

UNIVERSITY OF CALGARY

The Empirical Analysis of Oil Demand and GDP Relationship in Selected Countries

by

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The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies for acceptance, a thesis entitled “The Empirical Analysis of Energy Demand and GDP Relationship in Selected Countries” submitted by Dinara Mutysheva in partial fulfilment of the requirements for the degree of Master of Arts.



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Abstract

The objective of this thesis is to test the income growth hypothesis that oil consumption grows faster than GDP in developing countries, while the opposite is true for developed countries by comparing their long-run income elasticities. The results concluded that the income growth hypothesis has proven to be true, but not for all countries. This leads us to believe that the separation of countries into developed and developing classes might be too general to assume the hypothesis would apply. Also, the hypothesis might have been proven to be true if this analysis was not limited to estimating parameters involving only oil consumption, but included all types of energy to arrive at total energy demand. However, given these limitations, this thesis does provide an insight on oil demand – GDP - oil price relationship, even if it does not conform to the above stated income growth hypothesis.

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Dedication

I would like to dedicate this thesis to my family for their undeniable support and encouragement.

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CHAPTER 1

INTRODUCTION

1.1 Background

The relationship between energy demand and economic growth is a well-studied topic in energy economics. The literature shows that energy demand and gross domestic product (GDP) growth are highly correlated (Pesaran, M. H., et.al 1998). Following this stylized fact is a theoretical hypothesis that energy consumption grows more rapidly than GDP in developing countries while the opposite is true for developed countries (Hanneson 2002). This hypothesis arises from an insightful point of view that energy has diminished as a factor of economic growth for richer countries, whose national economies are more mature, whose population growth is expected to be relatively slower, and whose energy use is growing at much slower rate than in the developing world. Another observation that follows this hypothesis is a greater economy diversification among developed nations and a movement toward a more service-oriented and away from a very energy-intensive economy. This is evidently the case for developing countries currently facing the “industrialization” stage that demands a lot of energy to support economic and population growth. In other words, energy consumption per unit of economic growth is increasing.

Examining these two important variables will give the basis for empirically testing this hypothesis and determining whether energy consumption does grow more rapidly than GDP in developing countries. Once the specification for the demand equation has been determined, we can estimate the dynamic income and price elasticities of demand and evaluate whether the income elasticity of demand will be below one for developed countries – an indication that the energy component of GDP has diminished as a factor of economic growth. By contrast, the developing countries will likely show the opposite result: income elasticity of above one. These findings will have important policy implications for governments of developed as well as developing countries, since the adoption of suitable energy policies can improve energy conservation without impeding economic growth.

A large bulk of work concentrates on estimating energy demand using various statistical modelling approaches e.g., simple regression models or causality tests on energy consumption and GDP.¹ From this literature some general conclusions are available. First, it appears that this literature is not so much an exercise in understanding the relationship between energy consumption and GDP as it is an exercise in applied econometrics (Atkins and Jazayeri 2004). The research in this area has advanced, coinciding with an explosion of research in applied time series econometrics, notably, the unit root methodology. Next, the aggregation is a problem in two ways. First, aggregation across countries is problematic as the papers of Hannesson and Gately and Huntington

¹ For the discussion of papers that employ causality tests, see Chapter 2, Section 2.2.

point out. Their results both conclude that there is a great degree of diversity across countries – different countries with different characteristics should not be grouped together in the analysis, in particular the non-OECD² countries. Second, aggregation to annual data may diminish the power of statistical tests.³ Higher frequency data such as monthly or quarterly observations increase the power of statistical tests such as unit root tests and co-integration tests by capturing the co-movements of the variables better than annual data and thus provide improved results that lead to more accurate conclusions. Third, there is mixed support for the energy-GDP hypothesis.⁴

1.2 Objective

The objective of this thesis is to test the income growth hypothesis for the sample countries by comparing their long-run income elasticities. This research extends the work of Hanneson (2002). Hanneson's work provides some support for the basic hypothesis that energy consumption grows faster than GDP in developing countries, while the opposite is true for developed countries. However, his statistical evidence is based on simple regressions and subject to criticism. The vector error-correction model (VECM) is employed here as an alternative statistical tool to test the energy demand and economic growth hypothesis.

²Organization for Economic Cooperation and Development

³To construct a model using quarterly data, one can use data from 1986 onwards.

⁴See Literature Review section for references.

Economists claim that if a co-integrating vector is found among the variables, VECM should be employed, because it provides additional information on the behaviour of variables. The found co-integrating vector represents the long-run equilibrium relationship, from which the coefficients of the long-run income and price elasticities of demand for sample countries can be estimated. This vector then enters a model as an error-correction term. The idea is that variables are hypothesized to be linked by some theoretical equilibrium relationship in the long run but in the short run the variables may deviate from the long-run equilibrium due to short-run shocks to the system. The advantage of the error-correction mechanism is that the extent of adjustment in a given period to deviations from long run equilibrium is given by the estimated equation, thus tying the short-run to the long-run properties.

The VECM technique, which includes annual energy consumption per capita, real GDP per capita and real oil prices, will estimate the long-run income elasticity of demand for each of the countries. Income elasticity of demand below one indicates that the economy grows more rapidly than energy demand; income elasticity above one suggests the opposite: energy demand grows more rapidly than GDP. The income elasticity of one translates to one-for-one change in income and energy demand.

VECM technique also enables us to derive the long-run estimates of price elasticities of demand, which are then discussed in terms of an effect that income and price have on the demand in the long run.

The estimated short-run income coefficients are discussed in terms of short-run dynamics between oil demand and income, which are represented by graphing of the impulse response functions (IRFs) of the demand and GDP in response to a shock in the oil price. Generally, an impulse response function is a tracing of an impact (or shock) over time. Calculating the IRFs on the relationship between income and demand can yield more useful information than simply knowing the estimates of income elasticity.

1.3 Summary

Results concluded that the income growth hypothesis has proven to be true, but not for all countries. This leads me to believe that the separation of countries into developed and developing classes might be too general to assume the hypothesis would apply. Also, the hypothesis might have been proven to be true if this analysis had not been limited to estimating parameters involving only oil consumption, but had also included all types of energy to arrive at total energy demand. However, given these limitations, this thesis does provide an insight on the oil demand – GDP - oil price relationship, even if it does not fully conform to the above stated income growth hypothesis.

In brief, the results show that the estimate of the long-run income elasticity of oil demand for developed countries was found to be less than one (with an exception of France), thus indicating that oil demand grows slower than the economy, possibly pointing out that

developed countries are less reliant on energy to support their economic growth. The estimate of the long-run income elasticity of oil demand for developing countries was found to be greater than one (with exception of China and Mexico), which is consistent with our initial hypothesis that oil consumption growth is greater than income growth for developing economies. We label this occurrence as an “industrialization” phase that many developing economies are facing today.

CHAPTER 2

ECONOMIC MOTIVATION AND LITERATURE REVIEW

This chapter deals with the economic motivation behind the objectives of this thesis and provides literature review of the past work that relates to the topic of economic growth and energy consumption.

2.1 Economic Motivation

To describe the economic motivation behind the objective of this, the oil consumption shares of GDP are compared among selected countries. These selected countries are Canada, the United States, France, the United Kingdom, Brazil, Mexico, China and India. Canada, the U.S., France and the UK were selected as being representative of the most developed nations in the world; China and India as the fastest growing developing countries; while Brazil and Mexico may be classed as transition economies that are viewed as still developing but not fully developed. Based on the hypothesis, it is believed that the oil consumption share of GDP is decreasing for the developed nations and increasing for the developing countries over time. These ratios are shown and compared in Figure 2.1. They were calculated using log data of oil consumption per capita and real GDP per capita.

In Figure 2.1, judging by the slope of the lines, it is clearly visible that the energy demand share of GDP is increasing for China and India, while in the rest of the countries it is increasing in the earlier period of time and then levelling off in the later period. By far, China and India have the highest rate of growth in the oil consumption share of GDP over time. For developing Mexico and Brazil, the growth is not as evident as for China and India. Given that Mexico is a net exporter of crude oil and Brazil became less dependent on oil in the latter years of the time sample due to domestic ethanol production for transportation sector, it is reasonable to think their oil consumption share of GDP grows at a slower rate than more energy-dependent nations, such as China and India. For the developed countries, Canada, the U.S., France and the UK, the growth of energy demand ratio is not as impressive and the slope of the line is less steep. This falls in line with our earlier statement that developed countries are less reliant on energy for economic growth.

As it is impossible to describe each country from one graph, the countries were broken into groups of two based on their economic status and geography and graphed their respective ratios in Figures 2.2 through 2.5. There are eight countries and they are split into groups as follows:

1. Canada and the U.S.,
2. France and the United Kingdom,
3. Mexico and Brazil, and
4. China and India.

The ratios are described in the next two sections. Section 2.1.1 describes the graphs for developed countries (Groups 1 and 2) and the following Section 2.1.2 deals with the graphs for developing countries (Groups 3 and 4).

Figure 2.1 Energy Demand/GDP Ratios

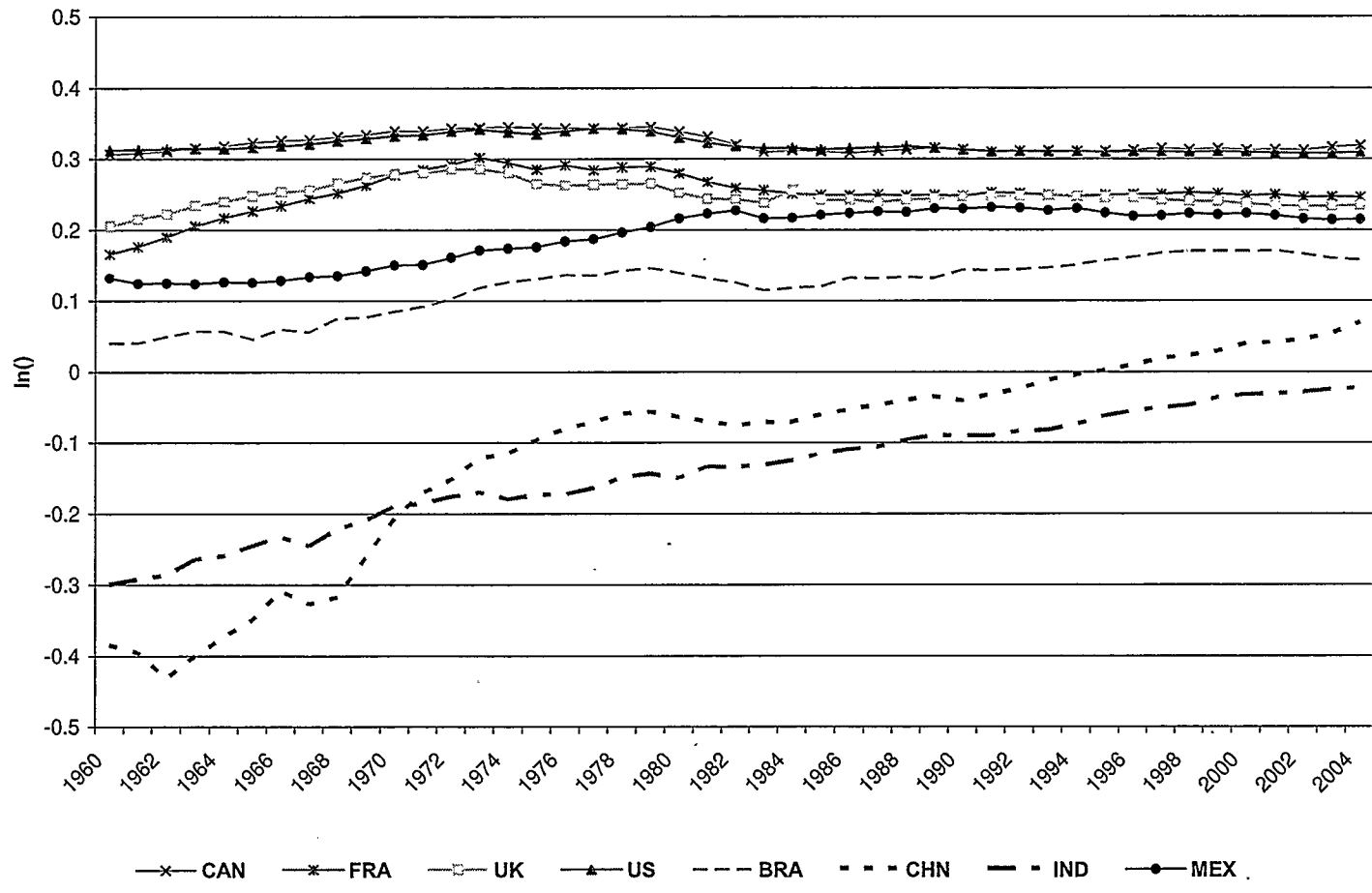


Figure 2.2 Energy Demand/GDP Ratios for Group 1

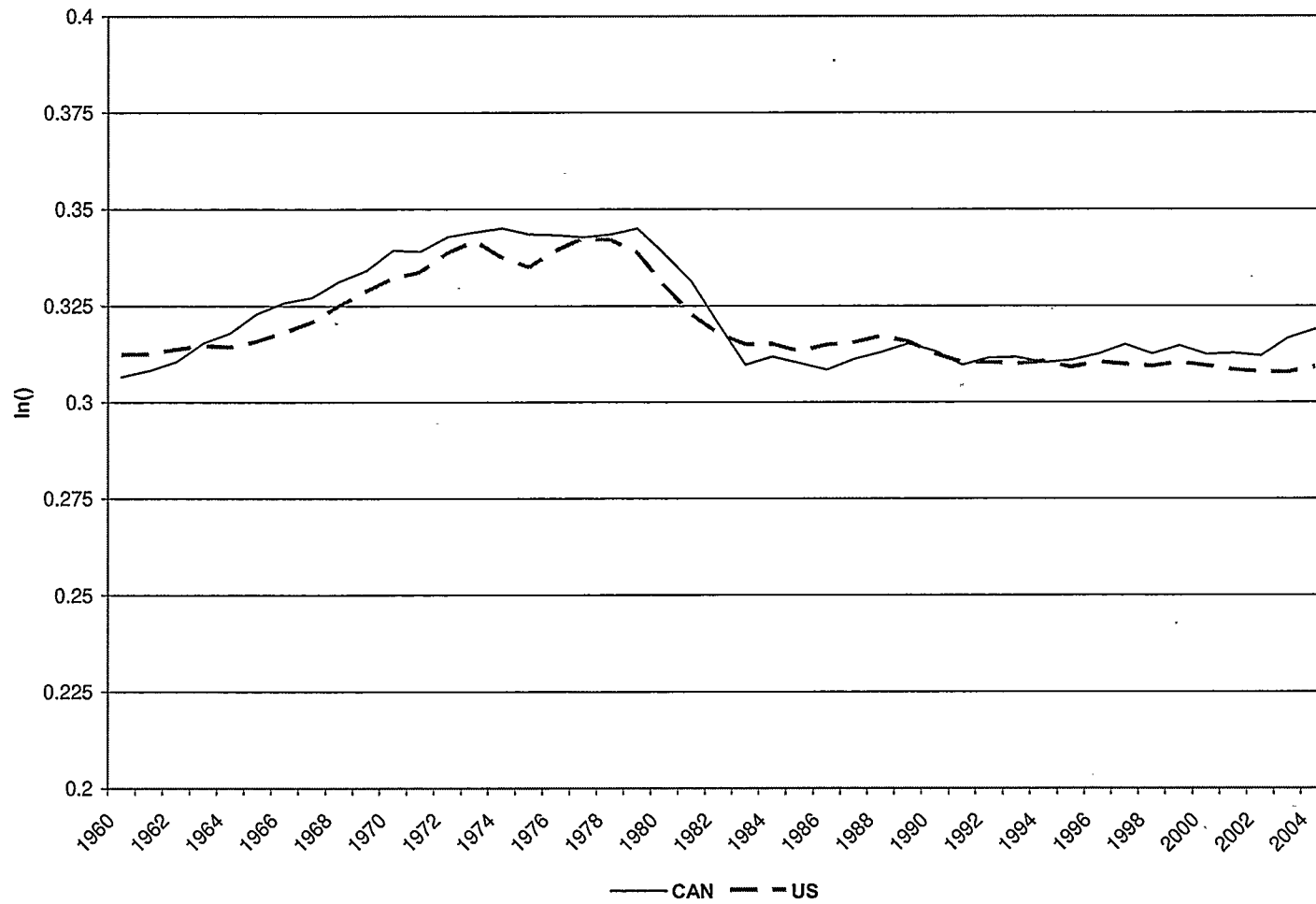


Figure 2.3 Energy Demand/GDP Ratios for Group 2

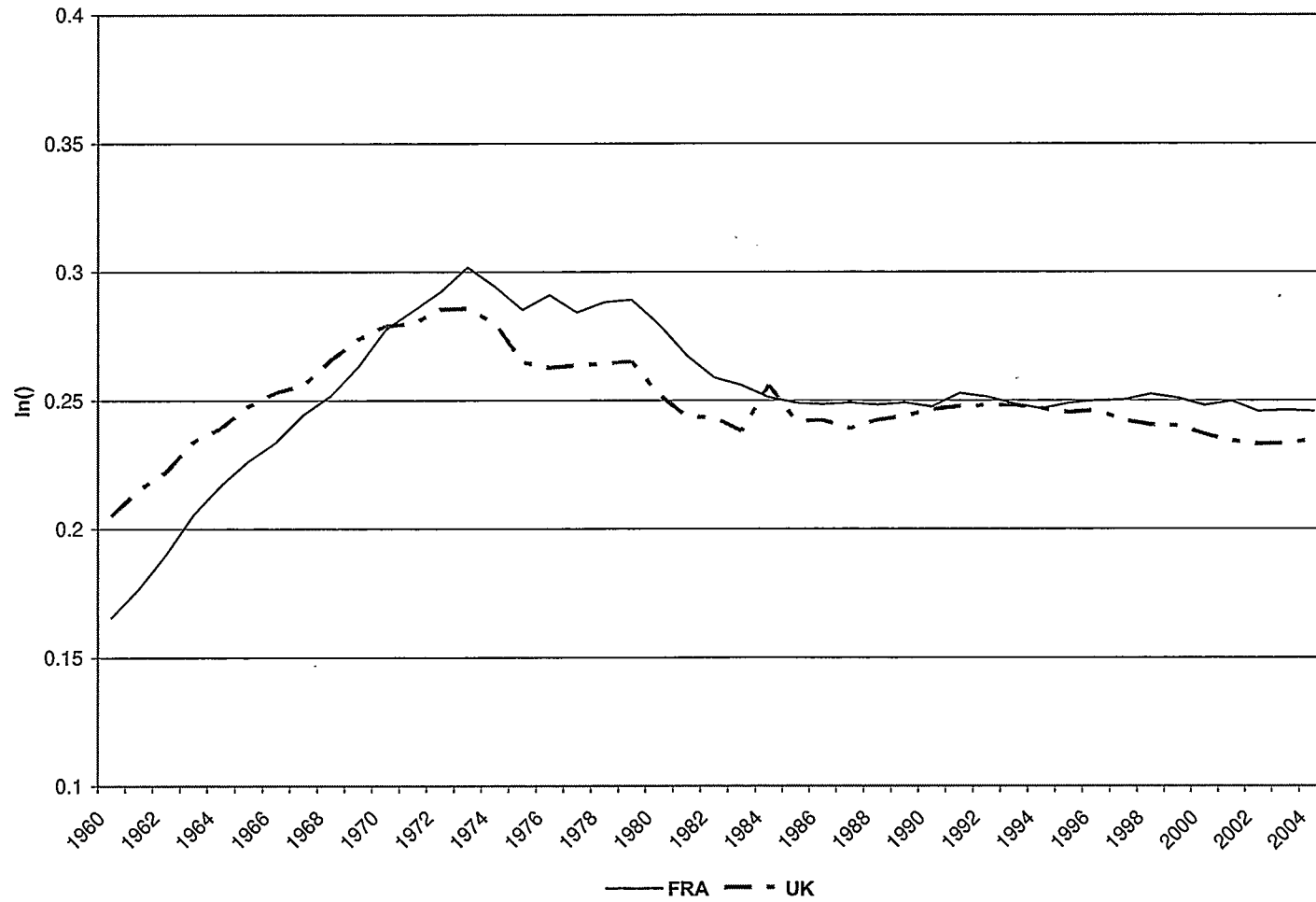


Figure 2.4 Energy Demand/GDP Ratios for Group 3

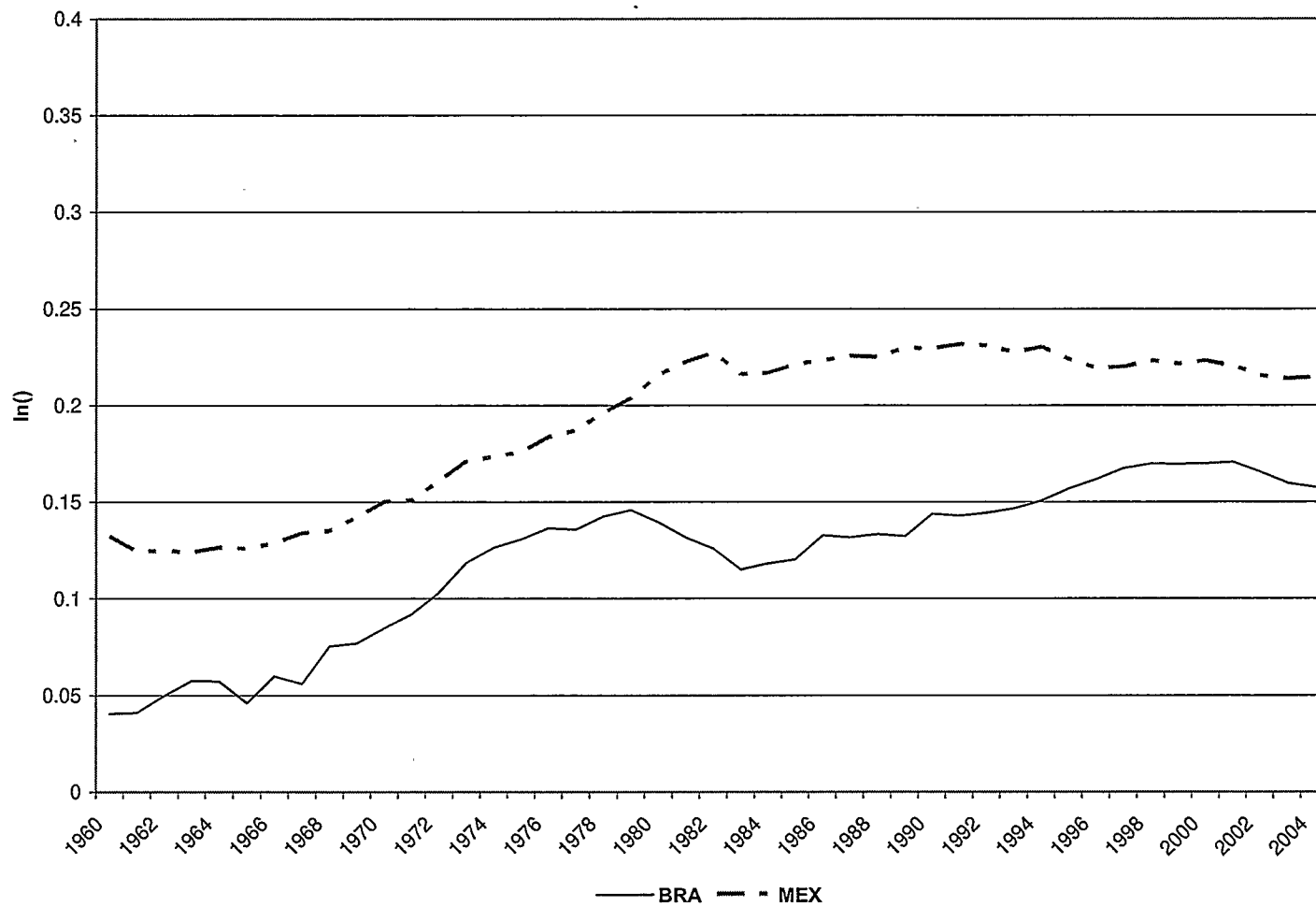
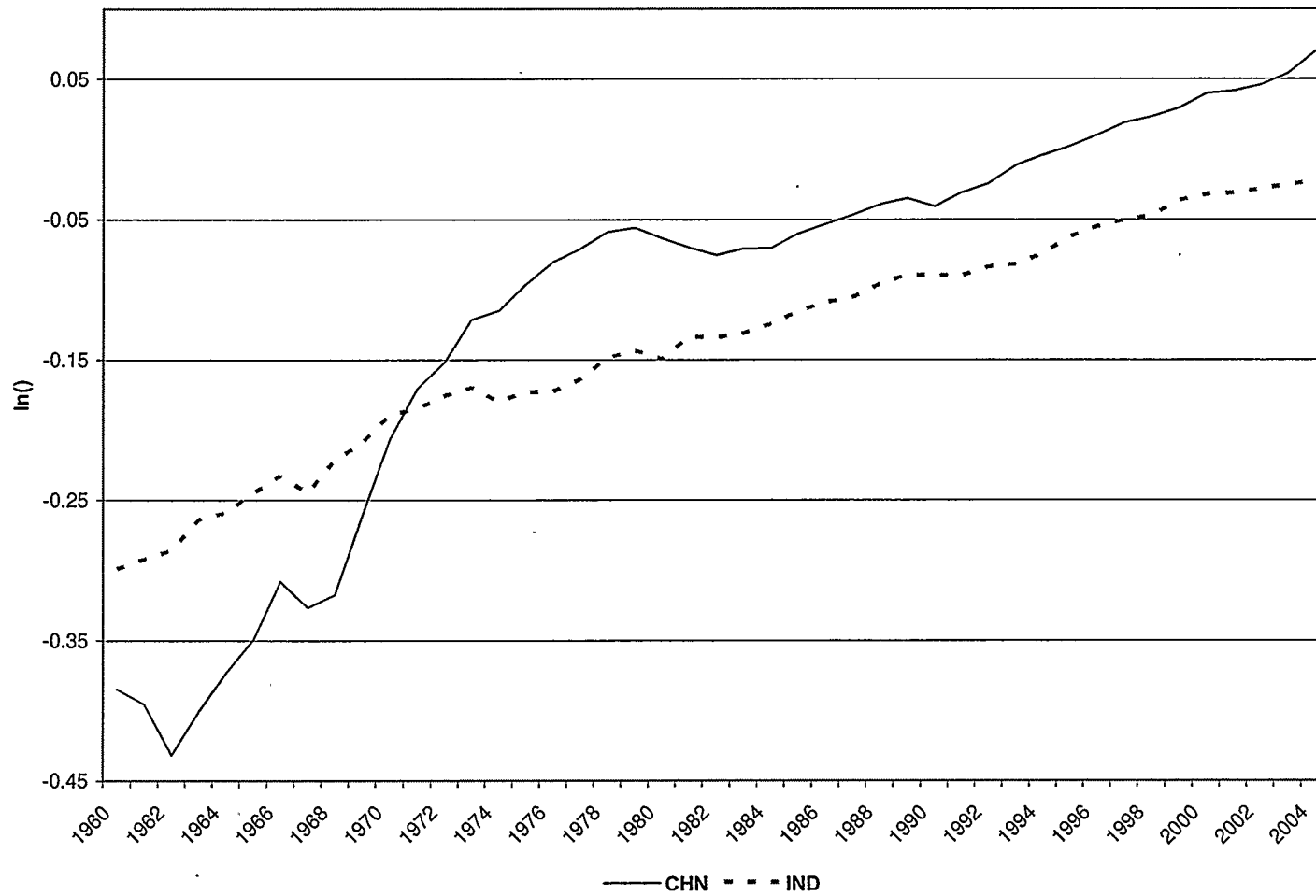


Figure 2.5 Energy Demand/GDP Ratios for Group 4



2.1.1 Developed Countries

The first noticeable similarity in Figures 2.2 and 2.3 is the slope of the demand ratios. The energy demand share is increasing from the beginning of the period until early 1980's, dipping to a lower level, and then steadily levelling off in the latter years. The period from the early 1960s to the late 1970s marks years of rapid economic development for Canada, the U.S., France and the UK, where it is clearly visible that energy demand share of GDP is rising, signifying higher growth rates for GDP and energy consumption. The later years where the ratios are levelling off represent the period when the economies of these countries have reached a certain level of maturity, population growth stabilized, and oil demand exhibited smaller growth rate.

The dip in the curves around the late 1970s and the early 1980s can be explained by the oil price shocks caused by the oil embargos of 1973 and 1979 that restricted oil exports from the Middle East around the same time period. These price shocks had a large negative effect on both GDP and oil demand. There was a direct negative impact on oil demand because the oil price increased and there was an indirect negative effect on GDP through oil demand. This is a problem of causality (i.e. Granger-type causality where one economic variable has an effect on another).

The similarity of the graphs for the sample developed nations is also suggestive of the earlier stated hypothesis that developed economies are less reliant on oil consumption for their prosperity and economic growth, especially in the later part of the sample period. Thus, we can make an initial observation that oil demand grows slower than GDP in developed economies.

2.1.2 Developing Countries

The remaining two groups fall into the class of developing countries, and are shown in Figure 2.4 for Brazil and Mexico and in Figure 2.5 for China and India. The oil demand ratios for both groups exhibit a positive slope, which is steeper for China and India and flatter for Brazil and Mexico. The upward-sloping line could be a potential sign of a long-term growth in the oil demand share of GDP. However, there are also few differences between the graphs.

In Figure 2.4 for Brazil and Mexico the 1979 oil price shock sent the curves in the opposite direction. As a response to this price shock, which caused gasoline shortages and raised awareness of the dangers of oil dependence, the Brazilian government began promoting bioethanol as a fuel, derived from sugarcane plantations.⁵ As for Mexico, it is unclear what caused the rise in the curve and it needs further investigation.

⁵ Kovarik, W. 2008. Ethanol's first century: Fuel blending and substitution programs in Europe, Asia, Africa and Latin America. *Radford University*.

Generally, both countries went through periods of rapid GDP growth and periods of economic stagnation throughout the chosen period. Both countries benefited from high revenues from their exports, either energy or other manufacturing goods, and suffered periods of debt repayment after accumulating foreign debt, which in some cases lead to devaluation of domestic currency. As a result, it is unclear whether the hypothesis holds true that energy demand grows faster than GDP in developing countries and needs further evaluation.

Figure 2.5 illustrates demand ratios for China and India. The curves have by far the largest positive slope of the other countries, clearly showing an increasing growth in oil demand share of GDP, which could potentially indicate a GDP growth that is dependent on the consumption of crude oil. However, it is also noticeable that China's curve is definitely steeper than India's, reflecting a higher oil demand share of GDP. The initial conclusion, which follows from the Figure 2.5, is that China and India are increasingly consuming more crude oil in order to support their growing economies. This supports the hypothesis that energy demand growth surpasses the GDP growth in developing countries.

Although China and India are still developing countries with a relatively low per capita GDP, they have experienced tremendous economic changes, both in terms of growth and stagnation periods due to various reasons, which are unique for each country. In China, GDP quadrupled between 1978 and 1998 (just in 2003 China's GDP grew 9.7%⁶), and the foreign investment soared during the 1990s, in large part as a result of economic liberalization policies⁷ that reduced bureaucratic intrusion in the Chinese petroleum markets and government-set prices. China's challenge in the early 21st century will be to balance its highly centralized political system with an increasingly decentralized economic system. Therefore, in the past few years, the Chinese government has tried to curb GDP growth by raising interest rates to avoid an economic explosion.⁸

In India the economy developed differently. The late 1970s marked the time when successive Indian governments sought to reduce state control of the economy. Progress toward that goal was slow but steady. In the late 1980s, however, India relied on foreign borrowing to finance development plans, thus boosting its GDP. When the price of oil rose sharply in August 1990⁹ following the invasion of Kuwait by Iraq, the nation could not repay its foreign debt and as a result, the country's GDP fell. The turn of the millennium marks a period of stabilization in the Indian economy with a growing GDP per capita and an increasing standard of living.

⁶ International Energy Agency (IEA). 2004. *Annual Energy Outlook, 2004*.

⁷ *The Columbia Electronic Encyclopedia*, 6th ed. Copyright © 2005, Columbia University Press

⁸ International Energy Agency (IEA). 2004. *Annual Energy Outlook, 2004*.

⁹ The price went up by 18% in 1980.

2.2 Literature Review

There have been many studies devoted to the understanding of the relationship between macroeconomic variables on one hand and resource related variables, such as energy or oil demand, on the other. The literature has divided into two main directions, each attempting to evaluate this "black box" relationship: i) evaluation of the causal relationship between energy demand and economic growth based on Granger-type causality tests and ii) a statistical modelling approach of energy demand in deriving elasticities using vector autoregressions and error correction models.

2.2.1 Causality Tests

There is a wide body of literature investigating the causal relationship between energy consumption and economic growth based on one of the stylized facts often mentioned in the literature that energy consumption and economic growth are highly correlated. The work relates to Granger-type causality tests. In this literature, the Granger (1969) test has traditionally been employed to test for causal relationships between two variables. This test states that, if past values of a variable Y significantly contribute to forecast the value of another variable X_{t+1} then Y is said to Granger-cause X and vice versa.

The pioneer work in this area began with Kraft and Kraft (1978) who found a unidirectional causality from Gross National Product (GNP) to energy consumption for

the period of 1947-1974 for the United States. The results of his work showed that energy preservation policies could be enforced without affecting GNP growth. However, Akarca and Long (1980) could not reproduce similar results when they shortened the time-series data sample of Kraft and Kraft (1978), implying that chosen time period might have influenced the results or the authors needed a different statistical tool.

Nevertheless, this shortcoming did not stop researchers from continuing to investigate this issue. Yu and Hwang (1984) updated the U.S. data for the period 1947-1979 and did not find causal relationship between energy consumption and GNP, possibly due to a different time-series data. Yu and Choi (1985) did a study on five countries and confirmed the absence of causality between GNP and energy consumption in UK, Poland, and the U.S. but found a causality going from GNP to energy consumption in South Korea and opposite causality for Philippines. The authors concluded that this finding of no causality in either direction could potentially imply that energy conservation policies have no effect on economic growth.

After these early papers where the authors employed simple log-linear models, the research in this area has advanced, coinciding with an explosion of research in applied time series econometrics, notably, the unit root methodology, which began in late 1980s. Unit root methodology involves testing the time-series variables for stationarity, i.e. whether the variables exhibit smooth or trendy behaviour. However, it is still not clear that the unit root hypothesis is appropriate in this literature (Atkins and Jazayeri 2004).

Some authors used this unit root co-integration methodology combined with a concept of Granger causality. The goal is to identify a direction of causality, rather than to uncover some elasticity measure. The results from applying this procedure are conflicting and inconsistent. For example, in more recent studies, Cheng (1999) found causality running from GDP to energy consumption in India, while Masih and Masih (1996) and Asafu-Adjaye (2000) found the opposite causality. For Indonesia, Yu and Choi (1985) and Masih and Masih (1996) both found causality in a direction from GDP to energy consumption, while Asafu-Adjaye (2000) found causality running from energy consumption to GDP. In another paper, Soytas and Sari (2003) uncovered a unidirectional causality from GDP to energy consumption in Korea, while Oh and Lee (2004) found the opposite: unidirectional causality running from energy consumption to GDP. The list of published papers on this topic goes on, and the results contradict one another from one paper to the next.

2.2.2 Modeling Approach

Other authors have used some version of vector autocorrelation models or vector error-correction models to estimate the energy demand. The abundance of papers using such methodology gave the basis for the methodology used in this thesis. The goal in this literature and, consequently, in this thesis is to concentrate on the specification or modelling approach of energy demand in deriving elasticities, in particular, estimating the income elasticity of demand and test whether this estimate is statistically below unity.

If the hypothesis is not rejected, then energy demand grows slower than GDP, which may be expected in developed countries; if the hypothesis is rejected, then energy demand grows faster than GDP, which could be expected in developing countries. This is the hypothesis that will be tested in the thesis.

One common procedure in evaluating the elasticities is to start with a graphical representation of the relationship between the growth in energy consumption per capita and the growth in GDP per capita. The graphical reference point is the 45° degree line, which corresponds to an income elasticity of unity. Thus, the reader is given some idea of whether the income elasticity in any nation is above or below unity. However, this visual inference is quite imprecise, given that there is no measure that tells us how close to the 45° degree line is close enough to be unity. This is why we gave a better graphical representation by using demand/GDP ratio and evaluating its slope, rather than make judgments on how close the curves are to 45 degree line.

Despite this shortcoming, Hannesson (2002) uses this procedure to come to some interesting, if uncertain results. His paper supports the stylized fact that energy consumption grows more rapidly than GDP in developing countries. It appears to be the case for India, Brazil, Mexico, Iran and Philippines, but not for other poor countries over some sub periods like for Turkey, Thailand, Egypt, Indonesia and Nigeria. Indeed, one of Hannesson's conclusions is that countries seem to exhibit different behaviours over different time intervals. He states that the relationship between energy consumption and

GDP was weakened after the oil price shocks of the 1970s, but has become stronger after 1986, especially in richer countries. However, Hannesson does not offer statistical evidence to support that claim.

Gately and Huntington (2002) also use this graphical approach in the introductory part of their paper. They report that the Organization for Economic Cooperation and Development (OECD) countries fall on 45 degree line with the exception of Ireland, Norway, Japan, Great Britain, Denmark and the U.S. These countries would appear to be lower energy growth countries. The results are consistent with Hannesson's results in that different countries have different characteristics. This appears especially true for non-OECD countries. In addition, oil demand tends to grow at the same rate as GDP in countries that start on a low base – Portugal, Greece, Mexico, Turkey and Spain.

Cooper (2003) in his paper portrays an analysis of the economic growth – energy growth question in a similar manner as above papers, but he presents no actual graphs. What he does is compare the average growth rate of GDP and the average growth rate of oil consumption for 23 countries for 1979-2000 period. He claims that the data is consistent with the hypothesis that economies are becoming more energy efficient over time, and oil demand is highly insensitive to price changes. Still, there is a great variation across the countries.

Few researchers came up with direct estimates of income elasticity. For example, in an exhaustive survey of relevant quantitative studies Dahl (1991) concluded that the demand for energy was price inelastic and slightly income elastic but found no evidence that the developing world's energy demand is less price elastic or more income elastic than for the developed world. Later, Dahl (1993) reports estimates of income elasticities for developing countries, which vary quite significantly from a low 0.3 to a high of 1.4, depending on the specification used. Pesaran et. al. (1998) show that the estimates for developing countries vary between 0.8 and 1.9, with an average income elasticity of 0.93.

Going back to Gately and Huntington (2002), they report results for OECD countries, which also vary depending on the employed specification. They have used three specifications for demand equation: omitting the price, omitting the dynamic adjustment and a specification where the price was decomposed into parts. For example, in a demand equation with no price, the short-run income elasticity for energy is 0.08 and for oil is 0.03; the corresponding long-run income elasticities are 0.57 and 0.31. The long-run elasticities for energy do not change substantially with asymmetric specifications, while for oil they increase to 0.56. So, despite a voluminous literature, there appears, however, to be lack of general agreement on representative values for these elasticities and in particular, whether the magnitude of these elasticities differs between countries with disparate incomes.

After a very extensive literature review, there are several conclusions that can be drawn from these papers. First, it appears that this literature was not so much of an exercise in understanding the relationship between energy consumptions and GDP as it was an exercise in applied econometrics. From this perspective, it is probably safe enough to say that the models should be more dynamic. And secondly, aggregation is a problem. Aggregation across countries causes differences in the results while aggregation to annual data in a time series framework involves a significant loss of information.

This thesis will try to address the above issues through employing a more dynamic model, where the lag structure of variables is constructed and taken into account. Secondly, each country is evaluated and discussed, hence getting rid of the aggregation problem across the countries. Since monthly or quarterly data is not available for developing countries for a long period of time, we have to use annual data. Future research in this area could employ higher frequency data, once that becomes available.

CHAPTER 3

DATA AND METHODOLOGY

This chapter describes the data series and econometric methodology used. First, section 3.1 covers the description of data and its sources and also what data manipulation was performed. Next, section 3.2 provides descriptive statistics of data series and presents the autocorrelation functions and partial autocorrelations. The next sections of this chapter deal with the methodology for empirical analysis. Section 3.3 explains the theoretical model behind our analysis; Sections 3.4 through 3.6 describe the econometric methodology.

3.1 Data Description

This section deals with data description and handling. The data is not available from a single source, so it was extrapolated from various international agencies and governments. Since the data is only available on an annual basis for developing countries, such as China and India, annual data was used for the sample of countries. Future work on this topic could involve analysis of quarterly or monthly data that, as stated before, performs better statistically.

As mentioned before, this exercise employs data for eight countries in total: Canada, the U.S., France, the UK, Brazil, Mexico, China and India. The data is annual time-series,

covering the period of 1960 to 2004. The variables used are natural logarithms of the real GDP per capita, oil consumption per capita and real oil price.

GDP per capita, measured in real (2000) U.S. dollars, from 1960 to 2004 was taken from *Penn World Table Version 6.2*. Oil consumption, measured in million barrels of crude oil per day, was sourced from the U.S. Energy Information Agency's (EIA) publication "Annual Energy Review, 2006" from 1960 to 2004. It was transformed into oil demand per capita, measured in thousand barrels of oil by dividing by population and by a factor of one thousand to generate thousands barrels of oil per capita and multiplying by number of days in a year. Population data for the period of 1960 to 2004 came from *Penn World Table Version 6.2*.

The annual oil price from 1960 to 2004 was sourced from BP's *Statistical Review of World Energy*. BP reports the West Texas Intermediate (WTI) spot price measured in US\$ per barrel from 1976 until 2004, prior to that it is Arabian Light posted at Ras Tanura from 1960 to 1975. Then annual WTI was deflated using U.S. GDP deflator sourced from Bureau of Economic Analysis at the U.S. Department of Commerce. The reason that I did not obtain other crude prices that are more local for some countries is because the oil market is the most globally interconnected of the fossil fuel markets; and therefore oil prices share a common cost structure and differ between one another by transportation cost.

3.2 Summary Statistics and Correlation

This section presents summary statistics and autocorrelation functions for all series.

3.2.1 Summary Statistics

The Table 3.1 shows the summary statistics for all variables used in this thesis. The statistics are calculated using the level form of time series data. The first three letters (in the case of the U.S. and the UK, it is the first two letters) identify the country and the rest are used as follows:

GDP – real gross domestic product per capita, measured in 2000 U.S. dollars;

D –oil demand per capita;

WTI –real oil price, measured in 2000 U.S. dollars.

The mean statistics of GDP and demand variables in Table 3.1 for developed countries such as Canada, the U.S., France and UK have a higher mean GDP per capita and oil demand per capita than the GDP and demand per capita for developing countries such as Brazil, Mexico, China and India. This is understandable, since developed countries have a higher standard of living and hence GDP/capita and oil demand per capita are higher. The mean of real oil price falls in line with real rather than nominal historical data of oil prices.

The standard deviation is a measure of dispersion or spread in the series. So, the smaller the standard deviation, the more efficient an estimation of that variable will be. However, skewness and kurtosis would perhaps be better measures. These statistics give a better overview of series distributions.

Skewness measures the asymmetry of the distribution of the series around its mean. The skewness of a symmetric distribution, such as normal distribution, is zero. Positive skewness means that the distribution has a long right tail and negative skewness implies that the distribution has a long left tail. The size the skewness, in absolute terms, determines how wide the tails of the distribution are. In Table 3.1, for example, the skewness for oil demand in Canada (0.01) and the U.S. (0.03) is close to zero, indicating normally distributed series. The distribution of the variables for Canada, the U.S., China and India and the distribution for the oil price all have a right tail, even though distribution for oil demand in Canada and the U.S. has narrowest tail, since their skewness values are the smallest in the group. The variables for the remaining countries have distributions with a left tail; however, it is a small left tail, judging by the small skewness numbers.

Kurtosis is a measure of the flatness or peakedness of the distribution of the series. The kurtosis of the normally distributed series is 3. If the kurtosis exceeds 3, the distribution is peaked relative to normal; if the kurtosis is less than 3, the distribution is flat relative to normal. In Table 3.1, the kurtosis for oil demand series in the U.S. equals 3.04, which

suggests that the series has normal distribution. However, the rest of the series have a kurtosis either above or below 3. Given the summary statistics, we can rule out normal distribution for the series.

Table 3.1 Summary Statistics

	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Observations
CAN_D	23.73	29.69	17.14	3.10	0.01	2.56	45
CAN_GDP	18,888.13	28,397.69	10,567.33	4,989.82	0.12	2.14	45
US_D	24.69	30.42	19.24	2.68	0.03	3.04	45
US_GDP	23,401.39	36,098.15	12,892.02	6,715.73	0.25	1.98	45
FRA_D	12.19	18.28	4.48	3.13	-0.50	3.34	45
FRA_GDP	17,681.68	26,168.42	8,530.82	5,082.91	-0.12	1.99	45
UK_D	11.36	15.47	6.66	1.79	-0.12	3.88	45
UK_GDP	17,060.53	26,762.36	10,323.29	4,764.16	0.43	2.08	45
MEX_D	5.72	7.78	2.78	1.87	-0.49	1.54	45
MEX_GDP	6,303.25	8,165.22	3,705.31	1,311.79	-0.58	2.19	45
BRA_D	3.04	4.54	1.38	0.99	-0.26	1.95	45
BRA_GDP	5,712.89	7,469.45	2,643.53	1,566.58	-0.77	2.01	45
CHN_D	0.68	1.82	0.08	0.45	0.55	2.72	45
CHN_GDP	1,569.68	5,332.53	365.09	1,423.43	1.24	3.32	45
IND_D	0.42	0.83	0.13	0.21	0.48	2.13	45
IND_GDP	1,623.87	3,140.28	891.52	618.83	0.86	2.71	45
RWTI	24.39	70.22	6.54	15.53	0.93	3.57	45

3.2.2 Autocorrelation Functions and Partial Autocorrelations

This section presents autocorrelation functions (ACF) for all variables used in this thesis. These functions characterize the pattern of temporal dependence in the series and are typically used for time-series data. The autocorrelation of a series Y at lag k is estimated by Equation (1):

$$\tau_k = \frac{\sum_{t=k+1}^T (Y_t - \bar{Y})(Y_{t-k} - \bar{Y})}{\sum_{t=1}^T (Y_t - \bar{Y})^2} \quad (1)$$

where \bar{Y} is the sample mean of Y . This is the correlation coefficient for values of the series k periods apart. A correlation coefficient describes the degree of dependence of series Y on its own lagged values. If τ_1 is nonzero, it means that the series is first order serially correlated. If τ_k dies off more or less geometrically with increasing lag k , it is a sign that the series obeys a low-order autoregressive (AR) process. If τ_k drops to zero after a small number of lags, it is a sign that the series obeys a low-order moving-average (MA) process.

The partial autocorrelation (PAC) at lag k is the regression coefficient on Y_{t-k} when Y_t is regressed on a constant, $Y_{t-1}, Y_{t-2}, \dots, Y_{t-k}$. This is partial correlation since it measures the correlation of Y values that are k periods apart after removing the correlation from the

intervening lags. If the pattern of autocorrelation is one that can be captured by an autoregression of order less than k , then the partial autocorrelation at lag k will be close to zero. The PAC of a pure autoregressive process of order p , $AR(p)$, cuts off at lag p , while the PAC of a pure moving average (MA) process asymptotically approaches zero.

The autocorrelation functions and partial autocorrelations, together with Ljung-Box Q-statistics and their p-values are presented in Tables 3.2 through 3.10. The Q-statistic at lag k is a test statistic for the null hypothesis that there is no autocorrelation up to order k . Q is asymptotically distributed as a chi-squared distribution (χ^2) with degrees of freedom equal to the number of autocorrelations. The asterisks in the tables indicate the autocorrelation and partial autocorrelation functions.

One certain similarity is visible among the ACFs for developed countries shown in Tables 3.2 to 3.5. The ACFs for oil demand seem to die off at lag 6, indicating that oil demand is correlated with past values up to lag 6. The ACFs for GDP series die off at lag 15, which means that GDP is correlated with its past values up to lag 15. Both ACFs and PACs suggest that the series of oil demand and GDP for developed countries follow an autoregressive process.

For Brazil and Mexico, which are presented in Tables 3.6 and 3.7, ACFs for both GDP and oil demand die off at lag 12, which implies that in less developed countries both series are correlated with past values for a longer period of time. Both ACFs and PACs

suggest that the series of oil demand and GDP for these countries follow an autoregressive process.

The ACFs shown in Tables 3.8 and 3.9 for China and India are not similar. For China, oil demand is correlated with its past values up to lag 12 and GDP – up to lag 14. For India, the ACFs for oil demand and GDP die off at lag 15, which indicates that both demand and GDP are correlated with past values up to lag 15. Both ACFs and PACs suggest that the series of oil demand and GDP for China and India follow an autoregressive process.

Table 3.10 shows the ACF and PAC for the oil price. In this case, oil price seem to be correlated with its past values up to lag 8. Both ACFs and PACs suggest that the series of oil price follows an autoregressive process.

Table 3.2 Autocorrelations and Partial Autocorrelations for Canada

CAN_D						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.883	0.883	37.449	0
. *****	** .	2	0.726	-0.242	63.349	0
. ****	. * .	3	0.56	-0.105	79.143	0
. ***	. * .	4	0.398	-0.084	87.303	0
. **	. * .	5	0.243	-0.084	90.429	0
. *	. * .	6	0.103	-0.062	91.009	0
. .	. .	7	-0.017	-0.051	91.025	0
. * .	. * .	8	-0.14	-0.169	92.151	0
** .	. * .	9	-0.252	-0.083	95.889	0
*** .	. * .	10	-0.352	-0.11	103.39	0
*** .	. * .	11	-0.429	-0.058	114.82	0
*** .	. * .	12	-0.495	-0.145	130.55	0
*** .	. .	13	-0.524	0.011	148.69	0
*** .	. .	14	-0.517	-0.021	166.89	0
*** .	. * .	15	-0.491	-0.068	183.87	0
*** .	. * .	16	-0.462	-0.124	199.46	0
*** .	. .	17	-0.414	-0.003	212.4	0
*** .	. .	18	-0.335	0.038	221.2	0
** .	. * .	19	-0.225	0.099	225.33	0
. * .	. .	20	-0.095	0.065	226.09	0
CAN_GDP						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.92	0.92	40.687	0
. *****	. * .	2	0.834	-0.079	74.925	0
. *****	. .	3	0.752	-0.024	103.39	0
. *****	. .	4	0.672	-0.028	126.72	0
. *****	. .	5	0.597	-0.023	145.56	0
. ****	. .	6	0.53	0.005	160.77	0
. ****	. .	7	0.472	0.014	173.14	0
. ***	. .	8	0.412	-0.049	182.87	0
. ***	. .	9	0.359	-0.004	190.43	0
. **	. .	10	0.307	-0.028	196.11	0
. **	. .	11	0.252	-0.055	200.07	0
. **	. .	12	0.205	0.013	202.77	0
. *	. .	13	0.162	-0.02	204.49	0
. *	. .	14	0.123	-0.01	205.52	0
. *	. * .	15	0.077	-0.079	205.94	0
. .	. * .	16	0.026	-0.074	205.99	0
. .	. .	17	-0.02	-0.014	206.02	0
. * .	. .	18	-0.06	-0.002	206.3	0
. * .	. .	19	-0.093	-0.005	207	0
. * .	. .	20	-0.123	-0.022	208.28	0

Table 3.3 Autocorrelations and Partial Autocorrelations for the U.S.

US_D						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.896	0.896	38.619	0
. *****	** .	2	0.742	-0.313	65.697	0
. ****	. .	3	0.584	-0.051	82.856	0
. ***	. .	4	0.43	-0.083	92.377	0
. **	. .	5	0.275	-0.12	96.38	0
. *	. .	6	0.126	-0.09	97.237	0
. .	. .	7	-0.012	-0.079	97.245	0
. .	. .	8	-0.141	-0.114	98.379	0
** .	. .	9	-0.247	-0.035	101.98	0
*** .	. .	10	-0.327	-0.039	108.45	0
*** .	. .	11	-0.4	-0.151	118.38	0
*** .	. .	12	-0.459	-0.074	131.9	0
*** .	. .	13	-0.471	0.102	146.56	0
*** .	. .	14	-0.435	0.057	159.5	0
*** .	. .	15	-0.401	-0.165	170.83	0
*** .	. .	16	-0.373	-0.087	180.99	0
** .	. .	17	-0.316	0.117	188.54	0
** .	. .	18	-0.225	0.094	192.52	0
. .	. .	19	-0.116	0.049	193.61	0
. .	. .	20	-0.009	-0.024	193.62	0
US_GDP						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.924	0.924	41.073	0
. *****	. .	2	0.846	-0.056	76.306	0
. *****	. .	3	0.773	-0.013	106.36	0
. *****	. .	4	0.699	-0.04	131.57	0
. *****	. .	5	0.627	-0.036	152.33	0
. ****	. .	6	0.56	-0.006	169.32	0
. ****	. .	7	0.499	0	183.19	0
. ****	. .	8	0.439	-0.039	194.21	0
. ***	. .	9	0.385	0	202.9	0
. ***	. .	10	0.334	-0.018	209.63	0
. **	. .	11	0.278	-0.067	214.45	0
. **	. .	12	0.226	-0.021	217.72	0
. *	. .	13	0.178	-0.013	219.81	0
. *	. .	14	0.136	0.001	221.06	0
. *	. .	15	0.086	-0.091	221.58	0
. .	. .	16	0.03	-0.082	221.64	0
. .	. .	17	-0.019	-0.012	221.67	0
. .	. .	18	-0.062	-0.002	221.97	0
. .	. .	19	-0.098	0.003	222.75	0
. .	. .	20	-0.131	-0.033	224.21	0

Table 3.4 Autocorrelations and Partial Autocorrelations for France

FRA_D						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.863	0.863	35.826	0
. *****	. * .	2	0.715	-0.119	60.976	0
. ****	. * .	3	0.568	-0.078	77.25	0
. ***	. * .	4	0.428	-0.069	86.701	0
. **	. * .	5	0.297	-0.064	91.352	0
. *	. * .	6	0.17	-0.086	92.914	0
. .	. * .	7	0.04	-0.122	93.002	0
. * .	. * .	8	-0.08	-0.081	93.366	0
** .	. * .	9	-0.191	-0.098	95.508	0
** .	. .	10	-0.281	-0.054	100.27	0
*** .	. .	11	-0.335	0.007	107.24	0
*** .	. .	12	-0.363	-0.014	115.67	0
*** .	. .	13	-0.362	0.015	124.34	0
*** .	. .	14	-0.327	0.064	131.65	0
** .	. * .	15	-0.296	-0.063	137.82	0
** .	. * .	16	-0.278	-0.104	143.46	0
** .	. .	17	-0.236	0.047	147.66	0
** .	. * .	18	-0.198	-0.06	150.73	0
. * .	. .	19	-0.141	0.043	152.35	0
. * .	. .	20	-0.073	0.037	152.8	0
FRA_GDP						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.92	0.92	40.644	0
. *****	. .	2	0.84	-0.037	75.332	0
. *****	. .	3	0.762	-0.032	104.56	0
. *****	. .	4	0.684	-0.046	128.66	0
. *****	. .	5	0.61	-0.018	148.32	0
. *****	. .	6	0.539	-0.025	164.09	0
. *****	. .	7	0.473	-0.018	176.53	0
. ***	. .	8	0.41	-0.019	186.16	0
. ***	. .	9	0.351	-0.027	193.38	0
. **	. .	10	0.296	-0.009	198.68	0
. **	. .	11	0.245	-0.018	202.43	0
. **	. .	12	0.198	-0.017	204.95	0
. *	. .	13	0.15	-0.046	206.44	0
. *	. .	14	0.107	-0.008	207.23	0
. .	. .	15	0.065	-0.038	207.52	0
. .	. * .	16	0.018	-0.068	207.54	0
. .	. .	17	-0.023	-0.006	207.58	0
. * .	. .	18	-0.06	-0.014	207.86	0
. * .	. .	19	-0.094	-0.026	208.58	0
. * .	. .	20	-0.124	-0.017	209.88	0

Table 3.5 Autocorrelations and Partial Autocorrelations for the UK

UK_D						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.819	0.819	32.211	0
. *****	. *	2	0.644	-0.08	52.593	0
. ***	. *	3	0.454	-0.151	62.983	0
. **	. .	4	0.309	0.007	67.918	0
. *	. *	5	0.171	-0.087	69.466	0
. .	. *	6	0.023	-0.164	69.494	0
. *	. *	7	-0.131	-0.154	70.452	0
**	. *	8	-0.282	-0.159	74.996	0
***	. *	9	-0.386	-0.058	83.75	0
***	. .	10	-0.432	0.004	95.007	0
***	. .	11	-0.445	-0.049	107.32	0
***	. .	12	-0.436	-0.046	119.51	0
***	. *	13	-0.382	0.067	129.16	0
**	. *	14	-0.281	0.101	134.56	0
**	. .	15	-0.189	-0.054	137.08	0
. *	**	16	-0.151	-0.21	138.75	0
. *	. .	17	-0.115	-0.054	139.75	0
. .	. .	18	-0.057	0.046	140	0
. .	. .	19	0.02	0.017	140.03	0
. *	. .	20	0.109	0.049	141.03	0
UK_GDP						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.928	0.928	41.412	0
. *****	. .	2	0.855	-0.047	77.374	0
. *****	. .	3	0.781	-0.049	108.06	0
. *****	. .	4	0.707	-0.033	133.86	0
. *****	. .	5	0.639	-0.009	155.44	0
. *****	. .	6	0.573	-0.025	173.22	0
. *****	. .	7	0.507	-0.041	187.51	0
. ***	. .	8	0.445	-0.017	198.81	0
. ***	. .	9	0.388	-0.004	207.63	0
. ***	. .	10	0.331	-0.037	214.27	0
. **	. .	11	0.276	-0.036	219.02	0
. **	. .	12	0.225	-0.01	222.27	0
. *	. .	13	0.177	-0.021	224.35	0
. *	. .	14	0.136	0.007	225.62	0
. *	. *	15	0.087	-0.099	226.15	0
. .	. *	16	0.031	-0.089	226.22	0
. .	. .	17	-0.021	-0.023	226.26	0
. *	. .	18	-0.067	-0.009	226.61	0
. *	. .	19	-0.106	0.004	227.53	0
. *	. .	20	-0.138	-0.004	229.15	0

Table 3.6 Autocorrelations and Partial Autocorrelations for Brazil

BRA_D						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.932	0.932	41.756	0
. *****	. * .	2	0.855	-0.104	77.709	0
. *****	. * .	3	0.771	-0.09	107.65	0
. *****	. .	4	0.689	-0.029	132.12	0
. *****	. * .	5	0.599	-0.104	151.1	0
. ****	. * .	6	0.495	-0.17	164.38	0
. ***	. .	7	0.398	0.009	173.2	0
. **	. * .	8	0.299	-0.094	178.31	0
. **	. * .	9	0.221	0.094	181.18	0
. *	. .	10	0.15	-0.012	182.54	0
. *	. .	11	0.089	0.003	183.04	0
. .	. .	12	0.036	-0.01	183.12	0
. .	. .	13	-0.005	0.03	183.12	0
. .	. .	14	-0.027	0.042	183.17	0
. .	. .	15	-0.041	0.017	183.29	0
. .	. .	16	-0.043	0.023	183.42	0
. .	. .	17	-0.042	-0.004	183.55	0
. .	. .	18	-0.042	-0.057	183.69	0
. .	. .	19	-0.04	-0.019	183.82	0
. .	. .	20	-0.028	0.06	183.89	0
BRA_GDP						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.923	0.923	40.933	0
. *****	. .	2	0.854	0.017	76.814	0
. *****	. .	3	0.782	-0.054	107.64	0
. *****	. * .	4	0.707	-0.065	133.45	0
. *****	. * .	5	0.628	-0.078	154.28	0
. ****	. .	6	0.55	-0.037	170.69	0
. ****	. * .	7	0.469	-0.072	182.93	0
. ***	. * .	8	0.383	-0.092	191.3	0
. **	. .	9	0.304	-0.012	196.74	0
. **	. .	10	0.227	-0.045	199.86	0
. *	. .	11	0.156	-0.017	201.37	0
. *	. .	12	0.093	0	201.93	0
. .	. .	13	0.04	0.008	202.04	0
. .	. .	14	-0.001	0.034	202.04	0
. .	. .	15	-0.04	-0.027	202.16	0
. * .	. * .	16	-0.081	-0.071	202.64	0
. * .	. .	17	-0.11	0.021	203.55	0
. * .	. * .	18	-0.141	-0.059	205.11	0
. * .	. .	19	-0.17	-0.043	207.46	0
. ** .	. .	20	-0.189	0.011	210.49	0

Table 3.7 Autocorrelations and Partial Autocorrelations for Mexico

MEX_D						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.959	0.959	44.191	0
. *****	. *	2	0.904	-0.188	84.405	0
. *****	. *	3	0.843	-0.081	120.23	0
. *****	. *	4	0.776	-0.104	151.26	0
. *****	. .	5	0.705	-0.053	177.52	0
. *****	. *	6	0.63	-0.072	199.07	0
. *****	. *	7	0.552	-0.077	216.04	0
. *****	. .	8	0.475	-0.026	228.92	0
. ***	. *	9	0.395	-0.08	238.09	0
. **	. *	10	0.314	-0.063	244.05	0
. **	. .	11	0.234	-0.049	247.45	0
. *	. .	12	0.154	-0.057	248.97	0
. *	. .	13	0.078	-0.021	249.38	0
. .	. .	14	0.009	0.005	249.38	0
. .	. .	15	-0.056	-0.04	249.61	0
. *	. .	16	-0.118	-0.042	250.62	0
. *	. .	17	-0.171	0.024	252.83	0
. **	. .	18	-0.22	-0.05	256.62	0
. **	. .	19	-0.261	0.015	262.17	0
. **	. .	20	-0.295	-0.002	269.51	0
MEX_GDP						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.914	0.914	40.155	0
. *****	. *	2	0.819	-0.102	73.108	0
. *****	. *	3	0.719	-0.076	99.124	0
. *****	. .	4	0.626	-0.015	119.31	0
. *****	. .	5	0.546	0.024	135.08	0
. *****	. .	6	0.474	-0.015	147.29	0
. *****	. .	7	0.404	-0.047	156.39	0
. *****	. .	8	0.338	-0.025	162.92	0
. **	. .	9	0.285	0.033	167.68	0
. **	. *	10	0.229	-0.059	170.86	0
. *	. *	11	0.167	-0.094	172.6	0
. *	. .	12	0.107	-0.025	173.33	0
. .	. .	13	0.052	-0.012	173.52	0
. .	. .	14	0.007	-0.001	173.52	0
. .	. .	15	-0.028	0.002	173.57	0
. .	. .	16	-0.055	0.001	173.79	0
. *	. .	17	-0.08	-0.024	174.27	0
. *	. *	18	-0.109	-0.066	175.2	0
. *	. .	19	-0.129	0.017	176.56	0
. *	. .	20	-0.145	0.002	178.34	0

Table 3.8 Autocorrelations and Partial Autocorrelations for China

CHN_D						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.928	0.928	41.387	0
. *****	. * .	2	0.852	-0.065	77.085	0
. *****	. * .	3	0.761	-0.147	106.26	0
. *****	. .	4	0.672	-0.033	129.58	0
. ****	. .	5	0.585	-0.036	147.66	0
. ****	. .	6	0.498	-0.054	161.08	0
. ***	. .	7	0.417	-0.012	170.75	0
. ***	. * .	8	0.328	-0.118	176.92	0
. **	. .	9	0.243	-0.046	180.39	0
. *	. .	10	0.174	0.061	182.22	0
. *	. .	11	0.119	0.043	183.11	0
. *	. .	12	0.077	0.012	183.49	0
. .	. .	13	0.042	-0.009	183.61	0
. .	. .	14	0.017	0.01	183.63	0
. .	. .	15	-0.005	-0.013	183.63	0
. .	. .	16	-0.024	-0.025	183.67	0
. .	. .	17	-0.039	-0.011	183.79	0
. .	. .	18	-0.051	-0.02	183.99	0
. * .	. .	19	-0.06	-0.01	184.28	0
. * .	. .	20	-0.069	-0.016	184.69	0

CHN_GDP						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.943	0.943	42.781	0
. *****	. * .	2	0.879	-0.1	80.781	0
. *****	. .	3	0.812	-0.048	114.02	0
. *****	. .	4	0.747	-0.024	142.82	0
. *****	. .	5	0.683	-0.029	167.47	0
. *****	. .	6	0.62	-0.025	188.33	0
. *****	. .	7	0.556	-0.053	205.54	0
. *****	. * .	8	0.489	-0.071	219.18	0
. ***	. .	9	0.42	-0.052	229.55	0
. ***	. .	10	0.353	-0.031	237.08	0
. **	. .	11	0.289	-0.022	242.3	0
. **	. .	12	0.231	-0.008	245.71	0
. *	. .	13	0.172	-0.054	247.67	0
. *	. .	14	0.116	-0.03	248.58	0
. .	. .	15	0.059	-0.05	248.83	0
. .	. .	16	0.006	-0.021	248.83	0
. .	. * .	17	-0.05	-0.084	249.02	0
. * .	. .	18	-0.105	-0.05	249.88	0
. * .	. .	19	-0.155	-0.022	251.83	0
. ** .	. .	20	-0.199	-0.008	255.2	0

Table 3.9 Autocorrelations and Partial Autocorrelations for India

IND_D						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.923	0.923	40.989	0
. *****	. .	2	0.847	-0.038	76.29	0
. *****	. .	3	0.769	-0.054	106.07	0
. *****	. .	4	0.697	-0.002	131.15	0
. *****	. .	5	0.623	-0.055	151.7	0
. ****	. .	6	0.555	-0.009	168.41	0
. ****	. .	7	0.495	0.016	182.07	0
. ***	. * .	8	0.422	-0.138	192.23	0
. ***	. .	9	0.358	0.023	199.77	0
. **	. .	10	0.299	-0.014	205.18	0
. **	. .	11	0.253	0.037	209.17	0
. **	. .	12	0.21	-0.013	211.99	0
. * .	. .	13	0.171	-0.018	213.92	0
. * .	. .	14	0.133	-0.03	215.12	0
. * .	. * .	15	0.087	-0.078	215.65	0
. .	. .	16	0.04	-0.056	215.76	0
. .	. .	17	-0.009	-0.052	215.77	0
. .	. .	18	-0.053	-0.023	215.99	0
. * .	. .	19	-0.091	0	216.66	0
. * .	. .	20	-0.125	-0.022	217.98	0
IND_GDP						
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.923	0.923	40.931	0
. *****	. .	2	0.847	-0.028	76.246	0
. *****	. .	3	0.774	-0.026	106.42	0
. *****	. .	4	0.708	0.005	132.25	0
. *****	. .	5	0.644	-0.021	154.17	0
. ****	. * .	6	0.574	-0.08	172.02	0
. ****	. .	7	0.507	-0.02	186.31	0
. ***	. .	8	0.446	0	197.7	0
. ***	. .	9	0.388	-0.029	206.56	0
. ***	. .	10	0.337	0.006	213.43	0
. **	. .	11	0.291	-0.002	218.68	0
. **	. .	12	0.246	-0.025	222.54	0
. * .	. * .	13	0.197	-0.064	225.1	0
. * .	. .	14	0.146	-0.049	226.55	0
. * .	. * .	15	0.085	-0.115	227.06	0
. .	. .	16	0.028	-0.032	227.12	0
. .	. .	17	-0.026	-0.036	227.17	0
. * .	. .	18	-0.075	-0.021	227.61	0
. * .	. .	19	-0.119	-0.011	228.76	0
. * .	. * .	20	-0.165	-0.06	231.06	0

Table 3.10 Autocorrelations and Partial Autocorrelations for WTI

		WTI				
Autocorrelation	Partial Correlation	Lags	AC	PAC	Q-Stat	Prob
. *****	. *****	1	0.902	0.902	39.074	0
. *****	. * .	2	0.8	-0.067	70.584	0
. *****	. .	3	0.712	0.011	96.083	0
. *****	. * . .	4	0.606	-0.143	115.04	0
. ****	. * .	5	0.499	-0.07	128.2	0
. ***	. * .	6	0.377	-0.163	135.9	0
. **	. * .	7	0.258	-0.065	139.6	0
. *	. * .	8	0.139	-0.109	140.7	0
. .	. * .	9	0.021	-0.083	140.73	0
. * .	. .	10	-0.078	-0.011	141.1	0
. * .	. * .	11	-0.181	-0.125	143.14	0
** .	. .	12	-0.272	-0.042	147.9	0
*** .	. * .	13	-0.327	0.071	154.94	0
*** .	. .	14	-0.371	-0.031	164.33	0
*** .	. ** .	15	-0.347	0.314	172.83	0
*** .	. * .	16	-0.327	-0.085	180.64	0
*** .	. * .	17	-0.32	-0.065	188.4	0
** .	. * .	18	-0.308	-0.122	195.84	0
** .	. * .	19	-0.268	0.109	201.7	0
** .	. .	20	-0.218	-0.045	205.74	0

3.3 Theoretical Model

The demand equation for oil has always been one of the topics of interest among academics, governments, industry and the Organization of Petroleum Exporting Countries (OPEC) since oil consumption takes up the largest share of total world energy consumption and oil is the largest of the world commodity fossil fuel markets. The model used in this analysis is dictated by the typical formulation suggested by economic theory for aggregate demand functions. This theory suggests that the energy demand is influenced by and affects many factors in an economy such as policy options, national GDP, prices, energy imports/exports and consumer spending.

As mentioned before, we employ vector error correction methodology (VECM) to estimate the oil demand equation. Economists claim that if a co-integrating vector is found among the variables, VECM should be employed, because it provides additional information on the behaviour of variables. The idea is that variables are hypothesized to be linked by some theoretical equilibrium relationship in the long run but may be out of equilibrium in the short run. The advantage of the error-correction mechanism is that the extent of adjustment in a given period to deviations from long-run equilibrium is given by the estimated equation, thus tying the short-run to the long-run properties.

The co-integration technique originated by Engle and Granger (1987) made an important contribution towards modelling stationary relationships while preserving the long-run

relationship, which is often lost by differencing. Two or more variables are said to be co-integrated (i.e., they exhibit long-run equilibrium relationship(s)) if they share common trend(s). According to this technique, as long as two variables are co-integrated, Granger-type causality must exist in at least one direction either unidirectional or bidirectional. A unidirectional causality is described as one variable Y Granger-causes the other variable X, but X does not Granger cause Y. The bidirectional causality is a causality that runs in both directions from Y to X and from X to Y. Evidence of co-integration among variables also rules out the possibility of the estimated relationship being spurious (i.e. nonsense regression).

The Johansen and Juselius (1991) (JJ) procedure is used to investigate the co-integrating relationship between integrated variables. It is believed that JJ procedure has several advantages over the residual-based Engle and Granger two-step method. The main difference between JJ procedure Engle and Granger one is that long-run co-integrating vector in the VECM and the short-run coefficients are estimated in one step. But in Engle and Granger two-step method the co-integrating vector is first estimated and then combined with the rest of the terms in the second stage. In particular, i) the JJ procedure does not, a priori, assume the existence of at most one co-integrating vector, rather it tests for a number of co-integrating relationships; ii) the JJ procedure assumes all variables are endogenous, unlike the Engle-Granger method which is sensitive to the choice of the dependent variable; iii) the JJ procedure avoids arbitrarily choosing a dependent variable when extracting residuals from the co-integrating vector and it is also insensitive to the

variable being normalized; iv) the JJ procedure provides appropriate statistics to test the number of co-integrating vectors and restrictions upon coefficients of the vectors; and finally v) JJ procedure is set up on a unified framework for estimating and testing co-integrating relationships within the VECM.

The JJ procedure involves the identification of rank of the m by m matrix Π in the equation given by:

$$\Delta X_t = \delta + \sum_{i=1} \Gamma_i \Delta X_{t-i} + \Pi X_{t-k} + \varepsilon_t \quad (2)$$

where X_t is a common vector of the m variables, Γ and Π are coefficient matrices, Δ is a difference operator, k denotes the lag length, and δ is a constant. If Π has zero rank ($r = 0$), no stationary long-run linear combination can be identified, in other words, the variables in X_t are not co-integrated. If the rank r of Π is greater than zero, there will exist r possible stationary linear combinations. If more than one linear combination occurs, we can normalize and combine them to investigate pair-wise effects between the variables. This co-integrating relationship, also called a co-integrating vector, represents the foundation of a complete dynamic error correction model. For this paper, the VECM and JJ co-integrating procedure allow for testing of the income growth hypothesis for developing versus developed countries and uncover short-run dynamics of oil demand among countries. If the variables are found to be co-integrated, there always exists a corresponding error-correction representation which implies that changes in the dependent variable are a function of the level of disequilibrium in the co-integrating relationship (captured by the

error correction term and estimated by the JJ procedure) as well as changes in other explanatory variable(s).

The demand equation within the VECM framework in this analysis takes the form given in Eq. (3) below. With $B=[c, \alpha, \beta]$ and $X=[1, P_t, GDP_t]$ the demand equation is:

$$\Delta D_t = \sum_{j=1} \phi_j \Delta D_{t-j} + \sum_{j=0} \eta_j \Delta P_{t-j} + \sum_{j=0} \lambda_j \Delta GDP_{t-j} + \sum_{i=1} \xi_j (D_{t-1} - B'X_{t-1}) + \varepsilon_t \quad (3)$$

where the coefficients η_j and λ_j represent short run price and income elasticities, respectively and ξ_j is the error-correction term. When the variables are found to be co-integrated, then in the short term, deviations from this long-term equilibrium will feed back on the changes in the dependent variable in order to force the movement towards the long-term equilibrium. If the dependent variable is driven directly by this long-term equilibrium error, then it is responding to this feedback. If not, it is responding only to short-term shocks to the stochastic environment. The significance tests of the 'differenced' explanatory variables give us an indication of the 'short-term' effects, whereas the 'long-term' causal relationship is implied through the significance of the lagged error-correction term(s) (i.e., the fourth term in the Eq. (3), which contains the long-term information since it is derived from the long-term co-integrating relationship(s). The coefficient of the lagged error-correction term ξ_i , however, is a short-term adjustment coefficient and represents the proportion by which the long-term disequilibrium (or imbalance) in the dependent variable is being corrected in each period.

Non-significance or elimination of any of the lagged error-correction terms implies that any equilibrium long-term relationship is pointless since the model never reaches it. The non-significance of any of the 'differenced' variables which reflects only a short-term relationship, however, does not involve such violations because theory typically has nothing to say about short-term relationships. The estimated VECMs for the demand equation are presented in Chapter 4.

3.4 Unit root tests

Estimation of the demand equation above implicitly assumes that the observed time series data are “non-stationary” (because they grow overtime and so do not have a fixed “stationary” mean). In fact, if we look at the graphs of most economic time series, such as GDP, income or energy consumption over time, we would find that most economic variables are non-stationary (integrated) in their level form.

Should one distinguish between stationary and non-stationary series? Generally speaking, if non-stationarity is not corrected for, then using those variables to build any meaningful economic relationship could yield ‘nonsense regression’. Yule (1926) first wrote about nonsense correlations. The ‘nonsense regression’ problem, also often sited as spurious regression, means that the variables exhibit high correlations among each other with no

real causal explanation, although the coefficient estimates might appear to be of theoretically correct sign and magnitude.

Other fundamental differences to look out for between stationary and non-stationary series are: stationary series has a mean, and there is a tendency for the series to return back to its mean if the series is shocked, whereas a non-stationary series is trending (i.e. the mean changes over time). Stationary series tends to exhibit smooth behaviour, non-stationary series are erratic. A stationary series has a finite variance, shocks are transitory and its autocorrelations fade out as the time difference grows; whereas a non-stationary series has an infinite variance, shocks are permanent, and its autocorrelations are close to or equal to one.

Due to these problems, it has become customary to investigate the existence of non-stationarity at first before proceeding to conduct formal inference. A test of stationarity that is commonly known as the unit root test is performed on our variables. Suppose the following auto regressive process of time series Y_t :

$$Y_t = \rho Y_{t-1} + \varepsilon_t \quad (4)$$

where ε_t is assumed to be white noise. Using the lag operator L , we have the following identity: $Y_{t-1} = LY_t$. Then, the equation (4) can be rewritten as:

$$Y_t = \rho LY_t + \varepsilon_t \quad (5)$$

After subtracting the term ρLY_t from both sides of the equation, taking out the common factor Y_t and dividing by $(1 - \rho L)$ we get:

$$Y_t = \varepsilon_t / 1 - \rho L \quad (6)$$

Interpreted as a polynomial in L , equation (6) has a factor of $1 - \rho L$, which has a root of $1/\rho$. So, when $\rho=1$, the equation (6) is called a unit root process. Hence, the unit root test investigates whether the value of ρ is equal to unity or not.

A wide variety of unit root tests have been developed in the last two decades, but the common trend in all of them is that they all have low power. Also, the presence of a unit root may signify the presence of a structural break; i.e., Dickey-Fuller tests can have low power to reject the null of a unit root in the presence of a structural break (Perron 1989). Taking account of these breaks often reverses the conclusion of a unit root test. Nevertheless, the data was tested for unit roots, using the augmented Dickey-Fuller (ADF). Phillips-Perron tests were also employed to illustrate the unit root tests with the presence of breaks.

The ADF test is the most popular unit root test among the class of unit root tests. In the ADF test, the following regression is estimated by Ordinary Least Squares (OLS):

$$\Delta Y_t = \alpha_0 + \alpha_1 t + \rho Y_{t-1} + \sum_{j=1}^p \beta_j \Delta Y_{t-j} + \varepsilon_t \quad (7)$$

The null hypothesis states that ρ equals to one, meaning that series has a unit root and the series is non-stationary. This is tested against the alternative hypothesis of stationarity. This test requires addition of lagged differences of the series until the residuals, ε_t , are white noise (i.e., random). Although the appropriate number of lagged differences, p is not known a priori, there are a number of methods that could be used for lag selection.

These include the Akaike information criterion (AIC), the Bayesian information criterion (BIC), the Schwartz information criterion (SIC), the Ljung-Box statistic, the Lagrange Multiplier (LM) test, and the general to simple selection methods. In general, the BIC, SIC, Ljung-Box and LM tests pick the same number of optimal lags for the ADF test (plus or minus one). The AIC and the general to simple selection methods will usually pick the same lag length, which is always at least as large as the lag length of BIC, Ljung-Box, and LM tests results. In the end, it is up to researcher to decide on lag length that is appropriate for the series (Gordon 1995). The SIC criteria was used to for lag selection in the unit root tests.

The majority of unit root tests have non-stationarity built in as a null hypothesis. Because the traditional classical testing methodology accepts the null unless there is strong evidence against it, unit root tests usually conclude that there is a unit root. This problem is even further intensified by the fact that unit root tests generally have low power. Perron (1989) introduced a different kind of unit root test that allows for break points in the series. Basically, Perron (1988) shows that if time series is trend stationary and if no account is made of this in implementing the testing procedure, this may lead to a high probability of making a Type II error. He claims that most macroeconomic time series are best construed as stationary fluctuations around a deterministic trend function if allowance is made for the possibility of a shift in the intercept of the trend function and a shift in slope of the function, where the date of possible change in the intercept or the

slope is not fixed a priori. The test statistics are constructed by adding dummy variables for different intercepts and slopes, extending the standard Dickey-Fuller procedure. The results are discussed in the next chapter.

3.5 Impulse Response Functions

For an explanation of the impulse response functions, consider a vector error-correction model (VECM). VECM is commonly used for analyzing the dynamic impact of random disturbances on the system of variables, which are said to be co-integrated. The VAR approach skips the need for structural modeling by treating every endogenous variable in the system as a function of the lagged values of all of the endogenous variables in the system. However, meaningful impulse response functions can be produced so long as the associated structural VAR is identified. Identification can be accomplished by using economic information in the form of recursive structures, coefficient restrictions, variance or covariance restrictions, symmetry restrictions, or restrictions on long-run multiplier values. Although VARs are usually estimated without restrictions, studies, such as Litterman (1986), have shown that imposing reasonable restrictions on VARs improves their performance. In this thesis the long-run constraints implied by the estimated co-integrating vectors are imposed by way of constraints in the simple VAR model.

Let's consider a simple two-variable, one-lag VECM system and for convenience omit the intercept term. With coefficient vectors, $A=[\alpha, \gamma]$ $B=[\theta, \omega]$ and co-integrating vectors $Z=[1, Y_t]$, $C=[1, X_t]$ VECM is:

$$\begin{aligned}\Delta X_t &= \beta_{11}\Delta X_{t-1} + \beta_{12}\Delta Y_{t-1} + \xi_{1t}(X_{t-1} - A'Z_{t-1}) + \varepsilon_{1t} \\ \Delta Y_t &= \beta_{21}\Delta X_{t-1} + \beta_{22}\Delta Y_{t-1} + \xi_{2t}(Y_{t-1} - B'C_{t-1}) + \varepsilon_{2t}\end{aligned}\quad (8)$$

where the errors in error vectors, ε_{1t} and ε_{2t} are assumed to be uncorrelated, β vectors represent coefficient vectors, ξ are error-correction coefficients for the long-run relationships between the two variables, expressed in the brackets. Now consider the effects of shock, or change in ε_{1t} . A change in ε_{1t} will immediately affect X_t variable in the first equation in the VECM system. Another change will occur on Y_t through the Z co-integrating vector. There will be further changes in all variables over time as the initial effects of the shock spread through the model. Similarly, a shock in ε_{2t} will affect Y_t immediately and then series X_t will be affected through the C co-integrating vector. Second, third, and any further period shocks will additionally affect both variables. The impulse responses are the tracings through these effects of shocks on ε_{1t} and ε_{2t} .

3.6 Application of Methodology

Theoretically, the methodology outlined above is not 'carved in stone'; it is up to a researcher to determine what to do and how to proceed. Therefore, summarization of my

own use of econometric techniques is as follows. First the unit root tests, the Augmented Dickey-Fuller (ADF) and the Phillips-Perron are used to determine whether the series are stationary, using the SIC statistic to find lag length. If unit roots are detected, Johansen-Juselius procedure is applied to test the variables for co-integration. If co-integration is found among the variables, I employ VECM to estimate oil demand among countries. The long-run income and price elasticities are derived and compared among countries. A sample of graphs of impulse response functions of oil demand and GDP for Canada, China and India in a hypothetical scenario where we apply a carbon tax of ten percent to the oil price and see how the demand and GDP are affected, concludes the empirical analysis.

CHAPTER 4

EMPIRICAL RESULTS

Chapter 4 presents the empirical findings of methodology that was laid out in Chapter 3. This chapter is organized as follows: Section 4.1 discusses the results of unit root tests, Section 4.2 presents the co-integration test results and long-run income and price elasticities, Section 4.3 covers the estimated VECMs of the demand equation and Section 4.4 presents the corresponding graphs of IRFs.

4.1 Unit Root Test Results

This section presents the results of unit root tests. Assessment of the GDP/demand ratio graphs in Chapter 2 suggests that the estimation part of this study might face some data challenges: the data appears to be subject to trending and also subject to abrupt regime shifts. This implies that using only the Dickey-Fuller type unit root test, which is considered to have low power when rejecting the null of a unit root in the presence of a structural break (Perron, 1989), might not provide accurate results. For this reason I implemented two unit root tests; the augmented Dickey-Fuller test and Phillips-Perron test that allows for shifts in the data. The results of the tests are presented below in Table 4.1.

Table 4.1 Augmented Dickey-Fuller and Phillips-Perron Test Results

	ADF-stat	ADF-stat after 1st differencing	PP-stat	PP-stat after 1st differencing
CAN_D	-2.669	-3.529*	-2.356	-3.494*
CAN_GDP	-1.551	-5.093*	-1.448	-5.132*
US_D	-2.849	-3.798*	-2.268	-3.183*
US_GDP	-1.256	-5.172*	-1.798	-5.303*
FRA_D	-2.728	-3.068*	-3.128	-3.617*
FRA_GDP	-2.697	-4.062*	-2.615	-5.135*
UK_D	-2.598	-5.245*	-3.275	-5.630*
UK_GDP	0.113	-4.967*	0.124	-4.774*
MEX_D	-1.682	-4.646*	-1.504	-4.647*
MEX_GDP	-2.299	-4.873*	-2.233	-4.889*
BRA_D	-2.085	-5.223*	-1.895	-5.188*
BRA_GDP	-3.327	-4.703*	-2.902	-4.753*
CHN_D	-1.445	-4.051*	-1.305	-4.414*
CHN_GDP	2.897	-6.308*	2.905	-6.271*
IND_D	-1.631	-8.099*	-1.914	-8.102*
IND_GDP	1.671	-5.756*	3.396	-5.705*
WTI	-1.351	-6.068*	-1.388	-6.069*

*indicates rejection of the null hypothesis of non-stationarity at 5% level of significance. Schwatz Information Criterion (SIC) was used to selection of lags in ADF test. In case of FRA_D, UK_D, lag length was user-specified: 2 lags for France and 3 lags for UK.

Both tests indicate that the null hypothesis, that the series are not stationary, (i.e. containing a unit root) cannot be rejected by the variables in their level form. However, once we take the first difference of these variables in both the ADF and Phillips-Perron tests, all test values exceed the critical value (in its absolute value). This leads us to a conclusion that the selected series are stationary in their first differences, while being non-stationary in their level form. In other words, the variables are integrated of order one or $I(1)$.

In cases of oil demand for France and UK the lag length was user-specified for the ADF test, instead of using SIC criteria, for the reason being that the latter found that series had no unit root, which is hard to believe for time-series data. Generally speaking, time series data tends to trend over time (i.e., no stationarity) and looking at the graphs of GDP/oil demand ratios for France and the UK, it is obvious that these data series are trending, and hence cannot be stationary in their level form. For the same variables during PP test, we used trend as well as intercept in the test equation and found a unit root in the level form. Without including a trend in the equation, the PP test found the data was stationary in level form, which again is hard to justify given that variables are time-series data.

4.2 Tests of Co-integration and Long-run Elasticities

Given the results from unit root tests, I then proceed to test for the presence of co-integration among oil demand per capita, real GDP per capita and real oil price by using

Johansen-Juselius's multivariate maximum likelihood estimation procedure. For reference, the JJ procedure involves the identification of rank of the m by m matrix Π in the equation given by:

$$\Delta X_t = \delta + \sum_{i=1}^k \Gamma_i \Delta X_{t-i} + \Pi X_{t-k} + \varepsilon_t \quad (9)$$

where X_t is a common vector of the m variables, Γ and Π are coefficient matrices, Δ is a difference operator, k denotes the lag length, and δ is a constant. If Π has zero rank ($r = 0$), no stationary long-run linear combination can be identified, in other words, the variables in X_t are not co-integrated. If the rank r of Π is greater than zero, there exist r possible stationary linear combinations. To determine the number of co-integrating relations r , I proceed sequentially from $r = 0$ to $r = k - 1$ until we fail to reject. Results of JJ trace and maximum eigenvalue tests are presented in Table 4.2. The corresponding co-integration vectors that arise from the co-integration testing can be interpreted as long-run equilibrium relations that enter the error correction model as error-correction mechanisms. These equilibrium equations are presented in Table 4.3.

Table 4.2 Johansen and Juselius's Test Statistics

H_0	H_a	Trace Stat	Max.-Eigen Stat
Canada			
$r = 0$	$r > 0$	75.68549 *	49.27100 *
$r \leq 1$	$r > 1$	26.41449*	25.11498*
$r \leq 2$	$r > 2$	1.299511	1.299511
US			
$r = 0$	$r > 0$	32.30633*	21.00320
$r \leq 1$	$r > 1$	11.30313	11.27516
$r \leq 2$	$r > 2$	0.027975	0.027975
France			
$r = 0$	$r > 0$	73.40455*	44.35220*
$r \leq 1$	$r > 1$	29.05235*	16.71828
$r \leq 2$	$r > 2$	12.33407	12.33407
UK			
$r = 0$	$r > 0$	62.90021*	32.89007*
$r \leq 1$	$r > 1$	30.01013*	18.57473
$r \leq 2$	$r > 2$	11.43541	11.43541
Brazil			
$r = 0$	$r > 0$	30.68193 *	15.23177
$r \leq 1$	$r > 1$	15.45016	9.498930
$r \leq 2$	$r > 2$	5.951228	5.951228
Mexico			
$r = 0$	$r > 0$	28.06069 *	15.69023
$r \leq 1$	$r > 1$	12.37046	9.460873
$r \leq 2$	$r > 2$	2.909584	2.909584
China			
$r = 0$	$r > 0$	43.24293 *	33.26311 *
$r \leq 1$	$r > 1$	9.979828	9.445552
$r \leq 2$	$r > 2$	0.534276	0.534276
India			
$r = 0$	$r > 0$	32.58189 *	25.68911 *
$r \leq 1$	$r > 1$	6.892777	6.437987
$r \leq 2$	$r > 2$	0.454790	0.454790

Note: r denotes the number of co-integrating vectors. *indicates rejection of the null hypothesis at the 5% level.

The test results in the Table 4.2 show that we can reject the hypothesis that no co-integration exists but fail to reject a hypothesis of more than one stationary linear combination, except for Canada, where trace and max.-eigenvalue tests found two co-integrating vectors. However, after examining two vectors, only one was found to be stable to be included in the error-correction model. The trace statistic and the maximum eigenvalue statistic yielded conflicting results for the U.S., France, UK, Mexico and Brazil. For such cases, it is recommended that the researcher examines the estimated co-integrating vectors and base their choice on the interpretability of the co-integrating relations (Johansen and Juselius 1990). After reviewing the co-integrating vectors for these countries, which are shown in Table 4.3, we concluded that the co-integrating vectors for these countries are robust and stable with expected signs and significant coefficients.

The long-run co-integrating vectors are shown in Table 4.3. These equations represent the long-run equilibrium relationship between oil demand, GDP and oil price. The coefficient on GDP is the long-run income elasticity of demand and coefficient on oil price is the long-run price elasticity of demand, the corresponding standard errors are presented in brackets just below the coefficients.

As you may recall, the income growth hypothesis suggests that the long-run income elasticity of demand below one indicates that the economy grows faster than energy

demand, income elasticity above one suggests the opposite: energy demand grows more rapidly than GDP.

Our estimates indicate that income elasticity of demand for Canada, the U.S., the UK, Mexico and China is below one and above one for France, Brazil and India. For the sample developed countries, except for France, as well as Mexico and China, we can conclude that the economic growth surpasses the energy demand growth. However, the opposite is true for France, Brazil and India, where the income elasticity above one suggests that energy consumption grows faster than income. These results almost fall in line with our initial assumption that the economic growth exceeds oil demand growth for developed countries and falls short of demand growth in developing countries. The exceptions that proved the assumption to be false are the results for France, Mexico and China. These results are somewhat surprising.

Since France is one of the most developed countries in the world, the results were expected to be similar to those of the rest of the developed countries; however, our hypothesis was proved false in this case. One of the reasons that can possibly explain this anomaly is that we are using oil demand and not total energy demand. Since France is one of the world's largest nuclear power producers and consumers and has limited fossil fuel resources, it might be more useful to evaluate the total energy demand equation in this case, which might overturn our result and actually accept the income growth

hypothesis of the economic growth exceeding total energy demand. Further research is needed to prove the income growth theory.

In the case of Mexico, the long-run income elasticity of 0.923 was remarkably close to estimates of income elasticity of some of the developed countries, which raises the question: should Mexico be classified as a developed country or more of a transition economy, moving towards a more stable economic growth, especially in the latter years of the time period. Another argument that supports that the economy growth surpasses oil demand growth in Mexico is that the country is a net oil exporter, which might suggest that Mexico's GDP growth is more correlated with revenue from oil exports than domestic consumption of oil. An interesting exercise could be conducted in evaluating GDP growth and oil exports in Mexico.

The estimates of income and price elasticities of 0.547 and 0.518, respectively, are indicative that both real income and real oil price almost equally influence the oil demand in China. Given that coal dominates China's overall energy consumption and this analysis was limited to estimating parameters involving only oil consumption, it is not surprising that income elasticity of oil demand was not larger than 0.547. A more thorough exercise would be to carry out similar analysis for deriving elasticities of China's other major conventional energy sources: coal, natural gas and hydropower. This would provide a much broader and general overview of energy demand behaviour in China and how it relates to GDP growth.

The estimates of long-run price elasticities vary quite a bit in magnitude among the countries. For the U.S. and Mexico the price elasticities are found to be low, suggesting that oil demand is not price elastic. In fact, the price elasticity for Mexico is nearly zero, suggesting oil consumption is not responsive to changes in oil price, which is reasonable, given that Mexico generated three quarters of its electric power from fossil fuels, including oil. In addition, the surge in oil prices of the 1970s provided a windfall to oil-rich Mexico, which allowed the country to maintain substantial subsidies for electricity generation.¹⁰ For the U.S., the largest consumer of oil per capita in the world, the demand is price inelastic because of its transportation sector, which relies on more crude oil than any other sector in a form of gasoline. Currently, the country has not developed alternatives at a large commercial level yet to rely less on crude oil and hence acts as a price-taker, when it comes to purchasing crude.

For Brazil, India, UK and China the oil demand is found to be somewhat responsive to oil prices. The estimates of price elasticity for Brazil and India are little lower than for UK and China, but all are still within the range of price elasticities estimated throughout published literature. For Canada and France the price elasticity is nearly unity, implying one-for-one change in oil demand as a result of price change.

¹⁰ Carreón et al, 2003. The Mexican Electricity Sector: Economic, Legal and Political Issues. Working paper.

Table 4.3 Long-Run Equilibrium Relations

Country	Equilibrium Equation
Canada	$D_t = 2.511 + 0.913GDP_t - 1.061P_t$ (0.19504) (0.18013)
US	$D_t = -3.475 + 0.014GDP_t - 0.127P_t$ (0.11413) (0.0834)
France	$D_t = 12.647 + 1.983GDP_t - 0.959P_t - 0.052TREND$ (0.60546) (0.15577) (0.01245)
UK	$D_t = -0.199 + 0.493GDP_t - 0.684P_t - 0.019TREND$ (3.32141) (0.13965) (0.07160)
Brazil	$D_t = 9.708 + 1.344GDP_t - 0.269P_t$ (0.21113) (0.09852)
Mexico	$D_t = 6.610 + 0.923GDP_t - 0.087P_t$ (0.20052) (0.05968)
China	$D_t = 5.948 + 0.547GDP_t - 0.518P_t$ (0.05443) (0.09242)
India	$D_t = 14.089 + 1.604GDP_t - 0.436P_t$ (0.12766) (0.07789)

Standard errors are provided in brackets.

4.3 Vector Error-Correction Model (VECM)

The error-correction model technique appropriately models the full dynamic behaviour of energy demand, by incorporating short-run adjustment factors along with the co-integrating vector, which is viewed as the long run equilibrium relationship. For ease of reference, the VECM in this analysis takes a form given in equation below. Since we are only interested in the demand equation we omit the results of the other system equation with GDP as a dependent variable. With $B=[c, \alpha, \beta]$ and $X=[1, P_t, GDP_t]$ the demand equation is:

$$\Delta D_t = \sum_{j=1} \phi_j \Delta D_{t-j} + \sum_{j=0} \eta_j \Delta P_{t-j} + \sum_{j=0} \lambda_j \Delta GDP_{t-j} + \sum_{i=1} \xi_j (D_{t-1} - B'X_{t-1}) + \varepsilon_t \quad (10)$$

where the coefficients η_j and λ_j represent short run price and income elasticities, respectively and ξ_j is the error-correction term, which contains the long-term information since it is derived from the long-term co-integrating relationship(s). The coefficient of the lagged error-correction term, however, is a short-term adjustment coefficient and represents the proportion by which the long-term disequilibrium (or imbalance) in the dependent variable is being corrected in each period.

The estimated results of the demand equation are presented in Table 4.4. We have chosen to use four lags in our demand equation, except for UK, where three lags were used. Given that our analysis is done using annual data, it is more appropriate to choose a smaller number of lags than what other information criteria, such as SIC or AIC might

suggest. The table shows the error correction coefficients, the estimated short-run coefficients of variables within VECM, the goodness of fit measure, R^2 and the ADF statistics on the residuals.

As can be seen, the coefficients are statistically significant for the most part, however, specific coefficients that were found significant vary country to country. A more useful approach to interpreting these coefficients for this thesis is to look at the IRFs that are discussed in Section 4.4. The models for each country seem to be robust and stable. Even though the R^2 is just above 50% for developing countries and well above 60% for developed ones, the ADF statistics indicate that there is no unit root among the residuals (i.e. residuals are white-noise), suggesting that the model fits the data well.

These estimates offer a few important results. First, we can determine if the variables actually adjust to disequilibrium by examining the error-correction term. This parameter will be stable if its absolute value is less than one, and its sign should be negative since a positive shock to a system should result in adjustment in the opposite direction. Our estimates of the error-correction term conform to the above statements: all our estimates of error-correction term are negative, less than one in absolute value and statistically significant from zero. For the developed countries the adjustment coefficient varies between (negative) 0.158 and 0.111, indicating that the oil demand will adjust to its long-run equilibrium with about 15.8% to 11.1% adjustment taking place within the first year. In other words, if there is a displacement of the long-run oil demand curve, economies of

the developed countries will take anywhere from five to eight consecutive years to restore a new equilibrium. For developing countries, the estimated coefficients of the error-correction term vary significantly in magnitude. For example, the adjustment coefficient for Brazil is -0.284 and for India is only -0.091. This means that in Brazil if oil demand is off the long-run equilibrium, 28.4% of adjustment in the oil demand takes place in the first year, which seems a little doubtful. In the case of India, only 9.1% of adjustment takes place in the first year, which for a developing country, seems probable. In case of China, the error-correction term is found to be quite small, only (negative) 0.007 (i.e. just under one percent of adjustment in the oil demand takes place in the first year). Since the error-correction terms vary so much in magnitude between countries, we cannot offer any general conclusions about the behaviour of oil demand in developed versus developing countries.

Table 4.4 Error-Correction Model: Demand Equation Estimates

Variable	Canada	US	France	UK	Brazil	Mexico	China	India
intercept	-0.008469 (0.4250)	0.013338 (0.2698)	0.019362 (0.3184)	0.035419 (0.01563)	0.022048 (0.0836)	0.02771 (0.0118)	0.159534 (0.0592)	0.043136 (0.0996)
ΔD_{t-1}	0.165757 (0.4028)	0.627377 (0.0293)	-0.094560 (0.6041)	-0.339658 (0.15377)	0.046308 (0.7967)	0.012315 (0.9576)	0.198657 (0.2137)	-0.691143 (0.0075)
ΔD_{t-2}	0.034525 (0.8619)	0.215815 (0.5046)	-0.341645 (0.0677)	-0.059273 (0.15646)	0.229889 (0.2227)	0.316006 (0.1754)	0.086231 (0.204898)	-0.229574 (0.4007)
ΔD_{t-3}	-0.237002 (0.2329)	-0.106133 (0.7306)	-0.133680 (0.4701)	-0.397931 (0.14757)	-0.166945 (0.3823)	0.273436 (0.2449)	0.199015 (0.185086)	0.125915 (0.6240)
ΔD_{t-4}	-0.419207 (0.0467)	-0.305689 (0.2646)	-0.419459 (0.0365)		0.134986 (0.4688)	0.031765 (0.8874)	-0.204451 (0.189571)	-0.093458 (0.6288)
ΔGDP_{t-1}	0.176694 (0.4920)	-0.417686 (0.1462)	0.104656 (0.8150)	-0.297200 (0.43020)	0.243232 (0.3969)	0.282448 (0.3387)	-0.186660 (0.413422)	0.849979 (0.0063)
ΔGDP_{t-2}	-0.430173 (0.1136)	-0.476705 (0.1010)	-0.384995 (0.4001)	-0.418938 (0.46156)	-0.213829 (0.4794)	-0.488017 (0.1013)	-0.953023 (0.383566)	0.54103 (0.1197)
ΔGDP_{t-3}	0.416013 (0.1232)	0.050290 (0.8649)	0.545635 (0.2351)	-0.114414 (0.42040)	-0.186741 (0.5234)	-0.559281 (0.0606)	-0.549181 (0.410643)	0.010719 (0.9747)
ΔGDP_{t-4}	0.404015 (0.1375)	0.280462 (0.3312)	-0.086572 (0.8477)		-0.256077 (0.3603)	-0.349349 (0.2453)	0.036791 (0.320788)	-0.271368 (0.3962)
ΔP_{t-1}	0.015503 (0.5315)	0.000887 (0.9667)	0.041655 (0.2637)	-0.066478 (0.03030)	0.053290 (0.2560)	-0.01683 (0.5376)	-0.037921 (0.053144)	-0.021428 (0.4830)
ΔP_{t-2}	0.025298 (0.2434)	0.034911 (0.0788)	0.073424 (0.0306)	-0.031002 (0.03287)	0.069470 (0.1047)	0.018352 (0.5266)	-0.060020 (0.050779)	-0.022469 (0.4321)
ΔP_{t-3}	0.004738 (0.8174)	0.014355 (0.4712)	-0.009881 (0.7385)	-0.051506 (0.03058)	0.000461 (0.9910)	-0.022617 (0.4156)	-0.064483 (0.051013)	-0.014854 (0.6107)
ΔP_{t-4}	0.040044 (0.0465)	0.018532 (0.2958)	0.051097 (0.0375)		0.033861 (0.3543)	0.023597 (0.3745)	-0.000254 (0.049760)	0.010241 (0.7312)
ξ_{t-1}	-0.157863 (0.0007)	-0.130721 (0.0016)	-0.144624 (0.0001)	-0.110862 (0.02364)	-0.283966 (0.0072)	-0.187252 (0.0027)	-0.007233 (0.069181)	-0.090857 (0.0648)
R ²	0.673811	0.692446	0.817032	0.646193	0.516349	0.541806	0.512904	0.523068
ADF - Choi Z-stat	-4.73189	-4.19531	-4.62139	-4.94689	-4.84844	-4.88825	-3.94513	-4.59708

Oil demand is a dependent variable. P-values are reported in the brackets. The ADF test is for unit root in the residuals.

4.4 Carbon Tax: Impulse Response Functions

In this section we evaluate a hypothetical but potentially plausible scenario, which we will call “Environmental Awareness”, where the global oil price (in this case we use WTI as such representation) is increased through a direct carbon tax. One might expect this to help curb oil demand and as a result decrease overall pollution on the environment. This example is similar to many policies that different countries are trying out or already implementing. One common goal among these policies is to curb air emissions by increasing taxes on fossil fuel prices to either comply with Kyoto protocol standards or internal country-specific requirements. One side effect of such policy would be decreased fossil fuel dependency through decreased fossil fuel demand. However, one of not so positive results of such tax is a potential fall in GDP growth.

In our example we will apply a one-time permanent ten percent carbon tax directly to oil price and evaluate how demand and GDP would behave to such a shock. For illustrative purposes, such an example is presented in Figure 4.1. If an oil price, P , is increased from P_1 to P_2 along a long-run demand curve, as can be seen in the first graph of Figure 4.1, this will have an immediate downward effect on the long-run demand fed through our demand equation (Eq. 10), where the long-run demand appears as a co-integrating vector in the short-run demand equation (represented by the fourth term in Eq. 10), which results are presented in Table 4.4. Then, there will be a further change in demand and GDP over time as the initial effect of the price shock spreads through the vector-error correction

system. This further change will be evident in the GDP equation, represented by Eq. 11 below. In similar fashion as the demand equation in Eq. 10, with $C=[\chi, \mu, \theta]$ and $X=[1, P_t, GDP_t]$ the GDP equation is:

$$\Delta GDP_t = \sum_{j=1} \phi_j \Delta D_{t-j} + \sum_{j=0} \eta_j \Delta P_{t-j} + \sum_{j=0} \lambda_j \Delta GDP_{t-j} + \sum_{i=1} \xi_j (D_{t-1} - B'X_{t-1}) + \varepsilon_t \quad (11)$$

As a result of a price increase, one would expect a drop in GDP from GDP1 to GDP2, as seen in the second graph of Figure 4.1. In later periods, the shock may even have a greater effect on the original variable (in this case demand) than it did initially because of feedback effects through the other variables.

The impulse responses are the tracings through these effects. The impulse response functions represented by the curving lines in the Figure 4.1 – demand response is between points P1 and P2 and GDP response between GDP1 and GDP2. The estimated VECMs were used to calculate a sample of impulse response functions for Canada, China and India where we introduce a shock to the oil price (in this case increasing it by ten percent in the first period) and tracing through the effects on demand and GDP in the model. The graphs presented below are the impulse response functions (IRFs) for these countries. We want to observe how demand and GDP in a highly developed country such as Canada would behave in comparison to demand and GDP in China and India, which are the two economies in the world that are experiencing tremendous growth, hence it would be interesting to see how their corresponding results will vary or not. The number

of periods that the IRFs are traced for varies according to the country's corresponding coefficient of the lagged error-correction term from Table 4.4, which is then translated into a number of periods (in this case years) it takes for a variable to return to its equilibrium state. The graphs are presented in Figures 4.2 through 4.4 below.

Figure 4.1 Long-Run Demand Relationships with Oil Price and GDP

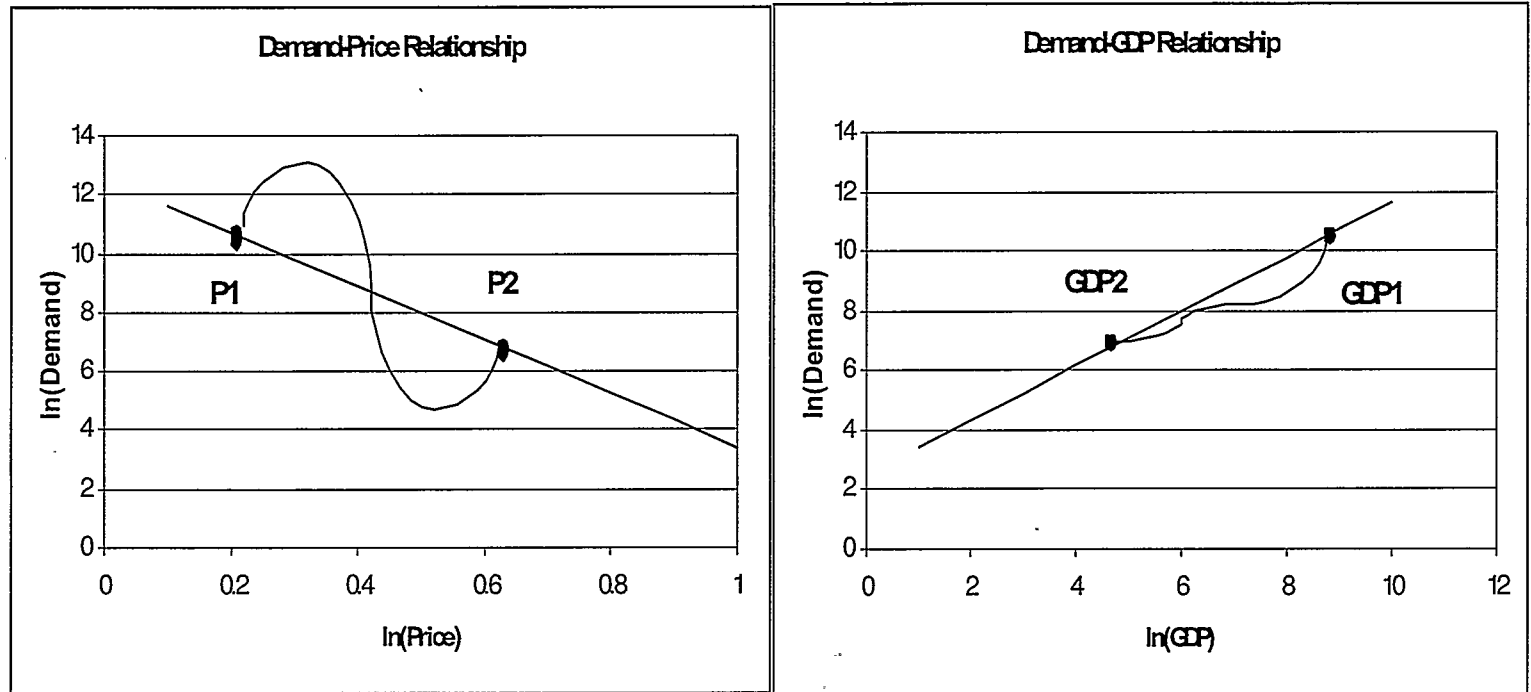


Figure 4.2 Canada's Responses

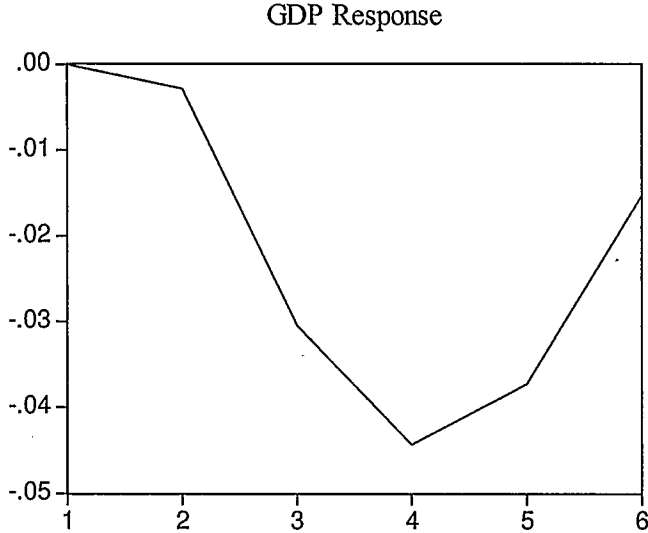
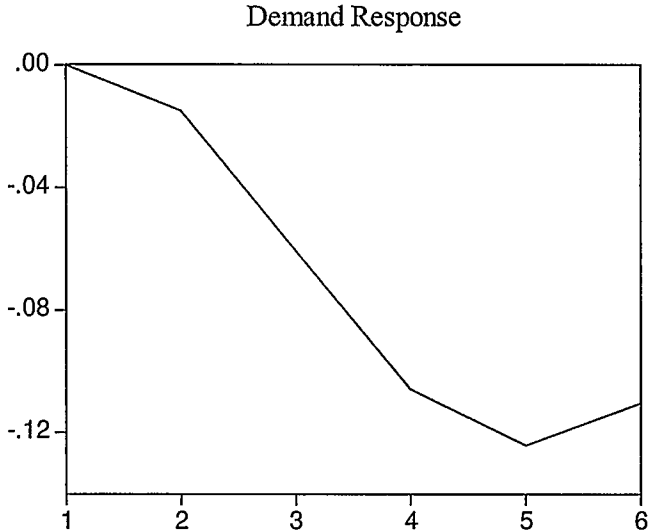


Figure 4.3 China's Responses

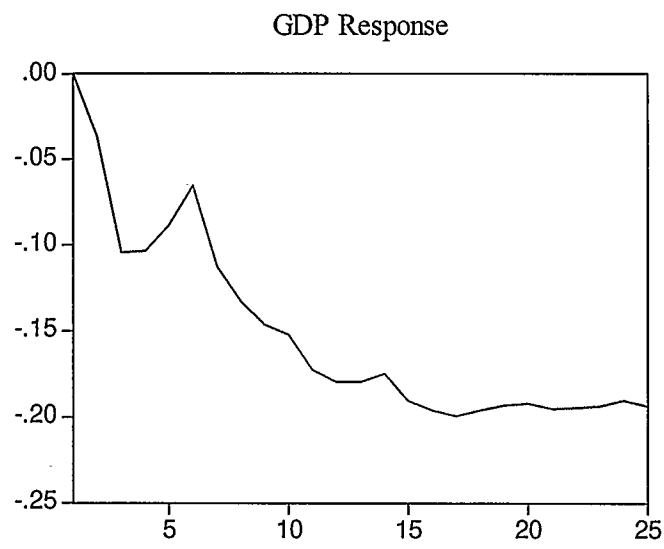
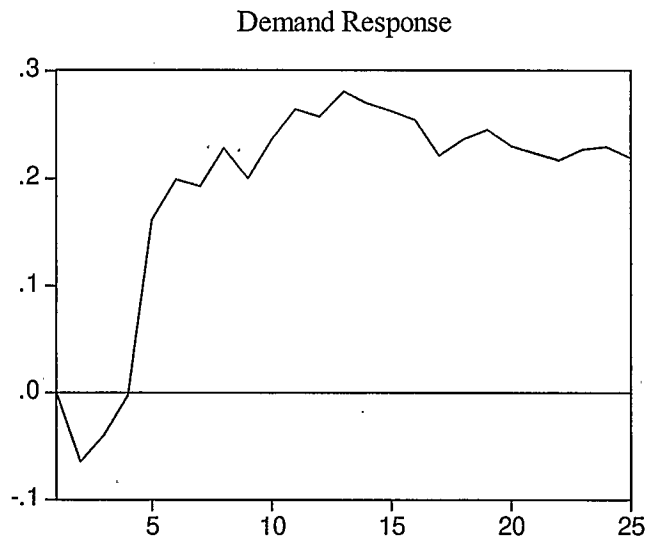
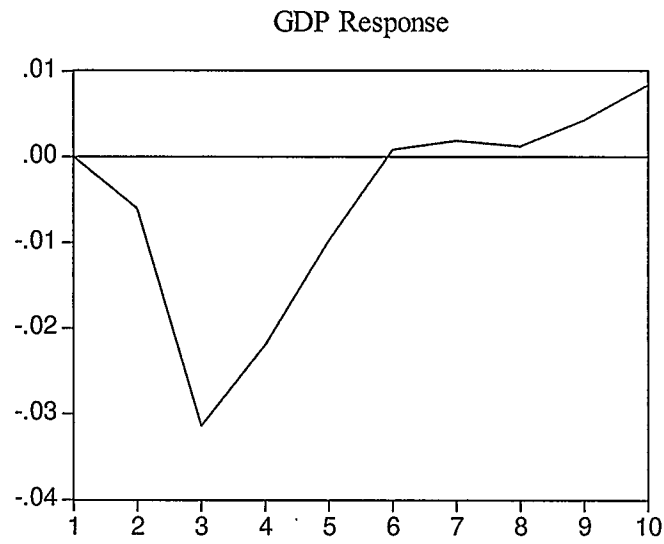
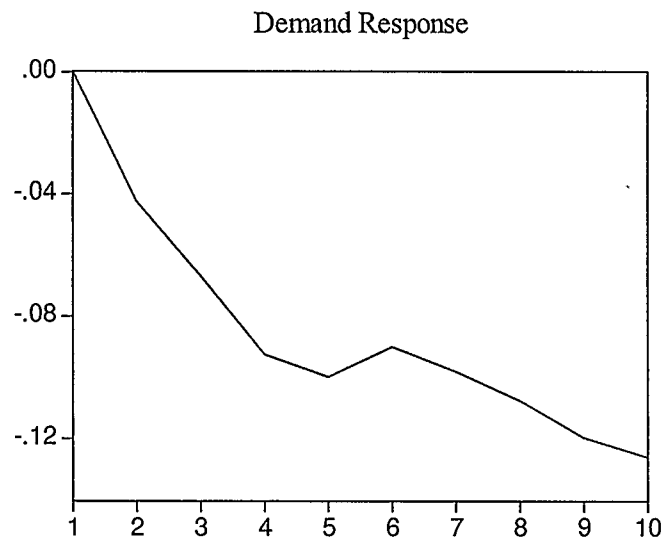


Figure 4.4 India's Responses



The coefficient of the error-correction term for Canada is (negative) 0.158, indicating that the oil demand will adjust to its long-run equilibrium with about 15.8% adjustment taking place within first year. In other words, if there is a displacement of the long-run oil demand curve (in this case displacement due to price shock), the economy will take approximately six consecutive years to restore to a new equilibrium – hence we traced the responses for six periods. As a result of a ten percent increase in price, Canada's demand fell for five consecutive periods, as seen in Figure 4.2, by approximately 12 percent overall but partially readjusted to the price shock by the sixth period and increased by one percent to a new equilibrium. Similarly, GDP dropped in the first four periods by 4.5 percent, after which it climbed back up by approximately three percent. So, overall, demand and GDP decreased by 11 and 1.5 percent, respectively. This result shows that an environmental policy that implements a carbon tax will curb the oil demand, which will readjust to a new equilibrium level after approximately six years, and have a 4.5 percent decrease effect on GDP for at least first four years.

The short-term coefficient adjustment for China is only 0.007, suggesting that the oil demand will adjust to its long-run equilibrium with only one percent adjustment taken place in the first year, which further suggests that it will take approximately 100 years for China's oil demand to reach a new equilibrium, if there was a displacement off the long-run demand curve. However, after estimating a few IRFs under different number of periods, we concluded that 25 periods was a sufficient number. In the case of China, the demand goes down by approximately six percent after the first couple of periods and then

recovers to its initial equilibrium at around the fifth period, after which it continues to increase and then settles for the remaining periods at 20 percent increase. This growth could be explained by the fact that the domestic fuel prices, including oil, are not set in a traditional market-based system, but rather, artificially determined by the government. Hence, a carbon tax applied to WTI, a free-market set oil price, might not affect the local demand as much, because consumers are never faced with true prices that could have had an effect on consumer behaviour otherwise. The GDP behaves sporadically, with short-term ups and downs, however overall it does decrease by approximately 18 percent. In such a planned economy, like China, a policy of carbon tax might not have the desired results to curb the overall oil demand but it negatively impacts GDP growth; a better way to curtail oil demand might be for a government to try to affect oil demand in a more direct way by adjusting consumption behaviour as opposed to through price mechanisms.

The coefficient of the error-correction term for India is (negative) 0.091, indicating that the oil demand will adjust to its long-run equilibrium with about 9.1% adjustment taking place within the first year. In other words, if there is a displacement of the long-run oil demand curve (in this case displacement due to price shock), the economy will take approximately ten consecutive years to restore to a new equilibrium – hence we traced the responses for ten periods. As a result of a ten percent increase in price, India's demand fell for all ten consecutive periods, as seen in Figure 4.4, by approximately 12 percent overall. However,

GDP only dropped in the first three periods by approximately 3.5 percent, after which it climbed back up to its initial equilibrium level by the sixth period and increased by almost one percent thereafter. This result signifies that in India, a policy of a carbon tax on oil price might curb oil demand for an extensive period of time without affecting GDP growth in the long-run after the initial drop wears off.

These results offer some insight into a scenario of an implementation of a carbon tax on oil prices. The differences between three economies are visible in the graphs of impulse response functions of demand and income. It seems that in a well developed economy with a market-based structure, a policy to curb oil demand by implementing some sort of tax on the oil price might cut down on demand growth but at the same time affect GDP growth in a negative way at least in the short term. In the developing countries the results vary depending upon what kind of market structure the economy has. In case of China, such a policy might not be as useful in curtailing oil demand as in the case of India; and in the case of India, GDP recovers and readjusts faster to its new equilibrium than in China, where it takes a long time for GDP to settle at a new level.

CHAPTER 5

CONCLUSIONS

The purpose of this thesis was to test the income growth hypothesis in developed and developing countries through estimating the long-run income elasticities of oil demand for eight countries using annual data from 1960 to 2004. We also present the estimates of the long-run price elasticities, as well as results of scenario-driven graphs of IRFs from estimated VECMs. A statistically sound error-correction model was used for estimating long-run income and price elasticities as well as impulse response functions of oil demand and GDP, to model the underlying short-run dynamics without losing any long-term information contained in the co-integrating vector. From a methodological and energy-related modelling approach, this study illustrated the statistical appeal this technique has to offer for future applied research in this area.

In brief, the results show that the estimate of the long-run income elasticity of oil demand for developed countries was found to be less than one (with an exception of France), thus indicating that oil demand grows slower than the economy, possibly pointing out that developed countries are less reliant on energy to support their economic growth. The estimate of the long-run income elasticity of oil demand for developing countries was found to be greater than one (with exception of China and Mexico), which is consistent with the initial hypothesis that oil consumption growth is greater than income growth for

developing economies. This occurrence is usually mentioned in literature as an “industrialization” phase faced by many developing economies today. The exception to that result was China, where the income and price elasticities of demand had an equal effect on oil demand.

The long-run price elasticities varied across all countries and in the case of Mexico the price elasticity was found to be nearly zero. The general conclusion we can draw from the estimates of long-run price elasticities is that the oil demand is quite price inelastic with the exception of Canada and France, where price elasticity was essentially unity. The literature agrees that energy demand is generally price inelastic, explained by the fact that there are few substitutes for energy, and hence the price does not play a significant role in energy demand determination.

From this empirical analysis, we may draw some conclusions, which may be of some assistance to economic policy-makers. First, the evidence of long-run elasticities being close to unity for Canada, France and Mexico implies that the aggregate intensity of oil demand should remain constant as future economic development takes place. Secondly, China’s oil demand is found to be almost equally affected by income and price (income however has a little more impact on oil demand). This could imply that the government might be able to influence the oil demand through resource-based policies better rather than through price-based ones. Also, given the results of IRFs for China, a resource-use policy might prove to be more effective than a price policy. Thirdly, the long-run income

elasticities above one for Brazil and India are indicative of the fact that both countries have been experiencing an increasing trend in energy consumption to fuel their economic growth to the point where demand for oil is surpassing the economic growth. In this case it would be advisable for policy-makers of those countries to set a policy that conserves energy without impeding economic growth.

Future analysis in this area could involve a broader study of all major resource types that make up the full energy consumption for each country. This would provide a better overview of energy demand behaviour and more importantly the interaction of energy demand with economic growth, especially for China and India, which are considered to be the new century energy consumers that we know so little about.

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