically allow for fewer than ten variables. Furthermore, small-scale models present users with the problem of deciding which variables to include. In practice, forecasters and policymakers often extract information from many series other than those that can be included in a small-scale model. In this set-up, factor models have received the most attention, and perhaps consequently, their use has become widespread. Several studies address this topic, including Stock and Watson (1998, 2002a,b) for the US; Forni et al. (2000), Forni et al. (2003), Marcellino et al. (2003) and Angelini et al. (2010) for the Europe; Artis et al. (2005) for the UK; and Schumacher (2007) for Germany. Exploiting information from large panels, normally, should help to improve forecasts, and early results were very promising in this respect (Stock and Watson, 2002a; Forni et al., 2000). However, more recent applications that use this approach find little-to-no improvement (Schumacher, 2007; Schumacher and Dreger, 2004; Gosselin and Tkacz, 2001; Angelini et al., 2001). These conflicting results have launched lively discussions regarding whether large-scale factor models are really as useful for forecasting practice as first expected (Eickmeier and Ziegler, 2008). At the same time, there is still a high demand for shortened lag in obtaining GDP flash estimates (i.e., a release of whole GDP without any further information regarding the composition of growth). Therefore, intensive research focuses on obtaining early GDP estimates. Currently, the US reports GDP estimates first, often within 25 days of the end of the quarter. However, estimates lag for Europe, as the earliest GDP flash estimates produced by Eurostat are available 45 to 48 days after the quarter's end, due to the slow release of data availability.

To date, the majority of empirical studies of early GDP estimates focus on developed countries, and the results regarding the usefulness of adding more data continue to be mixed. In Chapter 2 of this thesis, we adapt the methodology typically used in developed countries to obtain GDP flash estimates for Bahrain, which witnessed the projection of potential economic wealth in 1932 upon the discovery of oil in the country. In doing so, we also question whether using a larger dataset in a factor model framework produces better forecasts than small-scale models. Such research aims to provide early reliable estimates of GDP growth for Bahrain. In light of the above discussion, as well as previous empirical approaches that show that both timely and reliable GDP estimates are subject to data availability, we adopt simple regression and factor models using two different datasets. The first dataset includes the variable of interest (i.e., the quarterly GDP of Bahrain) with six other explanatory variables, which are components of GDP itself. As Bahrain is an oil exporting country, we include in this study the refined petroleum production index (RPPI), exports (EXPPP), metal price index (MI), oil price index (OILI), consumer price index (CPI), and the broad money aggregate (M3).[1] The second dataset includes 65 macroeconomic variables comprising industrial production, trade variables, monetary aggregates, exchange rates, and prices such as the consumer price index and share price index, among other financial variables. Both datasets span the period from 1995:Q1 to 2008:Q3.

Regression-based estimates derive from selecting a few indicators that are correlated with the target variable but published more promptly. Alternatively, the econometric approach of factor models summarises the information contained in a large set of indicators (in our study, 65 variables) in a small number of unobserved

[1]In the literature, many researchers argue that lagged oil price changes are helpful in forecasting the US real GDP growth (e.g. Bachmeier et al., 2008; Hamilton, 2011b; Ravazzolo and Rothman, 2013). Thus, oil prices are included here to improve the forecast performance for an oil exporting country.

principal components. The approach assumes that co-movements among variables have a common element that can be captured by a few underlying, unobservable variables, as seen in the static principal component model suggested by Stock and Watson (2002a) and the dynamic factor model produced by Forni et al. (2000). In this thesis, we use the static factor model of Stock and Watson (2002a) to nowcast Bahrain's GDP growth.[2]

Out-of-sample forecast simulations are carried out where the performance of models has been compared based on both point and density forecast criteria. The main finding of our out-of-sample forecast investigation is that the simple regression model including only industrial production as an indicator variable outperforms the static factor model of Stock and Watson (2002b), which summarises information from 65 variables. The most accurate flash estimates using the aggregated data are obtained after 84 days, while the official estimates are released after 90 days of the prospective quarter's end. However, using bridge equations for disaggregated industrial production shorten the lag significantly by 36 days.

Recently, empirical studies of GDP forecasts such as that of Kilian and Vigfusson (2013), question whether oil prices have a predictive power to forecast output on the basis of the approved potential links between oil prices and macroeconomic dynamics (Hamilton, 2009b; Kilian and Park, 2009). Several other studies indicate that changes in oil prices might react to or even forecast changes in intercontinental stability and macroeconomic aggregates (see the discussion in, Alquist et al., 2001; Kilian and Lewis, 2011; Kilian and Vigfusson, 2013; Malik and Nasereddin, 2006). However, by reviewing historical data, it is clear that oil prices experience wide price swings in times of either shortage or oversupply. In July 2008, the price of oil reached a record high in both nominal and real terms, with the benchmark of Europe Brent crude reaching \$147/bbl. The price rose steadily from early 2004, but the 18-month period beginning in January 2007 witnessed price surges of more than 150%. The situation subsequently changed dramatically as the price of oil collapsed by more than 75% by the end of the year(i.e., from \$147/bbl in July to \$36/bbl in December 2008) before rallying to roughly \$70/bbl in early June 2009, where the price remained throughout the year. By any measure, this episode is considered one of the greatest shocks to oil prices on record. Such extreme volatility in what is considered the primary source of energy has reopened discussions among researchers

[2] Boivin and Ng (2005) find that the static components serve quite well as predictors for various US time series compared to dynamic factor estimates.

seeking to enhance the understanding of the interaction between oil markets and the global economy (for example see, Kilian, 2013). Not surprisingly, forecasting crude oil prices also has become the focus of many economists and decision makers (Alquist et al., 2001). An accurate forecast of oil prices provides information that plays an important role in policymaking and preparing budget and investment plans for various users, including international organisations, central banks, governments, and a range of industries such as utilities and automobile manufacturers (Baumeister and Kilian, 2013). Hence, in Chapter 3 of this thesis, we contribute to the literature of forecasting oil prices by using a large dataset.

In literature, Hamilton (2009b) uses a small set of indicators and argues that the change in oil prices can be explained by their supply-demand balance by showing that large oil price increases during 2007 and 2008 were due to strong global demand for oil. On the production side, Hamilton (2011a) later avers that the cumulative contribution of shocks to real oil prices is related to a number of factors. For example, a general strike in Venezuela reduced oil production at the end of 2002 and beginning of 2003; later, the US attack on Iraq beginning in March 2003 further reduced oil production. Additional factors contributing to stagnation of oil production from 2002 to 2008 included instability in places such as Iraq and Nigeria and a fall in production in the North Sea and fields in Mexico and Indonesia, as well as that Saudi production was less in 2007 than 2005. During 2011, oil production was disrupted in Libya as well as in several Middle-Eastern countries that faced political turmoil. Hamilton (2009a,b) also shows that strong growth in demand for oil from new industrialised countries and the failure of global production to increase such production has triggered commodity speculation, which has made slightly decreased production an attractive option for Saudi Arabia.

By using a large dataset, Zagaglia (2010) alternatively argues that if oil futures contracts contain information about spot prices, then omitting futures prices would bias the view that oil prices are driven by demand and supply factors. In his study, Zagaglia (2010) employs a factor augmented vector autoregressive model (FARVAR) showing that financial variables include valuable information beyond that of demand and supply factors. Though the details of the above papers differ, the general framework involves the use of regression-based methods.

Recursive regression-based methods are criticized by (Koop and Korobilis, 2012) for three chief reasons. First, the coefficients on the predictors can change over time. More broadly, a significant amount of literature in macroeconomics documents structural breaks and other sorts of parameter change given many time-series variables (see Stock and Watson, 1996, among many others). Recursive methods are too poorly designed to capture such parameter change; instead, it is better to build models (i.e., with time-varying parameters) designed to capture it. Second, the number of potential predictors can be large and thus result in a huge number of models. If the set of models is defined by whether each of m potential predictors is included or excluded, then the researcher has 2^m forecasting models. This dynamic issues substantial statistical problems for model selection strategies. Third, the model relevant for forecasting can potentially change over time. Structural changes concerning the monetary and fiscal policies pursued by policymakers will affect the significance of potential predictors. For instance, some variables may predict output well during recessions but not during expansions; at the same time, the set of predictors for oil price may be different across periods of price booms and busts. In an application, Pesaran and Timmermann (2000) document how regressors that are useful for explaining stock returns change over time; this and other similar arguments suggest that the forecasting model changes over time.

All issues addressed by Koop and Korobilis (2011, 2012), who were the first applied a forecasting strategy called dynamic model averaging (DMA) in areas of economic research.[3] The DMA approach allows for the best forecasting model to change over time while parameters are simultaneously allowed to change. Their approach can also be used for dynamic model selection (DMS), in which a single (potentially different) model can be selected as the best forecasting model at each point in time. DMA or DMS seems ideal for the problem of forecasting oil price since either allows the forecasting model to change over time while at once allowing for coefficients in each model to evolve over time. These models involve only standard econometric methods for state space models, such as the Kalman filter but via empirically sensible approximations achieve vast gains in computational efficiency. Although Koop and Korobilis (2011, 2012) show that the DMA approach outperforms standard econometric models used to forecast macroeconomic and financial variables, this approach has not been employed to forecast oil prices. Here, this chapter contributes to the literature of forecasting oil prices by adopting the DMA and DMS approaches. We use a large dataset that embodies 147 time-series

[3]For a complete discussion on DMA, see Raftery et al. (2010).

variables, which are meant to capture the macroeconomic, financial, and geographic forces that drive oil prices. To the best of our knowledge, Zagaglia (2010) is the only study that exploits information from a large dataset to forecast oil prices. The empirical results can be summarised in two findings. First, results suggest that the forecast generated by the DMA/DMS approach outperforms all other alternative models. Second, findings illustrate that the number of predictors clearly varies across the out-of-sample forecasting period.

In reality, oil is not only of the greatest value among traded primary commodities, which makes it of interest to exporters and importers alike (Bacon, 1991); it is also a key primary energy source.[4] It is often argued that no other fuel can compete with oil in many of its uses in terms of price and convenience. Demand for oil comes mostly from developed and rapidly growing developing countries, such as the US, EU countries, Japan, China, and India. As countries develop, factors such as industrialisation, rapid urbanisation, and higher living standards drive up energy use, most often of oil. World demand for oil has recently grown faster than ever as the economies of China (6.5 mb/d) and India (2.3 mb/d) have grown by 10% annually, while the US continues to be the largest consumer. Since 2002, China's oil consumption has grown by 8% yearly, and by 2020, India's oil imports are expected to reach more than triple from 2005 levels and rise to 5 million barrels per day (IEA, 2006). Along with the growth in demand speed and volume, the structure of any country's oil consumption is important. This is so, because the impact of oil price volatility on an economy depends on how fast and cheap the economy can shift to alternative energy sources. The key difference between oil and other commodities used in the production process is that oil can have either positive or negative impact on growth.[5]

Given that energy plays a crucial role in the economic growth and development in both developed and developing countries, many studies examine the impact of energy consumption on such growth. Since the seminal contribution of Kraft and Kraft (1978), a considerable body of literature has investigated the short and long-term causal relationships between energy consumption and economic growth during the past three decades. Recent studies employ models that include at least three

[4] On the production side, oil is an essential input into the production of most goods and services. While most companies do not consume crude oil, they do consume petroleum products such as gasoline, heating oil, and jet fuel, all of which are made from crude oil. Moreover, the prices of these petroleum products closely move in line with the price of oil (Henriques and Sadorsky, 2011).

[5] Moroney (1992) argues that energy is a very important factor of production, as revealed by the oil crises in the 1970s and 1980s. Thus, the impact of energy on GDP is more than just a minor GDP expenditure.

variables to circumvent the shortcomings of bivariate analysis. Though bivariate analysis has its merits, it is more likely to suffer from the problem of omitted variable(s), which may conceal information on additional causal channels among system variables (see Ghali and El-Sakka, 2004; Oh and Lee, 2004; Stern, 1993, 2000, among others). Other studies add variables to their analysis, though through a demand-side specification with the inclusion of consumer or energy prices; in this case, representative studies include Asafu-Adjaye (2000), Belke et al. (2011), Hondroyiannis et al. (2002) and Masih and Masih (1997). However, the energy consumption variables utilized by existing literature are total energy consumption or electricity consumption (Lee and Chang, 2008; Ozturk, 2010; Payne, 2010b; Wolde-Rufael, 2009). Although two thirds of the world's total energy consumption depends on crude oil, yet relatively few studies address the relationship between oil consumption and economic growth (e.g. Yuan et al., 2008; Zou and Chau, 2006).[6] Furthermore, most studies ignore the impact of the interaction between this credible energy source with other energy sources and energy prices on economic growth.[7]

Currently, several concerns are associated with fossil fuels (e.g., coal, oil, gas) and their related technologies.[8] For oil, concerns include supply security, geopolitical sensitivity, price volatility, water pollution from off-shore installations and tanker accidents, soil contamination in processing plants, emissions of substances contributing to acid deposition (e.g., SO_x and NO_x) and to total climate change (CO_2), and the spectre of depletion (for a discussion of the relationship between energy and the environment, see Holdren and Smith, 2000). All of these issues have made the diversification of energy sources and finding a stable, safe, and clean energy supply a top priority in energy policymaking for many countries (Elliott, 2007; Toth and Rogner, 2006). As part of their strategies to increase energy security, many countries have built nuclear power plants to not only reduce the dependence on imported oil but also to increase the supply of a secure energy source and to

[6] For more details see Payne (2010b,a), who provides a thorough survey of the literature concerning energy consumption-economic growth and electricity consumption-economic growth.

[7] In an attempt to use different energy sources instead of total energy consumption, Yuan et al. (2008) employ cointegration analysis and a vector error-correction model for China for the period from 1963 to 2005 and use both aggregate total energy consumption and disaggregated series (i.e., coal, oil, and electricity consumption). As a result, they find evidence of unidirectional causality from electricity and oil consumption to real GDP, but not from total energy to GDP.

[8] Fossil fuels such as coal, oil, and gas currently provide 85% of the world's energy needs, and fossil-fuelled economic growth is the main factor for global warming given its release of carbon dioxide (CO2) into the atmosphere.

minimise the price volatility associated with oil imports (Toth and Rogner, 2006).[9] It is worth noting that the US Energy Information Administration's (EIA) reports on the world's primary energy consumption for the period from 1985 and 2011 have shown that the recent considerable growth of electrical consumption worldwide requires a massive use of nuclear energy.[10] In 2010, demands for nuclear energy and renewable energy increased due to the limitations of fossil fuels (de Almeida and Silva, 2009). The importance of nuclear power as a potential source of energy and as a partial replacement for fossil fuels to eliminate emission has therefore highlighted the need for further research that examines the relationship between nuclear energy consumption and economic growth (Apergis and Payne, 2010b). It is thus essential to understand the nature of this relationship and to identify the direction of causation, so that business people can provide logical reasons for investing in nuclear energy, that at once attend to economic, environmental, and social concerns (Chu and Chang, 2012).

To date, few empirical studies have focused on investigating the causal relationships between oil consumption and economic growth, on the one hand, and between nuclear energy consumption and economic growth on the other (Aktaş and Yılmaz, 2008; Yang, 2000; Yoo and Jung, 2005; Yoo and Ku, 2009; Zou and Chau, 2006; Zhao et al., 2008). At the same time, there is a dearth of empirical research that investigates the long-term relationships among oil consumption, nuclear energy consumption, oil prices, and economic growth by using modern advances in time-series econometrics associated with causality testing. Therefore, Chapter 4 of this thesis aims to investigate the long-term relationships among oil consumption, nuclear energy consumption, oil prices, and economic growth by using Johansen cointegration technique in a parsimonious vector equilibrium correction model (PVECM). In particular, we run our investigation among four industrialised countries: the US, Canada, Japan, and France, and four emerging economies: Russia, China, South Korea, and India, during the period from 1965 to 2010. This exercise provides information about the long-run relationship and the direction of linkage among the proposed variables by employing conventional time-series datasets. Each country has been examined separately to allow the use of a framework that accounts for country-specific issues, such as energy patterns and economic crises. The main

[9]One reason for reduced Japanese oil consumption during the period from 1979 to 1985 was the construction of several nuclear plants to generate electricity, which led to the substitution of crude and fuel oil and thereby caused a drop in demand of around 1.2 mb/d for the whole period (OPEC's World Oil Outlook, 2012).

[10]See http://www.eiagov/forecasts/steo/

reason for studying long-term relationships among oil consumption, nuclear energy consumption, and economic growth is that both oil and nuclear energy play important roles in designing effective energy policies, that account for economic growth, environmental protection, and sustainable development. The empirical results of the relationships among nuclear energy, oil market, and real GDP also play pivotal roles in the implementation of energy or environmental policies for both highly industrialised and emerging economies.

The results obtained illustrate that cointegration occurs in which at least one energy input cannot be excluded from the cointegrated space for each country model. This finding implies that a long-term relationship exists between energy consumption and economic growth. Insofar as the results of cointegration vectors are normalised with regard to real GDP growth, the coefficients of oil consumption are found to affect the level of economic growth significantly and positively in six of eight countries: the US, Canada, France, China, South Korea, and India. This finding implies that a greater use of oil stimulates real GDP growth. Alternatively, nuclear energy consumption is shown to influence economic growth positively and significantly in Japan, France, Russia, China, and South Korea. However, results show that nuclear energy consumption is negatively linked to real GDP growth in India. Though oil prices are excluded from the cointegration space in most countries, they have a significant negatively impact on economic growth in the cases of Canada and Russia. Also, results from PVECM show that oil consumption has a predictive power for economic growth in the US, Japan, France, and India. Additionally, there is feedback impact between oil consumption and real GDP growth in Canada, Russia, China, and South Korea, where oil can be considered a limiting factor to output growth. Regarding the nexus between nuclear energy consumption and growth, a bidirectional relationship emerged between nuclear energy consumption and output growth in Japan and India. Moreover, nuclear energy consumption is found to reveal information that could predict real GDP growth in the US, Canada, France, Russia, China, and South Korea. In most cases, oil prices are exogenous to economic growth models, except for the US, Canada, and China.

Structurally, this thesis contains five chapters. Chapter 2 includes estimates and forecasts for Bahrain's quarterly GDP growth by using simple regression and factor-based models. Therein, we assess and compare the performance of simple regression estimates, which exploit the information available for selected indicator variables, with that of factor-based estimates, which use 65 variables to obtain new factors embodying most of the potential information and treat it systematically by following the Stock-Watson approach. Subsequently, Chapter 3 forecasts crude oil prices by using a large dataset and DMA approach. Particularly, in this chapter, an approach that accounts for the presence of structural breaks in the series, as well as parameter and model uncertainty is employed. Chapter 4 then analyses the long-term relationships among oil consumption, nuclear energy consumption, oil prices, and economic growth by using the Johansen cointegration technique. In this chapter, empirical investigates for the long-term relationships among the suggested variables are provided for four industrialised countries and four emerging economies. Lastly, Chapter 5 gives an overall conclusion for this thesis. This chapter presents a summary for the significant findings and also gives some interesting areas to which new research can be directed.

Chapter 2

Estimating and Forecasting Bahrain Quarterly GDP Growth Using Simple regression and Factor-based methods

2.1 Introduction

Comprehensive research and investigations to achieve a clear understanding of the state of macroeconomic activity are important to policy makers. However, Gross Domestic Product (i.e., GDP) data, the broadest measure of economic activity, are published with a considerable delay after the end of the reference quarter. Earlier realistic estimates of GDP are recommended and would be of considerable benefit, because of the significant impact of GDP on the entire system of the national account. In fact, GDP is not only a summary measure used to assess the national well-being in a quantified manner, but it also plays an important role in the framing of governments and businesses' plans for the future.

To nowcast or forecast GDP, forecasters need to take into account a large amount of information, which arrives sequentially. Thus, new information becomes available continuously throughout the quarter and the nowcasts and forecasts may be adjusted in response to these changes. A part of the recent literature discusses the issue of the amount of information that is necessary to obtain robust GDP estimates. The answer seems to be mitigated (see Marcellino et al. (2003), Bernanke and Boivin (2003), Forni et al. (2009), Boivin and Ng (2006), and D'Agostino and Giannone (2012) for deep discussions on this problem).

In the context of growing data availability, recently, several approaches to tackle the above issues and exploit information from large datasets for forecasting have been developed. Within such an approach, factor models have received the most attention and their use has become widespread. Several studies have been made in this line of research, including (Stock and Watson, 1998, 2002a,b) for the US, Forni et al. (2000), Forni et al. (2003), Marcellino et al. (2003) and Angelini et al. (2010) for the Euro-area, Artis et al. (2005) for the UK, and Schumacher (2007) for Germany. Exploiting information from large panels, normally, should help to improve forecasts, and early results were very promising in this respect (Stock and Watson, 2002a; Forni et al., 2000). However, more recent applications of this approach find no or only minor improvements (Schumacher, 2007; Schumacher and Dreger, 2004; Gosselin and Tkacz, 2001; Angelini et al., 2001). These conflicting results have launched a lively discussion on whether large-scale factor models are really as useful for forecasting practice as first expected (Eickmeier and Ziegler, 2008). Also, there is still high demand to shorten the lag of obtaining flash estimates of GDP. Therefore, intensive research has been focused on obtaining early estimates of GDP. Currently, the US obtains a first estimate of GDP within 25 days after the end of the quarter. However, it lags much more for the Euro-area, as the earliest flash estimates produced by Eurostat for GDP growth are available in 45-48 days. This lag in the earliest estimates is subject to the availability of the related data that might help to produce these estimates.

To date, the majority of empirical studies on early estimates of GDP have focused on developed countries, where comparing models with different dimensions to evaluate the usefulness of adding more data, are still mixed. Hence, this chapter adapt the methodology used in developed countries to obtain flash estimates for the Kingdom of Bahrain.[11]Also, the present work questions whether the use of a larger data set in a factor model framework leads to better empirical results than smaller-scaled models.

Bahrain, as a pioneer of oil and metal producer in the Arabian Gulf region, witnessed the projection of potential economic wealth in 1932 with the discovery of oil. The dependency on oil products, crude oil and refined petroleum products has since been increasing day by day. Although oil exports have contributed significantly to achieving higher levels of GDP over the past few decades, their share of the growth of Bahrain's GDP has been gradually decreasing due to the volatile nature of oil prices. As a result, export base products were diversified into non oil products such as petrochemicals and aluminium whose share in GDP growth has progressively increased. In spite of diversifying sources of GDP, the rates of GDP growth have showed wide fluctuations over the period of the last ten to fifteen years. There are three main industries within manufacturing that make up to 74% of the output (at current prices) from 2001 to 2008. Although their proportions have changed dramatically, these industries are still the major components of Bahrain's GDP. Refined petroleum production is at the top of the major factors that make up the manufacturing output with 32%. Metals including aluminium constitute the second most important factor with a proportion of 22%, while the third is chemicals production which represents 20% of the total manufacturing output. In addition, the financial sector accounts for nearly 21% of Bahrain's economy (Bahrain Development Board, report released 2010), which has grown at 4.5 % in the last quarter of 2010.

The Central Information Organization of Bahrain (CIO) collects the key macroe-

[11]See Appendix (A) for more information about Bahrain's economic structure.

conomic variables including the value added in GDP at low frequency, typically on a quarterly basis, and releases the information with a substantial lag of 90 days after the closing of the prospective quarter. However, other variables that have a direct effect on the GDP level, such as trade and industrial production, are available on a monthly basis and are published within 84 days after the end of the concerned month.[12]

The aim of this chapter is to shorten the lag period and provide early reliable estimates of GDP using different models, and to find whether using large data-rich models improves the forecast performance or not in the case of the Kingdom of Bahrain. In the light of the above discussion and the previous empirical approaches, which show that both timely and reliable GDP estimates are subject to availability of information, we adopt simple regression and factor- based models using two different datasets.[13] The first data set comprises the variable of interest which is quarterly GDP for the Kingdom of Bahrain with six other explanatory variables including refined petroleum production index (RPPI), exports (EXPPP), metal price index (MI), oil price index (OILI), consumer price index (CPI), and broad money aggregate (M3).[14] The second dataset includes 65 macroeconomic variables including industrial production, trade variables, prices such as consumer price index and share price index, monetary aggregates, exchange rates and other financial variables. Both datasets cover the period between 1995:Q1 - 2008:Q3.

More concretely, regression-based estimates depend on the selection of a few indicators which are correlated with the target variable but are published more promptly than the target variable. Typically, these variables are components of the GDP itself such as industrial production, trade, or, at least proxies of these components based on, for example, qualitative surveys. Moreover, they are commonly available at a monthly frequency. The quarterly aggregates of these indicator variables, give their trending nature in (log) levels are then converted to stationary variables (if they are non-stationary) and related to quarterly GDP via linear regression. Simple regression estimates of quarterly GDP are then derived based on using in-sample estimated coefficients and contemporaneous values of the indicator variables, which

[12] Table (2-B.1) and Table (2-B.2) present the available data for the key macroeconomic indicators from year 1995 to 2008.

[13] Mazzi et al. (2009) assess the ability of both regression and factor-based approaches to nowcast the Euro-area quarterly GDP growth. The performance of the different statistical nowcasting models varies considerably according to which statistical model is used.

[14] Variables are selected based on in-sample correlation with the dependent variable. For more details, see data section.

by their nature are published ahead of the GDP. Under the importance of predicting earlier and reliable estimates of GDP due to its significant role in policy making, the main objective ought to avoid systematic forecasting errors arising from deterministic shifts. In the literature, a variety of methods have been suggested. For instance, intercept corrections, differencing, co-breaking, regime switching models, etc., for improving forecasting accuracies. Thus, we have augmented the simple linear equation with the intercept correction model as suggested by Clements and Hendry (1996). The intercept correction model (IC) offers a possible solution to deterministic shifts, as it adjusts an equation's constant term when forecasting using the residual obtained from previous periods, which could be informative about short-term forecast error. These features seem to be descriptive of operational economic forecasting, and provide a rationale for using intercept corrections to correct forecasting inaccuracy and improve the forecasts of econometric models as proposed by Clements and Hendry (1996). Due to the fact that hard monthly indicators, such as trade and industrial production, are published at 84 days after the end of the entire month concerned, we construct forecasts at 84 and 54 days after the end of the quarter. To achieve this improvement in timeliness, we use bridge equation (BE) model for GDP growth in Bahrain to bridge the gap between the information content of timely updated indicators and the delayed. Inclusion of specific explanatory indicators in the BE is not based on any causal relationship, but on the simple statistical fact that they embody timely updated information about the dependent variable (Baffigi et al., 2004).

Alternatively, the econometric approach of factor models summarises the information held in a large set of indicators (65 variables in our case) in a small number of unobserved principal components. It assumes that the co-movements among variables have a common element that can be captured by a few underlying, unobservable variables, as seen in the static principal component model promoted by Stock and Watson (2002a) and the dynamic factor model produced by Forni et al. (2000). The static factor model is based on the principal components of the variance-covariance matrix of a large data set of indicators, whereas the dynamic factor model is based on a principal component as computed by the inverse fourier transform of the estimated spectrum of a large data set. Although the development of more sophisticated dynamic models is favorable from a theoretical point of view, Boivin and Ng (2005) have shown recently that the factor model based on static principal components is quite robust to misspecification since fewer auxiliary parameters have to be specified compared with dynamic factor models. In their simulation and empirical applications for the US, Boivin and Ng (2005) find that the static principal components serve quite well as predictors for various US time series, compared with dynamic factor estimates. Therefore, in this paper, the static factor model proposed by Stock and Watson (2002b) has been utilized to summarise the available large data set into a small number of unobserved common factors in the first step of the approach. Then in the second step, these factors are used to predict the variable of interest, which is the GDP growth in our case.

To test robustness of models and compare simple regression models with static factor models, out-of-sample forecast simulations are carried out where the performance of models has been compared based on both point and density forecast criteria. The main finding of our out-of-sample forecast investigation is that the simple regression model including only industrial production as an indicator variable outperforms the static factor model of Stock and Watson (2002b), which summarizes information from 65 variables.

The remainder of the chapter is organized as follows. Section 2.2 provides a brief summary of the empirical literature, Section 2.3 presents the econometric methodology, Section 2.4 evaluate the forecast performance, and Section 2.5 discusses the data, empirical results. Finally, Section 2.6 concludes the chapter. More details on Bahrain's economic structure and on the utilised data-set are presented in Appendix A and Appendix B.

2.2 Literature Review

The standard small-scale models for practical short term macroeconomic forecasting comprise: the univariate models, low order VAR models and simple regression models. Starting from the growing use of linear autoregressive in this field, Sims (1980) has proposed the linear VAR model to forecast US macroeconomic variables. Although this approach has initially provided a reasonable results, the main disadvantage of VAR models is the problem of over parametrization with too many free insignificant parameters, even in small-size systems. In consequence of this over parameterizations, unrestricted VAR models might provide quite poor out-of-sample forecasts, even though within sample fitting is good. To cope with these problems, Litterman (1986) and others develop a new technique called Bayesian vector autoregression (BVAR) which aims at reducing VAR's parameters and accordingly allows the problem of over-fitting to be circumvented.[15] Alternatively, Engle and Granger (1987) propose the vector error correction model (VECM) that tackles the presence of long-run relationship between macroeconomic variables. Using US data, They find that the nominal GNP and M2 are cointegrated. Engle and Yoo (1987) examine the behavior of forecasts made from a co-integrated system. They argue that the two-step estimator proposed by Engle and Granger (1987) can be used to model the error correction structure and achieve a multi-step forecast gains. Gupta (2006) examines the extensions in forecasting models using South Africa data. The investigation focuses on forecasting a number of key macroeconomic variables including GDP, consumption, investment, short and long term interest rates, and the CPI. He concludes that the out-of-sample forecasts performance obtained from Bayesian vector error correction (BVECM) model outperform those which has been obtained from classical VAR and VECM.

The development of methods for forecasting GDP has enlarged first to capture the non-linearity. Many studies in the spirit of non-linear framework have examined the forecasting ability of non-linear modules such that of Markov switching (MS) (Hamilton, 1989) and self-exciting threshold autoregressive (SETAR) models (Clements and Smith, 1997). For example, Clements and Krolzig (1998) compare the performance of both MS and SETAR models in forecasting post war US GNP. They find that although both models are superior to linear models in capturing certain business cycle features, they are less convincing in forecasting exercise.

Although the above approaches show plausible results in forecasting GDP using aggregated data, they are less efficient in nowcasting exercise.[16] This is so because nowcasting is subjected to the availability of data within the entire quarter. Many nowcasting studies tend to use the total quarterly aggregates of monthly variables to generate short-term predictions of GDP. For example, Trehan (1992) updates a simple model for using contemporaneous and aggregated monthly data to predict quarterly real GDP for the US.[17]

[15] For detailed discussion on BVAR applications, see for example Sims and Zha (1998) and Kadiyala and Karlsson (1997).

[16] The projection that provides estimates of current GDP using all current information is called 'nowcast' in Giacomini and White (2006).

[17] Trehan (1992) uses only three variables out of sixteen to predict US GDP, namely real retail sales, industrial production and non agriculture employment. The selected indicators are available earlier within the quarter in comparison to the other variables.

However, an early picture of current economic activity is highly demanded regardless the aggregation of the full data. This can be done by combining various forecasts from different point of views through bridge equations (BE), which use incomplete data of the prospective quarter.[18] BE involves using the information available for the first two months and forecasting the last month in the quarter. Then this combination is used to achieve earlier prediction of the variable of interest such as output. Rathjens and Robins (1993), Ingenito and Trehan (1996) and Robertson and Tallman (1999) provide useful examples using US data, and efficiently deal with the new monthly information that becomes available within the quarter. Using UK data, GDP growth has been forecasted from bridge equations using a small set of selected monthly indicators, notably measures of production and sales (for example, see Diron, 2008). Mitchell et al. (2005) focus on the construction of a monthly indicator of UK GDP and the way it can be combined with short-term forecasting methods to produce an estimate of quarterly GDP growth. They examine the efficiency of their method and indicate that the outcomes are rather satisfactory. Another successful example is proposed by Baffigi et al. (2004), who shows that BE models are superior in nowcasting Euro-area GDP.

Yet, the above studies focus on forecasting economic activity by employing a few number of economic indicators selected on the basis of economic theories or/and statistical data selection process. This reveals that important information could be missed in the omitted variables (Marcellino et al., 2003).[19] Alternatively, Burns and Mitchell (1946) suggest that business cycle phenomena is characterized by simultaneous co-movement in many economic activities. Hence, the idea of modeling a large number of economic variables using a small number of factors has been employed in many economic analysis and forecasting exercise. This notation has been formally modeled by Sargent and Sims (1977), and then applied by many researchers. However, early applications of factor models have been restricted to use relatively small panels of time series to determine the common factors.[20] For example, Stock and Watson (1992) estimate a state-space model with an unobserved factor using

[18] A number of short-term indicators, such as business or consumer surveys or the industrial production indexes, which are released at monthly frequency can be used without being fully aggregated for the current quarter.

[19] Marcellino et al. (2003) discuss the uncertainty of the best approach of forecasting. They examine several time series methods for forecasting four Euro-area variables: real GDP, industrial production, inflation and the unemployment rate. They also propose that the small scale VAR model could miss important information in the omitted variables, which is said to be included in the error term.

[20] For more details, see Geweke (1977), Sargent and Sims (1977), Stock and Watson (1992), Camba-Mendez et al. (2001).

four variables. Computational difficulties make it necessary to abandon information on many series even though they are available. Hence, the inclusion of a broader data set is hardly possible in these approaches. More recent, Stock and Watson (2002a,b) develop the features of static factor model to accommodate the use of a larger dataset. In an application on the US data, Stock and Watson (2002b) static factors are estimated by static principal components (PC) of the sample covariance matrix. Then the forecast of the common component is simply the projection of the variables on the factors. Using 215 predictors in simulated real time from 1970 to 1998, the factor model of Stock and Watson (2002b) (SW) shows that there is a clear improvements in forecast performance. This has been extended later to more general dynamic factor models (DFM) in Bernanke and Boivin (2003) and Forni et al. (2000) (FHLR). They find that their approach can provide a substantial improvement in contrast to Stock and Watson (2002b) model. Although both static and dynamic factor models differ primarily in methodology used to estimate the factors, they are broadly accepted and implemented by various institutions. For example, the Center for Economic Policy Research (CEPR) coincident indicator of the euro-business cycle (EUROCOIN) is based on FHLR, while the Federal Reserve Bank of Chicago's Activity Index (CFNAI) as well as the model of Kitchen and Monaco (2003) at the US Treasury are based on SW. However, Boivin and Ng (2005) have shown that the factor model based on static principal components (SW) method outperforms the FHLR. They conclude that the dynamic restrictions implied by the latter method are harmful for the forecast accuracy of the model.

Empirically, gains in forecasts performance from factor models have been examined by a number of researchers. On the one hand, many studies such as those of Forni et al. (2001), Giannone and Matheson (2007), Stock and Watson (1989, 1992, 1999, 2002b,a) provide evidence of improvements in the forecasting performances of macroeconomic variables. On the other hand, some studies such as that of Angelini et al. (2001), Gosselin and Tkacz (2001) and Schumacher (2007) find only minor or no improvements in forecasting ability. Particularly, Angelini et al. (2001) discuss Stock and Watson (1998) technique for the Euro-area using a multi-country data set and a broad array of variables, in order to test the inflation forecasting performance of extracted factors at the aggregate Euro-area level. They find that the nominal phenomena in the original variables might be well-captured in-sample using the factor approach. Out-of-sample tests have a more ambiguous interpretation, as factors seem to be good leading indicators of inflation, but the comparative advantage of the factors is less clear. Nevertheless, alternative indicators such as unemployment or money growth do not outperform them. In another example, Banerjee et al. (2005) compare static factor and single indicator forecasts for Euro area inflation and GDP growth using not only Euro-area series but also US macroeconomic variables. Banerjee et al. (2005) suggest that the small models forecast macroeconomic variables better than large factor-based models. Using German economy data, Schumacher and Dreger (2004) examine the usefulness of a large-scale factor model using a data set of 121 time series. Principal component analysis has been implemented to determine the factors, which enter a dynamic model for Germany GDP. The model is compared with alternative univariate and multivariate models. These models are based on regression techniques and considerably smaller data sets. Out-of-sample forecasts show that the prediction errors of the factor model are smaller than the errors of the rival models. However, these advantages are not statistically significant, as a test for equal forecast accuracy shows. Therefore, the efficiency gains of using a large data set with this kind of factor models seem to be limited. These conflicting results have led to a fascinating debate as to whether or not the victory claimed by the proponents of large models was premature.

Some researchers attribute the success of large models to the different circumstances. For example, Banerjee et al. (2005) find that the performance of factor models differ between countries. Factor models are comparatively good at forecasting real variables in the US relative to the Europe, while the euro area nominal variables are easier to predict than the US nominal variables, using factor models. Furthermore, Boivin and Ng (2006) claim that the composition of the data set and the dimensions of the cross-section are important in producing better forecasts from factor models. They show that extending a data set not necessarily improves the forecasting performance if the additional series are noisy or unrelated to the target variable.

To date, the majority of empirical studies that attempt to obtain earlier flash estimates of GDP, and compare models (with different dimensions of datasets) to evaluate the usefulness of adding more data target the developed countries. Minor attention has been given to construct investigations on the usefulness of small and large scale models based on developing countries. In an attempt to do so, Gupta and Kabundi (2010) use both small and large-scale models, including DFM to construct a comparison for the forecasting ability of the models in predicting four key macroeconomic variables for the South African economy. The results indicate that data-rich models such as DFMs or large-scale BVARs, are better suited in forecasting key macroeconomic variables relative to small-scale models involving only the few variables of interest.[21]

Hence, this chapter aims not only to shorten the lag period in GDP estimates, it questions whether using large data-rich models leads to better empirical results than smaller scaled models in the case of Kingdom of Bahrain. Accordingly, we focus on both small and large-scale models to obtain Bahrain quarterly GDP growth. An application could be interesting, because large-scale factor-models have recently been successfully applied to forecast US and some Euro area macroeconomic variables as discussed above. To our knowledge, this is the first application of large-scale factor models to a very small open economy such as Bahrain. We follow the recent literature and investigate the gains of predictive accuracy when using a large number of macroeconomic time series, that provide an exhaustive description of the Bahrain economy. The broad data set is used to estimate the factor model, and to forecast Bahrain GDP.

2.3 Econometric Methodology

This section provides a brief description of the two main models used to forecast Bahrain's GDP growth, namely, the regression-based model and factor model.

2.3.1 Regression-based Approach

The modelling framework requires only a one-period-ahead forecast. The regression-based model is an automatic approach, which generates a large number of models that can be encompassed by a general model given by:

$$\Delta y_t = c + \sum_{i=1}^{p} \alpha_i \Delta y_{t-i} + \sum_{i=0}^{p} \sum_{j=1}^{k} \beta_i x_{t-i,j} + u_t \qquad (1)$$

Where, t=1, 2, ...T, y_t is the log of Bahrain GDP, $x_{t,j}$ is the jth indicator variable ($j = 1, 2, ...k$) in logs, c is an intercept, p is the number of lags, Δ is the first difference operator and u_t is a mean zero disturbance with variance σ^2. It is worth

[21] Gupta and Kabundi (2011) is an interesting paper that use large factor models for forecasting macroeconomic variables for the South African economy.

noting that equation (1) includes contemporaneous values of x_j. This is so because indicators x_j are published more timely than the target variable y.[22]

We employ a procedure for k indicators (total number of indicators in dataset) with p lags each, as follows: a study of $q = k(p+1)+p$ indicators (i.e. considering the lags of each variable in data-set as a potential indicator), constructs $M = \Sigma_{i=1}^{s} \frac{q!}{(q-i)!i!}$ possible models, where s is the maximum number of indicators. Thus, in our case for $s = 3$ (i.e. combination of three indicator variables) and $p = 4$, we compute 1,159 models.[23] At each time we estimate recursively Equation (1) for all possible models and the preferred model is selected by using the Bayesian Information Criterion (BIC). Then we use this model, and its estimated coefficients, and the time $t+1$ values of the explanatory variables in the preferred model to compute recursive out of sample forecast for Bahrain quarterly GDP growth recursively from 2003:Q4 to 2008:Q3 (i.e. Δy_{t+1}). This process is repeated by recursively adding one time period at a time.

Then, equation (1) is augmented with the intercept correction model as suggested by Clements and Hendry (1996). The intercept correction model (IC) offers a possible solution to deterministic shifts, as it adjusts an equation's constant term when forecasting using the residual obtained from previous periods, which could be informative about short-term forecast error. Clements and Hendry (1996) formally established that when the GDP is susceptible to structural breaks, forecasts made in ignorance of any such changes that have taken place recently can be improved by ICs, which reflect, and so offset, deterministic shifts that would otherwise swamp useful information from causal factors.

To attain improvement in timeliness, literature uses a strategy that has been employed to forecast quarterly aggregates of monthly indicators based on VAR models such as Camba-Mendez et al. (2001). Another strategy, which is indeed familiar to statistical offices, considers estimation of GDP growth when at least for some indicators there may be an incomplete set of within-quarter information, perhaps only two months of published data are available and the final month in the quarter must then be forecasted. This approach has been considered in many studies for the US (e.g., Rathjens and Robins, 1993) and for the Euro-area (see Baffigi et al., 2004;

[22] All indicator variables x_j that enter equation (1), if necessary, are differenced until stationary.
[23] The number of lags p has been selected based on Akaike and Bayesian Information Criterion, AIC and BIC, respectively.

Rünstler and Sédillot, 2003; Sédillot and Pain, 2003). Rünstler and Sédillot (2003) and Sédillot and Pain (2003) find that the estimates become increasingly better than those of a benchmark autoregressive (AR) model as more monthly data within the quarter being forecast become available. Given our aim to deliver earlier estimates of Bahrain quarterly GDP growth, using two months data, which are available for key indicators, such as industrial production, at 54 days after the end of the quarter, this chapter follows the literature in forecasting the third month in the quarter for these indicators. This means that the GDP growth would be available with a delay of 54 days only (i.e. shorten the lag by 36 days) as shown below.

2.3.1.1 Monthly Bridge Equation

There are different methods that use monthly indicator variables to nowcast a quarterly variable like GDP. Bridge Equations (BE) method is one of the popular approaches that has been implemented widely, specially in studies that are focusing on (small k) regression-based nowcast (Baffigi et al., 2004; Diron, 2008).

More concretely, bridging involves linking monthly data, typically released early in the quarter, with quarterly data like GDP (see Baffigi et al., 2004). In effect, a two-equations system is now used to forecast Δy_{t+1}, with the second equation comprising the forecasting model for the monthly variable $x_{t,j}$. The errors between the two equations, at the underlying monthly frequency, are assumed orthogonal so that the equations are estimated separately. In common with much previous work, for example Diron (2008), simple AR models for $x_{t',j}$ are considered as following:

$$x_{t',j} = \Sigma_{i=1}^{p} \beta_i x_{t'-i,j} + e_{t',j} \tag{2}$$

where $t' = 1, ..., T_m$ denotes the monthly data with $m = 3$ months in the quarter. The flash model for Δy_t, in equation (1), is therefore estimated using hard data on $x_{t,j}$. However, at the point of forecasting Δy_{t+1}, since a partial information are available on $x_{t+1,j}$ (for some indicator variables, j), the predicted values of $\hat{x}_{t+1,j}$ from the AR model are used in equation (1). Given that the aim of this chapter is to obtain earlier estimates of GDP growth, with only two months of hard data, BE approach, which uses the available two months information on Bahrain's petroleum production, and forecasts the final month in the entire quarter is employed.[24] This forecasted value is then combined with the two months of hard data to obtain $\hat{x}_{t+1,j}$.

2.3.2 Factor-based Approach

In modern economies the development of a large data set by statistical offices allow policy makers and forecasters to work with more than 100 indicators. This can lead to develop models with large numbers of indicators, and a small degree of freedom. To overcome this problem, researchers attempt to summarise the information included in large data-sets into a small number of (unobserved) common factors.[25]

There are mainly two leading factor- (or diffusion) based approaches, namely as the static (principal components) approach of (Stock and Watson, 2002a,b) and the dynamic (principal components) method of Forni et al. (2003) [FHLR].[26] Both the static and dynamic factor-based approaches aim to forecasting any target variable following a two-step approach. First, the time series of factors is extracted from the indicators. Secondly, these factors are used in forecasting. For concreteness, let y_t be the scalar time series variable to be forecasted and let $X_t = [x_{1t},\ x_{2t},...x_{Nt}]'$ is an N dimensional vector of predictors with observations for $t = 1, ..., T$, and it is assumed that the series have zero mean and variance-covariance Γ_0. The factor model representation is given by

$$X_t = \chi_t(F_t) + \xi_t \tag{3}$$

where $\chi_t(F_t)$ are the common components solely driven by factors F_t, and ξ_t is $N \times 1$ idiosyncratic components for each of the variables. The idiosyncratic component is that part of X_t not explained by the common components. The idea behind the factor model is that a small number $r(r << N)$ of factors (F_t) should be able to

[24] Since this component accounts for around 32% of Bahrain GDP, capturing its developments should be key to being able to forecast GDP.

[25] The extraction of factors that represent the "underlying state of the economy" has a long tradition going back to Burns and Mitchell (1946). Alternatives to principal components analysis are identification and estimation of the factors using a parametric model. For example the state space approach can be used when the set of indicator variables is quite small (say < 12); e.g. see Stock and Watson (1989) and Camba-Mendez et al. (2001).

[26] Boivin and Ng (2005) show that the key difference of these two approaches is that the latter approach extracts the factors from the unobserved common to all information variables component. In doing so, the dynamic principal component method of [FHLR] imposes the factor structure on the forecasting model. However, there is no empirical evidence that the latter method outperforms the former.

explain most of the variance of the data, then these factors are employed to predict the variable of interest (i.e., GDP growth in our case).

In this chapter, the static factor approach of Stock and Watson (2002b) is employed. In the first step, we extract the principal components $\hat{F}_t = [f_{1t}, f_{2t}, ..., f_{qt}]$ from variance-covariance matrix $\hat{\Gamma}_0 = \frac{1}{T}\Sigma_{t=1}^{T} X_t X_t'$. Then, in the second step, the estimated principal component $\hat{F}_t$ are used to forecast the target variable Δy_t . More concretely, we run a regression of the variable of Δy_t on $\hat{F}_{t-1}$ to obtain $\hat{\alpha}$ and $\hat{\beta}$ and then insert them in the forecast equation. This kind of method has been found to be an effective means of modelling a large number of noisy survey variables, undertaking both current and next period (Hansson et al., 2005).

Out-of-sample forecast for Bahrain quarterly GDP growth are computed recursively from 2003:Q4 to 2008:Q3. Following Stock and Watson (2002b), this exercise considers forecasting from various parameterization of equation (3).[27] These include (i) a regression with r factors and an intercept

$$\Delta y_{t+1} = \hat{\alpha} + \hat{\beta}\hat{F}_t + \varepsilon_{t+1} \tag{4}$$

and (ii) a regression with an intercept, lag values of factors, and of the dependent variable

$$\Delta y_{t+1} = \hat{\alpha} + \hat{\gamma}(L)y_t + \hat{\delta}(L)\hat{F}_t + \varepsilon_{t+1} \tag{5}$$

where $\hat{\gamma}(L)$ and $\hat{\delta}(L)$ are lag polynomials. Principal component is used to extract the factors from the selected six indicator variables for the first case and then from the full dataset that comprises 65 variables included in X_t. On the basis of AIC and BIC, we include two lags of each factor and two lags of the dependent variable in equation (5).

Following Stock and Watson (2002b), we consider forecast of equations (4) and (5), from a regression with r $(1 \leq r \leq 15)$ factors. In addition to including those r factors associated with the highest eigenvalue, we construct forecasts based on se-

[27]For more examples see Watson (2003) and Stock and Watson (2005).

lecting a potentially different set of factors. We select these factors most correlated in sample with the GDP itself.[28] We suggest that in a forecasting context, this is more sensible than selecting those factors with the highest associated eigenvalues as it isolates those factors that best explain the variable to be forecast rather than the independent variables. An alternative interesting method for selecting the optimal number of factors based on their information criteria is suggested by Bai and Ng (2002).[29]

2.3.3 Benchmark Model

To evaluate the performance of the models used in nowcasting, we consider as a benchmark the first order autoregressive model:

$$\Delta y_t = c + \alpha \Delta y_{t-1} + \varepsilon_t \tag{6}$$

Where, y_t is the log of GDP, Δ is the first differencing operator, ε_t is iid $(0, \sigma^2)$ disturbance term. We do so because Clements and Hendry (1999) argue that equation (6) is robust to structural breaks.

2.4 Assessing Forecast Performance

In this section, we discuss the evaluation criteria used to compare the predictive performance of the time series models in terms of point forecasts and density forecasts as shown below:

2.4.1 Point Forecast

The majority of research in economic forecasting pays high attention to producing and evaluating point forecasts. Point forecasts obviously receive the first-order importance in the forecast evaluation process as they are fairly easy to compute, very easy to understand, and lead directly to the proper direction and optimal model

[28] Stock and Watson proposed using BIC for selecting the optimal number of factors, but with a restriction of having a case where $N >> T$.

[29] Bai and Ng (2002) derive information criteria to determine the number of static factors r in Equation (4). The information criteria represent the usual trade-off between goodness-of-fit and overfitting. The information criteria can be seen as extensions to the familiar Bayes or Akaike criteria. This method does not have any restrictions between N and T.

to be chosen relative to this term. There are a number of ways to use statistics to evaluate point forecasts. In this paper, we use the root mean squared forecast error (RMSFE), residual standard deviation (RSD), and the directional accuracy test developed by Pesaran and Timmermann (1992) (PT), which assesses how well rises and falls in the forecast value follow actual rises and falls using the information of the signs of y_t and x_t.[30]

The optimality of these tests is based on the assumption that forecasts have a quadratic loss function and the target variable follows a linear process. Under such condition, we use the corrected Diebold and Mariano (1995) test of Harvey et al. (1997) to evaluate whether two different forecast models are significantly different from each other.[31]

2.4.2 Density Forecast

Although the forecast evaluation literature has traditionally focused on point forecasts, it is often difficult to summarise by a point forecast many forecasts generated by economic models. Therefore, the fundamental outcome, that a 'correct' forecast is optimal irrespective of the form of the loss function, was extended from point forecast to include density forecasts, which is less straightforward. The true density

[30]Let $x_t = E(y_t, \Omega_{t-1})$ be the predictor of y_t found with respect to the information set Ω_{t-1}, with n observations $(y_1, x_1), (y_2, x_2), ..., (y_n, x_n)$ available. The test proposed by Pesaran and Timmermann (1992) is based on the proportion of times that the direction of changes in y_t is correctly predicted by x_t. The test statistic is computed as: $S_n = \frac{P-P^*}{\sqrt{V(P)-V(P^*)}} \sim N(0,1)$ where $P = \bar{Z} = \frac{1}{n}\Sigma_{i=1}^{n} Z_i$, $P^* = P_y P_x + (1-P_y)(1-P_x)$, $V(P^*) = \frac{1}{n}P^*(1-P^*)$ and $V(P) = n[(2P_y-1)^2 P_x(1-P_x) + (2P_x-1)^2 P_y(1-P_y) + \frac{4}{n} P_y P_x (1-P_y)(1-P_x)]$. Z_i is an indicator variable, which takes value of one when the sign of y_t is correctly predicted by x_t, and zero otherwise, P_y is the proportion of times y_t takes a positive value and P_x is the proportion of times x_t takes a positive value . The null hypothesis, which illustrates that x_t and y_t are distributed independently is set against the alternative that x_t and y_t are not statistically independent.

[31]The Diebold and Mariano (1995) test examines the null hypothesis of equal forecast accuracy of two competing forecasts. It uses a forecast error loss differential $d_t = g(e_t^A) - g(e_t^B)$, which is assumed to be a weakly stationary process with short memory. The main rationale underlying this test is that forecast errors are usually serially correlated. In multi-step forecasting ($h > 1$), forecasts errors are assumed to be at most $h-1$ dependent. This is a plausible assumption, since two consecutive h-steps-ahead forecasts have $h-1$ periods with similar information in common. The Diebold and Mariano (1995) test is a modified $t-test$, whereby the modification accounts for the serial correlation of the loss differential. The mean $\bar{d}$ is assumed to be asymptotically normally distributed $\sqrt{T(\bar{d}-\mu)} \rightarrow^d N(0, V(\bar{d}))$, whereby $V(\bar{d})$ stands for the serially correlated errors' corrected variances of the sample mean $(\bar{d})$, given by the sum of the variance and the autocovariance up to lag $h-1$ assuming that there are no autocorrelations at a lag equal to or greater than $h: V(\bar{d}) = \frac{1}{T}(\gamma_0 + 2\Sigma_{\tau=1}^{h-1}\gamma_\tau$ where T denotes the sample size and the autocovariance is given by: $\gamma_\tau = \frac{2}{T}\Sigma_{t=\tau+1}^{T}(d_t - \bar{d})(d_{t-\tau} - \bar{d})$ the asymptotically normally distributed test statistic. Harvey et al. (1997) argued that the DM test can be quite over sized for small samples and this problem can be more dramatic as forecast horizons increase. They thus suggest a modified DM test as: $DM^* = \frac{DM}{\sqrt{\frac{T+1-2h+\frac{h(h-1)}{T}}{T}}}$.

is never observed, but still one can compare the distribution of observed data with density forecasts to check whether forecasts provide a realistic description of actual uncertainty.[32]

The basic idea is built on the probability integral transform (PIT), which goes back at least as far as Rosenblatt (1952).[33] Diebold et al. (1998) popularised a method based on the relationship between the data generating process, $f_t(y_t)$, and the sequence of density forecasts, $p_t(y_t)$, as related through the probability integral transform, z_t, of the realization of the process taken with respect to the density forecast. For a sample of n one step-ahead forecasts and the corresponding outcomes, the probability integral transform (PIT) is simply the cumulative density function corresponding to the density $p_t(y_t)$ evaluated at y_t,

$$\begin{aligned} z_t &= \int_{-\infty}^{y_t} p_t(u)du \\ &= P_t(y_t) \end{aligned} \tag{7}$$

The density of z_t, $q_t(z_t)$, is of particular significance.[34] Assuming that $\partial P_t^{-1}(z_t)/\partial z_t$ is continuous and nonzero over the support of y_t, then, because $p_t(y_t) = \partial P_t(y_t)/\partial y_t$ and $y_t = P_t^{-1}(z_t)$, z_t has support on the unit interval with density:

$$\begin{aligned} q_t(z_t) &= \left| \frac{\partial P_t^{-1}(z_t)}{\partial z_t} \right| f_t(P_t^{-1}(z_t)) \\ &= \frac{f_t(P_t^{-1}(z_t))}{p_t(P_t^{-1}(z_t))} \end{aligned}$$

Note that if $p_t(y_t) = f_t(y_t)$, then $q_t(z_t)$ is simply the $U(0,1)$ density. Hence, a test of the null hypothesis that PITs, $\{z_t\}_{t=1}^{T}$, is *i.i.d.* $U[0,1]$ is equivalent to a test that the model density forecast corresponds to the true predictive density.[35] Diebold et al. (1998) argue that tests of *i.i.d.* uniformity may often be of little practical use since, when the null hypothesis is rejected, it may not be apparent which leg of

[32] A density forecast of the realization of a random variable at some future time is an estimate of the probability distribution of the possible future values of that variable. It thus provides a complete description of the uncertainty associated with a prediction and stands in contrast to a point forecast, which by itself contains no description of the associated uncertainty. For more details on evaluating econometric forecasts, see Clements (2005).

[33] For more details on density forecast, see (Diebold et al., 1998; Granger et al., 1996; Granger and Pesaran, 2000; Pesaran and Skouras, 2002; Wallis, 2003).

[34] To describe the distribution, $q_t(z_t)$, of the probability integral transform.

[35] The null of *i.i.d.* uniformity is a joint hypothesis. For more details, see Clements (2005).

the joint hypothesis (*i.i.d.* or uniformity) is violated. Berkowitz (2001) suggests an alternative goodness-of-fit test where instead of testing for uniformity of probability integral transform it might be more fruitful to test for normality of the inverse cumulative distribution function (CDF) of standardised forecast errors, which becomes a standard normal variate under the null hypothesis that the model density forecast equals to the true predictive density. In this case, one would test whether the transformed realisations are *i.i.d.* $N(0, 1)$.

In this chapter, the density forecasts for regression-based approach are calculated analytically assuming the disturbance, u_t, in equation (1) is *i.i.d.* normal; the density is then normal with mean given by point forecast $\Delta\hat{y}_{t+1}$ and variance given by $\hat{\sigma}_t^2$. For the Stock-Watson factor method the density variance is recursively estimated from in-sample residuals (from the second step) forecasting regression. Precisely, if $\hat{y}_{t+1}$ is the one-step-ahead forecast of y_{t+1} made at time t, and $\hat{\sigma}_{t+1}$ is the standard deviation of $\hat{y}_{t+1}$ then the Gaussian density forecast is $F(y_{t+1}) = N(\hat{y}_{t+1}, \hat{\sigma}_{t+1}^2)$. The probability integral transform values are given by $\{z_{t+1}\} = \{\Phi((\frac{y_{t+1}-\hat{y}_{t+1}}{\hat{\sigma}_{t+1}}))\}$ where Φ is the Normal CDF. $\{z_{t+1}^*\} = \{(\frac{y_{t+1}-\hat{y}_{t+1}}{\hat{\sigma}_{t+1}})\}$ are the stadardised forecast errors that are distributed $N(0, 1)$ under the null.

In what follows, we consider two different tests, each of which focus on different properties that correctly specified PITs should satisfy. In choosing what test to implement, we follow Mitchell and Wallis (2011) and focus on the Ljung-Box (LB) and Doornik and Hansen (DH) tests. The first test aims only at detecting the absence of serial correlation in the PITs, while the second test operate not on the PITs directly, but rather on the inverse normal transformation of the PITs.

2.4.2.1 Test for Independence (Ljung-Box)

In order to explicitly test for independence in the PITs, z_t, Diebold et al. (1998) recommended looking for autocorrelation in the power transformed PIT series. Thus, Ljung-Box is implemented to test for first order autocorrelation in the power transformed PIT series, which is approximately distributed as chi- square under the null hypothesis (see Harvey, 1991).[36] According to Ljung and Box (1978), we test for linear independence in z_t using:

[36] Among others, Siliverstovs and Dijk (2003) and Mitchell and Wallis (2011) use the common choice Ljung -Box to test for serial autocorrelation.

$$Q = n(n+2)\sum_{j=1}^{h}\frac{\hat{r_j}^2}{n-j} \tag{8}$$

where n is the number of observation and $\hat{r_j}$ is the estimated sample autocorrelation function (ACF) at lag j. Under the null hypothesis, Q has an asymptotic chi-squared distribution with j degrees of freedom. The null hypothesis is rejected when the $p - value$ obtained is so small, which means that there is significant evidence of autocorrelation.[37]

2.4.2.2 Doornik and Hansen (1994) test (DH)

Berkowitz (2001) shows that if the PIT is *iid* $U(0,1)$, then the inverse standard normal transformation of the PIT is an *iid* Normal $(0,1)$.[38] Accordingly, we follow Mitchell and Wallis (2011), Clements and Smith (2000) and Siliverstovs and Dijk (2003) in testing standard normality of inverse standard normal transformation of the PIT, and use the test statistic suggested by Doornik and Hansen (1994) (DH).[39]

Doornik and Hansen (1994) (DH) develop a test for normality based on skewness and kurtosis which has good small sample properties. The test is based on the sum of squares of transformed measures of skewness and kurtosis, and has a χ^2 asymptotic distribution under the null of *iid* normality (i.e. absence of skewness and kurtosis).

2.5 Data and Empirical Results

2.5.1 Data

Since the main task of this chapter is to evaluate the gains of using a large data set compared with a small data set to predict GDP growth, we should collect a sufficiently large data set. Following the main stream in factor-based modeling literature

[37] The null hypothesis of Ljung-Box test is H_0: all correlation coefficients up to lag 'j' are zero and H_1 : not all lags up to lag 'j' are zero.

[38] Normality in statistics is used to evaluate the fitting of the data in the model applied. It tests whether it has been well-modelled by a normal distribution or not, or to compute how likely an underlying random variable is not to be normally distributed.

[39] Clements and Smith (2000) use density forecast performance to compare linear models with nonlinear forecasting models of output growth and unemployment.

(Stock and Watson, 2002a,b; Forni et al., 2000) that suggests collecting and using central banks data, paying little or no attention to preselecting process, this chapter uses the full data-set produced by the Central Bank of Bahrain. The collected data set for the Kingdom of Bahrain, which is explained in the data Appendix B, contains 65 quarterly series over the sample period 1995:Q1 - 2008:Q3. As discussed above, a recursive out-of-sample forecasting scheme is used to evaluate each model. Thus, the full sample is divided into two sub-samples. The first 35 observations (1995:Q1 - 2003:Q3) are used for estimation and the out-of-sample forecast exercises are computed recursively over the period from 2003:Q4 to 2008:Q3. We choose quarterly time series because we want to discuss the empirical properties of the factor model with respect to the GDP, which is available at the quarterly frequency.

We include components of industrial production, which concentrate on refined petroleum production as it represents the main product in Bahrain, trade variables, prices such as consumer price index and share price index, monetary aggregates and the financial variables, which comprise a number of series including exchange rates, interest rates, and others as shown in Table (2-B.1) and Table (2-B.2).[40] Data on metal and oil prices are available for the full period. All data are obtained from the International Financial Statistics (IFS) database published by International Monetary Fund (IMF) whereas energy and metal prices are obtained from Energy International Agency (EIA).

Preselecting the proper indicator variables to construct the small dataset for simple regression model is not an easy process. It might be easier whenever the range of GDP components are collected more frequently. However, in the case of Bahrain, we are forced to use the data that are available on a monthly basis such as the trade, international oil prices, international aluminium prices, refined petroleum production index, financial data, and monetary aggregates. Following Grasmann and Keereman (2001), the independent variables were chosen by a classical trial and error two-stage process: in the first step, these variables were identified, which due to economic reasons were supposed to show a close correlation to the dependent variable, either coincident or lagged. The second step consisted in retaining the variables that deliver the best in-sample test results. We use a simple model with six explanatory variables including exports (including oil products) (EXPPP), refined petroleum production index (RPPI), metal price index (MI), oil price index

[40]Table (2-B.1) and Table (2-B.2) describe both the indicators used in the empirical estimation and the source from which we obtain them.

(OILI), consumer price index (CPI), and broad money aggregate (M3). All variables are in log forms and if necessary, are differenced until stationary. The partial correlation of these variables used as regressors in the simple regression equation with quarterly GDP growth is generally strong as shown in Table (2.1). The strongest correlation exists for exports including oil products (positive) and oil price index (positive). The weaker relationship exists for consumer price index (CPI), while the other variables have a reasonable correlation with quarterly GDP growth. The Granger causality test applied on the relationship between GDP growth and the independent variables gives a similar picture. The null hypothesis of no Granger causality from the independent variables on the dependent variable can be rejected with reasonable probability as shown in Table (2.2). Also, jointly, they significantly cause GDP growth.[41]

As it is typical for the empirical indicator literature, the vector of time series will be preprocessed. Since the principal component analysis requires stationary time series for estimation, non-stationary time-series are appropriately differenced and normalised to have sample mean zero and unit variance. It is worth noticing that while the factor model previously described relies on a large dataset, the simple model has a considerably smaller data set which is the outcome of an explicit preselection. A comparison of forecasts of the factor model and the simple regression model will shed some light on the relative efficiency of such preselections.[42]

2.5.2 Empirical Work and Results

In this section we discuss the results obtained from evaluating recursively an out-of-sample period from 2003:Q4 to 2008:Q3.[43]As the results are classified in terms of the data sets used, we will start discussing the results of using 6 pre-selected indicator variables followed by the discussion of the results obtained from using 65 variables.

Table (2.3) reports the results obtained from point forecast evaluation tests for all the models employed. The upper row specifies the name of the tests as fol-

[41]Classical trial and error tests result are obtained using only the first 35 observations (1995:Q1 - 2003:Q3).

[42]In preliminary steps of this investigation, we utilize different combinations of data sets and found that the root mean square forecasted error become significantly different and varies from 1.979 to 13.585 in some cases. Empirical results using these alternatives can be obtained from the authors upon request. However, these models performed worse than the alternatives presented here.

[43]The model has been implemented in Gauss.

lows: the root mean square forecast error (RMSFE), the residual standard deviation (RSD), Diebold and Mariano (1995) test (DM_{pval}), and Pesaran and Timmermann (1992) test (PT). The models in the first column are: regression with three indicator variables (3IV), regression with one indicator variables (SIV), regression with forecasted industrial production (SIV_{IP}), first order autoregressive (AR(1)), static Stock & Watson based on highest eigenvalue (SW) and static Stock & Watson based on highest correlated factors (SWCORR), where (L) indicates the model augmented with the lags of factors and the dependent variable based on AIC and BIC. Noticing that some models were corrected using intercept correction (IC). The number inside parentheses in the second column is such that the model with smallest RMSFE is assigned rank 1, the second smallest rank 2, and so on. The RSD (in third column) reveals the goodness-of-fit measure. That is, the smaller the residual standard deviation, the closer is the fit to the data. Results of both RMSFE and RSD make it clear that the models differ dramatically where the regression models outperform both factor models and the AR benchmark model, and the best performing model is the IC model. As we discussed earlier, choosing the optimal combination of the variables to be used has been done by BIC, the choice of the combination among the period remained the same, where it includes the refined petroleum production index (RPPI), exports (EXPP), and oil price index (OILI). Based on point forecasts, we can observe that the minimum RMSFE is 0.0198, which is obtained from using a simple regression model with three indicator variables and intercept correction at 84 days (see Figures (2.1) and (2.2)).

Also, since the BIC is left to decide on the preferred single indicator to be used in the regression model, it selects refined petroleum production or its lags in production sometimes, then again pays to exclude it from the set of indicator variables considered. But in general, it is selected in most cases over time, which suggests examining the usefulness of this single indicator variable to further shorten the lag of obtaining the flash estimates. Particularly, using two months 'hard' data on industrial production and forecasted value of the final month in the quarter obtained from BE. Based on the results of this exercise shown in Table (2.3) (SIV_{IP} and SIV/IC_{IP}), there is a loss in accuracy when forecasts are produced at 54 days when industrial production is used as the sole indicator variable. However, we need to consider tests constructed for evaluating density forecasts in order to choose the optimal model. By looking carefully at the results obtained, we can notice that intercept correction model (IC) helps to improve forecast accuracy in some cases, particularly simple regression models with single and three-indicator variables as shown in Figure (2.1).

The fourth column of Table (2.3) provides the results of the Diebold and Mariano (1995) test, which is built on model comparisons in terms of MSFE summarised across series and across models, respectively. It is worth noting that the reported findings provide evidence for rejecting the null hypothesis of equal forecasts accuracy for most models. There is no equal accuracy at 95% level for most of the models except for $3IV$, SIV/IC , SIV/IC_{IP} and $SW3_L$. This means that statistically there are no equal loss functions among the models (assuming quadratic loss functions).[44] Looking at Flash estimates using single indicator variable, forecasts at 54 (SIV/IC_{IP}) days are not much less accurate than those at 84 days (SIV/IC). Although the RMSFE is in general higher when the third month in the quarter of industrial production is forecasted, the loss in accuracy of SIV/IC_{IP} is not significant in comparison to the best performing model.[45] According to the results of Pesaran and Timmermann (1992) (PT) test shown in the last column of Table (2.3), none of the results are above the 95% critical values of a standard normal variety and thus cannot reject the hypothesis that x_t and y_t are statistically independently distributed except for $SW1$ and $SW1_L$ models.

Substantially, tests concerning the density forecast criterion are reported in the second and third cloumns of Table (2.4). In relation to the Doornik and Hansen (1994) DH_{pval} test applied to the inverse normal cumulative density transformation, the $p-value$ associated to Doornik-Hansen statistic is 0.0033 for the best performing $3IV/IC$ model, so with a significant level of 0.050, the results suggest that the data analyzed do not have a normal distribution, in the sense of the 3IV/IC model. Thus, it could be an optimal model that depends on the loss function. The third column of Table (2.4) represents the $p-values$ obtained from the Ljung-Box test for autocorrelation in the PITs. It suggests not rejecting the null of uncorrelated error except for the SIV model as it is not significantly different from zero. The $SW1_L$ model could be considered a borderline case with a $p-value = 0.0509$. This means that there is no autocorrelation between the y in the other models and consequently, the residual of the models is white noise. The density forecast criteria show that the best performing $3IV/IC$ model fails to pass both the distribution

[44] Diebold and Mariano (1995) test has been applied for all the models against the benchmark model, and then for the optimal against the rest of the models.

[45] This is consistent with the findings of Rünstler and Sédillot (2003) for Eurozone GDP growth.

and the independence tests. Alternatively, models including $3IV$, SIV/IC, SIV_{IP}, SIV/IC_{IP}, AR and the factor models (except $SW1_L$) satisfy the density forecasts criteria.

Consequently, the $3IV/IC$ model is the optimal model based on the loss function only due to the failure in proving that it is *iid* and N (0, 1). Alternatively, there are four other models including $3IV$, SIV/IC , SIV/IC_{IP}, and $SW3_L$ that are not significantly different from the best performing model (i.e. 3IV/IC) based on the DM test. These models pass both point and density forecast tests. Although their RMSFE in general is higher than that of the $3IV/IC$, the, DM test shows that the difference in the RMSFE for these models relative to the optimal performing $3IV/IC$ model is insignificant at 95%. Moreover, these alternatives pass the independence and distribution tests.

In factor models, we can highlight two points. First, increasing the number of factors seems to facilitate forecasts in terms of reducing RMSFE, thus; we investigate whether increasing number of factors could obtain better results than simple regression models and find that it becomes worse when r > 9 for the estimation using equation (4) and mixed for the estimation using equation (4). In general, none of the results shown in Table (2.5) is better than simple regression models up to rank (3). Second, results obtained are improved by using the most correlated factors to GDP in comparison to those chosen based on highest eigenvalues.

To have a complementary view of the utilized forecast performance, we have to look at the values shown in Tables (2.6) and (2.7). Although the acquired results in these tables, which summarise the findings of evaluating the forecast performance of the models that embody the use of 65 time series does not help to achieve better outcomes, we can still prove that in our case, flash estimates that are obtained using simple regression models outperform the AR(1) benchmark model and the Stock and Watson factor-based models as well. However, there is no significant improvement for the use of intercept correction.

2.6 Conclusion

Early estimates of GDP are important for decision-making processes. However, data on GDP are often published with considerable delay. There are two approaches to produce flash estimates, the simple regression approach, which is based on a few number of indicators and the factor-based model, which explores the information of large data-sets.

Our findings can be summarised as follows. The most reliable estimates could be achieved using simple regression estimates augmented with the intercept correction model (3IV/IC). It outperforms the AR(1) benchmark and the static factor model as well. However, this could be considered only if the loss function is known and the forecaster is concerned about the point forecasts as it fails both distribution and independence tests. Alternatively, if the forecaster is concerned about the density forecast, $3IV$, SIV/IC , SIV/IC_{IP}, and $SW3_L$ models will be interesting choices based on both point and density forecast. Although their RMSFE is in general higher than the 3IV/IC, the DM test shows that the difference in the RMSFE for these two models relative to the optimal performing 3IV/IC model are insignificant at 95%. Moreover, both of these alternatives pass the independence and distribution tests. When we nowcast the GDP growth, industrial production appears to be both a timely and useful indicator. Simple regression estimates that use this indicator alone systematically outperform the other models including factor-based methods that exploit information not just on industrial production but over 65 other indicator variables. Our results also go in line with literature that suggests using preselected indicator variables might improve the forecasts using factor-based models (Caggiano et al., 2011). Stock and Watson (2004) find evidence that simple mean combination forecasts (derived from simple indicator regression augmented with AR terms with no more than three indicators) outperform dynamic factor model-based forecast in many cases.

Currently, the value added of real GDP is released at 90 days after the ending of the prospective quarter. We focus on producing forecasts of quarterly GDP growth to two timescales. The first forecast is produced at 84 days after the end of the quarter. At this point in time monthly key indicators are available for the three months of the entire quarter, and therefore, using the aggregated monthly indicator variables in models $3IV$, SIV/IC, and $SW3_L$ could minimize the lag a little bit and make it available one week earlier than the official release.

The second forecast is produced at 54 days when we have two month's hard data for industrial production, and only have to forecast the one remaining month in the quarter using BE approach shown in Equation (2). The forecasted series is used in the single indicator variable regression to obtain the quarterly GDP growth using the SIV/IC_{IP} model, and thus further shorten the lag significantly by 36 days.

As discussed earlier, flash estimates of GDP are recommended and would be of considerable benefit because of its significant impact on policy making, thus; considering either timeliness forecasts could be helpful to use especially since we have shown that the models applied are performing well based on recursive out-of-sample forecast performance.

Moreover, by looking at the results obtained from using only six explanatory variables, which are considered to have a significant direct effect on GDP growth, it is clear that they are much better than the results obtained using 65 time series. Accordingly, we can support the related argument in the literature that says that more information does not always help to produce more accurate results (Boivin and Ng, 2006). The simple regression-based models appear to offer the best means of handling the changes in the business cycle in comparison to AR and factor models, however, it will be interesting to see in a future study whether mixed-frequency factor models, of the sort used by Angelini et al. (2010), are able to pick up the rapid switch in the utility of hard indicators automatically. Our finding can be seen as an addition to the growing body of work that investigates how well factor-based methods work relative to alternative, often simpler methods.

Table 2.1: In Sample Correlation between the Indicator Variables and GDP Growth

Variable	Correlation
EXPP	0.9349
RPP	0.4469
MET	0.1719
OIL	0.6579
CPI	0.0141
M3	-0.1554

Note: The entries in the first column are: exports including oil products(EXPPP), refined petroleum production index (RPPI), metal price index (MI), oil price index (OILI), consumer price index (CPI) and broad money aggregate (M3).

Table 2.2: In Sample Granger Causality Test

Null Hypothesis	F-Statistic	Probability
EXPP does not granger cause GDP	19.217	0.001
RPP does not granger cause GDP	5.783	0.022
MET does not granger cause GDP	10.161	0.038
OIL does not granger cause GDP	31.783	0.000
CPI does not granger cause GDP	7.672	0.104
M3 does not granger cause GDP	17.029	0.002
All	120.160	0.000

Note: The symbols in the first column are: Gross domestic product (GDP), exports including oil products(EXPPP), refined petroleum production index (RPPI), metal price index (MI), oil price index (OILI), consumer price index (CPI) and broad money aggregate (M3).

Table 2.3: Point Forecast Evaluation using 6 Indicator Variables

Model	RMSFE	RSD	DM_{pval}	PT
$3IV$	0.0210(2)	0.0009	0.4104	-0.3191
$3IV/IC$	0.0198(1)	0.001	0.0000	1.1754
SIV	0.0401(7)	0.0028	0.0055	-0.319
SIV/IC	0.0266(3)	0.0011	0.1728	-0.319
SIV_{IP}	0.0521(9)	0.0041	0.0173	-0.8091
SIV/IC_{IP}	0.0343(5)	0.0025	0.1018	-0.8091
$AR(1)$	0.0851(15)	0.0083	0.0000	-1.531
$AR(1)/IC$	0.1202(16)	0.0188	0.0000	-0.319
$SW1$	0.0807(14)	0.008	0.0029	-9.99
$SWCORR$	0.0756(12)	0.0078	0.0055	1.1754
$SW1_L$	0.0703(11)	0.0078	0.0147	2.239
$SWCORR_L$	0.0583(10)	0.0044	0.0031	0.473
$SW3$	0.0760(13)	0.0077	0.0057	1.5953
$SWCORR3$	0.0467(8)	0.0028	0.0079	-0.951
$SW3_L$	0.0393(6)	0.0016	0.2264	0.809
$SWCORR3_L$	0.0334(4)	0.0023	0.0141	0.112

Note: This table shows the results of point forecast evaluation for predicting Bahrain's GDP growth using a small data-set. The data-set includes six explanatory variables; exports (EXPPP), refined petroleum production index (RPPI), metal price index (MI), oil price index (OILI), consumer price index (CPI), and broad money aggregate (M3). The upper row specifies the name of the tests as follows: the root mean square forecast error (RMSFE), the residual standard deviation (RSD), Diebold and Mariano (1995) test (DM_{pval}) in comparison to 3IV/IC, and Pesaran and Timmermann (1992) test (PT). The models in the first column are: regression with three indicator variables (3IV), regression with one indicator variables (SIV), regression with forecasted industrial production (SIV_{IP}), first order autoregressive (AR(1)), static stock & Watson based on highest eigenvalue (SW) and static stock & Watson based on highest correlated factors (SWCORR), where (L) indicates the model augmented with the lags of factors and the dependent variable based on AIC and BIC. Noticing that some models were corrected using intercept correction (IC). Numbers in parentheses indicate the assigned rank, where 1 corresponds to the model with smallest RMSFE, 2 to the second smallest, and so on.

Table 2.4: Density Forecast Evaluation using 6 Indicator Variables

	DH_{pval}	$QBOX_{pval}$
$3IV$	0.0647	0.0562
$3IV/IC$	0.0033	0.5537
SIV	0.2769	0.0054
SIV/IC	0.2554	0.9916
SIV_{IP}	0.289	0.6311
SIV/IC_{IP}	0.2721	0.982
$AR(1)$	0.9679	0.2791
$AR(1)/IC$	0.6422	0.1687
$SW1$	0.9094	0.7657
$SWCORR$	0.5101	0.2274
$SW1_L$	0.0723	0.0509
$SWCORR_L$	0.3698	0.9539
$SW3$	0.5948	0.1308
$SWCORR3$	0.1752	0.0691
$SW3_L$	0.2211	0.669
$SWCORR3_L$	0.0645	0.9035

Note: This table shows the results of density forecast evaluation for predicting Bahrain's GDP growth using a small data-set. The data-set includes six explanatory variables; exports (EXPPP), refined petroleum production index (RPPI), metal price index (MI), oil price index (OILI), consumer price index (CPI), and broad money aggregate (M3). Table entries are the results obtained from forecasts performance tests. The upper row specifies the name of the tests as follows: Doornik and Hansen (1994) (DH$_{pval}$) statistic for the null hypothesis that $z_t \sim N(0,1)$ and Ljung and Box (1978) (QBOX$_{pval}$)statistic for the null hypothesis of no first-order autocorrelation in $(z_t - \overline{z})^j$. The models in the first column are: regression with three indicator variables (3IV), regression with one indicator variable (SIV), regression with forecasted industrial production (SIV$_{IP}$), first order autoregressive (AR(1)), static stock & Watson based on highest eigenvalue (SW) and static stock & Watson based on highest correlated factors (SWCORR), where (L) indicates the model augmented with the lags of factors and the dependent variable based on AIC and BIC. Noticing that some models were corrected using intercept correction (IC).

Figure 2.1: **Actual and Forecasted GDP Growth using Small Data-set (Regression-based Approach)**

Figure 2.2: Actual and Forecasted GDP Growth using Small Data-set (Factor-based Approach)

Table 2.5: Point Forecast Evaluation: RMSFE for SW Approach with Different r

Model	RMSFE
$SW5_L$	0.0307
$SWCORR5_L$	0.0366
$SW7_L$	0.0359
$SWCORR7_L$	0.0341
$SW9_L$	0.0410
$SWCORR9_L$	0.0296
$SW12_L$	0.0366
$SWCORR12_L$	0.0387
$SW15_L$	0.0381
$SWCORR15_L$	0.0429

Note: Table entries are the root mean square forecast error (RMSFE) and the models are in the first column. Static Stock and Watson based on highest eigenvalue (SW) and static Stock and Watson based on highest correlated factors (SWCORR), noticing that L corresponds to model including lags of factors and the dependent variable and the numbers beside models indicate the assigned factors r, where $SW5_L$ for example corresponds to the model with five factors and lags of both GDP growth and so on.

Table 2.6: Point Forecast Evaluation using 65 Indicator Variables

Model	RMSFE	RSD	DM_{pval}	PT
$3IV$	0.0806(1)	0.0076	0.0000	0.4742
$3IV/IC$	0.1075(11)	0.0150	0.0696	0.8935
SIV	0.0899(9)	0.0077	0.5331	2.7828
SIV/IC	0.1441(13)	0.0200	0.0073	1.1754
$AR(1)$	0.0851(5)	0.0083	0.0000	-1.5310
$AR(1)/IC$	0.1202(12)	0.0188	0.0000	-0.3190
$SW1$	0.0838(3)	0.0089	0.3773	-9.9900
$SWCORR$	0.0851(5)	0.0088	0.3521	0.4727
$SW1_L$	0.0853(6)	0.0094	0.8362	0.8338
$SWCORR_L$	0.0835(2)	0.0090	0.8396	0.8338
$SW3$	0.0850(4)	0.0086	0.3667	1.4755
$SWCORR3$	0.0885(8)	0.0108	0.2593	1.4755
$SW3_L$	0.0883(7)	0.0092	0.8043	1.1464
$SWCORR3_L$	0.0916(10)	0.0115	0.7401	0.5270

Note: This table shows the results of point forecast evaluation for predicting Bahrain's GDP growth using a large data-set that comprises 65 explanatory variables. The upper row specifies the name of the tests as follows: the root mean square forecast error (RMSFE), the residual standard deviation (RSD), Diebold and Mariano (1995) test (DM_{pval}) in comparison to 3IV/IC, and Pesaran and Timmermann (1992) test (PT). The models in the first column are: regression with three indicator variables (3IV), regression with one indicator variables (SIV), regression with forecasted industrial production (SIV_{IP}), first order autoregressive (AR(1)), static stock & Watson based on highest eigenvalue (SW) and static stock & Watson based on highest correlated factors (SWCORR), where (L) indicates the model augmented with the lags of factors and the dependent variable based on AIC and BIC. Noticing that some models were corrected using intercept correction (IC). Numbers in parentheses indicate the assigned rank, where 1 corresponds to the model with smallest RMSFE, 2 to the second smallest, and so on.

Table 2.7: Density Forecast Evaluation using 65 Indicator Variables

	DH_{pval}	$QBOX_{pval}$
$3IV$	0.6242	0.6484
$3IV/IC$	0.4075	0.2124
SIV	0.4176	0.5330
SIV/IC	0.3336	0.0640
$AR(1)$	0.9679	0.2791
$AR(1)/IC$	0.6422	0.1687
$SW1$	0.9221	0.4144
$SWCORR$	0.9749	0.3551
$SW1_L$	0.9566	0.1807
$SWCORR_L$	0.7471	0.2096
$SW3$	0.9707	0.1263
$SWCORR3$	0.6870	0.6646
$SW3_L$	0.8498	0.2399
$SWCORR3_L$	0.6060	0.7981

Note: This table shows the results of density forecast evaluation for predicting Bahrain's GDP growth using a large data-set that comprises 65 explanatory variables. Table entries are the results obtained from forecasts performance tests. The upper row specifies the name of the tests as follows: Doornik and Hansen (1994) (DH$_{pval}$) and Ljung and Box (1978) (QBOX$_{pval}$). The models in the first column are: regression with three indicator variables (3IV), regression with one indicator variable (SIV), regression with forecasted industrial production (SIV$_{IP}$), first order autoregressive (AR(1)), static stock & Watson based on highest eigenvalue (SW) and static stock & Watson based on highest correlated factors (SWCORR), where (L) indicates the model augmented with the lags of factors and the dependent variable based on AIC and BIC. Noticing that some models were corrected using intercept correction (IC).

Appendix A: Bahrain's Economic structure

Bahrain is the smallest country in the Arabic Gulf with a population of just over 1 million including around 50% expatriate citizens. It witnessed a prompt modernization and economic growth since the discovery of oil in 1932. In the late 1990's, Bahrain was the first state in the Arabic Gulf who initiated the idea of diversifying the economy to prepare for the post-oil and post-gas period. Thus, serious actions have been taken and convert it to be the most diversified economy in the region. The GDP record in year 2005 has reached to USD 13 bn. and the level of income increased up to USD/capita 18.000, which is sufficient to classify it as a high-income country by World Bank standards.

However diversifying Bahrain's economy by expanding some primary economic sectors such as financial, aluminium and tourism could not diminish the fact that the country is still heavily reliant on the oil sector for the most part of its revenues. Frankly speaking, oil sector affords majority of exports and fiscal revenue in addition to being the dominant contributor to GDP providing about 43.8% of the total in 2000, excluding oil-based manufacturing activities. In cooperation with Saudi Arabia, Bahrain extracts oil from the Saudi Arabian owned Abu Saafa oil fields, which is then imported and processed further in Bahrain. Production from these oil fields is expected to remain constant in the next decade, but the government's efforts to increase the productivity of its Awali field should strengthen the national economic activity. For example, as a result of the growing investments into recovery methods, the Awali field would be able to produce over 100,000 barrels per day by 2016, in comparison with about 40,000 barrels per day in 2012. Petroleum processing and refining has been attributed for more than 70% of Bahrain's export revenues. It also shares with over two-thirds of government yields and sufficiently contributes in the output. In addition, the country takes the advantage from importing cheap oil from its neighbours which is beneficial for its economic activity for two main reasons. First, this imported oil is refined for exports to increase the revenue. It is worth to note that Bahrain is more of an oil-refining centre than an oil producer as refined oil exports exceed crude oil exports. Second, it is used as a cheap energy input in the aluminium industry. Both refined crude oil (petroleum) and aluminium are considered as the country's main exports with a respective share of 78% and 13% in total exports. Although crude oil production remains steady, oil related exports increased as new refinery capacity came under steam in year 2007. There are three industries within manufacturing which made up 74% of output (at current prices) from 2001 till 2008. Although their proportions have changed dramatically, these industries are still the major factors that drive the GDP. Refined petroleum production is top of the major factors that make up the manufacturing output with a percentage of 32%. Metals including aluminium constitute the second most important factor with a proportion of 22%, while the third is chemicals production which represents 20% of the total manufacturing output. In addition, the financial sector accounts for nearly 21% of the economy (Bahrain Development Board, report released 2010).

Alongside, the financial sector is one of the large sectors in Bahrain's economy and has been growing rapidly in the past three years through many different channels. For example, as Bahrain is a heavily oil dependent country, it benefits from the high oil prices, which led to larger bank deposits and greater financing opportunities, in stimulating the economic activity through government spending and development projects. High liquidity has also provided greater investment opportunities and a high level of construction activity which can support growth in the recent period. Moreover, public expenditure is deployed to lighten concerns over social stability. The government's ongoing liberalisation of utilities should also encourage more hasty inflows of overseas investment.

In addition to the above financial sector supports, many Gulf investors shifted their assets into the relatively well developed financial sector of Bahrain after the collapse of Lebanon during the civil war in the 1980's. This helped to expand the banking sector promptly to become one of the most outstanding in the region. Currently, Bahrain is the leading financial centre in the region, the largest in the Arab world and includes the largest number of international bank branches in the Gulf Cooperation Council. However, Bahrain's financial sector faces competition from other Gulf States seeking to diversify their economies. Steep fluctuations and a real estate boom have raised some concerns about dangers to regional banks, which led to the introduction of a new financial stability directorate in the beginning of 2006, charged with monitoring the financial system for potential threats. The non-performing loan ratio for fully commercial banks operating in the domestic market was 6.9% in June 2006. The capital to risk-weighted assets ratio of these banks was a more than satisfactory 27.5% in mid-2005. The services sector is dominated by banking and finance. The latter correspond to some 25% of GDP, while also business conferencing and tourism contribute significantly to GDP too.

Appendix B: Data-set

This appendix describes the panel of time series for the Kingdom of Bahrain economy. The whole data set for Bahrain contains 65 series over the sample period 1995:q1 - 2008:q3. The sources of the time series are the Central Bank of Bahrain (CBB), the Central Information Organization of Bahrain (CIO), the International Energy Agency (IEA) and the International Monetary Fund (IMF).

Since GDP is the reference series, all time series are taken in quarterly basis to get a better picture about the economy activities and situation. Moreover, natural logarithms were taken for all positive time series. Most of the data that are taken from the above sources are already seasonally adjusted. Following Stock and Watson (2002), Stationarity was obtained by appropriately differencing the time series, as the principal component (PC) estimation of the factors requires stationary time series.

Details on variables and transformation required for stationarity are provided below.

Table 2-B.1: Data by Economic Sectors and Sources

Economic Sectors	No.series	Source
Industrial Production	1	IMF
Consumer Prices	2	CIO
Monetary Aggregates	6	IMF and CBB
Interest rates	4	IMF
Trade	4	IMF
Exchange rate	7	IMF
International prices	2	EIA
Other Financial Variables	39	IMF
Total	65	

Table 2-B.2: **Descriptions of Bahrain Dataset**

No.	series	Group
1	Refined Petroleum Production	IndProd
2	Exchange Rate: SDR/BD	ExRate
3	Exchange Rate: USD/BD	ExRate
4	Exchange Rate: BD/SDR	ExRate
5	Exchange Rate: BD/USD	ExRate
6	Exchange Rate Index	ExRate
7	Real Effective Exchange Rate	ExRate
8	Nominal Effective Exchange Rate	ExRate
9	M1: National Currency	Money
10	M1: Seasonally adjusted	Money
11	Qusai-Money	Money
12	M2	Money
13	Broad Money	Money
14	Reserved Money	Money
15	CPI Index	Prices
16	CPI % change	Prices
17	Total Exports: BD	TrdFlow
18	Total Exports: USD	TrdFlow
19	Total Imports: BD	TrdFlow
20	Total Imports: USD	TrdFlow
21	Interbank Rate :% per annum	IntRate
22	Treasury Bill Rate :% per annum	IntRate
23	Time Deposit Rate: 3Months % per annum	IntRate
24	Commercial Lending Rate-Prime: IndexNum	IntRate
25	International Reserves: SDR	Financial
26	Gold:Million Ounces	Financial
27	Gold AC.to National Valuation: USD	Financial
28	SDR Holdings: SDRs	Financial
29	SDR Holding : % Allocation per Annum	Financial
30	Reserve Fun Position: USD	Financial
31	Foreign exchange : USD	Financial
32	Foreign exchange: SDRs	Financial
33	Central Bank : USD	Financial
34	Actual Holds'GS: % OF QUOTA per Annum	Financial
35	Fund holdings of currency: SDRs	Financial
36	Commercial banks: assets: USD	Financial
37	Deposit money banks: LIAB.: USD	Financial
38	Foreign assets: BD	Financial
39	Claims on central government: BD	Financial
40	Claims on deposit money bank : BD	Financial
41	Time and saving deposits : BD	Financial
42	Foreign liabilities : BD	Financial
43	Central government deposits :	Financial
44	Capital accounts : BD	Financial
45	Other items (NET): BD	Financial

Table 2-B.2 – Continued

No.	**series**	**Group**
46	Reserves :BD	Financial
47	Foreign assets : BD	Financial
48	Claims on central government : BD	Financial
49	Claims on other resident sectors : BD	Financial
50	Demand deposits : BD	Financial
51	Time and saving deposits : BD	Financial
52	Foreign liabilities : BD	Financial
53	Central government deposits : BD	Financial
54	Capital accounts : BD	Financial
55	Domestic credit : BD	Financial
56	Capital accounts : BD	Financial
57	Other items (NET) : BD	Financial
58	Foreign assets : BD	Financial
59	Claims on central government : BD	Financial
60	Claims on other resident sectors : BD	Financial
61	Liquid liabilities : BD	Financial
62	Foreign liabilities : BD	Financial
63	Central government deposits : BD	Financial
64	Oil price	Int'l
65	Aluminium price	Int'l

Chapter 3

Forecasting Crude Oil Prices Using a Large Data Set: A Dynamic Model Averaging (DMA) Approach

3.1 Introduction

Two thirds of the world's total energy consumption depends on crude oil, which plays a key role in the production process of modern economies. Hamilton (2003, 2005) shows that nine out of ten recessions in the US have been preceded by oil price shocks. Empirical research including Hamilton (1983), Daniel (1997), Rotemberg and Woodford (1996) and Carruth et al. (1998) also reject the hypothesis that the relationship between oil prices and output is just a statistical coincidence.

Recently, oil prices have made the headlines of the financial press on a daily basis. Since the beginning of 2008, the spot price of crude oil traded in the New York Mercantile Exchange (NYMEX) has almost doubled at its peak. Considerable and sudden fluctuations of oil prices often have significant impact on the economic performance of both oil importing and oil exporting countries. On one hand, a sharp increase in oil prices have a negative effect on economic growth and inflation in oil importing countries. On the other hand, a drop in oil prices creates a series of budgetary problems for oil exporting countries (Abosedra and Baghestani, 2004). This is so because oil prices play a vital role in determining macroeconomic aggregates, including real GDP and inflation (see the discussion in Kilian and Vigfusson, 2011a,b, 2013; Kilian and Lewis, 2011). Thus, an accurate forecast of oil prices provide a useful information which helps government agencies or other policy makers to plan and manage their resources in more efficient manner.[46] In this context, predictability of oil prices is a crucial input into the policymaking process. For example, the European Central Bank (ECB) uses oil futures prices to construct a proxy of inflation and output-gap forecast that guides monetary policy (Svensson, 2005). Likewise, the IMF utilizes future oil prices to forecast future and spot prices. Future-based forecasts of oil prices play an important role in policy discussion at the Federal Reserve Board.

Unsurprisingly, many researchers have implemented various models to forecast crude oil prices and its determinants. Empirical research on forecasting oil prices and its components follow two main approaches. The first approach focuses on analysing the long-term trend of oil prices by exploiting the long-run supply-demand relationship. In the long run, as petroleum is an exhaustible resource, the supply-demand

[46] Friedman (1969) argues that there is a positive relationship between the level of inflation and its volatility. Under such circumstances, an accurate forecast of inflation will help to reduce both inflation and inflation uncertainty. In doing so it will increase the information content of prices which plays a fundamental role in the efficient allocation of resources.

relationship is the fundamental factor that determines the long term trend in oil prices (see Hagen, 1994; Stevens, 1995).[47] It is worth noting that oil inventories are widely accepted as an important predictor of world oil prices. This is because oil inventories reflect the disequilibrium between the demand for and supply of oil.

The second approach has been inspired by the forward rate unbiased hypothesis (FRU). The FRU hypothesis tests the null that the forward rate is an unbiased predictor of the future spot rate. For instance, Coppola (2008) shows that future contracts reflect all available information of future spot of oil prices. In contrast, Hea and Hongb (2011) reject the null that future contract is an unbiased predictor of future spot prices. Alquist and Kilian (2010) provide evidence that the non-change forecast (i.e., the current spot price) is a better predictor than future prices. They argue that this result was driven by the variability of future prices about the spot price, as captured by the oil future spread.

Empirical results concerning the key determinants of oil prices are mixed. For example, Hamilton (2009b) using a small set of indicators supports the conventional view that the major oil price shocks were due to significant disruptions of crude oil production caused by geopolitical events such as the Suez crisis, the Arab-Israel war, the Iranian revolution, the Iran-Iraq war and the Gulf war.[48] Hamilton (2009a,b) also shows that strong growth of demand for oil from new industrialized countries and the failure of global production to increase have triggered commodity speculation which made a small production decline an attractive option for Saudi Arabia. Alternatively, Zagaglia (2010) argues that if oil futures contracts contain information about spot prices then omitting futures prices would bias the view that oil prices are driven by demand and supply factors. Zagaglia (2010) uses a factor augmented vector autoregressive (FARVAR) model, and shows that financial variables include valuable information beyond that of demand and supply factors.[49] The main difference between the papers of Hamilton and Zagaglia concerns the data-set used for explaining oil prices. The former paper uses carefully selected indicators based on economic theory, while the latter exploits the information of a large data-set sum-

[47] The factors which influence the supply-demand equilibrium relationship can be grouped into two main categories: variables that describe the role played by the Organization of the Petroleum Exporting Countries (OPEC) in the international oil market, and variables that measure current and future physical oil availability (Kaufmann et al., 2004) .

[48] Hamilton (2009b) shows that a reduction of oil production combined with low price and income elasticity of oil demand led to large increases of oil prices.

[49] Zagaglia (2010) shows that although factors extracted from a large panel of data improve the forecast performance of a model including only future contracts, one of the factors was strongly correlated with series used as proxies of financial development.

marised in a small number of factors. However, both authors use regression-based methods to explain and forecast crude oil prices.

However, Koop and Korobilis (2012) have underlined three issues that regression-based methods fail to account for.[50] First, forecasting models might be subject to structural breaks and other source of parameter instability. In this set-up, the influence that predictors have on the target variable is time-varying and recursive methods do not capture such time variation.[51] Second, the number of potential forecasting models can be large. If there are m potential predictors the researcher will end up with 2^m forecasting models. Third, the best forecasting model might not be constant over time.[52] Structural changes concerning the monetary and fiscal policy pursued by policy makers will affect the significance of potential predictors. For instance, the optimal forecasting model of inflation might have changed after the appointment of Volker as a chairman of Fed. Furthermore, forecasting output growth in recessions and expansions might require the use of different indicators.[53] Thus, regressors that are useful for explaining oil prices might be different across periods of oil price booms and busts.

All of these issues have been addressed by Koop and Korobilis (2011, 2012) who introduced a forecasting strategy known as dynamic model averaging (DMA). The DMA approach allows for the best forecasting model to change over time while parameters, at the same time, are also allowed to change. The same strategy can also be used for dynamic model selection (DMS) where a single forecasting model is chosen at each point of time. Although, Koop and Korobilis (2011, 2012) show that the DMA approach outperforms standard econometric models used to forecast macroeconomic and financial variables, this approach has not been employed before to forecast oil prices. Here, we contribute to the literature of forecasting oil prices by adopting the DMA and DMS approach. We also use a large data-set that embodies 147 time series variables. These variables are meant to capture the macroeconomic, financial and geographic forces that drive oil prices.[54] To the best of our knowl-

[50] The same approach have been used by Koop and Korobilis (2011) and Koop and Tole (2013).

[51] Although, recursive and rolling forecasting methods account partially for parameter variation, Groen et al. (2013) show that it is better to build a model that allows for time variation in parameters.

[52] Pesaran and Timmermann (2000) and Sarno and Valente (2009) show that best forecasting model is time-varying.

[53] Pesaran and Timmermann (1995) show how the best forecasting model for stock return changes over time.

[54] Details of variables, source of data and transformations are provided in Appendix (A), Table (3-A.1).

edge, Zagaglia (2010) is the only study that exploited a large data set to forecast oil prices. Our empirical results can be summarised in two findings. First, we show that the forecast generated by the DMA/DMS approach outperforms all the other alternative models. Second, we show that the number of predictors clearly varies across the out-of-sample forecasting period.

The remainder of the chapter is organised as follows. Section 3.2 summarises the background and literature review, Section 3.3 explains the econometric methodology, Section 3.4 describes the data and empirical results, and finally Section 3.5 concludes the chapter. Description of oil market dataset, additional information about theories and alternative oil price measures are provided in Appendix A, B, and C, respectively.

3.2 Background and Literature Review

3.2.1 Determinants of Oil Price

There is a vast and still growing literature that aims to explain the stochastic behavior of oil prices. Yet, the results concerning the key indicators are mixed. For example, Hagen (1994) and Stevens (1995) suggest that because oil is an exhaustible resource, the price of crude oil is determined by its supply and demand balance. Hamilton (2009a,b) argues that the recent price fluctuations were driven by a stagnant supply and increase in demand driven heavily by China.[55] In the same context, Aastveit et al. (2012) explore the role of demand from emerging and developed economies as a driver of the real price of oil. They find that demand from emerging economies (most notably from Asian countries) is more than twice as important as demand from developed countries in accounting for the fluctuations in the real price of oil and in oil production. Furthermore, Aastveit et al. (2012) find that different geographical regions respond differently to adverse oil market shocks that drive oil prices up, with Europe and North America being more negatively affected than emerging economies in Asia and South America. However, the supply-demand equilibrium is quite complex, due to many factors that can interact and accordingly affect this relationship (de Souza e Silva et al., 2010). The crude oil market emerges as a reflection of the interaction of numerous participants such as producers, governments, and consumers, and the features of exogenous effects such as economic, climate and environmental factors (Fattouh, 2007). Barsky and Kilian (2002) argue

[55] Tang et al. (2010) analyze the impacts of oil price on China's economy, and results show that an oil price increase negatively affects output and investment, but positively affects the inflation rate and interest rate.

that changes in monetary policy regimes are also a key factor behind fluctuations in the price of oil. They attribute these to the sharp increase observed in oil prices during the 1970s. Zagaglia (2010) and Fattouh et al. (2013) pay particular attention to investigating whether financial market information can help to forecast the price of oil in physical markets. Zagaglia (2010) states that oil price forecasts might be biased if one omits the impact of the financial market.

Yet, as oil prices are subjected to structural breaks that might affect the stability of the parameters, Chai et al. (2011) analyse the dynamic impact of oil market core factors on oil price in a time-varying framework. They include the WTI crude oil price, OPEC oil production, OECD oil inventories, and OECD oil consumption as endogenous variables. In contrast, China's net imports as well as dollar index are included as exogenous variables. The main outcomes of this analysis can be summarised in four perspectives. First, oil prices become more sensitive to oil-supply fluctuations, and delays in the oil supply impact become much shorter due to development in globalization and information technology. Second, the impact of oil inventories on oil prices has a time lag of two quarters but has a downward trend. Third, the impact of oil consumption on oil price has the same time lag, but its effect is increasingly greater. Finally, the US dollar index is always an important factor for oil price, and its power of control increases gradually; the financial crisis that occurred in 2008 further strengthens the influence of US dollar.

Hence, the literature has explored the forecasting ability of an enormous number of predictors, including oil-futures prices, oil inventories, the price of crack spread futures, the price of industrial raw materials (other than crude oil), the dollar exchange rate of major broad-based commodity exporters, US and global macroeconomic aggregates, and expert survey forecasts (Alquist and Kilian, 2010; Ye et al., 2005, 2006; Murat and Tokat, 2009; Reeve et al., 2011; Chen et al., 2010; Baumeister and Kilian, 2012). Subsequently, the empirical application of crude oil price forecasting focuses on two main approaches. The first approach explains the behavior of oil prices based on oil market fundamentals via structural models. The second approach has been inspired by the forward rate unbiased hypothesis (FRU) through financial models. The two subsections below provide discussion about these two main approaches used in the forecasting literature of crude oil prices.

3.2.2 Structural Models

The early class of structural models comes from the theory of exhaustible resources suggested by Hotelling (1931).[56] It has been widely accepted in oil price forecasting literature due to its early plausible results. Indeed, Pindyck (1999) is an interesting example of how the Hotelling model is employed to construct forecasting models of energy prices (coal, oil, and natural gas). Using a simple model, Pindyck (1999) shows that the models perform well only in forecasting oil prices. The insights from such frameworks have resulted in the derivation of non-structural models that fail to account for supply of and demand for oil and other factors that affect them (Fattouh, 2007).

In contrast, Bacon (1991) suggests that the price of oil is highly dependent on its market availability, which is, in turn, a function of supply and demand. This has initially trigged the interest in utilizing structural models to evaluate the role of OPEC in determining the price of oil (see Griffin, 1985; Hammoudeh and Madan, 1995; Tang and Hammoudeh, 2002, among others). Bacon (1991) suggests that the main factors that determine the OPEC supply of oil are production quotas (which are set by OPEC and affect supply decisions) and local demand by the member countries of the cartel. Other important indicators are: overproduction, capacity utilization, and surplus production capacity (Zamani, 2004; Dees et al., 2007). However, the success of pricing models that focus on OPEC behavior lasted for only a short time. Many researchers underline the practical limitations of these models as tools for analysis. Over much of the time between 1991 and early 1999, OPEC did relatively little to adjust production in order to accommodate consumption changes, and sometimes, when action was taken, it was either insufficient to stabilise prices or excessive (see Ye et al., 2006).

Alternatively, since the supply of oil is determined by the world's oil producing countries, including non-OPEC and OPEC production, key indicators that can be considered are not only those variables that account for the role played by OPEC. Other variables such as geological factors (reserves and discoveries), industrial and government stocks and oil-substitutes could be taken into account to determine the

[56]The theoritical model of non-renewable resource extraction proposed by Hotelling (1931) implies that the price of an exhaustible resource rises over time at the interest rate in a competitive market equilibrium. For more information, see Appendix (B).

global supply of oil.[57] Global demand for oil is associated with the direct measures that determine world oil consumption, such as OECD and non-OECD oil consumption. Other indirect factors such as world GDP growth, exchange rate and income elasticities of demand have been also considered in the literature (He et al., 2010; Krichene, 2006; Scandizzo and Dicembrino, 2012).

Under the scheme of the rational developments discussed above, a number of authors introduce the role of relative oil inventory level as a determinant of oil prices.[58] For instance, Ye et al. (2002, 2005, 2006) develop three different models based on the oil-relative inventory level to forecast the WTI spot price. In Ye et al. (2002), the authors develop a model based on a monthly data-set, where oil prices are explained in terms of OECD petroleum-inventory levels. The rationale behind this research is that inventory levels are an appropriate proxy for the demand and supply balances, or imbalances, which accordingly provide useful information for predicting the future price of oil.[59] In Ye et al. (2005), short-term forecasts of WTI spot prices are obtained using readily available OECD industrial petroleum inventory levels. The model developed by Ye et al. (2005) provides good in-sample and out-of-sample dynamic forecasts for the post-Gulf War time period. The outcomes of this forecast demonstrate that the model has good predictive accuracy and can indeed explain, to a large extent, oil price fluctuations (for further discussion, see Ye et al., 2005; Baumeister and Kilian, 2012; Alquist et al., 2001).

In addition, Kaufmann (1995) proposes a model that accounts for both inventory level and OPEC behavior in order to improve the forecast performance of the real price of oil. To do so, Kaufmann (1995) uses indicators that tackle changes in market conditions (world oil demand and the level of OECD oil stocks) and OPEC behavior (OPEC productive capacity as well as OPEC and US capacity utilization). Likewise, both Kaufmann et al. (2004) and Dees et al. (2007) use different models that pay particular attention to OPEC behavior in order to forecast crude oil prices. The independent variables included are the OPEC quota, OPEC overproduction (i.e., the quantity of oil produced that exceeds the OPEC quota), capacity

[57] Kaufmann et al. (2004) suggest that factors that influence the supply-demand equilibrium can be grouped into two main categories: variables that describe the role played by the Organization of the Petroleum Exporting Countries (OPEC) in the international oil market, and variables that measure current and future physical oil availability.

[58] Petroleum inventory changes are a measure of the balance or imbalance between supply and demand; they reflect the changing influence on crude oil price caused by deviation from the supply-demand equilibrium.

[59] A Johansen cointegration test with intercept, no trend, and four lags finds no evidence of cointegrating relationship between WTI crude oil spot prices and total OECD inventory variable.

utilization, and the ratio between OECD oil stocks and OECD oil demand. The key outcome of all the studies noted above is that OPEC is still able to influence real oil prices. In particular, Kaufmann (1995) indicates that OPEC can influence the price of oil over the medium and long term by adjusting the rate at which it adds capacity. This has stimulated the oil-price forecasting literature to take this advantage further and to develop models that are augmented by other global demand factors (Zamani, 2004). It has been proven that these models are helpful to industries and governments in making oil-related decisions, and investigating the impact of changes in inventory and OPEC production on oil prices (Weiqi et al., 2011). In contrast, Zamani (2004) finds that OPEC can hardly influence oil prices by shutting down in operable capacity.

Another strand in the oil price forecasting literature investigates the forecasting ability of non-oil variables on crude oil spot prices. For example, Lalonde et al. (2003) construct a model in which real WTI crude oil spot price is a function of the world output gap and the real US dollar effective exchange rate gap.[60] They also estimate an alternative specification of their model by adding the change in crude oil inventories as another key indicator for crude oil prices. The out-of-sample forecasting results indicate that this model outperforms the random walk model and the autoregressive model benchmarks. However, when inventory levels are excluded from the model, the forecasting ability is inferior to that of the two benchmarks.

However, Zamani (2004) suggests that the complexity in forecasting crude oil prices, especially in the short term, relates to several unpredictable characters both in economic and political aspects. It is not, therefore, just demand and supply or inventory and consumption that influence crude oil prices; to a greater extent, there are many irregular factors that are stochastic and unpredictable. This makes the task of forecasting crude oil prices difficult and complex. Alquist and Kilian (2010) also show that increased uncertainty about future oil supply shortfalls under plausible assumptions causes the oil futures spread to decline[61] and the precautionary demand for crude oil to increase. They claim that this has been reflected by an immediate increase in the real spot price that is not necessarily associated with an accumulation of oil inventories. In these respects, it can be seen that the main problem with this framework is the large number of potential predictors that one

[60]When allowing for structural breaks, Lalonde et al. (2003) reject the null hypothesis that crude oil price has a unit root. Accordingly, they estimate and forecast the level of WTI crude oil prices with allowance for up to three structural breaks.

[61]Oil futures spreads are simply the differential between two future contracts.

can consider, and the difficulty of establishing and understanding the relationships between them.

3.2.3 Financial Models

In oil price forecasting, financial models estimate the relationship between oil spot price at time t (S_t) and oil futures price at time t with maturity $T(F_t)$. It investigates whether future contract prices are unbiased predictors of future spot prices, and whether they are efficient, based on the efficient-market hypothesis (EMH).[62] Based on the following reference model:

$$S_{t+1} = \beta_0 + \beta_1 F_t + \varepsilon_{t+1}, \tag{9}$$

the joint null hypothesis of unbiasedness ($\beta_0 = 0$ and $\beta_1 = 1$) should not be rejected, and no autocorrelation should be found in the error terms (efficiency). A rejection of the joint null hypothesis on the coefficients β_0 and β_1 is usually rationalised by the literature in terms of the presence of a time-varying risk premium.[63]

A sub-group of models, that are also based on financial theory but have been less investigated, exploits the following spot-futures price arbitrage relationship:

$$F_t = S_t e^{(r+\omega-\delta)(T-t)} \tag{10}$$

where r is the interest rate, ω is the cost of storage and δ is the convenience yield.[64]

In this context, the long-run relationship between spot and futures oil prices has been examined and proven by many researchers (for example, see Gülen, 1998; Silvapulle and Moosa, 1999; Bekiros and Diks, 2008; Lee and Zeng, 2011).[65] However,

[62] In theory, the relationship between spot and futures prices is driven by interest rates, convenience yields, and warehousing costs (Kaldor, 1939).

[63] For more details on theoretical models, see Appendix (B).

[64] See, Clewlow and Strickland (2000) and Geman (2005), among others, for details on the arbitrage relationship in the equation (10) for energy commodities.

[65] Lee and Zeng (2011) revisit the relationship between spot and futures oil prices using data that cover a relatively long period. Lee and Zeng (2011) find that the length of futures contracts, not surprisingly, has an influence on cointegrating relationships between spot and futures oil prices.

testing market efficiency in this area offers mixed conclusions.[66] For example, while Quan (1992) and Moosa and Al-Loughani (1994) argue against futures market efficiency in crude oil, Gülen (1998) presents evidence that supports it.[67] Studies by Bopp and Sitzer (1987) and Bopp and Lady (1991) are in favor of market efficiency for the short-term (i.e., one month ahead of futures price), but reject the notion of efficiency for longer-term futures prices. Alternatively, Foster (1996) provides an evidence for a significant time variation characteristics in the price discovery relationship, which puts forward a new view on the nature of the relationship between oil futures and spot markets.

In a pure forecasting exercise, Zeng and Swanson (1998) examine the forecasting ability of futures prices on spot prices for four commodities including crude oil prices. Using various econometric models, Zeng and Swanson (1998) show that both in-sample and out-of-sample forecasting exercise provides plausible results. Abosedra and Baghestani (2004) compare the forecasting ability of the futures price with naive forecasts of the spot price for one, three, six, nine, and twelve-months-ahead. They find that both the futures price and the naive forecasts are unbiased and efficient predictors for the spot price at all forecast horizons. Yet, the one and twelve-month-ahead futures prices are the only forecasts outperforming the naive, suggesting their potential usefulness in policy making. Coppola (2008) shows that oil futures are well able to predict the spot prices; however, these results stand only for in-sample prediction. Coppola (2008) also suggests that, indeed, valuable information for forecasting spot oil price is embedded in the long-run spot-future relationship. Abosedra (2005) suggests that the futures price for one-month contracts tends to be efficient in forecasting. This has been accepted not only by the academics, but also by a number of institutions that use future contracts as predictors and proxies for the expected spot price. For instance, the European Central Bank (ECB) employs oil futures prices in constructing the inflation and output-gap forecasts that guide monetary policy (see Svensson, 2005). Likewise, the IMF relies on futures prices as a predictor of future spot prices (see, e.g., International Monetary Fund 2005, p. 67; 2007, p. 42). Futures-based forecasts of the price of oil also play a role in policy discussions at the Federal Reserve Board. However, literature

[66] In an efficient market, new information is reflected instantly in commodity prices. If this is true, then price patterns are random (see Chinn et al., 2005).

[67] Quan (1992) suggests that the spot and futures prices of oil are cointegrated for contracts of three months or less, but such a long-run relationship is rejected for longer-term futures contracts. Also, Moosa and Al-Loughani (1994) find that futures prices are neither unbiased nor efficient predictors of spot prices.

has lately explored the potential limitations of futures-based forecasts of oil prices (Chinn et al., 2005; Knetsch, 2007; Alquist and Kilian, 2010). Alquist and Kilian (2010) and Alquist et al. (2001) recently provide a comprehensive evaluation of the forecast accuracy of models based on monthly oil futures prices. They find that there is no compelling evidence that, monthly oil futures prices are more accurate predictors of the nominal price of oil than simple no-change forecasts. Hea and Hongb (2011) also recently find evidence of significant serial dependence on conditional mean of deviations, which is against the joint hypothesis of unbiasedness and market efficiency in crude oil futures markets.

Alternatively, Knetsch (2007) develops a forecasting model for oil prices based on convenience yield.[68] This approach suggests shifting the forecasting problem to the marginal convenience yield, which can be derived from the cost-of-carry relationship.[69] Although the approach does not significantly improve forecast accuracy against the random walk model, it suggests that the out-of-sample forecasts outperform the approach of using future prices as a direct predictor of future spot prices.

To tackle all the above issues, Zagaglia (2010) uses a large dataset that comprises information on both financial and fundamentals of the crude oil market.[70] The dataset includes all the data that are meant to capture information on energy demand and supply, energy prices, macroeconomic, financial, and geographical forces that move oil prices. Zagaglia (2010) argues that if oil futures contracts contain information about spot prices, then omitting futures prices would bias the view that oil prices are driven by demand and supply factors. Using a factor augmented VAR (FARVAR) model, Zagaglia (2010) shows that although factors extracted from a large panel of data improve the forecast performance of a model including only future contracts, one of the factors is strongly correlated with series that are used as proxies of financial development. This confirms that financial variables includes valuable information beyond that of demand and supply factors.

[68] The theory of storage introduces the important notion of convenience yield that accrues to the owner of the physical commodity but not to the owner of a contract for future delivery. This convenience yield on inventory can justify backwardation situations (Gabillon, 1991).

[69] The cost associated with holding the commodity until the delivery date is known as the cost of carry. The cost of carry consists of the cost of storing oil in a tank (and perhaps insurance) and the financial cost in the form of the opportunity cost of holding oil, or the cost of funding, and perhaps a risk premium (for more details, see Chinn et al., 2005)

[70] A very recent application by Baumeister and Kilian (2013) attempts to improve the forecasting performance of real oil prices by combining six different approaches. Each approach contains different set of predictors that cover, in general, some macroeconomic and financial information that affect the levels of oil price. The results from this exercise propose that the gains in accuracy are robust over time.

One common weakness of all the approaches that have been discussed above is that none account for the presence of structural breaks in the series, as well as parameter and model uncertainty, which might not be suitable for a highly volatile market such as oil market. Thus, in this chapter, we contribute to oil price forecasting literature in three main aspects. First, following Zagaglia (2010), we use a large data set that includes 147 time series variables that are meant to capture supply-demand, energy prices, macroeconomic, financial, and geographic forces that move oil prices.[71] Second, as forecasting oil price might be subjected to structural breaks that affect the stability of parameters, a time varying parameters framework has been considered. Third, even the most accurate forecasting models do not work equally well at all times'. For instance, the Baumeister and Kilian (2012) oil price forecasting model works well during times when economic fundamentals show persistent variation, as was the case between 2002 and 2011, but performing less well at other times. Likewise, there is considerable variation over time in the ability of oil futures prices to forecast the price of oil. Hence, we adapt a model that allows for a set of predictors to change over time. To do so, we implement dynamic model averaging (DMA) proposed by Koop and Korobilis (2011, 2012). The DMA allow the best forecasting model to change over time, while parameters, at the same time, are also allowed to change. The same strategy can also be used for dynamic model selection (DMS) where a single forecasting model is chosen at each point of time.

3.3 Econometric Methodology

The benchmark model is a naive pth-order autoregressive AR(p) model:

$$y_t = \alpha + \sum_{j=1}^{p} \phi_j y_{t-j} + \varepsilon_t \tag{11}$$

where the target variable y_t is the crude oil prices and p is the order of lags. A multivariate extension of the AR model based on a carefully selected vector of indicators is the vector autoregressive (VAR) model:

[71] To the best of our knowledge, Zagaglia (2010) is the only paper that employed a large dataset to forecast oil prices.

$$Y_t = c + \sum_{j=1}^{p} A_j Y_{t-j} + \epsilon_t \tag{12}$$

where Y_t is a $M \times 1$ vector of indicators including the target variable (i.e., oil prices), A_j is $M \times M$ matrix of coefficients at lag j, c is a $M \times 1$ vector of intercepts and ϵ_t is a $M \times 1$ vector of the error terms. VAR models include a small number of indicators selected on the basis of an underlying dynamic stochastic general equilibrium (DSGE) model. However, in modern economies the development of large data sets by national statistical offices allow policy makers and forecasters to work with more than 100 indicators. This can lead to models with a large number of indicators and a small number of degrees of freedom. Researchers get around this problem by summarising the information included in a large data-set in a small number of (unobserved) common factors.

The two leading factor (or diffusion) based approaches are the static (principal components) approach of Stock and Watson (2002a) and the dynamic (principal components) method of Forni et al. (2003) [FHLR]. Both the static and dynamic factor-based approaches to forecasting any target variable follow a two-step approach. First, the time series of factors is extracted from the indicators. Second, these factors are used in forecasting. For concreteness, let y_t be the scalar time series variable to be forecasted and let $X_t = [x_{1t}, x_{2t}, ... x_{Nt}]'$ is a $N-$dimensional vector of predictors. Assuming the data admit a factor structure:

$$x_{it} = \chi_{it} + e_{it} = \Lambda f_t + e_{it} \tag{13}$$

where Λ is a $N \times q$ matrix of factor loadings associated with the q-vector of static factors $f_t = (f_{1t}, ..., f_{qt})'$. The key aspect of the factor model is that the $q \times 1$ vector of the unobserved latent factors summarised information extracted by all N series (where $N > q$).

Here, we consider the static factor approach of Stock and Watson (2002a).[72] The

[72]Boivin and Ng (2005) show that the key difference of these two approaches is that the later approach extract the factors from the variance covariance matrix of χ_{it} rather than the variance covariance matrix of x_{it}. In doing so, the dynamic principal component method of [FHLR] imposes the factor structure on the forecasting model. However, there is no empirical evidence that the later method outperforms the former.

static (Stock-Watson) approach first estimates the factors $\widehat{f}_t$ by minimising $\sum_{i=1}^{N}\sum_{t=1}^{T} e_{it}^2$. Then, it uses these factors in a regression at step 2 to explain y_{t+1}; the variable of interest. To review:

$$\textit{Static Step } 1: \widehat{f}_t = \widehat{V}' X_t / N \text{ or in stacked form } \widehat{f} = X\widehat{V} \tag{14}$$

$$\textit{Static Step } 2\text{: Regression: } y_{t+1} = b'\widehat{f}_t + u_{t+1} \tag{15}$$

where $\widehat{V}$ denotes the $N \times q$ matrix of eigenvectors corresponding to the q largest eigenvalues of the $N \times N$ matrix $\Sigma_N = \frac{1}{N} X'X$.

The main shortcoming of basing factor-based indicators on latent variable is that it is difficult to explain to users what the resulting indicators represent. Alternatively, although a VAR model is the reduced form of a DSGE model, it is subject to the omitted variable problem.[73] A fundamental question raised by Bernanke et al. (2005) is whether we can explore the theoretical insights of VAR models conditional on a richer information set. Thus, interest in combining the structural implications of VAR models with the information of a large data-set, summarised in a small number of factors, lead to the development by Bernanke et al. (2005) of factor augmented VARs (FAVAR). The FAVAR can be written in a state-space form with the measurement and transition equation given by:

$$X_t = \Lambda^f f_t + \Lambda^y Y_t + \varepsilon_t \tag{16}$$

$$\begin{bmatrix} f_t \\ Y_t \end{bmatrix} = \widetilde{\Phi}(L) \begin{bmatrix} f_{t-1} \\ Y_{t-1} \end{bmatrix} + \widetilde{\varepsilon}_t^f \tag{17}$$

where Λ^f is $N \times q$ factor loading matrix, Λ^y is $N \times M$ matrix of coefficients, and the $N \times 1$ vector of errors ε_t is assumed either to be a mean zero $i.i.d$ or allowed to

[73] A standard illustration of this omitted variable problem is the the so-called 'price puzzle' observed by Sims (1992). The price puzzle is a conventional finding in the VAR literature that there is positive relationship between monetary policy shocks and inflation. Sims (1992) argues that the price puzzle is possibly an artifact of the omitted variables problem.

be autocorrelated.[74]

Alternatively, $\widetilde{\Phi}(L)$ is a conformable lag polynomial of order p and ε_t^f is $i.i.d$ $\sim N(0, \Sigma^f)$. The measurement equation (16) shows that the informational variables X_t are related to unobserved common factors and observed variables Y_t. The state equation (17) is a VAR in (f_t', Y_t') which can be reduced to the standard VAR given by (12) if the elements of $\widetilde{\Phi}(L)$ that reflect the impact of f_{t-1} on Y_t are equal to zero.

3.3.1 Dynamic Model Averaging

To explain DMA and DMS we modify the state space model in (16) and (17) as follow:

$$\begin{aligned} y_t &= Z_t\theta_t + \varepsilon_t \qquad (18) \\ \theta_{t+1} &= \theta_t + \eta_t \end{aligned}$$

where y_t is the target variable being forecast and Z_t is an $1 \times m$ vector of predictors contains lagged values of y_t and lagged values of the $q \times 1$ vector of the unobserved latent factors extracted from a large data-set X_t using principal components analysis. θ_t is an $m \times 1$ vector of coefficients, $\varepsilon_t \sim i.i.d.\ N(0, H_t)$ and $\eta_t \sim i.i.d.\ N(0, Q_t)$. Such time-varying models can be estimated using standard method involving a Kalman Filter and smoother (see Cogley and Sargent, 2005; Justiniano and Primiceri, 2008; Koop, 2003).[75]

However, the model in (18) assumes that the set of predictors included in Z_t remains constant at all points in time. This might be a strong assumption as explained in the introduction. Empirical evidence provided by Koop and Korobilis (2011, 2012) also shows that maintaining the same forecasting model over time performs poorly due to over-parameterisation problems. As a result, we adopt their strategy in this chapter and allow for K models which utilize different sets of predictors to be applicable at different time periods:

[74] Stock and Watson (2002a) show that while factors help to forecast the common component, inclusion of autoregressive terms (lags of Y) can be seen to help the forecast of the idiosyncratic component and hence relax the assumption of $i.i.d.$

[75] For an introduction to the Kalman Filter and Smoother see Hamilton (1994) and Kim and Nelson (2003).

$$
\begin{aligned}
y_t &= Z_t^k \theta_t^k + \varepsilon_t^k \\
\theta_{t+1}^k &= \theta_t^k + \eta_t^k
\end{aligned} \tag{19}
$$

where $Z_t^k \subseteq Z_t$, for $k = 1, 2..., K$, $\varepsilon_t \sim i.i.d.\ N(0, H_t)$ and $\eta_t \sim i.i.d.\ N(0, Q_t)$. The state-space model presented in (19) allows for different best performing model to hold at each point of time, to do model averaging (i.e. DMA) and to select the best performing model (i.e. DMS).

The fundamental shortcoming of model (19) is how to compute the evolution of models over time. More concretely, a random variable $S_t \in \{1, 2, ..K\}$ shows the model applied at time t. The random variable S_t is assumed to form a Markov chain with transition probability matrix $P = (p_{ij})'_{ij \notin \Lambda}$. The transition probability $p_{ij} = P(S_t = j | S_{t-1} = i)$ is the probability that the forecasting model at time $t-1$ is i and will switch to model j at time t. Such Markov switching models have been introduced to economics by Hamilton (1989) and have been widely used widely in economics and finance since then. However, in our framework the size of transition probability matrix will become computational infeasible even if the number of models is small. Koop and Korobilis (2011, 2012) get around the curse of dimensionality by using an approximation method suggested by Raftery et al. (2010).

Before explaining the main ideas of the algorithm developed by Raftery et al. (2010) it is worth noting that Bayesian estimates of a state-space model involves Markov Chain Monte Carlo (MCMC) methods which take draws of the states conditional on the parameters (i.e., $\theta_t^k | H_t, Q_t$) and then conditional on the states draws the other parameters.[76] With the large number of models estimated in our application the computation of MCMC will be impossible. The key aspect of the Raftery et al. (2010) algorithm is to avoid MCMC by obtaining a plug-in estimate of H_t and assuming $Q_t = (1 - \lambda^{-1})\Sigma_{t-1}$ where $0 < \lambda \leq 1$ and $\Sigma_t = (\theta_t - \widehat{\theta}_t)(\theta_t - \widehat{\theta}_t)'$. Note that $\widehat{\theta}_t$ is the Kalman filter estimate of θ_t and λ is known as a forgetting factor in the sense that observations j periods in the past have a weight of λ^j. Values of λ close to one suggests high parameter persistent. More concretely, $\lambda = 1$ implies that parameters remain constant. Alternatively, as $\lambda \to 0$ we end up with a model where

[76]For complete description of Bayesian estimation of state-space model see Koop (2003) and Kim and Nelson (2003).

only the last observation is used for forecasting.

The second approximation of the Raftery et al. (2010) algorithm concerns the efficient computation of posterior model probabilities. Let $\pi_{t|t-1,k}$ denote the probability that model k is applied at time t using information up to time $t-1$. We can use $\pi_{t|t-1,k}$ either to do model averaging or selecting the best forecast performing model. Hence, DMA use $\pi_{t|t-1,k}$ to weight K different models and DMS selects the model with the highest $\pi_{t|t-1,k}$. If we were to use Markov switching process to describe the evolution of K models with transition probability P and the predictive density of model k given by $p_k(y_{t-1}|y_{t-2}, y_{t-3}...y_1)$ then

$$\pi_{t|t-1,k} = \sum_{i=1}^{K} \pi_{t-1|t-1,k} p_{ij} \tag{20}$$

where

$$\pi_{t-1|t-1,k} = \frac{\pi_{t-1|t-2,k} p_k(y_{t-1}|y_{t-2}, y_{t-3}...y_1)}{\sum_{l=1}^{K} \pi_{t-1|t-2,k} p_l(y_{t-1}|y_{t-2}, y_{t-3}...y_1)} \tag{21}$$

However, we have noted above that such a strategy is computational impossible because P is too large even for cases where K is moderately large. Raftery et al. (2010) circumvent this problem by replacing (20) by

$$\pi_{t|t-1,k} = \frac{\pi_{t-1|t-1,k}^{\alpha}}{\sum_{l=1}^{K} \pi_{t-1|t-1,l}^{\alpha}} \tag{22}$$

where $0 < \alpha \leq 1$ is another forgetting factor with interpretation similar to λ but in terms of model rather than parameter evolution. The interpretation of α becomes apparent if we write (22) as:

$$\pi_{t|t-1,k} \propto \prod_{i=1}^{t-1} [p_k(y_{t-i}|y_{t-i-1}...1)]^{\alpha^i} \tag{23}$$

It can be seen that values of α close to one will imply that $\pi_{t|t-1,k}$ will be larger and the DMS will select model k at time t if it forecasted well in the recent past.[77]

3.4 Data and Empirical Results

3.4.1 Data

In our empirical investigation, we use monthly data-set, which covers the period from March 1983 to December 2011. Here, X_t embodies 147 time series variables that are meant to capture the macroeconomic, financial and geographic flow and stock forces that drive oil prices. The complete list of the series are available from Energy Information Administration (EIA), where the choice of filtering each single indicator variable is reported in Table (3-A.1) represented in Appendix (A). The first part of Table (3-A.1) shows the data available on prices of crude oil including the refiner price of residual fuel oil and other crude oil products, landed cost of crude oil imports from different regions cross the worldwide, F.O.B. cost of crude oil imports, and the refiner acquisition costs. Since the focus of this chapter is to generate forecasts for real WTI spot prices,[78] all nominal prices included in the data set $X_{\mathbf{t}}$ are deflated using the Consumer Price Index (CPI) of the United States.[79] The group of indicators reflecting the impact of macroeconomic and financial variables on oil prices consists of series such as futures prices, consumer price indices, gold prices and exchange rates for the major world currencies. Variables representing geographical flow and stock factors include series on crude oil production for the major members of the Organization of the Petroleum Exporting Countries (OPEC), Non- OPEC and world oil production including the Special Petroleum Reserves (SPR), petroleum consumption for major industrialised countries and total OECD, crude oil stocks, other important crude oil products stocks, petroleum stocks, and other key information on rigs and exploratory and developments wells drilled. For crude oil prices, this study employs the nominal WTI crude oil spot prices, which is considered a world benchmark crude oil spot price. The monthly spot prices were obtained from EIA and deflated using United States Consumer Price Index: for all urban consumers, all items, to construct real prices.

Figure (3.1) below plots spot and future prices of crude oil. The important fea-

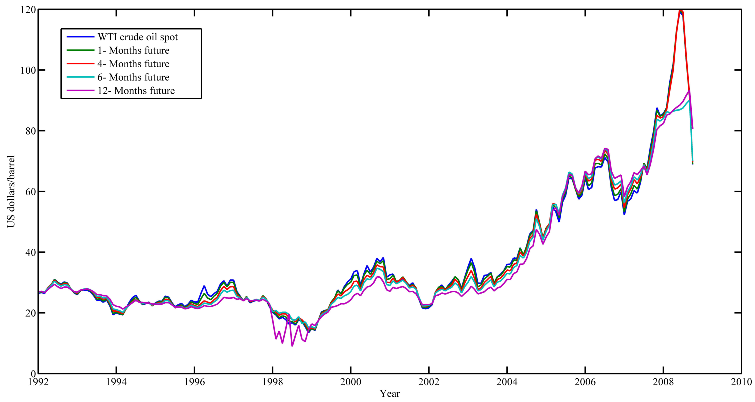
[77] For instance, if we use monthly data and $\alpha = 0.99$ then the forecasting model used two years ago receives 80% weight as much as the forecasting model used last period. If $\alpha = 0.95$ then forecast performance five years ago received only 30% weight.

[78] For more information on alternative oil price measures, see Appendix (C).

[79] As standard in the literature, all series are transformed to render stationarity, they are demeaned and standarised before extracting the principal components.

ture of Figure (3.1) is that there are evidence of structural breaks. More concretely, there is a drop of spot prices in 1986 from roughly $58 to $23. Subsequently spot prices remain stable up to 2004 and since then they start increasing reaching to $120 in 2008 before falling to $40 with a small increase at the end of our sample. To account for structural breaks we also forecast future prices as suggested by studies in the carbon market. This is because future prices are more stable than spot prices. For instance, Bredin and Muckley (2011), using future prices, show evidence of stable carbon market driven by fundamentals. Alternatively, Koop and Tole (2013) show that there is not a significant difference (in terms of RMSFE) in predicting future and spot prices of carbon permits.

Figure 3.1: Plot of Monthly Historical Oil Prices



A number of tests have been applied to examine the degree of integration of the real WTI crude oil spot prices. Using different conventional tests including the augmented Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP), and Elliott et al. (1996) (DF- GLS), results shown in Table (8) demonstrate that the real WTI prices has a unit root (i.e., I(1) process), which is consistent with many papers in literature (For example see, Coppola, 2008; Dees et al., 2007; He et al., 2010). However, although Ye et al. (2005) find that WTI exhibits a unit root, they decided not to use the first order difference of WTI price because of the resulting diminished forecasting ability. Their paper obtains short-term forecasts of the level of WTI spot prices with a good in-sample and out-of-sample dynamic forecasts for the post-Gulf War time period. [80] The success of using the levels of non-stationary WTI prices in the latent paper might be attributed to the weakness of the unit root test in

[80] Ye et al. (2006) state that not only levels are better than differenced series in forecasting the price of oil, it is also empirically proved that while the regressions using logarithmic variables give a constant inverse elasticity, the forecast results are not as good as those obtained from non-log variables.

accounting for major events, such as oil shocks observed above, and thus fail to reject the null hypothesis in the presence of structural breaks. Since the conventional tests such as ADF, PP, and DF-GLS do not account for structural breaks, they have been criticized thoroughly in literature. To overcome this problem, Perron (1989) propose to allow for an exogenous break in the ADF unit root test. However, Zivot and Andrews (1992) pointed out that the choice of exogenous breakpoints based on prior observation of the data could introduce pre-testing problems. Therefore, they introduce an alternative formulation to endogenously search for a break point and test for the presence of a unit root when the process has a broken constant or trend and have demonstrated that their tests are robust and more powerful than the conventional unit root tests. Here, since the price of oil is subjected to structural breaks, this study uses the endogenous one break Zivot and Andrews (1992) (ZA) test to examine whether WTI oil prices follow a unit root process or not. Zivot and Andrews (1992) introduce three different models to test for a unit root: model A allows for a one-time change in the level of the series; model B permits for a one-time change in the slope of the trend function, and model C combines one-time changes in the level and the slope of the trend function of the series.

Choosing a model from the above three models suggested by Zivot and Andrews (1992) is a key step in order to achieve a reliable result. For example, although Perron (1989) proposes that the majority of economic variables can be effectively modeled using either model A or model C, a later investigation held by Sen (2003) explains that if one uses model A when in fact the break occurs according to model C then there will be a substantial loss in power. He also notice that if the break is characterized according to model A, but model C is used then the loss in power is minor, suggesting that model C is superior to model A. Ben-David and Papell (1998) give an idea about the choice of model B. They illustrate that if the data do not exhibits either an upward/ downward trend, then the test power to reject the unit root null hypothesis is reduced as the critical values increase with the inclusion of a trend variable. Oppositely, if the variable is trended, then choosing a model without trend may fail to capture some important characteristics of the data.

Based on these findings and since the price of oil is clearly an upward trended variable, we choose to model it using both models B and C; which test for a unit root against the alternative of trend stationary process with a structural break in slope and in both trend and intercept. If the results are conflicting, results of model

C are preferred as it is considered a superior model. Table (9) represents the results obtained from ZA test where the null hypothesis of no-break is rejected for both models B and C at 5% and 10% level, respectively. This implies that the price of oil in Model B is stationary around a break in November, 1997. Alternatively, Model C suggests that the break occurs in January, 1999. Hence, we proceeded to use the level of WTI oil prices in our forecasting framework.

3.4.2 Estimation

We compute out-of-sample forecasts for oil prices recursively from May 2003 to December 2011.[81] We used the Bayesian information criterion (BIC) and Akaike information criterion (AIC) to select the number of lags for the AR(p) and VAR(p) model presented in (11) and (12).[82] We followed Stock and Watson (2002) and we consider forecast from various parameterizations of (15). These include (i) a regression with q factors and an intercept

$$y_{t+1} = c + \lambda f_t + \varepsilon_{t+1} \tag{24}$$

and (ii) a regression with an intercept, lag values of factors and of the dependent variable

$$y_{t+1} = c + \gamma(L) y_t + \delta(L) f_t + \varepsilon_{t+1} \tag{25}$$

where $\gamma(L)$ and $\delta(L)$ are lag polynomials. Principal component analysis is used to extract the factors from the 147 informational variables included in X_t. Four factors has been selected based on the information criteria suggested by Bai and Ng (2002). In order to provide some understanding on the information they convey, first we examine the correlation between extracted factors with dataset variables. Then, we regress each of the factors on the highest correlated macroeconomic variables. Table (3.1) reports the variance explained by each of those variables with factors. The first factor is strongly correlated with a price index of crude oil imports (Refiner acquisition cost of crude oil, imported). This can be interpreted as a cost indicator of the price pressure on oil prices as all five variables are price indexes and explain

[81] All data transformation, preliminary tests and forecasting models are done recursively.

[82] Results concerning the lag selection of the AR(p) and VAR(p) based on BIC and AIC are available from the authors upon request.

the first factor individually with relatively high variances. Second, third and fourth factors are highly related to stock volumes of crude oil and other crude oil products. Figure (3.2) plots the estimated factors together with the most correlated series of dataset. On the basis of AIC and BIC we include two lags of each factor and two lags of the dependent variable as potential predictors in (25). However, empirical results in our experiments show that excluding the lags of the dependent variable (i.e., $\gamma(L)y_t$) improves the forecast performance of (25). Consequently, the potential predictors in equation (25) are 13. In this set up, we could end up with tens of thousands (i.e., 2^{13}) different models.

To overcome the problem of dimensionality concerning the number of potential predictor, this chapter implements the the DMA and DMS approach suggested by Koop and Korobilis (2012). This has been done by using different combination of values for λ and α. More concretely, the values of λ and α are allowed to ranges between 0.93 and 1.0 with an increment of 0.005. This strategy leads us to work with 15 possible values of each of these forgetting factors and 225 combinations. The reported results include the findings obtained from $\lambda = \alpha = 0.99$, $\lambda = \alpha = 0.975$, and the best performing combinations based on minimum root mean square forecast error (RMSFE) for each type of oil price. We denote these forecasts as best in Table (3.4) and Table (3.6).[83]

This chapter also presents the results obtained from a special case of DMA/DMS known as Bayesian model average (BMA) where both forgeting factors are equal to one (i.e., $\lambda = \alpha = 1$). Alternatively, models, which allow parameters to change but the forecasting model to remain constant are used. More concretely, we look at time-varying first and second order autoregressive models (i.e., TVP-AR(1); TVP-AR(2)) with values of λ= 0.99 and $\lambda = 0.95$.[84]

3.4.3 Empirical Results

This section focuses on the forecast comparison of DMA/DMS models to various alternative models described above. Forecast evaluation based on the RMSFE and the Diebold and Mariano (1995) test. The DM test for the null of forecast equality where the best DMS is used as a benchmark. In terms of forecasting models, results

[83]The optimal values for forecasting WTI crude oil spot price using DMA/DMS are $\lambda = 0.93$ and $\alpha = 0.93$.

[84]All forecast models have been implemented using oil prices returns as well. However, results are qualitatively similar.

for the following models are reported:

1. Forecast using AR(1) and AR(2) model with intercept;
2. Forecast using AR(1) and AR(2) augmented with four factors and an intercept (i.e.,AR(1)-F and the AR(1)-F);
3. Forecast using first order vector autoregressive (VAR(1)) model with intercept, where the variables included are: total petroleum production (world), total OECD crude oil consumption, US treasury bill 10+, Federal fund rate (FFR) and the US inflation;
4. Forecast using the Stock and Watson (SW) factor model. We include the current values of four factors selected by the Bai and Ng (2002) information criteria;
5. Forecast using FAVAR, which includes WTI spot prices, one and three months futures prices of oil and the factors without an intercept;
6. Forecasting using first and second order autoregressive models with time-varying coefficients (i.e., TVP-AR(1) and TVP-AR(2));
7. Forecasting using factor model with time-varying parameter (i.e., TVP-F);
8. Forecasting using DMA with $\alpha = \lambda = 0.99$;
9. Forecasting using DMA with $\alpha = \lambda = 0.95$;
10. Forecasting using DMA with $\alpha = \lambda = 0.93$. This is the best performing DMA/DMS model;
11. Forecasting using DMA with $\alpha = \lambda = 0.975$;
12. Forecasting using DMA with $\alpha = 0.93$ and $\lambda = 1$; and
13. Forecasting using BMA as a special case of DMA (i.e., $\alpha = \lambda = 1$).

Table (3.2) presents OLS estimates of three models. The first model includes four factors selected based on the test suggested by Bai and Ng (2002). The second model adds to the first model two lags of the dependent variable. Finally the third model augments the second model with two lags of each factor.[85] Results show that

[85]We use the BIC to select the number of lags in model (2) and model (3).

in model (1), all four factors are significant. However, as the number of indicators are increased, many of them are not significant. For instance, in model (3), many of the factors and their lagged values were found to be insignificant. At least one of the lags of the dependent variable is insignificant. Evidence that many of the predictors being insignificant is what we expect to find if the predictors are correlated with one another and their significance is time-dependent (see Koop and Tole, 2013).

Tables (3.3) and (3.4) present the RMSFE of classical and Bayesian models for four forecast horizons h = one, four, six and twelve. The key message of these results is that the DMA/DMS approach outperforms any of the other alternatives. Figure (3.3) plots the actual and the forecasted values of the price of crude oil for the best performing DMA and DMS models. It illustrates that both models forecast better for short hrizons rather than long horizons. However, it is worth noting that there is model rather than parameter variation. This is because although the time-varying models perform poorly, the DM test presented in Table (3.6) shows that the DMA model is not significantly different from the BMA.[86] An exception to this is the best DMS model which outperforms the BMA\ BMS models at all forecast horizons. More specifically, the DM test shows that at forecast horizons of one, six and twelve the best DMS model, used as a benchmark, is significantly different from the other forecasting models.[87] The poor forecast performance of the TVP-AR(2) model justifies our choice to exclude the lagged dependent variables from the general model given by (25). The TVP-AR(2) model performs worse than the BMA which implies that exploring a large data set, by using factor models, brings benefits in terms of forecasting crude oil prices. This is consistent with the better forecast performance of the autoregressive models augmented with four factors (i.e. AR(1)-F and AR(2)-F) than the performance of autoregressive models both with a constant and time-varying coefficients.

Evidence that the extra information conveyed by the four factors outweight the information of lagged dependent variables raises questions whether the DMA favor parsimonious models. Figure (3.4) shows the expected number of predictors for each forecasting exercise. For example, if we let $Size_{k,t}$ be the number of predictors in model k at time t then

[86]The BMA is the same as the DMA except that the parameter variation is relaxed.

[87]It is worth noting that for forgetting factors $\lambda = \alpha = 0.975$ and forecast horizons above one, the forecast performance of DMA and of DMS models is equal to the forecast performance of the best DMS model.

$$E(Size) = \sum_{k=1}^{k} \pi_{t|t-1} Size_{k,t} \tag{26}$$

is the expected number of predictors included in a DMA at time t. The results indicate that for certain periods and forecast horizons we might argue that the DMA approach favors parsimonious models. Although the maximum number of indicators is twelve, Figure (3.4) shows that for the forecast horizon $h = 1$ and for the period up to mid 2007 the number of predictors is nine, after 2008 the number of predictors falls to eight. Alternatively, for forecast horizons above one and for the period before 2007 the number of predictors is jut below eight and increases to nine after 2008.[88] Figure (3.4) indicates the number of predictors selected at each point of time but it does not provide any information about what these indicators are.

Figure (3.5) illustrates the posterior importance of the four factors and their two lags at all forecast horizons. The posterior importance indicates the probability that the DMA attaches to models that include any particular indicator. There is clear evidence that for most of the sample the posterior importance of all twelve indicators is higher than 0.4. The importance of each indicator varies across time and forecast horizon. For example, for the one-step ahead forecast the probability that the current value of the first factor is included in the DMA is high at the beginning of the sample; almost 0.7, but it declines to low values after 2006. Also the weight of the first factor information decreases significantly to 0.3 at 12-steps ahead forecast. This might be attributed to the price information included in this factor, which comprises the refiner acquisition cost of crude oil, landed cost of crude oil imports, and average F.O.B. cost of crude oil imports. Oil prices are thus found to be highly responsive to costs in the short-run. Alternatively, the other three factors that provide information about the physical availability of crude oil such as stocks and consumption data receive less value in the forecasting exercises at short-run horizons. In the long-run, these fundamental inputs worth much more than the costs data and significantly improve the forecast performance. Figure (3.6) shows the best DMS and the probability of being selected. It is rather striking that although the DM tests show that best DMS outperforms any other alternative the probability of being selected is low. Thus, it is rather inadequate to rely only on the model constructed by the DMA approach.

[88]The size of model reduction achieved in our exercise by using the DMA approach is not comparable with similar exercises implemented by Koop and Korobilis (2012, 2011) and Koop and Tole (2013).

Table (3.7) presents the results obtained from a forecasting exercise, where the target variable is the price of crude oil future contract. Table (3.7) shows in line with the argument of Bredin and Muckley (2011) that it is easier to forecast future prices rather than spot prices. There is strong evidence across all forecast horizons and all models that the RMSFE is lower when the target variable is the future prices rather than the spot prices. This is not surprising because as argued by Bredin and Muckley (2011) and illustrated in Figure (3.1) future markets are less subject to structural breaks. Although, it is easier to forecast future prices rather than spot prices there is the argument that future prices might be a poor proxy of expected spot prices. Then, we use the relevant future prices in order to compute the RMSFE presented at the last row of Table (3.4). Results illustrate that the future prices used as a forecasting model outperforms all other alternatives except the best DMS model. The latter produces more accurate forecast in terms of RMSFE than future prices at all forecast horizons.[89]

3.5 Conclusion

Considerable and sudden fluctuations of oil prices have important implication for future inflation and economic growth. For this reason among others, future oil prices have been used by the ECB and FED as an important input into the policy making process. Therefore, it is not surprising that researchers have developed several different models to predict future oil prices. However, empirical researchers have failed to account for structural breaks, parameter and model uncertainty in forecasting oil prices. This chapter first exploits information from a large data-set that embodies 147 time series variables. Then, the DMA approach suggested by Koop and Korobilis (2012) is implemented in order to account for all three issues noted above. This approach; which has not been employed before in forecasting oil prices, allows for both the best forecasting model and parameters to change overtime.

The empirical results show that the forecasting models generated by the DMA and DMS outperform any other alternative model. Results also illustrate that there is model rather than parameter variation. For instance, not only the time-varying parameter models perform poorly but also DMA is not significantly different from the BMA. Furthermore, the results suggest that the DMA and the DMS are comple-

[89]It's worth noting that for h=1 future prices perform better than the best DMS model.

mentary rather than mutually exclusive. This is because although the best performing DMS model outperforms all other alternatives the probability of being included in the DMA is low. Finally, this exercise shows that although it is easier to forecast prices of future contracts, the best DMS model has better forecasting performance than the model based on future contracts.

Table 8: Results of unit root test without accounting for structural break

Variable	ADF (lags)	PP	DF-GLS(lags)
log (WTI)	-2.539 (4)	-0.814	-1.811 (1)

Note: Linear trend is included. The critical values of the ADF, PP, and DF-GLS tests at 5% level are: -3.427, -1.950, and -2.893, respectively. Number in parentheses shows the number of lags included in the estimation.

Table 9: Results of ZA unit root test with one structural break

Variable	Model B		Model C	
	t-statistics	Break year	t-statistics	Break year
log(WTI)	-4.798** (1)	1997:11	-5.060* (1)	1999:01

Note: The critical values of Model B are: -4.93, -4.42, and -4.11 at 1%, 5%, and 10% level. For Model C, the critical values are: -5.57, -5.08, and -4.82 at 1%, 5%, and 10% level. ***, ** and * denote significance at the 1%, 5% and 10% respectively. Number in parentheses shows the number of lags included using t-test which is based on mean comparison.

Table 3.1: **Share of Explained Variance of Highly Correlated Series**

Factor 1	R^2
Refiner Acquisition Cost of Crude Oil, Imported	0.9353
Landed Cost of Crude Oil Imports From All Non-OPEC Countries	0.9341
Refiner Acquisition Cost of Crude Oil, Composite	0.9327
Landed Cost of Crude Oil Imports	0.9296
Average F.O.B. Cost of Crude Oil Imports From All Non-OPEC Countries	0.9228
Factor 2	
US Ending Stocks of Asphalt and Road Oil	0.3169
Other Petroleum Products Stocks	0.1123
Petroleum Consumption, Japan	0.0692
US Ending Stocks of Gasoline Blending Components	0.0672
US Ending Stocks of Total Gasoline	0.044
Petroleum Consumption, South Korea	0.0441
Factor 3	
US Ending Stocks excluding SPR of Crude Oil and Petroleum Products	0.5093
Total Petroleum Stocks	0.5064
US Ending Stocks of Crude Oil and Petroleum Products	0.5055
Other Petroleum Products Stocks	0.2193
Crude Oil Stocks, Non-SPR	0.2097
Factor 4	
Crude Oil Stocks, Non-SPR	0.2931
US Ending Stocks excluding SPR of Crude Oil	0.2886
Crude Oil Stocks, Total	0.285
US Ending Stocks of Crude Oil	0.2779
Other Petroleum Products Stocks	0.1605

Note: This table reports R^2 of univariate regressions of factors on macro variables. We report the five variables with the highest correlation with the factors

Table 3.2: **Unrestricted Regressions of WTI Spot Prices on Factors**

	Model I	**Model II**	**Model III**
Constant	0.0004	0.0003	0.0004
	(0.0019)	(0.0017)	(0.0002)
L(1)WTI		-0.1789***	-0.0379
		(0.0247)	(-0.0559)
L(2)WTI		-0.0092	-0.0879*
		(0.0228)	(0.0533)
Factor 1	0.1717***	0.1877***	0.1929***
	(0.0043)	(0.0045)	(0.0049)
Factor 2	0.0308***	0.0271***	0.0115
	(.0069)	(0.0066)	(0.0008)
Factor 3	0.0140*	0.0171**	0.0040
	(0.0079)	(0.0075)	(0.0009)
Factor 4	-0.0154*	-0.0242***	-0.0484***
	(0.0086)	(0.0081)	(0.0097)
L(1)Factor 1			-0.0423***
			(0.0123)
L(1)Factor 2			0.0139
			(0.0089)
L(1)Factor 3			-0.0086
			(0.0082)
L(1)Factor 4			-0.0029
			(0.0099)
L(2)Factor 1			0.0239**
			(0.0107)
L(2)Factor 2			0.0335***
			(0.0091)
L(2)Factor 3			0.00329
			(0.0078)
L(2)Factor 4			0.00768
			(0.0096)
R^2	0.8291	0.8546	0.8709

Note: This table shows the results obtained from unrestricted regressions of WTI spot prices on factors.

Table 3.3: Measures of Forecast Performance for Classical Models: h-step ahead forecast RMSE

Classical models	1- Step	4- Step	6- Step	12- Step
AR (1)	0.9596	1.8172	2.1029	2.3304
AR (2)	0.8822	1.7617	2.0833	2.3107
VAR (1)	0.9297	1.6670	1.8423	1.8525
AR (1)-F	0.9083	1.4087	1.7165	2.1168
AR (2)-F	0.8653	1.4446	1.6787	2.0914
SW (4)	1.0008	1.1073	1.4781	1.9713
FAVAR	0.8756	1.5919	1.6702	1.7992

Note: This table shows the results obtained from forecasts performance tests that aim in predicting WTI crude oil prices. The upper row shows the number of forecast horizon. The models in the first column are: first order autoregressive (AR(1)), second order autoregressive (AR(2)), first order vector autoregressive model (VAR (1)), first order autoregressive augmented with levels of four factors (AR(1)-F), second order autoregressive augmented with levels of four factors (AR(2)-F), static stock & Watson factor model (SW), and factor augmented vector autoregression (FAVAR)

Table 3.4: Measures of Forecast Performance for Bayesian Models: h-step ahead forecast RMSE

Bayesian TVP- models	1- Step	4- Step	6- Step	12- Step
λ = **0.99**				
TVP-AR (1)	0.9240	1.9152	2.3080	2.6310
TVP-AR (2)	0.8815	1.9040	2.3381	2.6578
λ = **0.95**				
TVP-AR (1)	0.9315	1.8113	2.0613	2.0766
TVP-AR (2)	0.8829	1.7671	2.1095	2.1119
$\lambda = \alpha$ = **1.0**				
BMA	0.48640	1.0931	1.2901	1.5147
BMS	0.48524	1.0559	1.2852	1.5099
$\lambda = \alpha$ = **0.99**				
DMA	0.4838	1.0818	1.2793	1.4999
DMS	0.4793	1.0476	1.2599	1.4709
$\lambda = \alpha$ = **0.975**				
DMA	0.4822	1.0969	1.3006	1.4736
DMS	0.4639	1.0285	1.2563	1.4125
λ =**1**, α = **0.93**				
DMA	0.4782	1.0676	1.2837	1.5034
DMS	0.4219	0.8984	1.1585	1.3474
$\lambda = \alpha$ = **0.93**				
DMA (*Best*)	0.4874	0.9859	1.1667	1.2465
DMS (*Best*)	0.4281	0.7857	1.0224	1.0629
Future	0.4007	0.8375	1.04623	1.47165

Note: This table shows the results obtained from forecasts performance tests that aim in predicting WTI crude oil prices. The upper row shows the number of forecast horizon. The models in the first column are: time varying parameter-first order autoregressive (TVP-AR(1)), time varying parameter-second order autoregressive (TVP-AR(2)), bayesian model averaging (BMA), bayesian model selection (BMS), dynamic model averaging (DMA), and dynamic model selection (DMS).

Table 3.5: Measures of Forecast Performance for Classical Models: : DM-relative to best DMS

Classical models	1- Step	4- Step	6- Step	12- Step
AR(1)	-3.4730	-2.7706	-5.5987	-6.3613
AR (2)	-3.9452	-2.9963	-4.3288	-8.1974
VAR (1)	-3.3845	-2.0633	-4.1246	-5.5772
AR (1)-F	-3.5828	-2.9802	-2.4886	-8.4257
AR (2)-F	-3.5527	-2.8989	-3.3810	5.9114
SW (4)	-3.4292	-3.8788	-1.9954	-1.9805
FAVAR	-3.3796	-3.1480	-4.0099	-1.9960

Note: This table shows the results obtained from forecasts performance tests that aim in predicting WTI crude oil prices. The upper row shows the number of forecast horizon. The models in the first column are: first order autoregressive (AR(1)), second order autoregressive (AR(2)), first order vector autoregressive model (VAR (1)), first order autoregressive augmented with levels of four factors (AR(1)-F), second order autoregressive augmented with levels of four factors (AR(2)-F), static stock & Watson factor model (SW), and factor augmented vector autoregression (FAVAR)

Table 3.6: Measures of Forecast Performance for Bayesian Models: DM-relative to best DMS

Bayesian TVP- models	1- Step	4- Step	6- Step	12- Step
$\lambda = \mathbf{0.99}$				
TVP-AR (1)	-3.6895	-2.1934	-2.8441	-2.5485
TVP-AR (2)	-4.7397	-2.4098	-2.0495	-2.5962
$\lambda = \mathbf{0.95}$				
TVP-AR (1)	-3.6678	-2.9489	-2.4245	2.1885
TVP-AR (2)	-6.4867	-2.2400	-2.9861	2.7401
$\lambda = \alpha = \mathbf{1.0}$				
BMA	-3.9573	-1.8150*	-2.9449	-2.8571
BMS	-3.8694	-1.7087*	-2.8978	-2.7895
$\lambda = \alpha = \mathbf{0.99}$				
DMA	-3.9249	-1.6232*	-2.7112	-2.7999
DMS	-3.8093	-1.3293*	-2.5287	-2.8176
$\lambda = \alpha = \mathbf{0.975}$				
DMA	-4.0746	-1.3428*	-1.7368*	-2.0018
DMS	-2.9247	-1.1625*	-1.5098*	-1.8737*
$\lambda = \mathbf{1}, \alpha = \mathbf{0.93}$				
DMA	-4.0034	-1.6292*	-2.8024	-2.7598
DMS	0.6466*	-0.8278*	-2.4800	-2.3026
DMA (*Best*)	-6.7704	-1.3323*	-2.5630	-2.4659

Note: This table shows the results obtained from forecasts performance tests that aim in predicting WTI crude oil prices. The upper row shows the number of forecast horizon. The models in the first column are: time varying parameter-first order autoregressive (TVP-AR(1)), time varying parameter-second order autoregressive (TVP-AR(2)), bayesian model averaging (BMA), bayesian model selection (BMS), dynamic model averaging (DMA), and dynamic model selection (DMS).

Table 3.7: RMSE for Bayesian TVP models ($e = F_h - \widehat{S_h}$)

	1- Step	4- Step	6- Step	12- Step
WTI-Spot price				
$\lambda = \alpha =$ **1.0**				
BMA	0.1315	0.3804	0.4133	0.58747
BMS	0.1420	0.3688	0.4288	0.5821
$\lambda = \alpha =$ **0.99**				
DMA	0.1202	0.3484	0.4228	0.5620
DMS	0.1453	0.3462	0.4275	0.5762
$\lambda = \alpha =$ **0.95**				
DMA	0.2079	0.4347	0.5664	0.6032
DMS	0.2348	0.5055	0.6036	0.6631
$\lambda = \alpha =$ **0.975**				
DMA	0.1459	0.3574	0.5513	0.5621
DMS	0.1703	0.3956	0.5628	0.5771
$\lambda = \alpha =$ **0.94**				
DMA	0.2286	0.4848	0.5546	0.6205
DMS	0.2454	0.8322	0.6304	0.7478
$\lambda = \alpha =$ **0.93**				
DMA	0.2468	0.8802	0.5529	0.6424
DMS	0.2631	0.8432	0.6643	0.8024
$\lambda =$ **0.93**, $\alpha =$ **0.94**				
DMA	0.2471	0.5437	0.5544	0.6388
DMS	0.2512	0.8584	0.6676	0.7953

Note: Table entries are the results obtained from a forecasting exercise where the target variable was the price of crude oil future contract. The upper row shows the number of forecast horizon. The models in the first column are: Bayesian model averaging (BMA), Bayesian model selection (BMS), Dynamic model averaging (DMA), and Dynamic model selection (DMS).

Figure 3.2: Extracted Factors and the Highest Correlated Variables

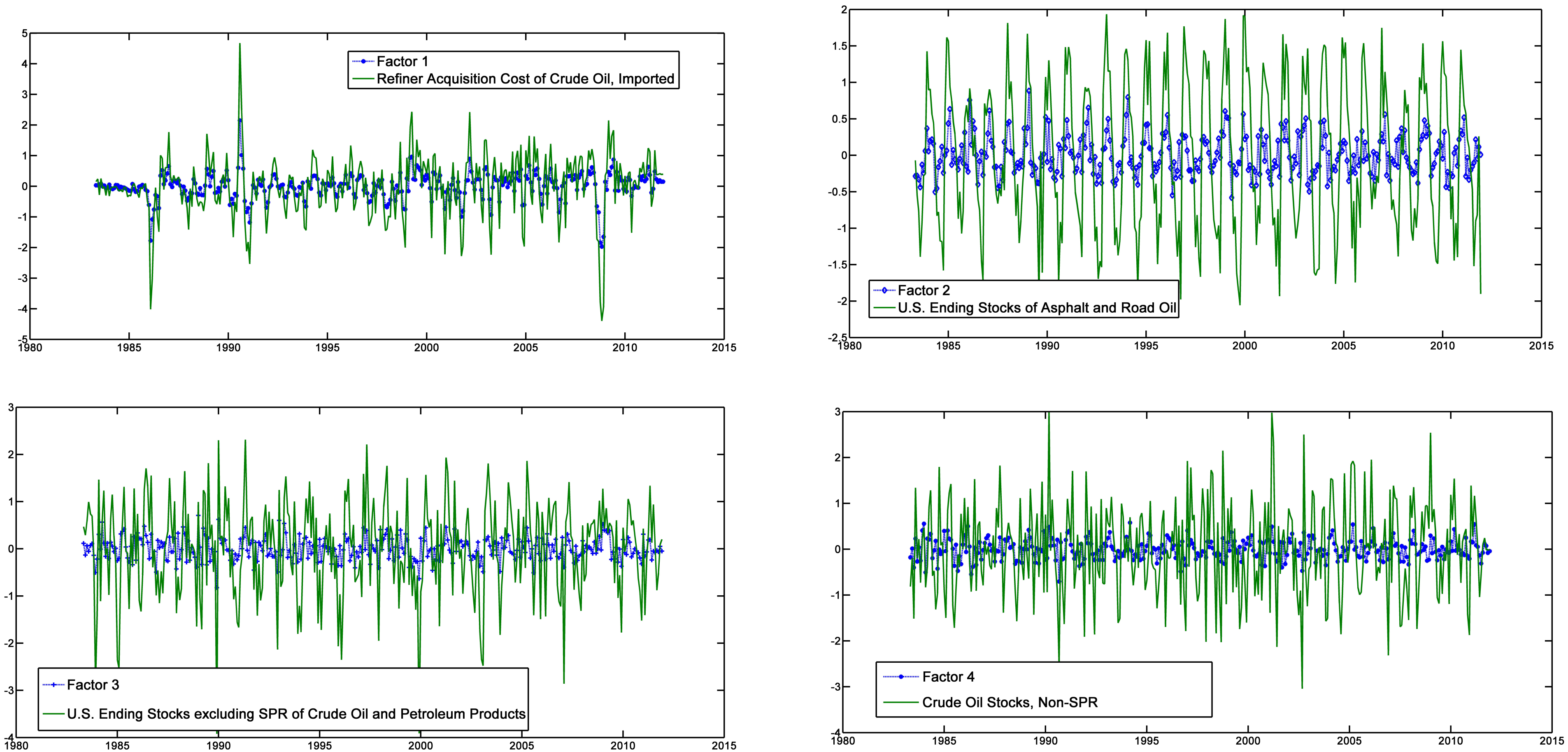


Figure 3.3: Plots of Actual and Best Fitted WTI Spot Oil Prices for Best DMA/DMS Models

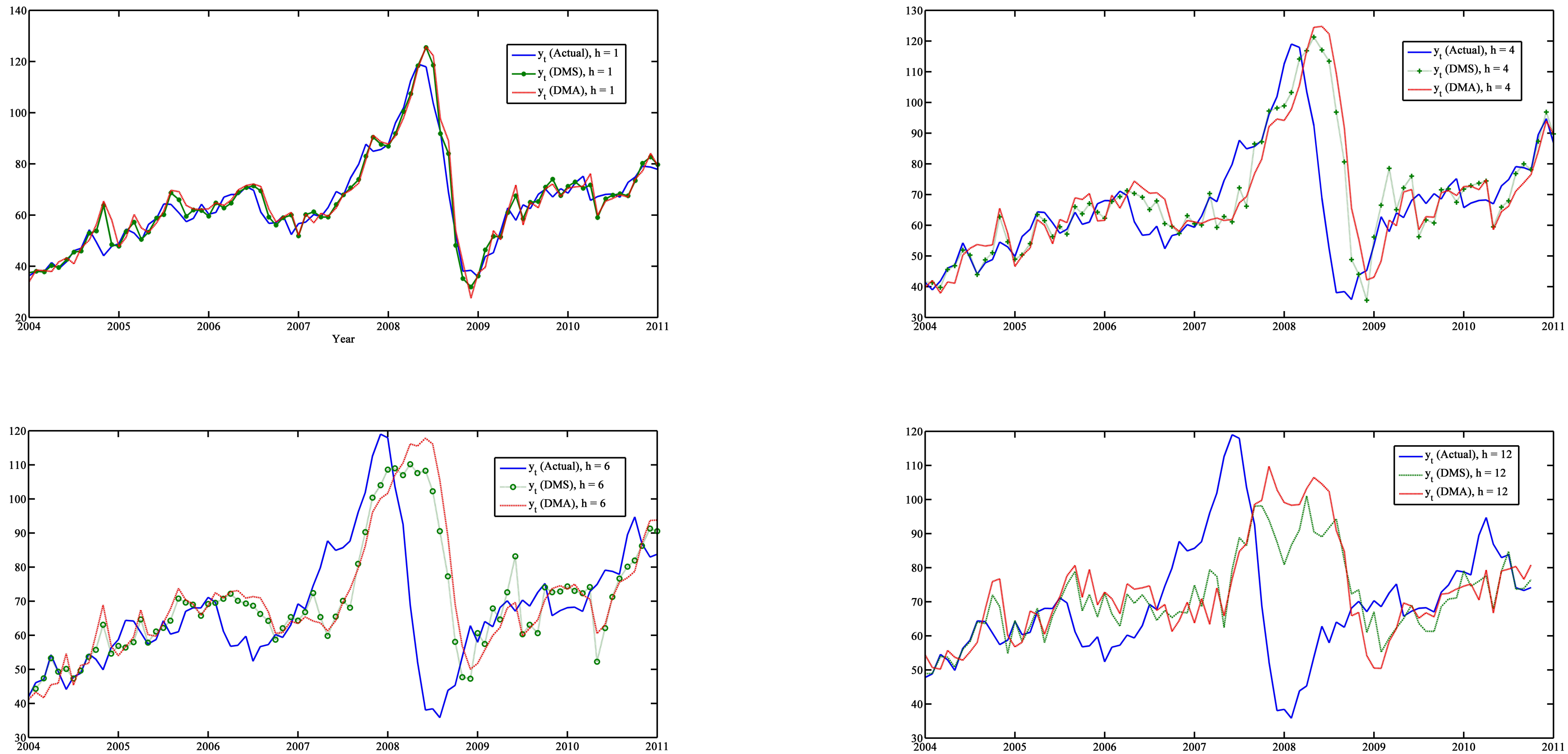


Figure 3.4: Expected Number of Predictors Chosen by DMA

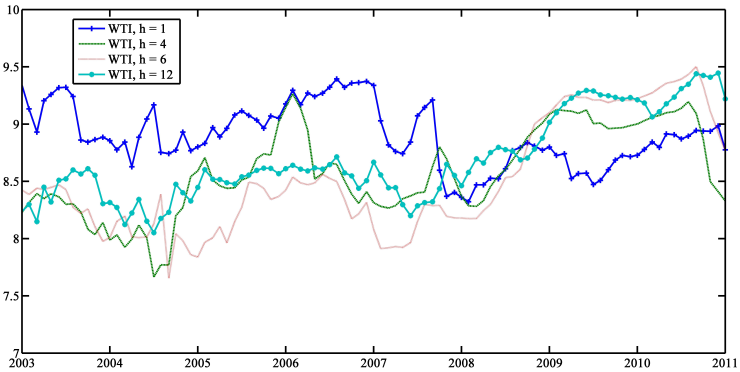


Figure 3.5: Posterior Importance of Factors in DMA

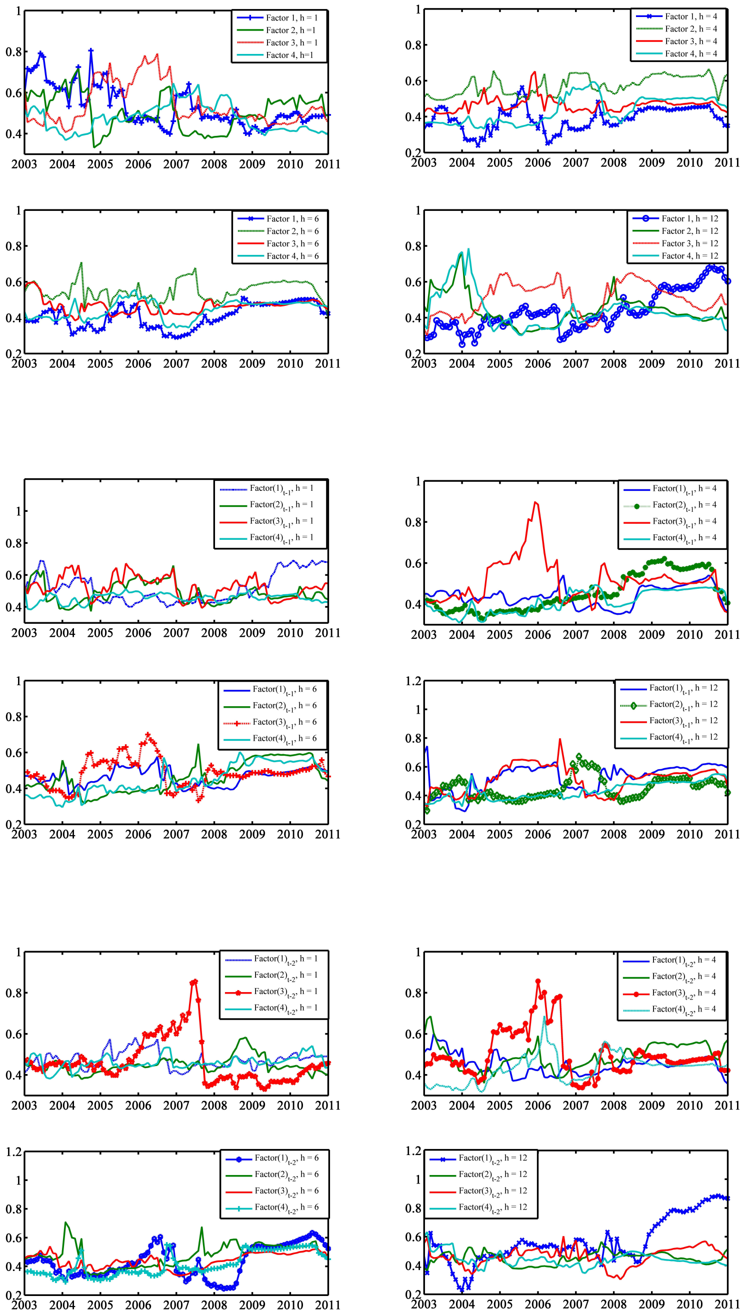
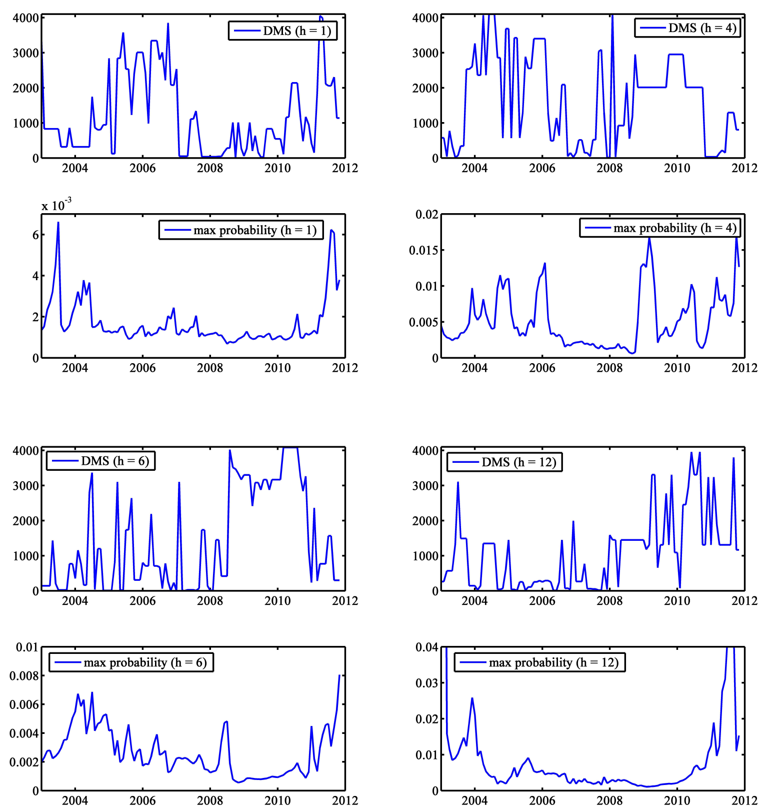


Figure 3.6: Best Choosen Model (DMS) at each Point of Time



Appendix A: Oil Market Data-set

The variables used in this study are taken from Energy Information Agency (EIA). All nominal prices deflated using US-CPI: all urban, all products. Transformation to stationary has been done following Zagaglia (2010). Tcode column show the transformation method used for each variable, where; 1 - at level, 2- first difference, 3- second difference, 4- log of level, 5- first difference of logs , 9- percentage, log of first difference and 6- log of second difference.

Table 3-A.1: Oil Market Dataset

#	Series Title	Unit	Tcode
	Data Prices		
1	Refiner Price of Residual Fuel Oil, Sulfur Content $\leq$ 1%, Resale	Nominal Dollars per Gallon Exc. Tax	5
2	Refiner Price of Residual Fuel Oil, Sulfur Content $\leq$ 1%, End Users	Nominal Dollars per Gallon Exc. Tax	5
3	Refiner Price of Residual Fuel Oil, Sulfur Content $\geq$ 1%, Resale	Nominal Dollars per Gallon Exc. Tax	5
4	Refiner Price of Residual Fuel Oil, Sulfur Content $\geq$ 1%, End Users	Nominal Dollars per Gallon Exc. Tax	5
5	Refiner Price of Residual Fuel Oil, Average, Resale	Nominal Dollars per Gallon Exc. Tax	5
6	Refiner Price of Residual Fuel Oil, Average, End Users	Nominal Dollars per Gallon Exc. Tax	5
7	Refiner Price of Finished Motor Gasoline to End Users	Nominal Dollars per Gallon Exc. Tax	5
8	Refiner Price of Finished Aviation Gasoline to End Users	Nominal Dollars per Gallon Exc. Tax	5
9	Refiner Price of Kerosene-Type Jet Fuel to End Users	Nominal Dollars per Gallon Exc. Tax	5
10	Refiner Price of Kerosene to End Users	Nominal Dollars per Gallon Excluding Tax	5
11	Refiner Price of No. 2 Fuel Oil to End Users	Nominal Dollars per Gallon Exc. Tax	5
12	Refiner Price of No. 2 Diesel Fuel to End Users	Nominal Dollars per Gallon Exc. Tax	5
13	Refiner Price of Propane (Consumer Grade) to End Users	Nominal Dollars per Gallon Exc. Tax	5
14	Landed Cost of Crude Oil Imports From Angola	Nominal Dollars per Barrel	5
15	Landed Cost of Crude Oil Imports From Canada	Nominal Dollars per Barrel	5
16	Landed Cost of Crude Oil Imports From Mexico	Nominal Dollars per Barrel	5
17	Landed Cost of Crude Oil Imports From Nigeria	Nominal Dollars per Barrel	5
18	Landed Cost of Crude Oil Imports From Saudi Arabia	Nominal Dollars per Barrel	5
19	Landed Cost of Crude Oil Imports From United Kingdom	Nominal Dollars per Barrel	5
20	Landed Cost of Crude Oil Imports From Venezuela	Nominal Dollars per Barrel	5
21	Landed Cost of Crude Oil Imports From Persian Gulf Nations	Nominal Dollars per Barrel	5
22	Landed Cost of Crude Oil Imports From All OPEC Countries	Nominal Dollars per Barrel	5
23	Landed Cost of Crude Oil Imports From All Non-OPEC Countries	Nominal Dollars per Barrel	5
24	Landed Cost of Crude Oil Imports	Nominal Dollars per Barrel	5
25	Crude Oil Domestic First Purchase Price	Nominal Dollars per Barrel	5
26	Free on Board Cost of Crude Oil Imports	Nominal Dollars per Barrel	5
27	F.O.B. Cost of Crude Oil Imports From Angola	Nominal Dollars per Barrel	5
28	F.O.B. Cost of Crude Oil Imports From Mexico	Nominal Dollars per Barrel	5

Table 3-A.1 – Continued

#	Series Title	Unit	Tcode
29	F.O.B. Cost of Crude Oil Imports From Nigeria	Nominal Dollars per Barrel	5
30	F.O.B. Cost of Crude Oil Imports From Saudi Arabia	Nominal Dollars per Barrel	5
31	F.O.B. Cost of Crude Oil Imports From United Kingdom	Nominal Dollars per Barrel	5
32	F.O.B. Cost of Crude Oil Imports From Venezuela	Nominal Dollars per Barrel	5
33	F.O.B. Cost of Crude Oil Imports From Persian Gulf Nations	Nominal Dollars per Barrel	5
34	Average F.O.B. Cost of Crude Oil Imports From All OPEC Countries	Nominal Dollars per Barrel	5
35	Average F.O.B. Cost of Crude Oil Imports From All Non-OPEC Countries	Nominal Dollars per Barrel	5
36	Refiner Acquisition Cost of Crude Oil, Domestic	Nominal Dollars per Barrel	5
37	Refiner Acquisition Cost of Crude Oil, Imported	Nominal Dollars per Barrel	5
38	Refiner Acquisition Cost of Crude Oil, Composite	Nominal Dollars per Barrel	5
	Macroeconomic and Financial Data		
39	Gold price in US dollar	US$/oz	5
40	New York Harbor No. 2 Heating Oil Future Contract 1 (NYMEX)	Nominal Dollars per Barrel	5
41	New York Harbor No. 2 Heating Oil Future Contract 3 (NYMEX)	Nominal Dollars per Barrel	5
42	US CPI index for all Urban consumers: All items	Index	5
43	US PPI index Producer Price Index: All Commodities	Index	5
44	US inflation rate	Percent	5
45	Federal Fund rate	Percent	5
46	US Loan %	Percent	5
47	US 3-Tbill %	Percent	5
48	US 6-Tbill %	Percent	5
49	US Treasury Bond Yield, 10 yrs+	Percent	5
50	Australian Dollar in terms of US Dollars	AUD/USD	5
51	Great Britain Pounds in terms of US Dollars	GB/USD	5
52	Japanese Yen in terms of US Dollars	YEN/USD	5
53	S & P 500	Index	5
54	Russia Industrial Production index	Index	5
	Flow and Stock Data		
55	Petroleum consumption, France	Thousand Barrels per Day	9
56	Petroleum consumption, Germany	Thousand Barrels per Day	9
57	Petroleum consumption, Italy	Thousand Barrels per Day	9
58	Petroleum consumption, United Kingdom	Thousand Barrels per Day	9
59	Petroleum consumption, OECD Europe	Thousand Barrels per Day	9
60	Petroleum consumption, Canada	Thousand Barrels per Day	9
61	Petroleum consumption, Japan	Thousand Barrels per Day	9
62	Petroleum consumption, South Korea	Thousand Barrels per Day	9
63	Petroleum consumption, United States	Thousand Barrels per Day	9
64	Petroleum consumption, Other OECD	Thousand Barrels per Day	9
65	Petroleum consumption, Total OECD	Thousand Barrels per Day	9
66	Crude oil production, Algeria	Thousand Barrels per Day	9
67	Crude oil production, Angola	Thousand Barrels per Day	9
68	Crude oil production, Ecuador	Thousand Barrels per Day	9
69	Crude oil production, Iran	Thousand Barrels per Day	9
70	Crude oil production, Iraq	Thousand Barrels per Day	9
71	Crude oil production, Kuwait	Thousand Barrels per Day	9
72	Crude oil production, Libya	Thousand Barrels per Day	9

Table 3-A.1 – Continued

#	Series Title	Unit	Tcode
73	Crude oil production, Nigeria	Thousand Barrels per Day	9
74	Crude oil production, Qatar	Thousand Barrels per Day	9
75	Crude oil production, Saudi Arabia	Thousand Barrels per Day	9
76	Crude oil production, United Arab Emirates	Thousand Barrels per Day	9
77	Crude oil production, Venezuela	Thousand Barrels per Day	9
78	Crude oil production, Total OPEC	Thousand Barrels per Day	9
79	Crude oil Stocks, SPR	Million Barrels	9
80	Crude oil Stocks, Non-SPR	Million Barrels	9
81	Crude oil Stocks, Total	Million Barrels	9
82	Distillate Fuel Oil Stocks,	Million Barrels	9
83	Jet Fuel Stocks	Million Barrels	9
84	Propane/Prophylene Stocks	Million Barrels	9
85	Liquefied Petroleum Gasses Stocks	Million Barrels	9
86	Motor Gasoline Stocks (Including Blending Components and Gasohol)	Million Barrels	9
87	Residual Fuel Oil Stocks	Million Barrels	9
88	Other Petroleum Products Stocks	Million Barrels	9
89	Total Petroleum Stocks	Million Barrels	9
90	Crude oil production, Persian Gulf Nations	Thousand Barrels per Day	9
91	Crude oil production, Canada	Thousand Barrels per Day	9
92	Crude oil production, China	Thousand Barrels per Day	9
93	Crude oil production, Egypt	Thousand Barrels per Day	9
94	Crude oil production, Mexico	Thousand Barrels per Day	9
95	Crude oil production, Norway	Thousand Barrels per Day	9
96	Crude oil production, Former U.S.S.R	Thousand Barrels per Day	9
97	Crude oil production, Russia	Thousand Barrels per Day	9
98	Crude oil production, United Kingdom	Thousand Barrels per Day	9
99	Crude oil production, United States	Thousand Barrels per Day	9
100	Crude oil production, Total Non-OPEC	Thousand Barrels per Day	9
101	Crude oil production, World	Thousand Barrels per Day	9
102	US Ending Stocks of Crude Oil and Petroleum Products	Thousand Barrels	9
103	US Ending Stocks excluding SPR of Crude Oil and Petroleum Products	Thousand Barrels	9
104	US Ending Stocks of Crude Oil	Thousand Barrels	9
105	US Ending Stocks excluding SPR of Crude Oil	Thousand Barrels	9
106	US Crude Oil Stocks in Transit (on Ships) from Alaska	Thousand Barrels	9
107	US Ending Stocks of Crude Oil in SPR	Thousand Barrels	9
108	US Ending Stocks of Total Gasoline	Thousand Barrels	9
109	US Ending Stocks of Finished Motor Gasoline	Thousand Barrels	9
110	US Ending Stocks of Gasoline Blending Components	Thousand Barrels	9
111	US Ending Stocks of Kerosene-Type Jet Fuel	Thousand Barrels	9
112	US Ending Stocks of Distillate Fuel Oil	Thousand Barrels	9
113	US Ending Stocks of Residual Fuel Oil	Thousand Barrels	9
114	US Ending Stocks of Propane and Propylene	Thousand Barrels	9
115	US Ending Stocks of Unfinished Oils	Thousand Barrels	9
116	US Ending Stocks of Kerosene	Thousand Barrels	9
117	US Ending Stocks of Asphalt and Road Oil	Thousand Barrels	9
118	Petroleum stocks, France	Million Barrels	9
119	Petroleum stocks, Germany	Million Barrels	9
120	Petroleum stocks, Italy	Million Barrels	9
121	Petroleum stocks, United Kingdom	Million Barrels	9
122	Petroleum stocks, OECD Europe	Million Barrels	9
123	Petroleum stocks, Canada	Million Barrels	9
124	Petroleum stocks, Japan	Million Barrels	9

Table 3-A.1 – Continued

#	Series Title	Unit	Tcode
125	Petroleum stocks, South Korea	Million Barrels	9
126	Petroleum stocks, United States	Million Barrels	9
127	Petroleum stocks, Other OECD	Million Barrels	9
128	Petroleum stocks, Total OECD	Million Barrels	9
129	U.S. Crude Oil, Natural Gas, and Dry Exploratory and Developmental Wells Drilled	Number of wells	9
130	US Crude Oil Exploratory and Developmental Wells Drilled	Number of wells	9
131	US Natural Gas Exploratory and Developmental Wells Drilled	Number of wells	9
132	US Dry Exploratory and Developmental Wells Drilled	Number of wells	9
133	US Crude Oil, Natural Gas, and Dry Exploratory Wells Drilled	Number of wells	9
134	US Crude Oil Exploratory Wells Drilled	Number of wells	9
135	US Natural Gas Exploratory Wells Drilled	Number of wells	9
136	US Dry Exploratory Wells Drilled	Number of wells	9
137	US Crude Oil, Natural Gas, and Dry Developmental Wells Drilled	Number of wells	9
138	US Crude Oil Developmental Wells Drilled	Number of wells	9
139	US Natural Gas Developmental Wells Drilled	Number of wells	9
140	US Dry Developmental Wells Drilled	Number of wells	9
141	U.S. Total Footage Drilled for Crude Oil, Natural Gas, and Dry Exploratory and Developmental Wells	Thousand Feet	9
142	US Crude Oil and Natural Gas Rotary Rigs in Operation	Number of rigs	9
143	US Onshore Crude Oil and Natural Gas Rotary Rigs in Operation	Number of rigs	9
144	US Offshore Crude Oil and Natural Gas Rotary Rigs in Operation	Number of rigs	9
145	US Crude Oil Rotary Rigs in Operation	Number of rigs	9
146	US Natural Gas Rotary Rigs in Operation	Number of rigs	9
147	US Crude Oil and Natural Gas Active Well Service Rigs in operation	Number of rigs	9

B Theoretical Background

There are three main separate economic theories that focus on predictions for the dynamic behavior of crude oil prices, which should all hold in equilibrium as briefed below:

B.1 Scarcity Rent

In the case of an exhaustable resource; such that of oil, Hotelling (1931) emphasized that the price should exceeds marginal cost and would exhibit particular dynamic behavior over time even if the oil market were perfectly competitive.[90] If there is any unavoidable geological limits for example, global production of crude oil next year could be less than the amount being produced this year. Under such condition, buying the oil today in order to store it in a tank for a year, and wait to sell it into the next year's would be favorable. It would be even more efficient, however, for the owner of any oil reservoir to 'store' the oil directly by just leaving it in the ground, waiting to produce it until the price has risen (Hamilton, 2009a).

This scarcity rent at time t, λ_t , as the difference between price P_t and marginal production cost M_t as following:

$$\lambda_t = P_t - M_t \tag{3-B.1.1}$$

suppose the owner produces the oil today and invests the profits at interest rate i_t. Then in the next year, the owner would have $(1 + i_t)\lambda_t$. If that is bigger than the benefit from producing next year (i.e. $(1+i_t)\lambda_t > \lambda_{t+1}$), then the owner is better off producing more today and leaving less in the ground. Under a reversed inequality in the above condition, the owner better off producing less. Thus in equilibrium, Hotelling's principle claims that the scarcity rent should rise at the rate of interest as below:

$$P_{t+1} - M_{t+1} = (1 + i_t)(P_t - M_t) \tag{3-B.1.2}$$

The initial price P_0 is then determined by the transversality condition that if the

[90]Perfect competitive market is the market such that nor participants are large enough to have the market power to set the price of a homogenous product.

price P_t follows the dynamic path given by (3-B.1.2) from that starting point, the cumulative production converges to the total recoverable stock as $t \to \infty$.

Although Hotelling's theory and its extensions are elegant,[91] there are challenges in using it to explain the observed data. Krautkraemer (1998) surveyed some of the literature in this area, a fair summary of which might be that efforts along these lines are ultimately not altogether satisfying. As a result, many economists often think of oil prices as historically having been influenced little or not at all by the issue of exhaustibility.

B.2 Returns to Storage

As it is possible to invest by borrowing money today (denoted date t) in order to purchase a quantity Q barrels of oil at a price P_t dollars per barrel and the agent pay a fee to the owner of the storage tank of C_t dollars for each barrel stored for a year, then there will be a need to borrow $(P_t + C_t)Q$ total dollars. Next year the agent must pay this back with interest, owing $(1 + i_t)(P_t + C_t)Q$ dollars for it the interest rate. However, the agent will have the Q barrels of oil that can be sell for next year's price, P_{t+1}. The agent can make profit only if the following condition holds:

$$P_{t+1}Q > (1 + i_t)(P_t + C_t)Q \tag{3-B.2.3}$$

The agent doesn't know today what next year's price of oil will be, but there are some available information that can help to draw expectation which could be denoted as E_tP_{t+1}. From (3-B.2.3), profit from oil storage is expected whenever:

$$E_tP_{t+1} > Pt + C_t^* \tag{3-B.2.4}$$

where C_t^* reflects the combined interest and physical storage expenses:

$$C_t^* = i_tP_t + (1 + i_t)C_t \tag{3-B.2.5}$$

Suppose investment agents did expect P_{t+1} to be greater than $P_t + C_t^*$. Then anyone could expect to make a profit by buying the oil today, storing it, and selling it

[91] See Pindyck (1978) for more discussion on estimation of optimal pricing models for exhaustible resources, taking into account the effects of cartelization in the oil market

next year. If there are enough potential risk neutral investors, the result of their purchases today would be to drive today's price P_t up. Knowledge of all the oil going into inventory today for sale next year should reduce a rational expectation of next year's price E_tP_{t+1}. As long as the inequality (3-B.2.4) held, speculation would continue, leading us to conclude that (3-B.2.4) could not hold in equilibrium.

If the inequality were reserved, then anyone putting oil into storage is expecting to lose money. However, this does not mean that storage become zero, because inventories of oil are essential for the business of transporting and refining oil and delivering it to the market. This is equivalent to a negative storage cost for oil in the form of a benefit to your business of having some oil in inventory, which is referred to as a 'convenience yield'. We might then subtract any convenience yield from physical and interest storage costs C_t^* to get a magnitude $C_t^\sharp$, the net cost of carry. If $E_tP_{t+1} < P_t + C_t^\sharp$ holds, there is an incentive to sell oil out of inventories today, driving P_t down and $C_t^\sharp$ up. Thus, we conclude that the following condition should hold in equilibrium:

$$E_tP_{t+1} = P_t + C_t^\sharp \tag{3-B.2.6}$$

Insofar as expectations, convenience yield and risk premia are impossible to observe directly, one might think that (3-B.2.6) does not imply any testable restrictions on the observed relation between P_{t+1} and P_t.[92] It seems inconceivable that risk aversion or convenience yield would exhibit quarterly movements of anywhere near this magnitude. The implication of (3-B.2.6) is that big changes in crude oil prices should be mostly unpredictable. Given that it is the big changes that dominate this series statistically, the finding in the previous section that oil price changes are very difficult to predict is exactly what the theory sketched here would lead us to expect.

B.3 Futures Markets

Instead of storage, entering into a futures contract is an alternative investment strategy, which would be an agreement the agent reach today to buy oil one year from now at some price, F_t, at a price agreed today by both of them. If the agent agreed

[92] We could in principle modify our definition of the cost of carry $C_t^\sharp$ further to incorporate any risk premium that may induce investors to want to hold more or less inventories.

to buy oil at the price F_t, then the profit will exist whenever $F_t < P_{t+1}$. In this case, the agent will be able to re-sell the oil on next year's spot market at price P_{t+1}, where the difference is a pure profit. In such case, equilibrium requires the following:

$$F_t = E_t P_{t+1} + \widetilde{H}_t \tag{3-B.3.7}$$

where $\widetilde{H}_t$ is a term incorporating any risk premium or complications induced by margin requirements. Note that (3-B.3.7) is not an alternative theory to (3-B.2.6)- both conditions have to hold in equilibrium. For example, if there were an increase in F_t without a corresponding change in P_t, that would create an opportunity for someone else to buy spot oil at time t for price P_t, store if for a year, and sell it through a futures contract. If we chose to ignore cost of carry and risk premia, conditions (3-B.2.6) and (3-B.3.7) together would imply that the futures price simply follows the current spot price, $F_t = P_t$. In practice, one finds in the data that the futures price and spot price differ, but often not by much, and when news causes the spot price to go up or down on a given day, futures prices at every horizon usually all move together in the same direction as the change in spot prices. Enormous studies aim to understand the predictive power of futures prices and the nature of the relationship between oil spot and futures price. For instance, Bopp and Sitzer (1987) found that futures prices quoted one month ahead significantly contributed to the price forecasting models. But, futures prices quoted more than one month ahead did not. Chinn et al. (2005) stated that futures do not appear to well predict subsequent movements in energy commodity prices, although they slightly outperform time series models. Studies by Bopp and Lady (1991), Abosedra and Baghestani (2004), and Alquist and Kilian (2010) found that P_t provides as good or even a better forecast of P_{t+s} than does the futures price F_t.

C Measures of Oil Price

The crude oil pricing system was first under the control of large multinational oil companies. Then the Organization of the Petroleum Exporting Countries (OPEC) was formed to try to counter the oil companies cartel, and had achieved a high level of price stability until 1972.[93] After the collapse of the OPEC-administered pricing system in 1985, the oil pricing regime experienced a short lived experiment with netback pricing, which was associated by means of a dramatic price collapse during most of 1986 (Fattouh, 2011).

Currently, the main method for pricing crude oil in international trade is known as market-related pricing system. It has been introduced in the second half of the 1980s and received a wide acceptance by 1988. The oil prices associated with this pricing system are set by 'market'. Since, crude oil is not a homogenous commodity, there are various types of internationally traded crude oil with different qualities and characteristics.[94] In the current system, the prices of these crudes are usually set at a discount or premium to a marker or reference price according to their quality (Fattouh, 2006). The variation of the quality depending upon crudes sulfur and gravity contents, which are meant mainly for two primary products including gasoline and heating oil. This implies that different crudes fetch different prices.

Based on crudes quality, there are four major pricing benchmarks in crude oil world.[95] First, West Texas Intermediate (WTI) crude oil, which is of a very high quality. It has a light-weight and low sulphur content. For these reasons, it is often referred to as 'light, sweet' crude oil. These properties make it excellent for making gasoline, which is why it is the major benchmark of crude oil in the Americas. Second, Brent Blend crude oil, which is a combination of crude oil from 15 different oil fields in the North Sea. It is less 'light' and 'sweet' than WTI, but still excellent for making gasoline. Third, Dubai crude oil, which is the benchmark crude oil representing the medium-heavy sour crude oils traded in the Middle and Far East. Fourth is the Maya crude oil, representing the heavy sour crude oils sold at a significant discount compared to WTI and Brent. Only the best known WTI and Brent crudes have a similar quality and are actively traded in highly liquid future market with low transaction costs, facilitating speedy price adjustment through arbitrage operations. In contrast, Dubai has only forward contracts, tradeable over the counter, and Maya is illiquid, since it is not actively traded on any oil futures market.[96]

[93] OPEC has been created in 1960 to coordinate and unify petroleum policies among Member Countries. The role of the OPEC was not only to secure fair and stable prices for petroleum producers, it was extended to guarantee an efficient economic, and regular supply of petroleum to consuming nations, and a fair return on capital to those investing in the industry.

[94] For detailed discussion on history of oil price regimes, see Mabro (2005).

[95] See Bacon (1991) for more details on crudes benchmarks.

[96] See Fattouh (2010) for more discussion on the dynamic behavior of crude oil price differentials.

The prices of these benchmark crudes, often referred to as 'spot' market prices, are central to the oil pricing system. The prices of these benchmarks are used by oil companies and traders to price cargoes under long-term contracts or in spot market transactions, by futures exchanges for the settlement of their financial contracts, by banks and companies for the settlement of derivative instruments such as swap contracts, and by governments for taxation purposes (Fattouh, 2011).

Empirical studies that include oil prices had diversified the measures of crude oil prices for different purposes. Among others, Yu et al. (2008) propose an empirical model for world crude oil spot price forecasting. They use two main crude oil price series including WTI and Brent spot prices to test and verify the model efficiency. Chen and Chen (2007) investigate the long-run relationship between real oil prices and real exchange rates considering different measures of oil prices including the world price of oil, the United Arab Emirates price of oil (Dubai), the British price of oil (Brent), and the US West Texas Intermediate price of oil (WTI). However, in literature WTI has been widely used by enormous studies aiming to forecast and analyse the stochastic behavior of crude oil price. This is so, because WTI is the available for a larger period and is excessively traded in New York Mercantile Exchange (NYMEX). For instance, Hamilton (1983, 1985) analyse the relationship between WTI crude oil prices and the US GNP. He et al. (2010) investigates the cointegrating relationship between WTI prices with the global economic activity. Others like Coppola (2008); Ye et al. (2002, 2005, 2006), and Zagaglia (2010) construct forecasts of WTI crude oil prices.

The nominal price of crude oil receives much attention in the press. However, the variable most relevant for economic modeling is the real price of oil.[97] Many authors specify their models in terms of real price of oil such as that of Elder and Serletis (2010), Herrera et al. (2011), Lee et al. (1995), Mork (1989), and Zamani (2004). However, Alquist et al. (2001) propose that there is still a need of empirical studies that employ real price of oil rather than nominal prices. In this chapter, our focus is to generate forecasts both for real spot and future prices. Thus, we use the spot and futures prices of WTI crude oil, and deflate all the nominal prices using the Consumer Price Index (CPI) of the US.

[97]For further discussion of the distinction between nominal and real energy prices see, e.g., Hamilton (2005) and Kilian (2008).

Chapter 4

Analysing The Long-run Relationship between Oil consumption, Nuclear energy consumption, Oil price and Economic growth

4.1 Introduction

In recent years there have been concerns among economists about the relationship between energy consumption and economic growth. Early models such as that of Solow (1956) do not explain how improvements in technology come about, since this model assumes that technological change is exogenous. More recently, the main stream of growth models of Aghion and Howitt (2009) do not include resources or energy. However, many researchers believe that energy plays a crucial role in economic growth view energy as being an important factor in explaining the industrial revolution (e.g. Wrigley, 1990; Allen, 2009). Furthermore, some authors such as Cleveland et al. (1984), Hall et al. (1986) and Hall et al. (2003) argue that there are two main determinants for the noticeable growth in productivity. They are increase in energy use, and the fact that innovation in technological change mainly increases productivity by allowing the use of more energy. Therefore, high level of energy consumption is an important factor in stimulating economic growth. This fact has triggered interests in identifying the nature of the relationship between energy consumption and economic growth in order to design an effective energy policy that promotes economic growth.

In these efforts, Apergis and Payne (2010a) shed light on the relationship between energy consumption and GDP growth and explain how energy policies and their objectives may affect GDP under four major hypothesis. First, under the growth hypothesis, energy saving policies that reduce energy consumption may have an adverse impact on real GDP.[98] Accordingly, negative energy shocks and energy conservation policies may depress economic growth. Second, the conservation hypothesis proposes that an implementation of a conservation energy policy, would not slow down economic growth. Third, the neutrality hypothesis suggests that energy consumption has little or no impact on GDP; therefore, energy conservation policies do not affect economic growth (Asafu-Adjaye, 2000). Fourth, the feedback hypothesis implies that energy consumption and economic growth are jointly determined and affected at the same time. This encourages the implementation of energy expansionary policies for long run sustainable economic growth.

Despite the great significance of a possible relationship between energy consumption and economic growth, there is no consensus yet either on the existence and on

[98]This impact is so because the economy is very dependent on energy to grow (Masih and Masih, 1997).

the direction of causality between them (Ozturk, 2010). These conflicting results may arise due to different data set, countries' characteristics, variables used, and different econometric methodologies employed (Ozturk, 2010; Menegaki, 2014). The findings from studies vary not only across countries, but depend also on different methodologies within the same country (Soytas and Sari, 2003). Energy consumption variables that are utilised in the existing literature are generally total energy consumption or electricity consumption (Alvarez-Ramirez et al., 2003). However, Sari and Soytas (2004) argue that the use of aggregate energy consumption or electricity consumption, rather than utilising different energy resources, may be another reason behind the inconsistency in the empirical studies' results. It is possible that the importance of a certain energy resource for a country changes over time, which implies that distinguishing the relationship between energy consumption and economic growth based on empirical analysis requires utilising different energy sources rather than using aggregate energy consumption (Sari and Soytas, 2004). The lack of agreement on the direction of causality provides a channel for analysing and discussing the nature of the relationship between energy consumption and economic growth. Vaona (2012) tests for causality between energy use and GDP in Italy using three different approaches, including the Toda and Yamamoto (1995) procedure, the Johansen cointegration test, and the Lütkepohl et al. (2004) cointegration test. In the Vaona (2012) paper, energy has been disaggregated into renewable and non-renewable energy (fossil fuels). The main finding shows that there is a causation relationship between non-renewable energy and GDP, and another relationship from one measure of renewable energy to GDP. However, the standard procedure of the Johansen test does not find cointegration between GDP and fossil fuels at all. Using the approach suggested by Lütkepohl et al. (2004) approach, Vaona (2012) finds cointegration with a structural break.

Based on OPEC's World Oil Outlook 2012, fossil fuels currently account for 87% of the energy demand and will still make up to 82% of the global total energy by 2035. For most of the projection period, oil will remain the energy type with the largest share since it plays a key role in the production process of modern economies. The demand for oil is expected to reach 99.7 mb/d in 2035, rising from 87.4 mb/d in 2011. This demand will be driven mainly by population and economic growth in the emerging economies.[99] However, oil is not only a credible fossil fuel source, it is the major reason for global warming because of the carbon dioxide emission. It

[99] http://www.polsci.chula.ac.th/pitch/ep13/weo12.pdf

also involves risks in terms of security of the supply of energy needs for many energy importing countries, especially because it is concentrated in the unstable region of the Middle East. These reasons have driven the interest among researchers and policy makers to study the linkage between oil consumption and economic growth in both developing and developed countries.

Although oil plays a crucial role in stimulating economic growth as shown above, prices of oil have been exceptionally volatile over the past several years. Historical data show that WTI spot oil prices increased sharply up to $145 in July 2008, and dropped down to a very low level of $30 in December 2008. There are many reasons that support the increase in oil prices rather than its stabilisation. Researchers such as Hamilton (1983, 1988, 1996, 2003), Hooker (1996), and Mork (1989) suggest that the growing demand from developing economies and unrest in many oil-supplying countries of the Middle East and North Africa have caused oil price increases in previous years. During these years, the fluctuations in the prices of oil resulted in many problems that dampened the economy of both oil importing and oil exporting countries. For instance, as oil is an important input in the production process, a rise in the prices of oil follow-on an increase of production costs, which slows down the economic growth of an oil importing country. These effects have been supported through many empirical investigations such as that of Hamilton (2003, 2005), who shows that nine out of ten recessions in the US have been preceded by oil price shocks.

From the previous discussion, it can be seen that while there is a rapid increase in international crude oil demand, crude oil prices have suffered from high volatility problem over the last few decades. Therefore, the priority of energy policy for many countries has become diversifying the sources of energy, and finding a stable, safe, and clean energy supply (Toth and Rogner, 2006; Elliott, 2007). As a part of their strategy of increasing energy security, many countries have built nuclear power plants, not only to reduce the dependence on imported oil, but also to increase the supply of a secured energy source and to minimise the price volatility associated with oil imports (Toth and Rogner, 2006).[100] The US Energy Information Administration (EIA) reports of primary energy consumption between 1985 and 2011, show that the considerable growth of electrical consumption in the world requires a mas-

[100]One of the reasons for the shrinking of Japanese oil consumption during the period 1979 - 1985 was the construction of several nuclear power plants for electricity generation. This led to the substitution of crude and fuel oil, and caused a drop in demand of around 1.2 mb/d for the whole period (OPEC's World Oil Outlook 2012).

sive use of nuclear energy.[101] In 2010, demands for nuclear energy and renewable energy increased due to the limitations of fossil fuels such as oil, natural gas, and coal (de Almeida and Silva, 2009).

Thus, the importance of nuclear power as a potential source of energy, and as a partial replacement for fossil fuels to eliminate emissions creates the need for further research to examine the relationship between nuclear energy consumption and economic growth (Apergis and Payne, 2010b). It is essential to understand the nature of the relationship and identify the direction of causation, to provide logical reasons for investing in nuclear energy for economical concerns or for environmental and social concerns (Chu and Chang, 2012).

To date, few empirical studies have focused on investigating the nature of the relationship between oil consumption and economic growth (see Yoo, 2006; Zou and Chau, 2006; Zhao et al., 2008; Aktaş and Yılmaz, 2008, among others) on the one hand, and between nuclear energy consumption and economic growth on the other (see Yoo and Jung, 2005; Yoo and Ku, 2009; Wolde-Rufael, 2010, among others). There is a dearth of empirical research that looks into the dynamic relationship between oil consumption, nuclear energy consumption, oil price, and economic growth using modern advances in time series econometrics associated with causality testing. The purpose of this chapter is to fill this gap by investigating the long run relationship between oil consumption, nuclear energy consumption, oil price, and economic growth using Johansen cointegration analysis.

In particular, we run our investigation among four industrialised countries (the US, Canada, Japan, and France) and four emerging economies (Russia, China, South Korea, and India) over the period from 1965 to 2010. Our results provide information about the nature and direction of linkage between nuclear energy consumption and economic growth, oil consumption and economic growth, and oil prices and economic growth. We examine each country separately to allow us to use a framework that accounts for country specific issues such as energy patterns and economic crisis. The main reason for studying the long run relationship between oil consumption, nuclear energy consumption and economic growth is that both oil and nuclear energy play an important role in designing effective energy policies that accounts for both economic growth and environmental protection. Empirical results of the

[101] http://www.eiagov/forecasts/steo/

relationship between nuclear energy, the oil market, and the real GDP also play a pivotal role in the implementation of energy or environmental policies for both highly industrialised countries and emerging economies.

Cointegration analysis illustrates that we cannot exclude at least one energy input from the cointegration space. This implies that a long-run relationship exists between energy consumption and economic growth. As far as the results of cointegration vectors normalised with respect to real GDP growth, the coefficients of oil consumption are found to affect the level of economic growth significantly and positively in six out of eight countries, including the US, Canada, France, China, South Korea, and India. This finding implies that the use of more oil stimulates the real GDP growth. Alternatively, nuclear energy consumption has been found to influence economic growth positively and significantly in five countries including: Japan, France, Russia, China and South Korea. However, we find that the nuclear energy consumption is negatively linked to real GDP growth in India. Although oil price is excluded from the long-run equilibrium error in most countries, it is endogenous and negative in the case of Canada and Russia. Furthermore, results from the parsimonious vector equilibrium correction model (PVECM) show that oil consumption has predictive power for economic growth in the US, Japan, France, and India. Additionally, there is a feedback impact between oil consumption and real GDP growth in Canada, Russia, China, and South Korea. Hence, oil can be considered an important factor to output growth in these countries. Regarding the nuclear energy consumption - growth nexus, there is a bi-directional relationship between nuclear energy consumption and output growth in Japan and in India. Moreover, nuclear energy consumption is found to have information that could predict real GDP growth in the US, Canada, France, Russia, China and South Korea. In most of the cases, oil prices are exogenous to equilibrium error, except for the US, Canada and China.

In what follows, we first provide background and a literature review in Section 4.2. Section 4.3 describes the econometric methodology. Section 4.4 illustrates the data sources and definitions of the variables. Section 4.5 shows the empirical results, and a conclusion is provided in Section 4.6.

4.2 Background and Literature Review

4.2.1 Oil Price and Economic Growth

Given the essential role of crude oil in the world economy, the impact of crude oil price movements on economy has been a matter of great interest to economists since the 1970s. This interest has been fueled by the oil price shock of 1973 and the subsequent recessions. Therefore, many researchers study the nature of the relationship between oil price and economic activities. Early theoretical studies focus on the traditional aggregate channels of supply shocks and demand adjustments (Bruno and Sachs, 1982; Pierce et al., 1974), while empirical investigations generally start with the regressing GDP on oil prices and several other variables (Rasche and Tatom, 1977a,b). However, both approaches confirm the inverse relationship between oil prices and the aggregate economic activity. In particular, Hamilton (1983) demonstrates that an oil price increase had proceeded all but one recession in the US since the end of World War II. Gisser and Goodwin (1986) reinforced Hamilton's findings for the US, and Burbidge and Harrison (1984) find supporting evidence from the UK and Japan as well as the US.

Theoretically, researchers propose various transmission channels through which oil prices may have an impact on economic activity. First, the most basic channel is the classic supply-side effect. It suggests that rising oil prices are indicative of the reduced availability of a basic input to production, leading to a reduction in the overall potential output (see Abel and Bernanke, 2001; Brown and Yuecal, 1999, among others). Accordingly, if the cost of production increases, growth of the output and productivity will slow down. Second, the transfer of income from oil-importing countries to oil-exporting countries leads to a fall in the purchasing power of firms and households in oil-importing countries (Dohner, 1981; Fried et al., 1975). Third, a rise in oil price would drive an increase in money demand based on real balance effect, as proposed by Pierce et al. (1974) and Mork (1994). Then, a failure of the monetary authority to meet growing money demand with increased supply would boost interest rates and retard economic growth (see Brown and Yücel, 2002, for more details).[102] Fourth, as consumption is positively linked with disposable income, oil price increase may have a negative impact on consumption. Also, this increase in oil prices may affect investment negatively by increasing firms' costs. Fifth, a long-lasting increase in oil price would change the production structure and, accordingly,

[102] Bohi (1989, 1991) and Bernanke et al. (1997) argue that confectionary monetary policy accounts for much of the decline in aggregate economic activity following an oil price increase.

affect the level of unemployment.[103] Indeed, a rise in oil prices may encourage firms to adapt and construct new production methods that are less intensive in oil inputs. This change generates capital and labour reallocations across sectors that can affect unemployment in the long run (Loungani, 1986). In addition, an increase in oil price generates inflationary pressures, which is accompanied by direct and indirect effects (see Álvarez et al., 2011, for more details). Neither the real balance effect nor monetary policy can alone yield both slowing GDP growth and an increase in inflationary pressure (Brown and Yücel, 2002).

Empirical research has generated evolving impressions about the magnitude of oil price effects on aggregate economic activity. The empirical evidence presented in Hamilton (1983) suggests that exogenous shocks to oil prices have significant impacts on real economic activity in the US. Mork (1989) confirms that the negative correlation with oil price increases is persistent. Beyond establishing a relationship between oil price movements and aggregate economic activity, researchers have been assigned prominent roles to both in a number of macroeconomic models (Bruno and Sachs, 1982; Hamilton, 1988; Rasche and Tatom, 1981). For example, Hall (1991) uses oil prices to identify labour supply and demand. Others, such as Phelps (1994) and Carruth et al. (1995), associate oil price shocks with the natural rate of unemployment. Kim and Loungani (1992) explain how oil prices reduce the role of technology shocks in real business cycle models, and depress irreversible investment through their effects on uncertainty (Ferderer, 1996).

4.2.2 Energy Consumption and Economic Growth

Given that energy plays a significant role in economic growth (Beaudreau, 2005; Stern and Cleveland, 2004), energy economists emphasised that it is a prime agent in the generation of wealth (Stern, 2011). The ecological view reveals that energy has a considerable role in income determination, which implies that the economies that are highly dependent on energy use will be significantly influenced by the variation in energy consumption (Cleveland et al., 1984). In addition, the historical data attest that there is a strong relationship between the availability of energy, economic activity, and improvements in standards of living and overall social well-being (Nathwani et al., 1992). Therefore, many empirical studies attempt to assess the effect of energy use on economic output. However, the theoretical and empirical

[103] In a recent study, Doğrul and Soytas (2010) find that the real price of oil and interest rates in Turkey improve the forecasts of unemployment in the long run.

findings indicate that the contribution of energy to productivity improvements and economic growth has been greatly underestimated (Sorrell, 2010).

Since the seminal work of Kraft and Kraft (1978), several researchers have investigated the causal relationship between energy consumption and economic growth. However, empirical studies do not provide any clear-cut answer, and currently there is no consensus among economists either on existence or on direction of causality. For instance, using Sims (1972) causality test, Kraft and Kraft (1978) provide evidence that supports a unidirectional causality running from real GNP to energy consumption for the US using annual data that covers the period from 1947 to 1974. This finding is contested by Akarca and Long (1980), who show that Kraft and Kraft's study suffer from temporal sample instability. They exclude the years 1973-1974 from the sample and argue that the causal order suggested by Kraft and Kraft (1978) is spurious and is sensitive to the sample period.

In a bivariate framework, Yu and Hwang (1984) apply both the causality test proposed by Sims (1972) and Granger (1969) for the extended the US annual data from 1947 to 1979. In line with Akarca and Long (1980), they find that there is no causal linkage between income and energy usage in the US. However, repeating the exercise using quarterly data show evidence of a unidirectional causality running from GNP to energy consumption from 1973 to 1981. These tests also have been applied to a number of other industrialised countries to examine the causal linkage between energy consumption and economic growth. The results of those applications provide evidences that support the absence of causation between energy and growth (Yu and Choi, 1985; Erol and Yu, 1987). Yu and Jin (1992) extend the work to examine whether energy consumption and output are cointegrated for the US. They find that energy consumption has no long term relationship with income and employment. More recently, using the cointegration analysis proposed by Johansen and Juselius (1990), Soytas and Sari (2003) test the causal linkage between real GDP and energy usage in ten emerging economies and G7 countries. They find that there is a long run unidirectional causality running from energy consumption to real GDP for Turkey, France, West Germany and Japan, while the reverse causality exists for Italy and Korea. However, they are unable to find a cointegration relationship between energy usage and real GDP in the US. Zachariadis (2007) examine the usefulness of bivariate framework using three different time series approaches including VECM, ARDL, and the Toda and Yamamoto (1995) model. The sample used in his study cover a number of industrialised countries including Canada, France, Germany, Italy, Japan, the UK, and the US. Using aggregate and sectoral data, Zachariadis (2007) finds that there is a cointegrating relationship for all energy-economy pairs in the case of Japan only. On the other hand, he shows that there is no evidence for causality at the level of the total economy, while for services as well as transport sectors, GDP Granger causes energy consumption.

Although early studies which use a bi-variate approach are attractive because they can be used for developing countries that suffer from a complete lack of data on some variables of interest, one should be cautious when drawing policy implications with the aid of bivariate causality tests on small samples (Zachariadis, 2007).[104] Zachariadis (2007) underlines the importance of utilising as large a sample size as possible and using multivariate models, which are closer to economic theory, accommodate several mechanisms and causality channels and provide a better representation of real-world interactions between energy use and economic growth. Thus, recent papers employ either a trivariate or multivariate time series framework when examining an energy-growth nexus to overcome the weakness of omitting variables problem in bivariate approach. Most of these papers employ a neo-classical aggregate production function, which supports the idea that capital, labour, and technological change play a significant role in determining output. Yet, early studies implicitly assume that energy is the only input in production. If this assumption is not true, studies will lead to omitted variables bias. Moreover, in the case of stochastically trending variables, there will be no evidence of cointegration, and, hence, spurious regression outcomes will result (Stern and Common, 2001).

Using a multivariate framework, Stern (1993) tests for Granger causality in a multivariate setting using a VAR model of GDP, capital, labour inputs, and a Divisia index of energy use measured in heat units.[105] When both the multivariate approach and the quality adjusted energy index were employed, he finds that energy Granger caused GDP. Stern (2000) extends the work applied in Stern (1993) by estimating a cointegrating VAR for the same variables. The analysis shows that there is a cointegrating relationship between the four variables and that energy Granger causes GDP either unidirectionally or possibly through a mutually causative relationship. Warr and Ayres (2010) replicate this model for the US using their measures

[104] Payne (2010b) notes that a large body in the literature (26 of 35 studies surveyed) employ bivariate models, which might suffer from omitted variables bias.

[105] Divisia index is a method of aggregation used in economics that allows variable substitution in material types without imposing a priori restrictions on the degree of substitution.

of energy and useful work in place of Stern's Divisia index of energy use.[106] They find both short and long run causality from either energy or useful work to GDP but not vice versa. After these plausible results, the methodology of Stern (1993, 2000) has been used to examine the relationship between energy consumption and economic growth for many countries. For instance, Oh and Lee (2004) and Ghali and El-Sakka (2004) apply it for Korea and Canada, respectively. Using the Johansen cointegration technique, Ghali and El-Sakka (2004) indicate that the long-run movements of the proposed variables in Canada are related by two cointegrating vectors. However, Oh and Lee (2004) show that there is only one cointegrating vector for Korea. In respect to causality testing, both studies obtain exactly the same conclusion as Stern's investigation for the US. Using an alternative approach proposed by Toda and Yamamoto (1995), Bowden and Payne (2009) demonstrate that the relationship between energy consumption and real GDP is not uniform across sectors in the US. They suggest that prudent energy and environmental policies should recognise the differences in the relationship between energy consumption and real GDP by sector.

Some studies use panel data to investigate the relationship between energy consumption and economic growth. For example, Lee and Chang (2008) and Lee et al. (2008) use panel data cointegration methods to examine the relationship between energy consumption, GDP, and capital in 16 Asian and 22 OECD countries over a three and four decades period, respectively. Lee and Chang (2008) find a long-run causal relationship from energy to GDP in the group of Asian countries while Lee et al. (2008) find a bi-directional relationship in the OECD sample. Similarly, Apergis and Payne (2009) employ panel cointegration and panel causality tests for six Central American countries and find evidence of the growth hypothesis for the period 1980 - 2004. Taken together, this body of work suggests that the inconclusive results of earlier work are possibly due to the omission of non-energy inputs. By contrast, in recent bivariate panel data studies, Joyeux and Ripple (2011) find causality flowing from income to energy consumption for 56 developed and developing economies, while Chontanawat et al. (2008) find causality from energy to GDP to be more prevalent in the developed OECD countries compared to the developing non-OECD countries in a panel of 100 countries.

Many researchers argue that if the estimated model does not account for other possible determinants such as that of energy prices, then results may be biased. For

[106] 'Useful work' is a measure that captures energy flow and energy efficiency effects.

example, Glasure (2002) indicates that the real oil price is a major determinant of real national income and energy consumption. Hence, literature has included oil prices in many studies including panel data studies as an additional explanatory variable in energy growth models. An interesting example is provided by Costantini and Martini (2010) for 26 OECD countries (1978-2005). Using a panel vector error correction model (VECM) of GDP, energy use and energy prices, they find that in the short-run, energy prices cause GDP and energy use and that energy use and GDP are mutually causative. However, in the long-run they find that GDP growth drives energy use and energy prices. Other researchers who model a cointegrating relationship between GDP, energy, and energy prices for individual countries produce mixed results. For example, Glasure (2002) finds very similar results to Costantini and Martini (2010) for Korea, while Masih and Masih (1997) and Hondroyiannis et al. (2002) find mutual causation in the long run for Korea, Taiwan, and Greece, respectively.

Although econometric techniques among researchers are diverse, investigating whether economic growth takes precedence over energy consumption, or if energy consumption can boost economic growth or employment, is not unanimous. The findings from studies vary not only across countries, but they depend also on methodologies within the same country (Soytas and Sari, 2003). Moreover, Yang (2000) argues that countries may differ in their energy consumption patterns and their economic activity may depend on different energy resources. These differences could be other explanations for the lack of unanimity in the literature regarding the relationship between aggregate energy consumption and income. Furthermore, the importance of a specific energy resource may change in a country through time. Therefore, studies conducted for different time periods may yield different results even for the same country. Additionally, energy is known to influence the productivity of capital and labour, and there is a lack of consensus on the relationship between energy and employment.[107] For instance, in a study on Taiwan, Yang (2000) finds a bidirectional causality between aggregate energy consumption and GDP. However, he observes different directions of causality when energy consumption is disaggregated into different kinds, including coal, oil, natural gas, and electricity. His results imply the importance of analysing the relationship between different sources of energy consumption and GDP.

[107] Studies such as those by Cheng (1995), Erol and Yu (1987) and Yu and Jin (1992) yield contradictory results regarding the relationship between energy consumption and employment.

In this context, Zou and Chau (2006) examine both the equilibrium relationship and the predictability between oil consumption and economic growth in China. Cointegration tests applied in their paper suggest that these two variables tend to move together in the long run. In addition, Granger causality tests indicate that oil consumption could be a useful factor that forecasts changes in the economy in the short run as well as in the long run. Oil consumption is found to have great effects on the economy. This finding indicates that the enormous use of oil in sectors like the industry may directly drive the economy. However, this finding would probably stimulate faster growth in oil consumption, and therefore, should be regard with care. Conversely, economic growth could be used as a predictive factor forecasting oil consumption only in the long run. Economic growth appears to have small effects on oil use; this lack of growth could be attributed largely to China's energy consumption structure.

Yoo (2006) investigates the short- and long-run causality between oil consumption and economic growth in Korea by applying modern time-series techniques. The study employs annual data covering the period of 1968 - 2002. Tests for cointegration, and Granger-causality based on an error-correction model display that there is a bidirectional causality running from oil consumption to economic growth in Korea. This causality means that an increase in oil consumption directly affects economic growth and that economic growth also stimulates further oil consumption.

Lee and Chang (2005) study the stability between energy consumption and GDP in Taiwan during the period of 1954 - 2003. They use aggregate as well as various disaggregate data of energy consumption, including coal, oil, gas, and electricity, to employ the unit root tests and the cointegration tests allowing for structural breaks. The main finding is that there are different directions of causality between GDP and various kinds of energy consumption. This conclusion indicates that there are bi-directional causal linkages between GDP and both total energy and coal consumption. However, there is a unidirectional causality running from oil consumption to GDP. Furthermore, there is a unidirectional causality running from gas consumption and electricity consumption to GDP that is detected in these cases. Thus, energy acts as an engine of economic growth. The empirical result shows unanimously that in the long run energy acts as an engine of economic growth, and that energy conservation may harm economic growth.

Even though the relationship between oil consumption and economic growth in developing countries has been questioned in a number of studies, the literature on industrialised countries is still scarce. To my knowledge, Payne (2011) provides evidence on uni-directional causality from petroleum consumption to real GDP in the US economy during the period of 1949-2006 by using the Toda and Yamamoto (1995) long-run causality test. Royfaizal (2011) investigates the relationship between crude oil import and real income in Japan. The Granger causality test on the data covering the time span from 1992:q1 to 2006:q4 shows uni-directional causality from crude import to economic growth. Authors thereby conclude that reducing crude import could lead to a fall in Japan's national income.

Serious concerns over rising fossil fuel prices, energy security, and greenhouse gas emissions have brought the importance of nuclear energy to the forefront of the energy debates' wider issue. As the International Energy Agency (IEA) notes, nuclear energy is attracting new interest for increasing the diversity of energy supplies, for improving energy security, and for providing a low-carbon alternative to fossil fuels (International Energy Agency, IEA, 2008). On the other hand, many researchers believe that nuclear energy, as a virtually carbon-free source of energy, is one of the solutions to global warming and energy security (Elliott, 2007; Ferguson, 2007). Thus, the importance of nuclear energy as a potential source of energy security and as a virtually carbon free source of energy necessitates not only further research but also the use of alternative testing methodologies to examine the causal relationship between nuclear energy consumption and economic growth.

For instance, Yoo and Jung (2005) and Yoo and Ku (2009) investigate the nuclear energy consumption and economic growth nexus for Korea. Yoo and Jung (2005) employ annual data from 1997 to 2002 into a vector error-correction model(VECM). One-way Granger causality running from energy consumption to economic growth has been detected. Yoo and Ku (2009) employ time-series data to investigate 20 countries but only use the Granger causality test for six countries. The growth hypothesis supported by South Korea, while on the other hand, the conservation hypothesis supported by France, and Pakistan, the feedback hypothesis supported by Switzerland, and the neutrality hypothesis supported by Argentina and Germany. Wolde-Rufael and Menyah (2010) consider nine industrialised countries using nuclear consumption and economic growth data and find mixed results. Their results suggest existence of growth hypothesis for Japan, the Netherlands, and Switzerland, while the opposite uni-directional causality running from economic growth to nuclear energy consumption in Canada and Sweden. They also find that there is bidirectional causality for France, Spain, the UK and the US. The results are different from those of Lee and Chiu (2011a), who find an evidence that supports the growth hypothesis for Japan, and a bidirectional causality for Canada, Germany and the UK.[108] Heo et al. (2011) conclude that there is a unidirectional causality running from nuclear energy consumption to economic growth in India by using the cointegration and error-correction models. In a panel cointegration and panel causality study, Apergis et al. (2010) find a bidirectional causality running between nuclear energy consumption and economic growth, providing support for the feedback hypothesis associated with the relationship between nuclear energy consumption and economic growth.

To date, few empirical studies have focused on investigating the relationship between oil consumption and economic growth, on the one hand, and between nuclear energy consumption and economic growth on the other (Yang, 2000; Zou and Chau, 2006; Zhao et al., 2008; Aktaş and Yılmaz, 2008; Yoo and Jung, 2005; Yoo and Ku, 2009). It is worth noting that the crude oil prices are considered as a key determinant of both oil consumption and demand for nuclear energy. Its importance is associated with the key roles played by its components in industrial production. This is so because the crude oil comprises ten most essential products including natural gas, butane, propane, gasoline, home heating oil, plastics, diesel, and kerosene and jet fuel. Therefore, it is widely believed in literature that many other energy sources such that of nuclear energy has glow brighter only when the price of oil was threatening at $150 a barrel in the summer of year 2008. If the prices of oil remains relatively at low-level in comparison with alternatives in the short-run, the widespread nuclear power plants around the world will be postponed. Roger (2000) claim that although uranium resources are ample and spread across wide regions of the world and nuclear plants can easily store several years worth of fuel stock in a backroom, the inflamed spark toward nuclear power, seemed oppressed when the price of oil decreased to $32 a barrel in December 2008 and swing around $50 for most of year 2009. This might be attributed to the fact that uranium are accounts for only 2 - 3% of the total cost of nuclear plants generating costs, which

[108] Lee and Chiu (2011a) state that while the factors that drive different type of energy sources have been well investigated, little only known about the drivers of nuclear energy demand. Thus, even they aim on testing causality among nuclear energy consumption and economic growth in a nuclear demand model, they have included only oil market information (oil prices and consumption) as additional predictors to overcome the problem of omitted variables.

made the prices of nuclear fuel stable at low level over a long period.[109]Although oil prices are found to have a significant impact on oil consumption, demand for nuclear energy and macroeconomic activities, it have been neglected in most energy consumption - economic growth investigations. Observing that minor attention has been given in the literature to tackle the interaction between oil and a new clean energy source (nuclear energy) and taking into consideration the vital role of fluctuations in oil prices, we choose in this chapter to link two literature streams and employ the parsimonious vector equilibrium correction model (PVECM). We aim to analyse the long-run relationship between oil consumption, nuclear energy consumption, oil price and economic growth. Additionally, we search for a causality relationship between the proposed variables and output growth.

4.3 Econometric Methodology

The objectives of our empirical estimation are to examine how the variables (i.e., GDP, oil and nuclear energy consumption, and oil prices) are related in the long-run and to assess the long-run causal relationship between these variables. In line with these objectives, our methodological approach focuses on examining the long-run relationship(s) using the cointegration technique. Early cointegration techniques pioneered by Engle and Granger (1987), Hendry (1986), and Granger (1986) have made a significant contribution towards cointegration and long-run relationship(s) analysis and causality testing between time series variables. Thus, these techniques have become popular both as a topic for theoretical investigation of statistical issues and as a framework within which many empirical propositions can be re-evaluated (Perron and Campbell, 1994). The basic idea of the cointegration, in general, suggests that two or more variables are said to be cointegrated, that is they exhibit long-run equilibrium relationship(s), if they share common trend(s). More concretely, Engle and Granger (1987) demonstrate that once a number of variables are found to be cointegrated, there always exists a corresponding error-correction representation that denotes that changes in the dependent variable are a function of the level of disequilibrium in the cointegrating relationship (captured by the error-correction term) as well as changes in other explanatory variable(s). In this setup, a method of estimation and testing that has received a particular attention is the maximum likelihood approach based on a finite VAR Gussian system developed

[109]The US Department of Energy provides the public with uranium prices and quantities within its borders, as well as historical data starting from 1981. Therefore, it is not worth to think about including it here as this study cover the period 1965 - 2010.

by Johansen (1991).[110] This technique has several advantages over the Engle and Granger (1987) approach.[111] For instance, Johansen and Juselius method tests for all the number of distinct cointegrating vectors between the variables in a multivariate setting and estimates the parameters of these cointegrating relationships. All the tests are based on the trace statistics test and the maximum eigenvalue test. It also treats all variables as endogenous, thus avoiding any arbitrary choice of dependent variable. Moreover, this technique provides a unified framework for testing and estimating relationships within the framework of a vector error correction mode (VECM) (Enders, 2008). According to this technique, evidence of cointegration rules out the possibility of the estimated relationship(s) being 'spurious'. Also, as long as the variables included in the cointegration space have common trend, causality; in the Granger sense must exist in at least one direction (Granger, 1986, 1988).[112]

Since the focus of this chapter is to investigate the relationship between energy consumption (oil and nuclear energy) and economic growth and to assess the causal linkage between them, whose analysis requires estimation techniques appropriate for long-run equilibria, the Johansen test (Johansen, 1988; Johansen and Juselius, 1990; Johansen, 1991) are used as discussed below.[113]

4.3.1 Cointegration Modeling

Assume that Z_t is a vector including integrated series at the same order, which have at least one cointegrating vector in the system. A general-to-specific approach is adopted in this chapter to model both the long-run and short-run structure of vector Z_t . First, the Johansen Maximum Likelihood approach is employed to estimate and identify the cointegrating relationships among the variables included in vector Z_t . More concretely, Z_t can be written as a vector autoregressive process of order k (i.e., VAR(k)):

[110] For description of the procedure and detailed empirical applications, see Johansen (1988), Johansen (1989), and Johansen and Juselius (1990).

[111] Engle and Granger (1987) indicate that the statistical inference for a VAR in levels can be undertaken appropriately only if all the variables are stationary. Otherwise, one can use VAR in differences if all the variables are integrated of order one but are not cointegrated, and through the specification of a vector error correction model (VECM) if all variables are integrated of order one and cointegrated.

[112] Failure to reject the null hypothesis that x does not cause y, does not necessarily mean that there is in fact no causality. A lack of sensitivity could be due to a misspecified lag length, insufficiently frequent observations (Granger, 1988), too small a sample (Wilde, 2012), omitted variables bias (Lütkepohl, 1982), or nonlinearity (Sugihara et al., 2012).

[113] Although there exists a number of co-integration tests, such as the Engle and Granger (1987) method and the Stock and Watson (1988), Johansen's test has a number of desirable properties as shown above.

$$Z_t = A_0 + \sum_{i=1}^{k} A_i Z_{t-i} + u_t \tag{27}$$

$$\Delta Z_t = A_0 + \Pi Z_{t-1} + \sum_{i=1}^{k} \Gamma_i \Delta Z_{t-i} + u_t \tag{28}$$

$$\Delta Z_t = A_0 + \alpha\beta' Z_{t-1} + \sum_{i=1}^{p} \Gamma_i \Delta Z_{t-i} + u_t, \qquad u_t \text{ is } iid \sim N(0, \Sigma) \tag{29}$$

Where Z_t denotes (4×1) vector containing GDP, oil consumption, nuclear energy consumption, and oil prices (i.e., $Z_t = (RGDP_t, OC_t, NC_t, ROP_t)$. The four variables are measured by their natural logarithm so that their first difference approximate their growth rates. Any long-run relationship(s) are captured by the (4×4) matrix Π shown in Equation (28). However, this matrix can be decomposed as shown in Equation (29) to provide better understanding for the full system, where β is the $(4 \times r)$ matrix of the cointegrating vector and α denotes the $(4 \times r)$ matrix of speed of adjustment to last period equilibrium error. Γ_i represents (4×4) matrices that guide short run dynamics of the model. In the second step, the vector equilibrium correction models presented by Equation (29) are estimated, where the identified matrix of cointegrating vectors β is explicitly taken into account:

$$\Delta Z_t = \hat{A}_0 + \hat{\alpha}(\sum_{i=1}^{r} \hat{\beta}_i{}' Z_{t-1}) + \sum_{i=1}^{p} \hat{\Gamma}_i \Delta Z_{t-i} + u_t \tag{30}$$

At this stage, Equation (30) is re-estimated by excluding any insignificant regressors. The resulting parsimonious vector equilibrium correction model (PVECM) is a reduced form model and consequently, there are simultaneity effects among the endogenous variables including in Z_t. Having estimated the PVECM, we examine the causal linkage between the variables through exogeneity test by testing the null α_i is not significantly different from zero ($i.e., H_0 : \alpha_i = 0$). If the null is true then the variables included z_i is exogenous with respect to all cointegrating vectors. In the third step, we estimate Equation (30) conditional on exogenous variables.

$$\Delta Z_{1,t} = \hat{A}_0 + \Delta Z_{2,t} + \hat{\alpha}(\sum_{i=1}^{r} \hat{\beta}_i{}' Z_{t-1}) + \sum_{i=1}^{p} \hat{\Gamma}_i \Delta Z_{t-i} + u_t, \qquad u_t \text{ is } iid \sim N(0, \Sigma_1) \tag{31}$$

where $\hat{\alpha} = [\alpha_1, 0]'$, and Z_2 is the vector of exogenous variables. In the fourth step, we model any simultaneous effects in equation (31). If any of the off diagonal elements of Σ_1 is close to zero we can apply OLS to estimate each equation of (31) separately.

4.4 Data Source and Description

We use annual data-set from 1965 to 2010 for four industrialised countries (the US, Canada, Japan, and France) and four emerging economies (Russia, China, South Korea, and India). The variables employed include nuclear energy consumption per capita (NC), oil consumption per capita (OC), real economic growth (GDP) per capita (Y), and real oil price (ROP). Both Nuclear energy and oil consumption are obtained from BP Statistical Review of World Energy (2011) where NC is expressed in terms of Terawatt-hours (TWh) and OC is measured in thousand barrels daily. Oil consumption (OC) is the sum of inland demand, international aviation, marine bunkers, oil products consumed in the refining process, and consumption of fuel ethanol and biodiesel. Real GDP per capita measured based on purchasing-power-parity (PPP) per capita in constant 2000 international dollars from the World Development Indicators (WDI, 2011). Real WTI oil price is defined as the US dollar price of oil. Following Lee and Chiu (2011b), oil price is converted to the domestic currency and then deflated by the domestic consumer price index (CPI), which is derived from International Financial Statistics (IFS, 2011) published by the International Monetary Fund (IMF). All data are expressed in natural logarithms in the empirical analysis.

Table (4.1) presents the descriptive statistics for the variables across all countries. Specifically, we calculate descriptive statistics (mean, standard deviation, minimum, maximum, skewness, kurtosis and Jarque-Bera statistic for normality) of the variables included in the analysis for our full sample of countries. It appears that the highest mean real GDP is observed in Japan followed by the US, Canada, France, South Korea, Russia, China, and India during the sample period (1965 - 2010). The US has the mean highest oil consumption and nuclear energy consumption among the other countries. Majority of variables have negative skewness values, which denote that the distribution of the data is skewed to the left. However, results obtained from Jarque- Bera test show that real oil price, oil consumption, and real GDP exhibit normal distribution, while nuclear energy consumption seem to be characterised by a non-normal distribution.

4.5 Empirical Results

4.5.1 Preliminary Tests

Before conducting the cointegration analysis and causality testing, it is important to determine the order of integration of the series, I_d, and the optimal lag length, k, to avoid any spurious results (Clarke and Mirza, 2006). To assess the order of integration, this study utilises three different unit root tests including the augmented Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP), and the stationarity test by Kwiatkowski et al. (1992) (KPSS). This is because of the controversies surrounding the unit root testing (see Maddala and Kim, 1998), which may make comparing results from different alternative tests more likely to provide the opportunity to examine whether the preponderance of the evidence makes a convincing case for stationarity or non-stationarity. Table (4.2) reports the results of unit root tests, which indicate that the results are slightly contradictory. However, all variables are roughly non stationary at level and integrated of order one- I(1).

In order to select the optimal number of lag length, k, Akaike (AIC), Hannan and Quinn (HQIC), and Schwarz's Bayesian (SIC) information criteria are used to build a decision.[114] Following Lütkepohl (1993) procedure, in this chapter we link the maximum lag lengths ($kmax$) and the number of endogenous variables in the system (m) to the sample size (T) according to the formula $m * kmax = T^{\frac{1}{3}}$ (Konya, 2004). In the case of conflicting results of the different Information criterion, the choice done based on AIC results as suggested by Pesaran and Pesaran (1997). Results of the lag selection criteria for each country are reported in Table (4.3). Then, diagnostic tests including normality and autocorrelation have been employed for further investigation. Based on Lagrange-multiplier (LM) test for autocorrelation shown in Table (4.4), we cannot reject the null hypothesis that there is no autocorrelation in the residuals for any of the orders tested at 5% level. Also, all models pass the normality test at 10% level or better. Thus, there is no evidence of model misspesification in this case.

[114] In cointegration analysis and causality testing, if the chosen lag is less than the true lag length, this can cause bias due to omission of relevant lags.

4.5.2 Cointegration Analysis

After preliminary tests, the cointegration vectors are estimated using the reduced-rank approach suggested by Johansen (1988); Johansen and Juselius (1990) to examine the long-run relationship between oil consumption, nuclear energy consumption, oil price and economic growth using CATs in RATs. To do so, Johansen (1988) test has been established in order to test for the existence of $r \leq 3$ cointegration relationships among the four variables of the model. This is equivalent to testing the hypothesis that the rank of matrix Π in Equation (28) is at most r. Reduced-rank regression can then be used to form a likelihood ratio test of that hypothesis on the basis of the so-called trace statistic, or alternatively, the maximum eigenvalue statistic. Lüutkepohl et al. (2001) investigate the small sample properties of both tests and concluded that the trace test is slightly superior, and therefore, we favour it in our analysis. The results of testing for the number of cointegrating vectors are reported in Table (4.5), which presents both the maximum eigenvalue (λ_{max}) and the trace statistics. Results of trace statics in the fifth column of Table (4.5) show that the null hypothesis of no cointegration can be rejected at the 1% and 5% significance level, except for Canada.[115] These findings suggest the existence of one cointegration vector in each country model. Hence, a cointegration rank of one is imposed on the VAR and the coefficients are estimated using Equation (29) as shown in Table (4.6).

However, from the β vectors presented in Table (4.6), we can see that there are some insignificant coefficients of different variables in the cointegration space of each country model. Accordingly, following Johansen (1996), we test for excluding all the proposed variables to identify the cointegrating relationship by using zero restriction on β as shown in Table (4.7). In the US, testing the exclusion of nuclear energy consumption and real oil price yield likelihood ratio test of 0.943, and 0.084, respectively, which enable us to easily accept the null hypothesis. Following the same method, nuclear energy consumption and real oil price are excluded from the cointegrating vectors of Canada and France, respectively. Japan looks little bit different as the cointegration vector can be identified by excluding both oil consumption and real oil price. In emerging economies, Russia cannot reject the null hypothesis of the exclusion test for oil consumption, which suggests, excluding it from the cointegrating space. The exclusion test statistics exposed in Table (4.7) for China, South Korea and India suggest that the relation could, however, be identified by excluding

[115] In Canada, we reject the null hypothesis of no-cointegration at 10% level.

real oil prices only in these countries.

Next, we test for weak exogeneity against the null hypothesis $H_0 : \alpha = 0$ as proposed by Johansen (1992, 1996). A rejection of the null hypothesis means that there is evidence of long run causality going from the variables in the ECT to the variable of interest (Arestis et al., 2001).[116] Results shown in Table (4.8) indicate that oil consumption is exogenous in the US, Japan, France, and India, with a test statistics of 0.361, 0.366, 0.248, and 0.145, respectively. This implies that oil consumption has a predictive power to economic growth in these countries. Nuclear energy consumption also can not reject the null hypothesis of exogeneity in five out of eight countries including the US, Canada, Russia, China, and South Korea. This result illustrates that the nuclear energy consumption stimulates economic growth in these countries.[117] The results presented in Table (4.8) also show evidence to support the weak exogeneity hypothesis for real oil price in most of the investigated economies except for the US, Canada, and China. Accordingly, there is a unidirectional causality running from real oil price to economic growth in Japan, France, Russia, South Korea, and India.[118]

Then, we re-estimate the model at this point using the parsimonious vector equilibrium correction model (PVECM) shown in Equation (30). The results of β and α estimates are based on the above exclusion and weak exogeneity restrictions for the investigated countries. Since all variables are in natural logarithms, the estimated long-run coefficients can be interpreted as elasticities. In the US, we observe that the long run oil consumption elasticity of economic growth is 0.759, which is positive and statistically significant at 1% level. This implies that increasing oil consumption by 1%, increases the real GDP growth by 0.759% in the US. The coefficient on the time trend component can be interpreted as a measuring for the rate of technical change in the US The estimated rate of technical change is 0.12%, which is close to that estimated by Stern (2000).

[116] Hall and Wickens (1993) and Hall and Milne (1994) interpret weak exogeneity in a cointegrated system as a notion of long-run causality. For example, if we consider the economic growth equation as following: $\Delta GDP_t = \hat{A}_0 + \hat{\alpha}_{11} ECT_{t-1} + \hat{\gamma}_{11}\Delta GDP_{t-1} + \hat{\gamma}_{12}\Delta OC_{t-1} + \hat{\gamma}_{13}\Delta NC_{t-1} + \hat{\gamma}_{14}\Delta ROP_{t-1}$, where $ECT_{t-1} = \hat{\beta}_{11} GDP_{t-1} + \hat{\beta}_{12} OC_{t-1} + \hat{\beta}_{13} NC_{t-1} + \hat{\beta}_{14} ROP_{t-1}$ is the error correction term, i.e. the cointegration relationship between the variables. Then restricting $\hat{\alpha}_{11} = 0$ is a test for weak exogeneity where rejection of the null hypothesis means there is evidence of long run causality going from the variables in the ECT to GDP.

[117] Payne and Taylor (2010) find that there is no causal relationship between nuclear energy consumption and economic growth in the US.

[118] Empirical research including Hamilton (1983), Daniel (1997), Rotemberg and Woodford (1996) and Carruth et al. (1998) also reject the hypothesis that the relation between oil prices and output it is just a statistical coincidence.

In the case of Canada, it can be seen from the estimated long run relationship that oil consumption has a positive and high significant impact on economic growth, while output is negatively linked with oil price.[119] An increase of 1% in oil consumption increases the growth by 3.1% approximately. In contrast, increasing oil price by 1% decreases the growth in Canada by 0.499 %.

Alternatively, the long run nuclear energy consumption elasticity to economic growth in Japan shows that an increase of 1% in nuclear energy consumption increases the real GDP by 0.108 %. Lee and Chiu (2011a) find that nuclear energy demand is elastic with respect to real income in Japan, and a 1% rise in real income raises nuclear energy consumption with a 1.436 %. They suggest that countries with higher income levels are more likely to have their basic needs and are concerned with environmental problems, since they have more money to invest in nuclear energy development. Thus, for highly industrialised countries, economic development leads to higher nuclear energy demand (Lee and Chiu, 2011a).[120] The estimated technological change impact on GDP growth is 0.12% for every 1% increase.

In France, the long run relationship includes both energy sources (oil and nuclear power), trend and economic growth. These findings suggest that the process of economic development in France is heavily dependent on both oil and nuclear energy consumption, and the rate of technical change. An increase of 1% in oil consumption increases the real GDP by 0.262%, and an increase of 1% in nuclear energy consumption increases the real GDP by 0.049%. The coefficient on the time trend component reveals that the rate of technical change in France improves the real GDP by 0.11%.

The error-correction terms, α_1, shown in Table (4.9) are with the expected sign (negative) and highly significant for all for industrialised countries, except for nuclear energy consumption equation in Japan. The magnitude of loading factors, α_1, show the speed of adjustment to disequilibrium from its long run equilibrium value.

[119] Canadas' economy is relatively energy-intensive when compared to other industrialized countries, and is largely fueled by Petroleum, which represents the highest primary energy consumption, while nuclear energy usage is much less, with about 32% and 7% respectively from the total energy consumption (EIA, 2012).

[120] In 2008, the government introduced New National Energy Strategy in light of global developments, which was heavily focused on achieving energy security. Under this strategy, the government targeted to improve energy efficiency to 30%, increase share of electric power generated from nuclear energy to 30-40%, cut down the oil dependency ratio to about 80% and increase domestic investment in oil exploration and related development projects (Sami, 2011).

On this basis, it can be seen that when per capita real GDP deviates from its long-run trend, 28%, 5%, 35% and 32% of that deviation will be corrected within a year for the US, Canada, Japan, and France, respectively. Thus, the speed of adjustment in the case of any shock to the real GDP equation is sufficiently fast and support the notion that there is a reasonable control over economic growth, except for Canada. Bidirectional causality hypothesis in the long-run can be tested by the significance of the speed of adjustment, α, in Table (4.9). The t-statistics of the coefficients of the error correction term (ECT) is used to examine the existence of long-run causal effects. There is a strong evidence that there is a bi-directional causal linkage between oil price and economic growth in the US, which is in line with the finding of Hamilton (1983) and Hooker (1996). In Canada, we find a bidirectional causality between oil consumption and economic growth at 10% significance level, which is in line with Ghali and El-Sakka (2004). Oil price, also, has a feedback effect on Canadian real GDP growth in the long-run. Alternatively, Japans' results suggest the existence of a bidirectional relationship between nuclear energy consumption and economic growth. This means that nuclear energy use derive economic growth, and that economic growth for Japan needs to use more nuclear power. Lee and Chiu (2011a) find that a 1% rise in Japanese income rises nuclear energy consumption by 1.436%. They argued that countries with higher income levels are more likely to have their basic needs and are concerned with environmental problems, as well as they have more money to invest in nuclear energy development. The speed of adjustment to disequilibrium is moderately high in France economic growth model, supporting long run causality running from oil consumption, nuclear energy consumption and real oil price to economic growth.

Likewise, after investigating the long run relationship between the proposed variables in industrialised countries, the marginal impacts of oil consumption, nuclear energy consumption and real oil price on economic growth have been examined for emerging economies. Starting with Russia, although the sample is the smallest among countries, there is evidence of a long run relationship between nuclear energy consumption, real oil price and economic growth. The results reported in Table (4.9) indicate that the nuclear energy consumption has a positive and statistically significant impact on economic growth in Russia. This shows that an increase in nuclear energy consumption contributes to Russian economic growth at 1% significance level. A rise of 1% in nuclear energy consumption is linked with a 2.503 % increase in economic growth. On the other hand, real oil price has a negative impact on economic growth. An increase of 1% in real oil price decreases economic growth by 0.140 %. Both oil and nuclear energy consumption cannot be excluded from the cointegration space of China, South Korea and India. The estimated coefficients of oil consumption and nuclear energy consumption are highly significant in these countries. In China, increasing oil consumption by 1% increases the economic growth by 0.82%, and increasing nuclear energy consumption by 1% rise the output by 0.33% approximately. [121] This finding is supported by Zou and Chau (2006), who find that oil consumption has a great effect on Chinese economy due to the enormous use of oil in sectors like the industry, which may have direct impact on the economy. In South Korea, increasing oil consumption by 1% increases real GDP by 0.214%, and an increase of 0.05% approximately can be achieved by increasing nuclear energy consumption by 1%. In India, on one hand, oil consumption coefficient is positive and has a high impact on economic growth. An increase in oil consumption by 1% increases economic growth by 1.15%. On the other hand, decreasing nuclear energy consumption by 1% increases the economic growth of India by 0.104%. In literature, Wolde-Rufael (2010) examine the long run relationship between nuclear energy consumption and economic growth in India. He finds that nuclear energy consumption has a positive and a statistically significant impact on Indian economic growth.[122]

Table (4.9) shows that all the associated loading factors, α_1, in economic growth equations for emerging economies are negative and significant, which is consistent with our normalization. The speed of adjustment to long run equilibrium is found to be highest in South Korea (35%) and lowest in India (3%). It can be seen that the coefficient of ECT is significant in oil consumption equations, in Russia, China, and South Korea. This implies that there is a bi-directional causality between oil consumption and real GDP.[123] Results of South Korea are in line with Glasure (2002), who finds a bi-directional causality between energy consumption and GDP

[121] China is the largest oil consumer in the world based on BP-Statistical Review of World Energy 2012. The level of oil consumption in China increased from 720.8 to 1676.2 (million tonnes oil equivalent) between 2001 to 2010.

[122] India is rich in coal and abundantly endowed with renewable energy resources in the form of solar, wind, hydro and bio-energy. Around 53% of Indias total energy need has been met by coal followed by oil(31%),natural gas(8%), hydroelectric power(6%), nuclear and renewable(1%each). Accordingly, Indian government has been opposing the mandatory emission cut as proposed by developed nations since such measure might hurt Indian economic growth (Ghosh, 2010).

[123] The alpha coefficient that that loads the cointegration relationship into oil consumption equation for South Korea is positive and significant, which implies that when oil consumption is above its long-run equilibrium, it tends to accelerate further. Also, if the economic growth is deviated, nuclear energy consumption and real price of oil interact with each other to adjust this deviation in the long-run.

growth. However, it is inconsistent with Oh and Lee (2004), who have detected a uni-directional causality running from energy consumption to GDP growth in South Korea. The coefficient of the ECT in nuclear energy consumption equation is negative and significant only in the case of India. Although this result is inconsistent with Cheng (1999), who examine the long-run relationship between nuclear energy consumption and economic growth in India using a bivariate model, here, we employ a multivariate model to overcome the bias results, that might be obtained from using bi-variate models. Our result show that there is a feedback relationship between nuclear energy consumption and economic growth in India. Also, there is an evidence of a bi-directional relationship between real oil price and economic growth in China. This implies that the economic growth in China could be considered as a factor for oil price fluctuation, which is consistent with the finding of Hamilton (2009a,b).[124]

Substantially, the results above show that the emerging economies are very dependent on energy to grow. Accordingly, energy saving policies that reduce energy consumption may have an adverse impact on emerging economies. Our results seem to significantly reject the neoclassical assumption that energy is neutral to growth. Consequently, we conclude that energy is an important factor to GDP growth in emerging economies, and, therefore, shocks to the energy supply, particularly oil supply will have a negative effect on the economic growth of those countries.

Hansen and Johansen (1999) propose a multivariate recursive procedure to evaluate the constancy of both the cointegration space and the loadings of the cointegration vector. Figure (4.2) shows the output of the former and consists of a graph where values over unity imply that there is a change in the cointegration space for a given cointegration rank. This test is performed using either **X** or its **R** representation. In the former, the recursive estimation is performed by re-estimating all parameters in the VECM, while in the later the dynamics are fixed and only the long run parameters are recursively estimated. Thus, the re-representation is more suitable when the constancy of the long run parameters are tested. The results support the existence of a stable long run relationship although there is some instability when the short and long run parameters are estimated for most of the cases. Specially, in the starting year of each recursive estimation for the different countries, and from 1993 to 1994 in China, and from 1996 to 1998 in India. Such instability

[124]Hamilton (2009a,b) argues that the recent fluctuations in the price o oil were driven by a stagnant supply and increase in demand driven heavily by China.

might be due to regime switching, however, this is beyond the investigation of this paper.

Figure (4.3) presents the test for the stability of the adjustment coefficients of the VECM with asymptotic 95% error bounds. This test is performed once the cointegration space has been uniquely identified, and allows one to test whether the responses of the variables to of the variables to long-run disequilibrium are stable over time. The results suggest that the adjustment coefficients are stable.

4.6 Conclusion

Understanding the nature of relationship between energy consumption and economic growth is a key issue that both energy and environmental policy makers have to take into consideration to develop effective policies. While the linkage between energy consumption measures and economic growth has been examined for developed and developing countries, interaction between different energy sources, energy prices and economic growth received a little attention (for instance, Asafu-Adjaye, 2000; Lee and Chiu, 2011a,b). This paper fills this gap in energy-economic literature by investigating the long-run relationship between oil consumption, nuclear energy consumption, oil price, and economic growth for four industrialized countries (the US, Canada, Japan, and France), and four emerging economies (Russia, China, South Korea, and India).

We employ the Johansen cointegration analysis to investigate the long-run relationship between the proposed variables over the period from 1965 to 2010. Empirical results show that a long-run relationship exists between economic growth and at least one energy source (oil or nuclear energy), which implies that energy is an essential factor for production in all countries included in our sample. Additionally, we find that oil consumption enters significantly in the cointegration space, particularly in six out of eight countries including the US, Canada, France, China, South Korea, and India. We also found that nuclear energy consumption has a positive and significant impact on real GDP growth in five countries including Japan, France, Russia, China, and South Korea. However, as it can be seen from the results, the Indian economic growth is negatively linked to nuclear energy consumption. It is beyond the scope of this paper to through examine the underlying reasons behind this negative relationship.[125] Finally, we show that oil prices do not have a long-run impact on economic growth. This is because oil prices do not have significant effect in the cointegration space. Exception to this are the cases of Canada and Russia.

In addition, exogenous test with respect to the speed of adjustment shows that oil consumption has a predictive power for real GDP in the US, Japan, France, and India. Regarding nuclear energy consumption - growth nexus, results illustrate that nuclear energy consumption has predictive power for real economic growth in six countries including the US, Canada, France, Russia, China, and South Korea. On the basis of speed of adjustment, we conclude that there is a bi-directional causality between oil consumption and economic growth in Canada, Russia, China, and South Korea. On the other hand, there is a bidirectional causal relationship between nuclear energy consumption and real GDP growth in Japan, and in India. In the same spirit, results show that there is a bi-directional causality between oil price and economic growth in the US, Canada, and China.

Overall, it is clear that the investigated countries are highly dependent on energy consumption to stimulate economic growth. Given that six out of eight countries are having positive and highly significant impact of oil consumption on economic growth, and either a unidirectional or bidirectional causal relationship between them (i.e., oil consumption and economic growth) in all countries, call for caution. These findings reveal that high level of economic growth leads to a high level of energy demand and/or vice versa, which has a number of implications for policy analysts and forecasters. In order to deal with the lately concerns about the reliance on fossil fuels and not adversely affect economic growth, energy conservation policies that aim to curtailing energy use have to rather find ways of reducing demand on fossil fuel. Efforts must be made to encourage industries to adapt technology that minimise pollution. Alternatively, there is a keen interest in developing nuclear energy in many countries as a mean of ensuring energy security, reducing emissions, coping with the increase in energy demand all over the world, and stabilizing oil price.[126] However, nuclear safety is a global concern that needs a global solution.

[125] It is worth noting that only 3% of India's total electricity comes from nuclear power plants. An assessment of India's nuclear sector, especially after the IndoUS Nuclear Deal suggests that although investing in nuclear energy is relatively expensive, it could be a sustainable and a robust alternative to fossil fuels in India. It could also reduce Indias increasing dependence on petroleum imports. For more information, see $http://www.idsa.in/system/files/book_NuclearEnergyIndia.pdf$

[126] Social aims like development of technologies in medicine, public health and agriculture call attention to invest more in nuclear energy sector (Nazlioglu et al., 2011).

The right balance should be struck between the quest of economic growth, nuclear safety, clean energy and the drive towards making these countries relatively energy independent.[127]

[127] Apergis et al. (2010) attempt to explore the causal relationship between CO_2 emissions, nuclear energy consumption, renewable energy consumption, and economic growth for 19 developed and developing countries. Their empirical results indicate that in the long-run, nuclear energy eliminates emission, a 1% increase in nuclear energy consumption is associated with with a 0.477% decrease in emission.

Table 4.1: Descriptive Statistics

Country	USA	Canada	Japan	Russia	France	China	South Korea	India
Real Oil price								
mean	3.522	3.6605	8.4359	6.7203	5.1796	5.3209	10.5258	7.2539
SD	0.6686	0.6826	0.26712	1.2176	0.6619	0.9533	0.66087	0.8252
Skewness	-0.2381	-0.4131	-2.3461	-0.3376	0.0749	-0.5632	-0.2513	-0.801
Kurtosis	2.0607	2.31001	8.1485	1.8919	1.8462	2.2831	2.0582	2.6872
Normality	2.042	2.156	4.342	2.054	2.567	3.432	2.105	5.342
$p-value$	(0.360)	(0.340)	(0.114)	(0.358)	(0.276)	(0.179)	(0.349)	(0.069)
Oil consumption								
mean	9.7474	7.46502	8.4359	8.1374	7.5514	7.6534	6.5171	6.9171
SD	0.14054	0.17309	0.26712	0.2636	0.1675	0.9734	1.2298	0.7599
Skewness	-0.9139	-0.49156	-2.3461	0.6236	-1.4939	-0.6255	-0.7881	-0.0834
Kurtosis	3.6263	3.2065	8.1485	1.6038	6.3212	2.8466	2.8889	1.783
Normality	4.209	2.248	111.79	4.134	1.310	5.974	5.093	8.208
$p-value$	(0.106)	(0.329)	(0.000)	(0.127)	(0.089)	(0.050)	(0.078)	(0.017)
Nuclear energy consumption								
mean	5.5738	3.60489	4.13701	4.8534	4.55549	3.2153	3.5608	1.6704
SD	1.4991	1.4474	2.2125	0.17093	1.84321	0.9646	1.71201	0.9729
Skewness	-1.499	-1.0539	-1.70747	-0.004128	-0.95198	-1.092	-1.75475	-0.1867
Kurtosis	4.1014	2.5759	5.3321	1.82433	2.5257	4.5034	6.2271	1.9581
Normality	22.03	9.316	38.390	1.472	7.716	5.974	6.038	22.038
$p-value$	(0.078)	(0.009)	(0.000)	(0.48)	(0.021)	(0.050)	(0.048)	(0.000)
Real GDP								
mean	10.1748	9.8133	10.2127	7.7009	9.7285	5.9354	8.5953	5.7386
SD	0.2652	0.2433	0.3463	0.23174	0.2637	1.0011	0.76788	0.4146
Skewness	-0.0872	-0.2224	-0.7878	-0.3089	-0.6127	0.27946	-0.17963	0.68227
Kurtosis	1.7459	2.067	2.6553	1.58637	2.4121	1.7831	1.70897	2.3097
Normality	3.1010	1.958	5.200	2.766	3.585	3.481	3.506	3.111
$p-value$	(0.212)	(0.375)	(0.074)	(0.251)	(0.166)	(0.175)	(0.173)	(0.211)

Table 4.2: **Tests of Unit Root**

Country	Variable	ADF	lags	PP (4)	PP (8)	KPSS	
Panel A: Highly Industrialized Countries							
USA							
levels	OP	-1.698	(0)	-1.854	-1.962	0.129	(4)
	OC	-3.344	(1)	-2.746	-2.720	0.086	(4)
	NC	-3.451	(1)	-3.748*	-4.339**	0.230**	(4)
	Y	-3.203	(1)	-2.098	-1.820	0.098	(4)
first difference	OP	-6.566**	(0)	-6.802**	-6.808**	0.109	(4)
	OC	-4.165*	(1)	-3.606*	-3.846	0.104	(4)
	NC	-4.340**	(0)	-4.742**	-4.847**	0.163	(4)
	Y	-5.195**	(1)	-5.602**	-5.721**	0.081	(4)
Canada							
levels	OP	-1.843	(0)	-1.948	-2.052	0.130	(4)
	OC	-2.782	(1)	-2.659	-2.666	0.104	(4)
	NC	-0.712	(0)	-0.743	-0.684	0.247**	(4)
	Y	-2.476	(1)	-2.261	-2.032	0.127	(4)
first difference	OP	-7.113**	(0)	-5.461**	-5.922**	0.096	(4)
	OC	-3.752*	(0)	-0.630	-0.359	0.128	(4)
	NC	-6.276**	(1)	-1.953	-1.791	0.082	(4)
	Y	-5.012**	(0)	-0.935	-0.831	0.066	(4)
Japan							
levels	OP	-1.809	(0)	-1.926	-2.066	0.116	(4)
	OC	-2.153	(6)	-4.108*	-3.979*	0.159*	(4)
	NC	-3.156	(7)	-6.627*	-6.385**	0.247**	(4)
	Y	-3.257	(0)	-3.149	-3.165	0.243**	(4)
first difference	OP	-6.188**	(0)	-6.444**	-6.422**	0.100	(4)
	OC	-3.707*	(0)	-3.774*	-3.88*	0.137	(4)
	NC	-4.742**	(4)	-12.75**	-12.96**	0.20	(4)
	Y	-4.566**	(1)	-4.482**	-4.369**	0.0925	(4)
France							
levels	OP	-1.654	(0)	-1.835	-1.936	0.158*	(4)
	OC	-3.999*	(1)	-3.592*	-3.545*	0.124	(4)
	NC	-1.548	(0)	-1.563	-1.592	0.114	(4)
	Y	-2.110	(1)	-2.009	-2.114	0.261**	(4)
first difference	OP	-6.297**	(0)	-6.522**	-6.528**	0.108	(4)
	OC	-3.733*	(0)	-3.899*	-3.984*	0.141	(4)
	NC	-1.974*	(2)	-5.741**	-5.672**	0.059	(4)
	Y	-4.990**	(0)	-5.105**	-5.031**	0.093	(4)

Table 4.2 – Continued

Country	Variable	ADF	lags	PP (4)	PP (8)	KPSS	
Panel B: Emerging Economies							
Russia							
levels	OP	-2.183	(0)	-5.461**	-5.922**	0.1072	(4)
	OC	-2.563	(2)	-0.630	-0.359	0.145	(4)
	NC	-0.990	(0)	-1.953	-1.791	0.121	(4)
	Y	-2.326	(2)	-0.934	-0.830	0.158*	(4)
first difference	OP	-4.488*	(0)	-6.096**	-7.148**	0.144	(4)
	OC	-5.130**	(4)	-3.005	-2.778	0.109	(4)
	NC	-3.940**	(0)	-4.077*	-4.145*	0.087	(4)
	Y	-2.201*	(0)	-2.862	-2.709	0.090	(4)
China							
levels	OP	-1.536	(0)	-1.729	-1.843	0.153*	(4)
	OC	-1.552	(1)	-2.859	-2.859	0.133	(4)
	NC	-1.751	(1)	-6.754**	-9.197**	0.114	(4)
	Y	-1.513	(2)	-2.443	-2.772	0.241**	(4)
first difference	OP	-6.051**	(0)	-6.288**	-6.378**	0.118	(4)
	OC	-3.772*	(0)	-3.965*	-3.920*	0.141	(4)
	NC	-13.323**	(0)	-12.320**	-16.28**	0.124	(4)
	Y	-5.159**	(0)	-5.239**	-5.358**	0.085	(4)
South Korea							
levels	OP	-2.086	(0)	-2.124	-2.253	0.126	(4)
	OC	-1.354	(2)	-3.556*	-3.479	0.194*	(4)
	NC	-1.495	(0)	-0.926	-0.594	0.177*	(4)
	Y	-0.799	(0)	-0.926	-0.594	0.191*	(4)
first difference	OP	-7.668**	(0)	-8.048**	-7.960**	0.103	(4)
	OC	-3.714*	(1)	-3.485	-3.401	0.108	(4)
	NC	-4.478**	(4)	-3.823*	-3.756*	0.064	(4)
	Y	-6.190**	(0)	-6.434**	-6.443**	0.088	(4)
India							
levels	OP	-2.136	(0)	-2.217	-2.176	0.143	(4)
	OC	-2.706	(1)	-2.987	-2.828	0.097	(4)
	NC	-0.896	(1)	-4.454**	-4.291**	0.065	(4)
	Y	1.118	(4)	0.967	1.467	0.025**	(4)
first difference	OP	-6.962**	(0)	-7.243**	-7.279**	0.082	(4)
	OC	-6.316**	(0)	-6.583**	-7.127**	0.054	(4)
	NC	-9.373**	(0)	-10.46**	-12.54**	0.064	(4)
	Y	-5.350**	(3)	-8.220**	-8.586**	0.085	(4)

Notes: Table entries are the results obtained from unit root tests. Tests are shown in the first row: augmented Dickey and Fuller (1979) (ADF), Phillips and Perron (1988) (PP), and the stationarity test by Kwiatkowski et al. (1992) (KPSS). Regression include an intercept and trend. The variables are specified in the first column: oil price (OP), oil consumption (OC), nuclear energy consumption (NC) and real GDP (Y). All variables are in natural logarithms, while the lag length determined by Akaike Information Criteria and are in parentheses. '*' and '**' indicate significance at the 10% and 5% level, respectively. The nulls for all test except for the KPSS test are unit root.

Table 4.3: lag Selection Criteria

Country	K	AIC	HQIC	SBIC
Panel A: Highly Industrialized Countries				
USA	1	-11.6764*	-11.3731*	-10.849*
	2	-11.665	-11.119	-10.176
	3	-11.673	-10.884	-9.522
	4	-11.612	-10.581	-8.799
Canada	1	-9.819	-9.515*	-8.991*
	2	-9.655	-9.109	-8.166
	3	-9.889*	-9.101	-7.738
	4	-9.851	-8.820	-7.038
Japan	1	-8.635	-8.332	-7.808*
	2	-8.286	-7.740	-6.796
	3	-8.313	-7.525	-6.162
	4	-9.536*	-8.505*	-6.722
France	1	-10.757*	-10.453*	-9.929*
	2	-10.499	-9.953	-9.010
	3	-10.344	-9.555	-8.193
	4	-10.721	-9.690	-7.908
Panel B: Emerging Economies				
Russia	1	-1.820	-1.768	-1.623
	2	-8.443	-8.183	-7.461
	3	-9.553*	-9.084*	-7.786*
China	1	-11.081	-11.1664	-10.169
	2	-12.606	-12.758	-10.963
	3	-122.346	-122.566	-119.972
	4	-243.045*	-243.282*	-240.489*
South Korea	1	-7.918	-7.619*	-6.984*
	2	-7.771	-7.233	-6.089
	3	-8.097	-7.320	-5.669
	4	-8.577*	-7.561	-5.401
India	1	-8.744	-8.437*	-7.882*
	2	-8.667	-8.115	-7.116
	3	-8.316	-7.519	-6.076
	4	-8.831*	-7.789	-5.901

Notes: AIC, HQIC and SBIC stand for Akaike, Hannan and Quinn and Schwarz's Bayesian information criteria, respectively. In the case of conflicting results, we use AIC results as suggested by Pesaran and Pesaran (1997). '*' indicates significant at 5% level.

Table 4.4: **Multivariate Misspecification Tests**

Country	**Test**	**Test statistics**
Panel A: Highly Industrialized Countries		
USA		
	LM (1)	$\chi^2(16)$=17.185 (0.374)
	LM (2)	$\chi^2(16)$=14.543 (0.558)
	Normality	$\chi^2(8)$= 13.216 (0.105)
Canada		
	LM (1)	$\chi^2(16)$=17.185 (0.374)
	LM (2)	$\chi^2(16)$=16.449 (0.422)
	Normality	$\chi^2(8)$= 4.690 (0.790)
Japan		
	LM (1)	$\chi^2(16)$=17.185 (0.374)
	LM (2)	$\chi^2(16)$=22.756 (0.120)
	Normality	$\chi^2(8)$= 14.046 (0.081)
France		
	LM (1)	$\chi^2(16)$=17.185 (0.374)
	LM (2)	$\chi^2(16)$= 22.149 (0.138)
	Normality	$\chi^2(8)$= 11.790 (0.161)
Panel B: Emerging Economies		
Russia		
	LM (1)	$\chi^2(16)$= 16.846 (0.396)
	LM (2)	$\chi^2(16)$= 12.777 (0.689)
	Normality	$\chi^2(8)$= 12.447 (0.132)
China		
	LM (1)	$\chi^2(16)$= 20.705 (0.190)
	LM (2)	$\chi^2(16)$= 17.946 (0.327)
	Normality	$\chi^2(8)$= 12.429 (0.133)
South Korea		
	LM (1)	$\chi^2(16)$= 21.901 (0.146)
	LM (2)	$\chi^2(16)$= 16.628 (0.410)
	Normality	$\chi^2(8)$= 15.811 (0.045)
India		
	LM (1)	$\chi^2(16)$= 15.897 (0.460)
	LM (2)	$\chi^2(16)$= 16.234 (0.437)
	Normality	$\chi^2(8)$= 14.040 (0.081)

- Notes: $p-values$ are given in parentheses.
- Lagrange-multiplier (LM): H_0: No autocorrelation at lag order.
- Normality: H_0: Disturbances are normally distributed.

Table 4.5: Johansen's Cointegration Test

Country	H_0	H_1	λ_{max}	Trace*	95% c.v	P-Value*
Panel A: Highly Industrialized Countries						
USA	$r = 0$	4	0.783	76.347	63.659	0.002***
	$r \leq 1$	3	0.495	34.703	42.770	0.261
	$r \leq 2$	2	0.396	20.706	25.731	0.195
	$r \leq 3$	1	0.216	6.987	12.448	0.356
Canada	$r = 0$	4	0.596	51.751	53.945	0.079*
	$r \leq 1$	3	0.452	28.681	35.070	0.215
	$r \leq 2$	2	0.295	7.614	20.164	0.850
	$r \leq 3$	1	0.078	1.796	9.142	0.811
Japan	$r = 0$	4	0.572	68.773	63.659	0.017**
	$r \leq 1$	3	0.465	39.232	42.770	0.111
	$r \leq 2$	2	0.365	19.752	25.731	0.243
	$r \leq 3$	1	0.250	7.554	12.448	0.299
France	$r = 0$	4	0.455	68.158	63.659	0.048**
	$r \leq 1$	3	0.398	27.715	42.770	0.643
	$r \leq 2$	2	0.281	17.022	25.731	0.421
	$r \leq 3$	1	0.207	7.649	12.448	0.290
Panel B: Emerging Economies						
Russia	$r = 0$	4	0.878	54.149	53.945	0.048**
	$r \leq 1$	3	0.767	27.568	35.070	0.265
	$r \leq 2$	2	0.393	11.807	20.164	0.475
	$r \leq 3$	1	0.260	4.986	9.142	0.295
China	$r = 0$	4	0.695	51.771	47.707	0.019**
	$r \leq 1$	3	0.351	20.476	29.804	0.402
	$r \leq 2$	2	0.127	5.83	15.408	0.718
	$r \leq 3$	1	0.089	2.818	3.841	0.093
South Korea	$r = 0$	4	0.779	77.884	63.659	0.002***
	$r \leq 1$	3	0.349	28.399	42.770	0.603
	$r \leq 2$	2	0.237	12.181	25.731	0.798
	$r \leq 3$	1	0.097	3.226	12.448	0.840
India	$r = 0$	4	0.486	45.637	40.095	0.012**
	$r \leq 1$	3	0.386	14.833	24.214	0.474
	$r \leq 2$	2	0.217	8.117	12.282	0.229
	$r \leq 3$	1	0.08	2.643	4.071	0.122

Notes: The entries of the upper row show the name of the country in the first column, followed by the null hypothesis H_0, that tests for a cointegration rank of r, then H_1 shows the alternative. λ_{max} shown in the fourth column represents the maximum eigenvalue statistics, $Trace*$ shows the trace statics, $95\% c.v$ represents the critical values at 5% level, and finally $p-values$ are provided in the last column. '*', '**', and '***' indicate significance at the 10%, 5% and 1% level, respectively.

Table 4.6: Un-restricted Long-run Relationship using Johansen's Cointegration Technique

Country		β_1		α_1
Panel A: Highly Industrialized Countries				
USA	OC	-0.786***	Δ GDP	-0.224***
		(-5.200)		(-3.745)
	NC	-0.015	Δ OC	0.060
		(-1.203)		(0.679)
	ROP	0.007	Δ NC	0.704**
		(0.380)		(2.026)
	T	-0.012***	Δ ROP	-2.998***
		(-8.882)		(-2.969)
Canada	OC	-2.433***	Δ GDP	-0.092***
		(-12.012)		(-3.144)
	NC	-0.023	Δ OC	-0.065
		(-1.035)		(-1.442)
	ROP	0.357***	Δ NC	-0.288
		(7.621)		(-1.084)
			Δ ROP	-1.766***
	Constant	7.091***		(-5.620)
		(5.222)		
Japan	OC	0.101	Δ GDP	-0.261***
		(1.427)		(-3.638)
	NC	-0.123***	Δ OC	0.156
		(-10.413)		(1.158)
	ROP	0.009	Δ NC	2.510***
		(0.592)		(3.451)
	T	-0.011***	Δ ROP	0.024
		(-9.351)		(0.022)
France	OC	-0.249***	Δ GDP	-0.238***
		(-7.656)		(-2.588)
	NC	-0.039***	Δ OC	-0.279
		(-5.402)		(-0.987)
	ROP	0.038***	Δ NC	3.382***
		(3.898)		(4.295)
	T	-0.015***	Δ ROP	-4.847***
		(-15.891)		(-2.438)

Table 4.6 – Continued

Country		β_1		α_1
Panel B: Emerging Economies				
Russia	OC	-0.002	Δ GDP	-0.166***
		(-0.016)		(-2.734)
	NC	-2.973***	Δ OC	-0.112**
		(-7.347)		(-2.068)
	ROP	0.245***	Δ NC	0.093
		(3.073)		(-1.298)
			Δ ROP	-0.51
				(-1.558)
China	OC	-0.917***	Δ GDP	-0.058***
		(-6.445)		(-3.574)
	NC	-0.279***	Δ OC	-0.049**
		(-3.264)		(-2.036)
	ROP	0.151	Δ NC	0.014
		(0.891)		(0.116)
			Δ ROP	-0.0247**
				(-2.395)
South Korea	OC	-0.215***	Δ GDP	-0.349***
		(-29.818)		(-2.662)
	NC	-0.042***	Δ OC	1.679***
		(-6.374)		(4.460)
	ROP	0.005	Δ NC	-1.027
		(1.051)		(-1.132)
	T	-0.035***	Δ ROP	-1.970
		(-37.381)		(-0.928)
India	OC	-1.214***	Δ GDP	-0.029**
		(-12.508)		(-2.563)
	NC	0.091	Δ OC	-0.006
		(1.489)		(-0.401)
	ROP	0.091	Δ NC	-0.258***
		(0.621)		(-4.660)
			Δ ROP	-0.024
				(-0.149)

Notes: Table entries are the estimates of the un-restricted long-run relationship using Johansen's Cointegration Technique. The long-run relationship has been normalized on the economic growth (GDP). The variables in the first column are: oil consumption (OC), nuclear energy consumption (NC) and real oil price (ROP). β_1 represents the estimated long-run parameters and α_1 shows the speed of adjustment in each equation. Numbers in parentheses are t-statistics where ***, ** and * denote significance at the 1%, 5% and 10% respectively.

Table 4.7: **Variables Exclusion Test**

Country	**Variable**	**LR test**	$p - value$
USA	GDP	3.824**	0.050
	OC	10.136***	0.001
	NC	0.943	0.332
	ROP	0.084	0.772
	T	1.537**	0.025
Canada	GDP	5.157**	0.023
	OC	11.946***	0.001
	NC	0.276	0.599
	ROP	12.184***	0.000
	Constant	9.485***	0.002
Japan	GDP	6.729***	0.009
	OC	0.457	0.499
	NC	6.790***	0.009
	ROP	0.072	0.788
	T	4.931**	0.026
France	GDP	11.108***	0.001
	OC	6.070**	0.014
	NC	8.093***	0.004
	ROP	0.754	0.385
	T	7.265***	0.007
Russia	GDP	4.728**	0.030
	OC	0.000	0.996
	NC	11.573***	0.001
	ROP	3.543**	0.045
China	GDP	5.372**	0.020
	OC	4.455**	0.035
	NC	4.820**	0.028
	ROP	0.337	0.561
South Korea	GDP	41.347***	0.000
	OC	47.101***	0.000
	NC	10.819***	0.000
	ROP	0.751	0.386
	T	44.228***	0.000
India	GDP	3.934**	0.047
	OC	4.669**	0.031
	NC	0.723**	0.039
	ROP	0.180	0.671

Notes: Table entries in the second column show the name of the variable tested for exclusion from the cointegration relationship including: economic growth (GDP), oil consumption (OC), nuclear energy consumption (NC) and real oil price (ROP). Tests are on the null hypothesis that the particular variable listed is not in the cointegration space. The test is constructed by re-estimating VECM model which which cointegration coefficient β in Equation (29) for corresponding variable is restricted to zero. Under the null hypothesis, the test statistics is distributed chi-squared with one degree o freedom. '***', '**' and '*' relates to the decision to reject the null hypothesis at 1%, 5% and 10% significant level, respectively.

Table 4.8: Variables Exogeneity Test

Country	Variable	LR test	$p - value$
USA	GDP	8.094***	0.004
	OC	0.361	0.548
	NC	3.155	0.076
	ROP	4.366**	0.037
Canada	GDP	5.154**	0.023
	OC	1.424**	0.033
	NC	0.692	0.406
	ROP	10.091***	0.001
Japan	GDP	4.060**	0.044
	OC	0.366	0.545
	NC	5.970*	0.015
	ROP	0.000	0.987
France	GDP	3.903**	0.048
	OC	0.248	0.618
	NC	3.708*	0.054
	ROP	1.170	0.279
Panel B: Emerging economies			
Russia	GDP	4.735**	0.030
	OC	2.373**	0.045
	NC	1.251	0.263
	ROP	1.952	0.162
China	GDP	9.033***	0.003
	OC	6.555**	0.010
	NC	0.859	0.354
	ROP	2.817*	0.093
South Korea	GDP	3.903**	0.048
	OC	13.846***	0.000
	NC	1.220	0.269
	ROP	0.765	0.382
India	GDP	7.374***	0.007
	OC	0.145	0.703
	NC	5.149**	0.023
	ROP	0.015	0.904

Notes: Table entries in the second column show the name of the variable tested for weak exogeneity including: economic growth (GDP), oil consumption (OC), nuclear energy consumption (NC) and real oil price (ROP). Tests are on the null hypothesis that the particular variable listed is not responsive to deviation from previous period cointegration relationship. That is the variable's speed of adjustment α in Equation (30) is zero. Under the null hypothesis, the test statistics is distributed chi-squared with one degree o freedom. '***', '**' and '*' relates to the decision to reject the null hypothesis at 1%, 5% and 10% significant level, respectively.

Table 4.9: **Restricted Long-run Relationship using Johansen's Cointegration Technique**

Country	β_1		α_1
Panel A: Highly Industrialized Countries			
USA restricted model test $\chi^2(4)$=4.515 (0.704)			
OC	-0.759***	Δ GDP	-0.283***
	(-6.255)		(-4.770)
NC	0	Δ OC	0.000
	(0.000)		(0.000)
ROP	0	Δ NC	0.000
	(0.000)		(0.000)
T	-0.012	Δ ROP	-2.238**
	(-9.187)		(-1.992)
Canada restricted model test $\chi^2(2)$= 0.749 [0.688]			
OC	-3.078***	Δ GDP	-0.053**
	(-13.568)		(-2.433)
NC	0.000	Δ OC	-0.053*
			(-1.652)
ROP	0.499***	Δ NC	0.000
	(7.501)		
		Δ ROP	-1.355***
C	11.319***		(-6.341)
	(7.494)		
Japan restricted model test $\chi^2(4)$= 3.782 (0.436)			
OC	0.000	Δ GDP	-0.353***
			(-4.823)
NC	-0.108***	Δ OC	0.000
	(-13.265)		
ROP	0.000	Δ NC	2.662***
			(3.289)
T	-0.012***	Δ ROP	0.000
(-12.701)			
France restricted model test $\chi^2(4)$=8.446 [0.077]			
OC	-0.262***	Δ GDP	-0.320***
	(-6.183)		(-2.862)
NC	-0.049***	Δ OC	0.000
	(-5.363)		
ROP	0.000	Δ NC	0.000
T	-0.011***	Δ ROP	0.000
	(-9.452)		

Table 4.9 – Continued

Country		β_1		α_1
Panel B: Emerging economies				
Russia restricted model test $\chi^2(3)$= 4.871 [0.181]				
	OC	0.000	Δ GDP	-0.249***
				(-4.888)
	NC	-2.503***	Δ OC	-0.156***
		(-6.286)		(-3.071)
	ROP	0.140*	Δ NC	0
		(1.986)		
			Δ ROP	0
China restricted model test $\chi^2(2)$=				
	OC	-0.819***	Δ GDP	-0.054***
		(-29.207)		(-3.944)
	NC	-0.327***	Δ OC	-0.043**
		(-4.251)		(-2.027)
	ROP	0.000	Δ NC	0.000
			Δ ROP	-0.179*
				(-1.941)
South Korea restricted model test $\chi^2(3)$=2.815[0.421]				
	OC	-0.214***	Δ GDP	-0.348**
		(-29.403)		(-2.027)
	NC	-0.048***	Δ OC	1.624***
		(-8.532)		(4.154)
	ROP	0.000	Δ NC	0.000
	T	-0.035***	Δ ROP	0.000
		(-43.800)		
India restricted model test $\chi^2(3)$= 0.377[0.945]				
	OC	-1.150***	Δ GDP	-0.028**
		(-36.988)		(-2.308)
	NC	0.104**	Δ OC	0.000
		(2.229)		
	ROP	0.000	Δ NC	-0.267***
				(-4.478)
			Δ ROP	0.000

Notes: Notes: Table entries are the estimates of the un-restricted long-run relationship using Johansen's Cointegration Technique. The long-run relationship has been normalized on the economic growth (GDP). The variables in the first column are: oil consumption (OC), nuclear energy consumption (NC) and real oil price (ROP). β_1 represents the estimated long-run parameters and α_1 shows the speed of adjustment in each equation. Numbers in parentheses are t-statistics where ***, ** and * denote significance at the 1%, 5% and 10% respectively.

Figure 4.1: Country Data

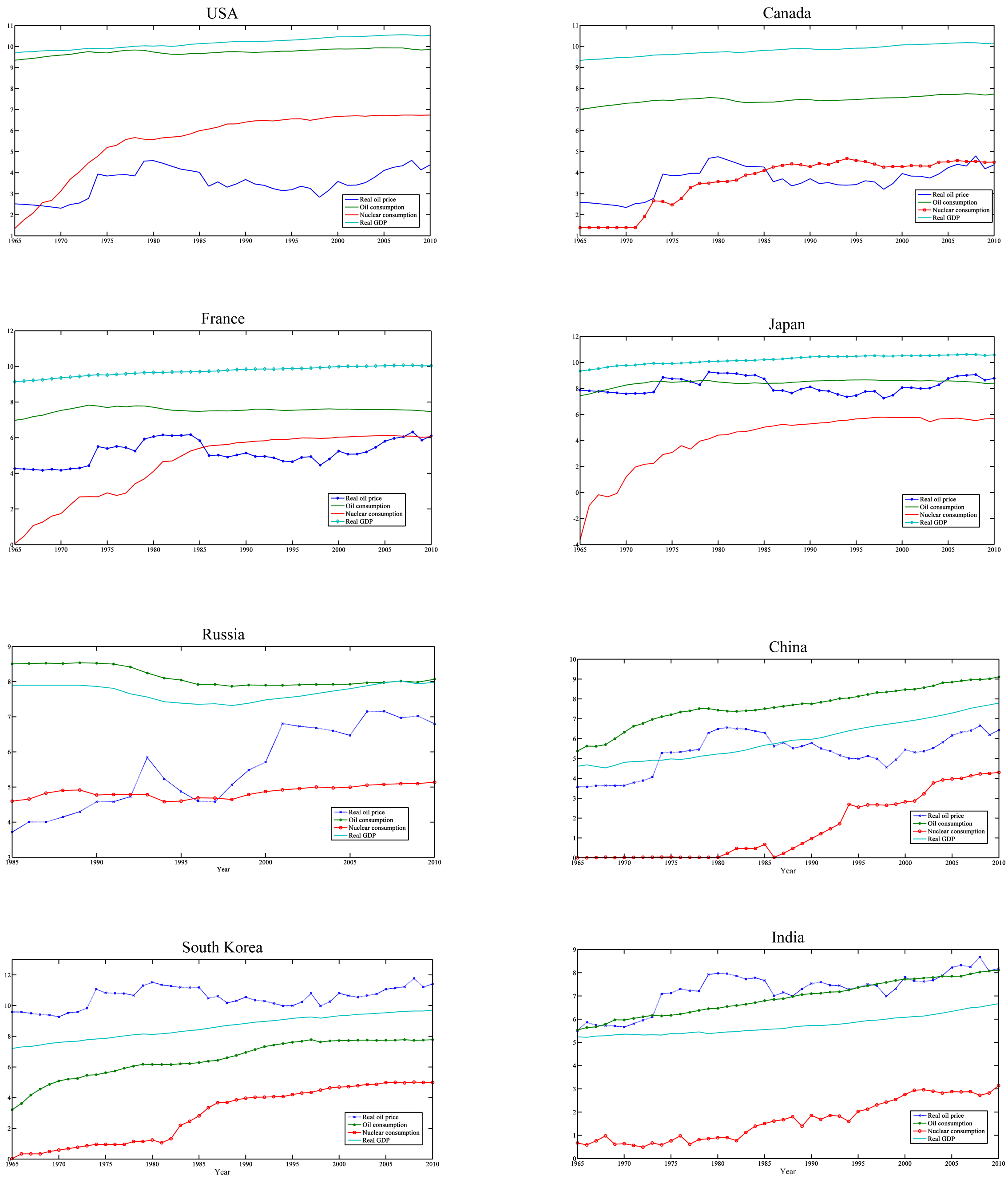


Figure 4.2: Hansen and Johansen (1999) test of constancy of $\hat{\beta}$

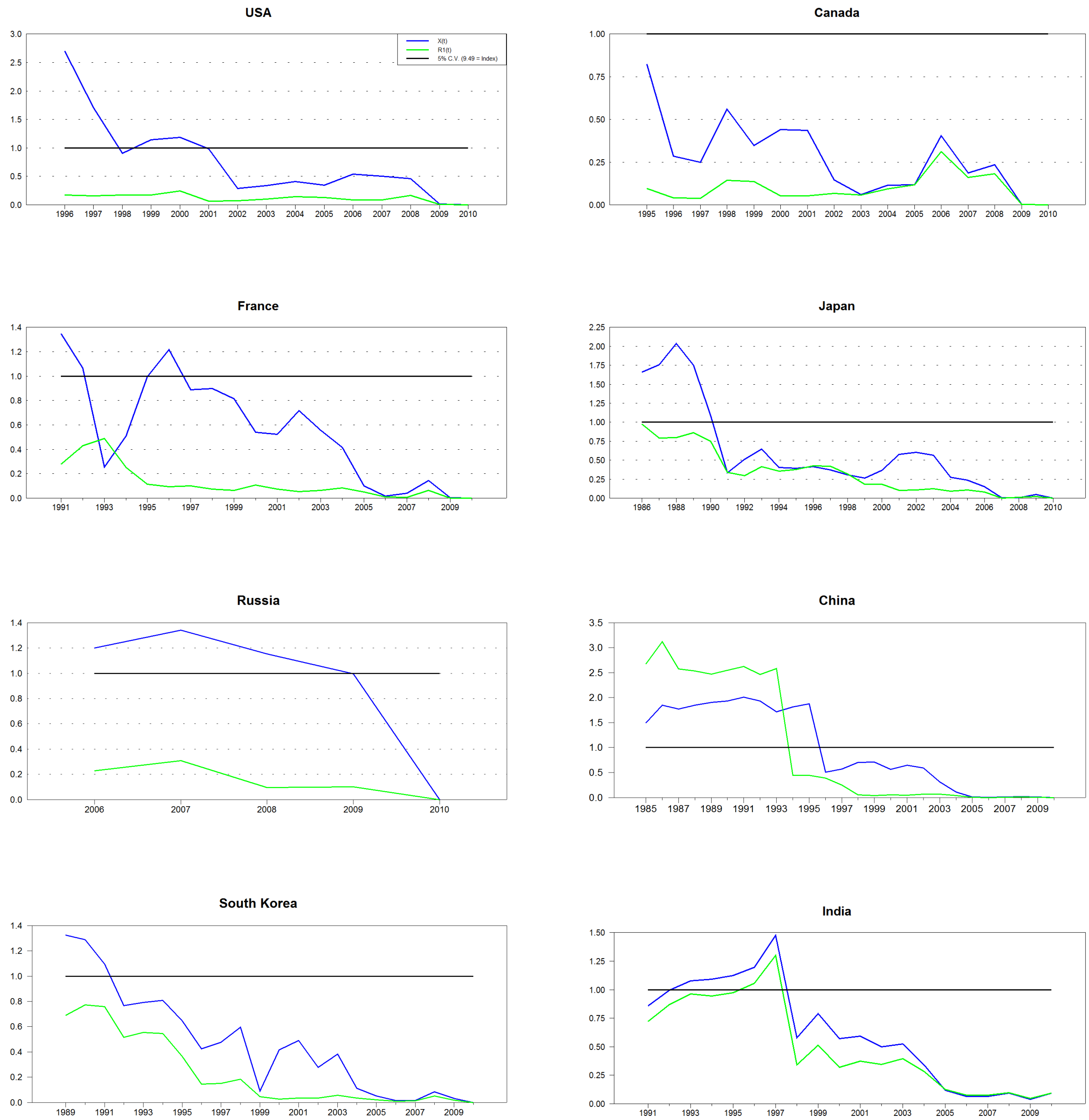


Figure 4.3: Hansen and Johansen (1999) test of constancy of $\hat{\alpha}$

Chapter 5

Conclusion

This thesis comprises three separated yet related empirical studies on different macroeconomic variables. Here in Chapter 5 we provide a summary for the major findings from the three empirical chapters and acknowledge their possible limitations. In the first study that is presented in Chapter 2, we assess the ability of two widely used approaches to predict quarterly GDP growth for Kingdom of Bahrain. The first approach is meant to explain and forecast GDP growth by exploiting the information from selected indicator variables. These variables are suppose to have a close relationship with GDP but are published more promptly than the GDP. The second approach is factor based model, which utilizes extensive data set of macroeconomic indicators. Particularly, a factor model summarizes the information from the large dataset into small number of un-observed common factors that help in predicting GDP growth. The data that are used at quarterly frequency and cover the period from 1995:Q1 - 2008:Q3. We implement an out-of-sample forecast evaluation based on point and density forecasts.

Results based on the root mean square forecasts error (RMSFE) indicate that intercept correction model with three indicators ($3IV/IC$) outperforms any other alternative model. However, results show that other models such as the three indicators ($3IV$), intercept correction with single indicator (SIV/IC) , intercept correction using industrial production index (SIV/IC_{IP}), and the three factor-based ($SW3_L$) models, pass the density forecast criterion. The Diebold and Mariano (1995) (DM) test demonstrates that the difference in the RMSFE between these models and the best performing model ($3IV/IC$) are insignificant at 95%. Industrial production appears to be both a timely and useful indicator for nowcasting using simple regression approach based on single indicator variable (SIV/IC). Our results support Caggiano et al. (2011) argument of efficiency of forecasts using preselected indicators.

The most accurate FLASH estimates are achieved at 84 days using $3IV$, SIV/IC, and $SW3_L$. To produce further earlier estimates, bridge equation is a useful approach. It forecasts a key indicator of GDP growth (refined petroleum production in our case) for the final month in quarter. This forecasted value is then combined with the two months of hard data to obtain FLASH estimates using SIV/IC_{IP} at 54 days (shorten the lag significantly by 36 days). Out-of-sample forecast evaluation of SIV/IC_{IP} model shows insignificant loss in accuracy, which is in line with literature arguments on the role of hard data such as industrial production (Bańbura and Rünstler, 2011; Angelini et al., 2010).

In sum, early and accurate estimates are achieved at two different timelines. A key finding in our study is that using preselected indicator variables that are related directly to GDP is helpful in the case of Bahrain, which implies that more data are not always useful (Boivin and Ng, 2006). The simple regression-based models appear to offer the best means of handling the changes in the business cycle in comparison to AR and factor models, however, it will be interesting to see in a future study whether mixed-frequency factor models, of the sort used by Angelini et al. (2010), are able to pick up the rapid switch in the utility of hard indicators automatically. Our finding can be seen as an addition to the growing body of work that investigates how well factor-based methods work relative to alternatives, often simpler methods.

In the second study (Chapter 3), we contribute to the literature of forecasting crude oil prices in three main folds. First, we use a large dataset that comprises 147 time series variables which are intended to capture the information on oil market. The data-set is on monthly basis and cover the period from March 1983 to December 2011. To our knowledge, Zagaglia (2010) is the only study that exploits information from large data-set in an attempt to forecast crude oil prices. Second, forecasting a highly volatile variable such as crude oil prices face structural breaks problem, which consequently affects the stability of models parameters. Therefore, we use a model that allows the parameter to change over time. Third, oil price is very sensitive to market, regional, political and speculation changes, which makes a single best model over the full period is unattractive. The best model at some times could be a bad model at other times. Thus, we use a model that accounts for model uncertainty. To do so, we implement the dynamic model averaging (DMA) approach, which is suggested by Koop and Korobilis (2012), which allows for parameter and model evolution over time.

To our knowledge, other than the application of Koop and Korobilis (2012, 2011); Koop and Tole (2013), the dynamic model averaging (DMA) and the dynamic model selection (DMS) have not been used by macroeconomic forecasters. The present study extend the use of DMA and DMS models to factor models with monthly large data-set to forecast crude oil prices.

In our empirical work, we present evidence that indicates the benefits of DMA and DMS. In particular, the forecasting models that are generated by the DMA and DMS outperform the other competing models in this study. Also, it does seem that the best predictors for forecasting oil prices are changing considerably over time. There is model rather than parameter variation in our case, and the DMA is not significantly different from the BMA. Our results also suggest that the DMA and the DMS are complementary rather than mutually exclusive. This is so, because although the best performing DMS model outperforms all other alternatives, the probability of being included in the DMA is low. Finally, we show that although it is easier to forecast prices of future contracts, the best DMS model has better forecasting performance than the model based on future contracts. By allowing for parameter and model change, DMA and DMS lead to substantial improvements in forecast performance.

Since the primary contribution of this study is to add to the literature of forecasting crude oil prices and compare the performance of the applied models, we may consider alternative forecast evaluation methods such as mean absolute percentage error (MAPE).

The primary focus of the third study, which is presented in Chapter 4, is to examine the long run relationship between energy consumption and economic growth in selected industrialized and emerging countries. We implement this investigation using two different energy sources including oil consumption (OC), nuclear energy consumption (NC), real economic activity (GDP), and real oil prices (ROP) for the period from 1965 - 2010. The sample includes four developed countries: the US, Canada, France and Japan, and four emerging economies: Russia, China, South Korea and India. Since the results of previous studies are found to be sensitive to the period of time and the use of total energy consumption (for instance, Asafu-Adjaye, 2000; Lee and Chiu, 2011a,b), our empirical investigation extends the period of time in the existing literature and utilizes two different energy sources using Johansen cointegration technique. Also, as energy prices have been neglected in many previous studies, the long-run parameters and the evidence of causality may be biased, (see, Masih and Masih, 1997; Asafu-Adjaye, 2000). Hence, we include oil prices in our empirical analysis.

Empirical results of this chapter can be summarized in four findings. First, oil consumption, nuclear energy consumption, oil prices and real GDP are cointegrated which implies the existence of a long-run equilibrium relationship among these variables. There is at least one energy source (oil or nuclear energy) that enters significantly in the cointegration space for all investigated countries. This reveals that energy is an essential factor for economic growth. In particular, oil consumption is found to be highly significant in six out of eight countries including the US, Canada, France, China, South Korea, and India, where an increase of 1% in oil consumption increases real GDP growth by 0.759%, 3.078%, 0.262%, 0.819%, 0.214% and 1.15%, respectively. Nuclear energy consumption also has a positive and significant impact on real GDP growth in five countries including Japan, France, Russia, China, and South Korea. We observe that France, China, and South Korea are highly dependent on both energy sources, oil and nuclear power to stimulate economic growth. However, the Indian economic growth is negatively linked to nuclear energy consumption. This indicates that decreasing the use of nuclear energy consumption by 1% increases the economic growth for India by 0.104%, suggesting that energy conservation measures that are applied to reduce nuclear energy consumption may help to lower the adverse effects of nuclear energy consumption on economic growth. Oil prices are found to have significant and negative impact on the real GDP of Russia and Canada, which support the inverse relationship between oil price and economic activities that is suggested by Hamilton (1983).

Second, the coefficients of the error correction terms (ECTs) are found to be significant in ΔGDP and ΔOC equations for Canada, Russia, China, and South Korea. These results imply that the GDP and OC are not weakly exogenous, suggesting a bi-directional long-run causality (feedback effect) between the GDP and OC in thes countries. Alternatively, oil consumption is weakly exogenous and has a predictive power for real GDP growth in the US, Japan, France, and India. Oil consumption can be considered as an important factor for economic growth in these countries.

Third, we observe that nuclear energy consumption has a predictive power for real economic growth in six countries including the US, Canada, France, Russia, China, and South Korea. Also, Japan and India have a bidirectional causal relationship between nuclear energy consumption and real GDP growth. These results reveal that nuclear energy is an important factor for economic growth and it is also widely accepted by many countries. Restricted measures on developing nuclear energy may suppress economic growth in these countries. Therefore, both governments and industries have to pay further attention and put on more efforts to overcome the restricted measures in order not to harm economic growth. In other words, a nuclear consumption growth policy should be tailored in such a way to encourages economic growth. Especially that nuclear power is virtually carbon free energy source, that can serve as a potential solution to both energy security and climate change problems, when safety measures are basically taken carefully into account.

Fourth, there is a strong evidence that the level of international oil price is very important and has a predictive power for the economic growth in five out of eight countries including: Japan, France, Russia, South Korea, and India. Thus, the international crude oil price upsurge has significant impacts on economic growth in these countries. Also, there is a bidirectional causality between real oil price and real economic growth in the US, Canada, and China.

Overall, as most investigated countries are oil dependent oil-importing countries, oil could be considered as a limiting factor to their economic growth. Thus, designing efficient energy policies is a real challenge for these countries especially in the short run. Scarcity in the supply of oil will slow down the economic growth badly. It is vital to continue to diversify their economic base in order to insulate themselves from the possible depletion of oil as a natural resource along with their susceptibility to volatile oil prices in international markets. Furthermore, while energy conservation policies that reduce energy consumption may have an adverse impact on growth, policy makers need to also recognise the environmental consequences of oil usage in the design and implementation of a sustainable energy consumption mix that ensures future economic growth. Policy makers need to balance the needs for sustained economic growth with the environmental costs associated with excessive energy consumption. As such, policy makers should continue to enhance energy efficiency usage and reduce the long-run environmental consequences associated with dependence on oil production and consumption. The appropriate balance should properly taken into account in order to achieve the pursed level of economic growth, satisfying the need of massive energy, being more energy independent, and using a clean energy source for sustainable development.

Different countries have different energy consumption patterns and various sources of energy (Sari and Soytas, 2007). Hence, different sources of energy may have varying impacts on economic growth. In our third study, we empirically investigate the relationship between energy consumption and economic growth using disaggregate data for both oil and nuclear energy rather than using the aggregate data. We have included the energy prices (oil prices) as one of the important fundamental variables which affect both the output growth and energy consumption. In a similar econometric framework, the relationship between other sources of energy such as electricity, natural gas or coal and output growth may also be analyzed in future work. Further, a simple overall analysis of the relationship between energy consumption and real GDP may very well mask the differential impacts associated with the energy consumption of various sub-sectors in relation to output in the economy. The shift in the composition of output in the economy could affect the energy consumption-output relationship due to the fact that different industries may have different energy intensities. Accordingly, it might be worth to take into account the sectoral differences and use sector level data to search whether there are changing patterns in the relationship between sectoral output growth and energy consumption in different sub-sectors.

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