Essays on Commodity Prices

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A Thesis Submitted

for the Degree of Ph.D.

University of York

Department of Economics and Related Studies

June 2013

Abstract

This thesis is a collection of five empirical essays which examine microeconomic and macroeconomic aspects of high and volatile commodity prices. The first three chapters focus more on microeconomic issues of commodity prices. The second chapter examines the dynamic relationship between the commodity futures curve and inventory levels and finds a long-run cointegrating relationship between base metal spot prices, futures prices, inventories, and interest rates. This study presents some evidence that a temporary scarcity shock, modeled as a spot price shock which changes the slope of the futures curve, does cause a reaction in commodity markets. The third chapter investigates the gasoline price and income elasticities in the U.S. which confirms the structural change in the U.S. gasoline market where demand elasticity of gasoline price and income became more inelastic over the last decade. The fourth chapter examines the dynamic impact of demand and supply shocks in the U.S. and U.K. gasoline market where results show that the U.S. gasoline prices are impacted by the global demand shock. The last two chapters concentrate more on macroeconomic impacts of commodity prices on commodity exporting countries. The fifth chapter studies the fiscal behavior in developing oil-producing countries and examines whether it is procyclical. The results reveal that total expenditure is highly procyclical in the low and middle-income groups but countercyclical in high-income countries in the sample. The results confirm that political and institutional factors, as well as financing constraints, play a role in the cyclicality of fiscal policies in the oil producing developing countries. Finally, the sixth chapter examines the dynamic relationship between exchange rates and commodity prices to determine whether commodity prices Granger cause exchange rate or exchange rates Granger cause commodity prices for a group of advanced and developing commodity-exporting economies. The study finds stronger evidence of in-sample causality from exchange rates to commodity prices for most of the countries in the sample. One of the key findings is the consistent significant causality from exchange rates to commodities for Korea.

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Acknowledgements

I would like to start with thanking my supervisors Professor Gulcin Ozkan and Professor Peter N. Smith for their academic support and guidance. I express my deepest gratitude to Prof. Ozkan for her encouragement and moral support throughout years. I appreciate the trust she put in me. I wish to thank Professor Mike Wickens a member on my thesis advisory group, for his helpful comments and suggestions in early stage of my thesis.

I am grateful to my co-author and colleague Shaun K. Roache in IMF for his modesty, kindness and generosity sharing his vast knowledge. I would like to give special thanks to my colleagues in IMF: Oya Celasun, Thomas Helbling, Cemile Sancak, Mitali Das, and Thomas Walter for their invaluable help and feedback at different stages of the thesis. I am grateful to Mauricio Villafuerte for sharing his data set and his valuable comments. I would like to thank Dr. Barbara Rossi, Dr. Yu-Chin Chen and Dr. Jonathan Hughes for answering my questions related to their research.

I would like to also thank my managers at Mondelez International Roger Lebreton for his support and Paul Nicholson for his guidance, support and enthusiasm.

I would like to thank two special friends who were always behind me when I needed a push: Bonita J. Brindley and D. Filiz Unsal. I cannot express my gratitude enough to have them in my life as a friend.

Finally, I would like to thank my family for their support and love.

Author's Declaration

One study in this thesis is based on joint research. Chapter 2 was jointly written with Shaun K Roache and was presented in an IMF seminar and published as an IMF Working Paper in 2010. Chapter 4 was presented at the Economic Research Forum's 17th Annual Conference in Turkey in 2011 and was published as an Economic Research Forum working paper as well as an IMF working Paper in 2011.

1 INTRODUCTION

Periodically the global economy experiences episodes of commodity booms and busts that are characterized by broad and sharp co-movements of commodity prices. Commodity booms and busts have substantial economic, political, social and macroeconomic impacts on commodity producing and consuming countries. Two major episodes have occurred since the 1950s; the first episode peaked in 1974 and was primarily supply-driven; the second episode peaked in 2008 which was mainly demand-driven. The 1970s commodity boom was sparked primarily by the 1973 OPEC-imposed oil embargo on the United States and European countries, which led to energy shortages and a subsequent sharp rise in energy and a few other commodity prices. After the embargo was lifted in 1974, commodity prices started to decline and by the 1980s, they returned to the pre-embargo levels.

Commodity prices remained low until the early 2000s, when most commodity prices began to rise and reached record high levels in mid-2008. But in the second half of 2008, the global financial crisis erupted, followed by severe recession; in 2009, commodity prices had crashed and a demise of the commodity boom appeared imminent. Instead, prices rebounded and by 2011, many commodities had matched or even exceeded their pre-crisis price peaks. Not only was this recent commodity boom relatively prolonged but also all commodity prices rose in unison. This contrasts markedly with the 1970s, when only a few commodity prices rose--energy, grains and vegetable oils; non-energy commodities never attained the extraordinary levels of 2008. The literature offers three major explanations for the noteworthy strength and duration of this commodity price boom.

First is strong and prolonged global growth which boosted the demand for commodities. Beginning in 2000, rapid industrial development and urbanization in emerging economies especially in China and India increased demand for commodities. Second is prolonged low interest rates, which have contributed to increases in commodity prices. During 2001-2004, and again in 2008, the U.S. Federal Reserve Bank cut real interest rates sharply. This reduced the cost of holding inventories, which made stock-building more attractive, thereby contributing to increased demand. Third is the most contentious explanation: financialization of commodity markets or financial speculation. Due to low interest rates in the 2000's, many investment funds explored other asset classes which would bring higher returns. Starting in the 2000's, the index and other investment funds began increasing their exposure in commodity futures market. Their commodity related asset holdings rose in value from less than US$10 billion in 2000 to around US$450 billion by mid- 2011. Some argued that fund's frequent trading large amount of commodity assets supported the rise in commodity prices above fundamental values.

Each explanation may have contributed individually and certainly the combination of the three contributed to the recent commodity price boom which was mainly driven by increased demand for commodities and differed from the previous supply-driven commodity boom during which demand was somewhat steady, while drastic drop in supply of commodities was the spark of the commodity price rise. The recent commodity boom however, was triggered by a sharp and persistent increase in demand while supply struggled to keep pace causing unexpected large draws on inventories. Subsequently, supply shocks have been a major determinant of short term price trends, while long term prices trends have been governed by lagging supply response to increased demand. All of these major global structural changes precipitated structural shifts in commodity market supply, demand and inventory dynamics. Hence, it is more important than ever to revisit and examine the interaction of commodity prices with the other market variables and the impact of volatile commodity prices on consumers and the economies of commodity producing countries.

This thesis comprises five chapters that explore issues related to high and volatile commodity prices. The first three chapters focus on microeconomic aspects of commodity prices, while the last two chapters investigate macroeconomic impacts of volatile commodity prices. Chapter 2 examines the dynamic relationship between the commodity futures curve and inventory levels. Chapter 3 discusses gasoline price and income elasticities in the U.S. Chapter 4 examines the dynamic effect of demand and supply shocks on gasoline prices in the U.S. and the U.K. Chapter 5 investigates fiscal behavior in developing oil-producing countries. Chapter 6 explores the dynamic relationship between exchange rates and commodity prices for a group of advanced and developing commodity-exporting economies. Detailed chapter descriptions are as follows.

Chapter 2 examines implications of commodity inventory levels on futures price curves. The relationship between commodity spot and futures prices reflects a perception of short-term physical scarcity and prevailing inventory levels. Thus the slope of the futures curve can provide information on whether market participants anticipate relative abundance (an upward sloping curve) or scarcity (a flat or downward sloping curve) in the physical market. Price curves also provide incentives for market participants to change their exposure to commodity prices.

Chapter 2 attempts to answer three key questions: Is there a long-run cointegrating relationship between base metal spot prices, futures prices, inventories and interest rates? In the event of a short-run shock, how does a commodity market adjust to a temporary scarcity shock which moves the price curve away from this equilibrium? How quickly do inventories and prices adjust following such shocks? The study focuses on temporary shocks to physical market balances that change the slope of futures curve; in contrast, permanent or long-lasting shocks should have an impact across the futures curve, which may change the level of the curve but leave the slope little changed.

Chapter 2 provides several contributions to the literature. First, we adopt a comprehensive self-exciting threshold approach which includes both inventories and interest rates along with spot and futures prices, building on previous work, which has omitted one or more of these variables. Second, we compare the empirical results to predictions of a widely accepted theoretical model. Finally, we use higher-frequency daily data, which should provide important insights, given the relatively high liquidity and rapid adjustment patterns of major commodity markets. Until now, only few studies examined interactions between inventories and commodity prices at a daily frequency, partly due to poor and infrequent data. Base metals, which include aluminum, copper, lead, nickel, tin and zinc, provide the richest data set, particularly as trading of spot, futures, and options is concentrated on the London Metals Exchange (LME).

Chapter 3 investigates whether the demand elasticity of gasoline price and income in the U.S. has changed in recent years compared to earlier periods that experienced similar high gasoline prices. Understanding gasoline demand elasticity is especially important for a country such as the U.S., which relies heavily on crude oil and gasoline. In fact, the U.S. is the largest crude oil consumer in the world and more than half of total crude oil goes into gasoline consumption. The greenhouse gas emissions produced by the transport sector comprise nearly half of national total gas emissions. Among OECD countries, the U.S. has the lowest average fuel economy standards, the highest transportation fuel consumption per capita, and the lowest fuel tax and prices.

Similar to the rest of the world, the U.S. experienced a wealth increase over the past decade that led to changes in demographics, habits, and lifestyles. Great distances between cities, dispersed urbanization, and limited public transportation services mean that American citizens rely heavily on personal vehicles for transport. Over the past 30 years, the share of public-transportation passenger miles relative to other types of transportation has steadily decreased, suggesting that American consumers may be more dependent on automobiles than during previous decades. However, since the financial crisis and subsequent recession, gasoline consumption and income began to show signs of decline.

With these changes, identifying the patterns and evolution of responses of gasoline demand to shifts in gasoline prices and income is central to implementing effective fiscal, tax and environmental policies in the U.S. and has been studied extensively in the 1970s and the early 1980s when prices were very high and supplies were tight. In recent years there has been a renewed interest in price-based policies such as gasoline or carbon taxes, as pressures increase to reduce greenhouse gas emissions produced by the transportation sector. In this context, it is important to review whether gasoline demand elasticities have changed by incorporating recent developments using the latest data.

Consequently Chapter 3 examines price and income elasticities of gasoline demand in the U.S. during 1975-2013. Since elasticity estimates in the literature vary according to data type and empirical model specification, using a consistent set of data and models during 1975-2013 makes the elasticities comparable over time. The sample is split into three sub-samples that cover periods of high gasoline prices. In addition to three sub-samples, the elasticity estimates are arrived at using the full sample to study long-term elasticity behaviors. Elasticities are estimated using several simple econometric models similar in form to those used in previous gasoline demand studies. These models include OLS, a partial adjustment dynamic model in which a lagged dependent variable is included to allow for adjustment to the equilibrium level, Instrumental Variable (IV) to correct for the endogeneity between gasoline price and consumption and a price-income interaction model. In addition to the simple econometric models, a dynamic time series approach involving a bivariate vector autoregression (VAR) is applied to estimate the short-run price elasticity of gasoline demand. The VAR method focuses on unpredictable changes in gasoline prices and on measuring gasoline demand responses. The gasoline consumption response to 1.0% shocks to gasoline prices within 12 months can be interpreted as short-run price elasticity of gasoline demand. The disadvantage of this approach, however, is that income changes very slowly over time making it difficult to estimate income elasticity. Hence, only demand price elasticity is estimated using this model on three sample periods as well as on the full sample as is done with the simple models explained earlier. The contribution of this study to the literature is to include the latest period of data and apply several econometric techniques to estimate gasoline demand responsiveness to price and income changes in the U.S. and compare results between periods that have high gasoline prices but differ in underlying economic conditions to draw policy implications such as; implementing a gasoline tax would be a viable solution to reduce gasoline consumption.

Chapter 4 is an extension of Chapter 3 and examines the dynamic effect of demand and supply shocks on gasoline prices in two very different markets: the U.S. and U.K. Both the U.S. and the U.K. extract and refine crude oil to produce gasoline and both are close to self-sufficiency in terms of gasoline production. However they differ markedly in market and consumption structure. The U.K. has the highest excise tax rate among industrial countries and the U.S. has the lowest. In the U.K. public transportation is widely available; in the U.S. it is almost essential to own and drive a motor vehicle to be mobile. In the U.S. most vehicles run on gasoline; in the U.K. diesel fuel usage is higher than that of gasoline. Finally, fuel efficiency standards are stricter in the U.K. and more relaxed in the U.S. These structural dissimilarities account for differences among determinants of gasoline prices and the dynamics of supply and demand conditions during the recent commodity boom followed by a recession in both countries.

The majority of work on gasoline markets focuses on determining the short-term or long-term sensitivity of gasoline consumption to changes in prices or income level. Some studies link movements in crude oil and gasoline prices. For example, Kilian (2009a) develops a joint structural VAR model of the global market for crude oil and the U.S. market for gasoline during sample periods of 1975-2008 and 2002-2008. He finds that each demand and supply shock had distinct dynamic effects on the real price of imported crude oil and on the retail price of gasoline in the U.S. He concludes that the *origin* of the shocks mattered when assessing price and consumption responses because price and consumption responses differed in magnitude, pattern and persistence to each demand and supply shock. Kilian also shows that the surge in gasoline prices in the U.S. between 2002 and mid-2008 was due to positive demand shocks in the global commodity market.

Chapter 4 follows a similar approach but *without* linking the domestic gasoline market to the global crude oil market. Instead the focus will be on the domestic gasoline market in each country. The price and the supply of crude oil are included indirectly through gasoline supply, since gasoline production depends on crude oil and its availability. Any shock to crude oil supply or price will impact gasoline supply. Hence, in this study by adopting a structural VAR model, the real price of gasoline is disaggregated into three components: gasoline supply shocks, global demand shocks and gasoline-specific demand shocks. It is important to split the effect of supply and two diverse demand shocks on gasoline prices but it is also important to understand the reverse: the response of supply and demand to shocks to gasoline prices. Because not only we attempt to explain the origin of the fluctuations in price of gasoline, but also to explain the consumer responses to price fluctuations in order to implement effective fuel or vehicle tax, energy and environmental policies.

Chapter 4 contributes to the empirical literature by attempting to explain the dynamic effects of shocks on gasoline markets in two distinctly different markets; the U.S. and U.K. during 1983-2012 and 1998-2012, respectively. To date no study has applied this framework on two structurally different countries and compared the results. Applying the same model to the U.S. and U.K. is helpful to observe the different market dynamics.

Chapter 5 and Chapter 6 focus on the impact of the volatility of commodity prices on the macroeconomic balances of the commodity producing countries.

Chapter 5 examines the procyclicality of fiscal policies in developing countries that produce crude oil. These countries are especially vulnerable to oil price volatility; for example, a small fall in prices could lead to a substantial increase in financing needs due to the lack of diversification in exports—oil revenue accounts for a large portion of their total revenue. In addition, developing countries that produce oil are typically characterized by an inability to accumulate financial assets or to gain access to credit markets, plus political, institutional, or budget structures that force their governments to react to oil price volatility by adopting procyclical fiscal policies. Many studies show that procyclical fiscal policies have damaging consequences for developing countries. When governments move to cut expenditures in response to a fall in oil revenue, poor people suffer the most due to the lack of social safety nets, and long-term economic growth is hampered as resources are withdrawn from productive projects.

Few studies have examined the procyclicality of fiscal policies and observed the main structural drivers—such as credit constraints, political structures and institutional quality of developing countries that produce oil, particularly during the recent period of high oil prices. Chapter 5 examines whether fiscal behavior is procyclical in 28 developing oil-producing countries (OPCs) by employing various econometric tests and using multiple variables to control for political structure, institutional quality and financial constraints. With this analysis, the study makes three contributions to the literature.

First, fiscal behavior is studied among different groups of OPCs by disaggregating the country sample into three subgroups according to their level of development, then conducting the cyclicality tests on the full sample, as well as on the subsamples. Since the OPCs are not a homogenous group, it is likely that their fiscal policies respond differently to oil price shocks due to significant variations in the extent of their dependency on oil revenue, economic development, political and institutional structure, financial positions, the level of existing oil reserves, and the degree of maturity in oil production. These variations make it essential to study both large-group and smaller-group fiscal behavior to discover whether countries with particular characteristics exhibit consistent fiscal policy patterns, which could be useful for designing effective policies.

Second, the cyclical behavior of several fiscal policy variables is tested: total expenditure and its components, public consumption and investment; the non-oil primary balance; and non-oil revenue. Most studies use either expenditure or consumption as a dependent variable. However, this chapter examines total government expenditure and its components, which will be a key contribution of the chapter for the following reason. Focusing only on aggregates can be misleading if their subcomponent movements offset one another. Thus, looking at the subcomponents separately may further illuminate the preferred direction of fiscal policy and reveal important policy implications; for example, a government may change either consumption or investment more in response to a change in output. Furthermore, the non-oil primary balance as a dependent variable will measure the injection/use of oil revenue in the economy and the overall level of fiscal effort. Finally, non-oil revenue will be a useful measure of the tax collection mechanism.

Chapter 6 examines another significant impact of commodity price volatility on the economies of commodity exporting countries: the volatility of their floating exchange rates. Their currencies appreciate when commodity prices increase due to sizeable export earnings which lead to a balance-of-payment surplus and accumulation of foreign reserves. Usually the reverse occurs—currencies depreciate during periods of commodity price declines, which subsequently reduces export revenues. High price volatility during the past commodity boom, which lasted more than 10 years, proved the key importance of forecasting commodity prices and understanding their effect on the exchange rates and economies of commodity producing countries.

Most of the earlier research explaining commodity price and exchange rate interaction is based on fundamental exchange rate models. Commodity prices are one determinant for nominal or real exchange rate behavior. These studies show the long-run effects commodity price changes on exchange rates as well as on macroeconomic fundamentals; interest rates, money supply, trade balance, wages, employment, and output. However these studies discovered that over the long run the link between fundamentals and exchange rates is insufficiently robust for consistent forecasting because the strength of the link varies among currencies and sample periods. Main explanation offered in the literature for this is that the fundamental variables are themselves endogenous to exchange rates and jointly determined with exchange rates in equilibrium. For example exchange rates might Granger-cause money supplies because monetary policy makers react to the exchange rate in setting the money supply.

To circumvent the endogeneity issue, recent studies pursue an asset-pricing approach. Instead of determining exchange rates through commodity prices, they argue that the exchange rates should be the predictor of commodity prices. Chen, Rogoff and Rossi (2010) (CRR thereafter) follow this approach, take the exchange rates as prices of forward looking financial assets and claim that exchange rates would better predict exogenous variables such as commodity prices than *vice-versa*, because exchange rates are fundamentally forward looking; i.e., incorporates expectations about the values of its future fundamentals whereas commodity prices tend to be very sensitive to small changes in current demand or supply balances. This would especially apply to currencies of commodity exporting small countries, because world commodity prices can reasonably be assumed independent of their exchange rates.

Chapter 6 pursues the asset-pricing approach and explores Granger causality for both directions; from the exchange rates to commodity prices and from commodity prices to the exchange rates, checks for parameter instability in Ganger-causality tests and finally tests out-of-sample forecasting ability of the exchange rates and commodity prices.

Chapter 6 makes two contributions to the literature. First, it analyzes a broader range of emerging and advanced countries which have a significant portion of their production and exports in primary commodity products. The set of countries is expanded to include countries that have not been studied before such as Brazil, Mexico, Indonesia, Norway and Korea. Second, the focus is on the type of commodities that these countries produce to see if that creates different dynamics between commodity prices and currencies. For example, Korea heavily depends on semiconductor chip exports whereas countries such as Chile or Mexico predominantly produce one type of mineral source or others such as Brazil, Australia or Canada produce and export minerals as well as various crops.

Finally, Chapter 7 presents the concluding remarks and future research ideas. Some of the key findings are as follows. Chapter 2 found a long-run cointegrating relationship between base metal spot prices, futures prices, inventories, and interest rates. Chapter 3 confirmed the structural change in the U.S. gasoline market where demand elasticities of gasoline price and income became more inelastic over the last decade. Chapter 4 showed that the impact of a positive aggregate demand shock on the gasoline market was larger than that of the other shocks in the U.S. Chapter 5 found that total expenditure was highly procyclical in the low and middle-income groups but countercyclical in high-income countries in the sample. Chapter 6 found stronger evidence of in-sample causality from exchange rates to commodity prices for most of the countries in the sample. One of the key findings was the consistent significant causality from exchange rates to commodities for Korea.

2 How Commodity Price Curves and Inventories React to a Short-Run Scarcity Shock

2.1 Introduction

The relationship between commodity spot and futures prices reflects, in part, the perception of short-term physical scarcity and the prevailing level of inventories. The slope of the futures curve, measured here as the difference between the price of a futures contract at some given maturity and the spot price, can thus provide information on whether market participants anticipate relative abundance (an upward sloping curve) or scarcity (a flat or downward sloping curve) in the physical market. Price curves also provide incentives for market participants to change their exposure to commodity prices.

A greater understanding of futures price curves and inventory dynamics can help market participants plan their responses to supply and demand shocks. It may also enrich the information that can be obtained from commodities futures markets, providing for a more informed interpretation of price developments. In this context, this chapter seeks to fill a gap in the existing literature and asks three key questions: In the event of a short-run shock, is there such a thing as a "normal" commodity market back towards which spot and futures prices and inventories adjust over time? How does a commodity market adjust to a temporary scarcity shock which moves the price curve away from this equilibrium? How quickly do inventories and prices adjust following such shocks?

Our interest is in temporary shocks to physical market balances which cause changes in the futures curve slope; in contrast, permanent or long-lasting shocks should have an impact across the futures curve, which may change the level of the curve but leave the slope little changed. The slope of the futures curve can change for one of three reasons: a change in interest rates; a change in physical storage costs; or a change in the market's perception of short-term scarcity and a compensating adjustment in the utility afforded by holding inventories. (Shifts in the risk premium afforded by holding commodity futures or in expected future spot prices should lead to a shift across the curve.)

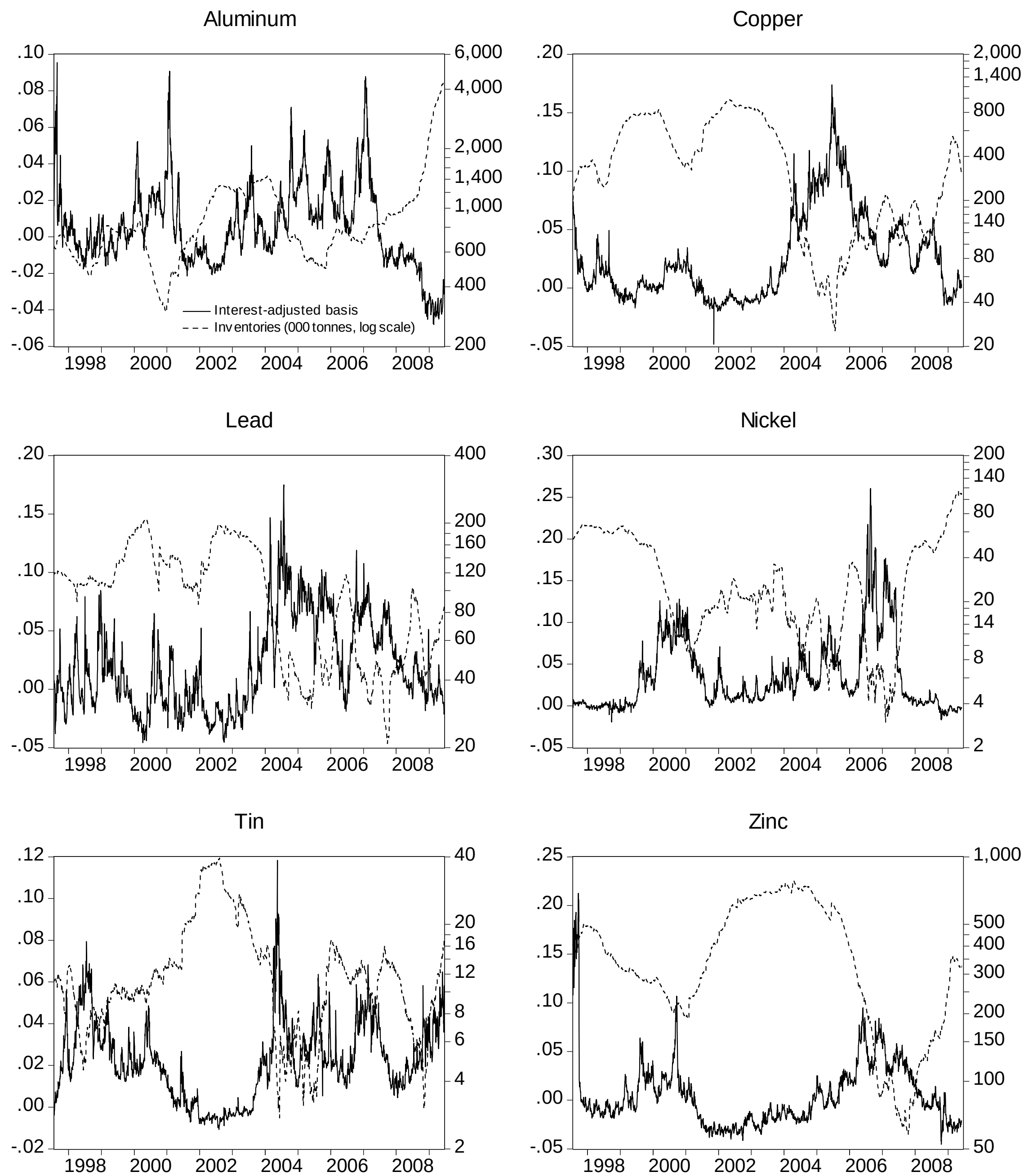
Large changes in the futures curve slope are rarely caused by the first two explanations. Although both interest rates and storage costs can move significantly over time, the very large discrete changes required to steepen or flatten futures curves sharply and rapidly are unlikely. Our analysis thus pertains to the effects of changes in actual or expected scarcity over short horizons. In most cases, these shocks will reflect actual or expected supply disruptions, as most demand shocks exhibit a higher degree of persistence.

We compare the adjustment of spot and futures prices and inventories to the predictions from a theoretical model developed by Pindyck (2001). In this framework, commodity cash and storage markets are interconnected and commodity market reaches equilibrium only when both markets clear via adjustment in spot and futures prices and inventory levels in case of a short-run demand or supply shock. Inventories play the role of a buffer to ease the pressure on spot and futures prices in response to a temporary shock.

We also focus on the possible existence of asymmetries in market reactions to temporary shocks. A strong clue about the nature of base metal price adjustment to shocks in different market states (usually defined by the inventory cycle) is provided by the interest rate-adjusted difference between spot and futures prices (which is a measure of the slope of the futures curve). As Figure 2.1 shows for six metals, this variable appears to be stationary over time. There also appears to be a degree of nonlinearity when the variable deviates from its average value, with large but short-lived spikes higher (backwardation) coexisting with more sustained, yet less dramatic, declines (contango).[1]

[1] Descriptive statistics of interest-rate adjusted basis are presented in the Table 2.A.1 in Appendix which show the average basis across metals are very similar in magnitude.

Figure 2.1 Base Metals: Interest rate-adjusted Basis and Inventories



The interest-adjusted basis is calculated as $s(t) - f(t,T) + r(t,T)$, where s is the log spot price, $f(t,T)$ is the log price of a futures contract at maturity T at period t, and $r(t,T)$ is the interest rate for over the period $T - t$.

Theory also guides us to expect asymmetric adjustment in the relationship between these variables. To address possible nonlinearity in commodity market adjustment, we apply self-exciting threshold vector autoregression models, in which the thresholds are determined by the nature of the disequilibrium; in practice, this is largely determined by the slope of the futures curve itself, which often reflects current and expected levels of inventories, and is thus closely related to the inventory cycle.

Most of earlier empirical studies which examined the relationship between commodity spot and futures prices ignored non-stationarity, even though it is now generally accepted that commodity prices are I(1) processes, at least over shorter-run samples. However, recent research work has focused on the cointegrating relationships between spot prices, futures prices, and inventories. There are only a few studies which applied an asymmetric threshold model to three base metals spot and futures prices without taking into account of the interest rate or inventory levels. Furthermore, these studies only used lower frequency data, i.e. monthly.

This chapter provides a technical contribution to the literature in a number of ways. First, we adopt a comprehensive self-exciting threshold approach which includes both inventories and interest rates along with spot and futures prices, building on previous work which has omitted one or more of these variables. Second, we compare the results from an empirical model to the predictions of a widely accepted theoretical model. Finally, we use higher frequency daily data, which should provide important insights given the relatively high liquidity and rapid adjustment patterns of the major commodity markets. Until now, there have been few studies on the interaction between inventories and commodity prices at a daily frequency, partly due to poor and infrequent data. Base metals, which include aluminum, copper, lead, nickel, tin and zinc, provide the richest data set, particularly as trading of spot, futures, and options is concentrated on the London Metals Exchange (LME).

The plan of the chapter is as follows. In the next section, we will give a brief literature review then followed by a discussion of the methodology and description of the model in section 3. We will discuss the data in section 4 and present and discuss the results in section 5 and finally conclude in section 6.

2.2 Literature Survey

The Keynes' (1930) theory of normal backwardation was first to examine the relationship between commodity futures and spot prices; it argued that futures prices should be discounted to compensate for the risk of holding the contract, therefore they would be below expected future spot price. Kaldor (1939) disagreed with this simple transfer of risk to determine commodity spot and futures prices, instead suggested the theory of storage (or cost-of-carry). In this model, the price of futures must be high enough to offset the spot price *plus* costs of carrying before delivery, which include charges for interest, insurance, and storage. Working (1948, 1949) pointed out that if a futures contract matures more than one period ahead, its price is not necessarily equivalent to the price of stored commodity. Thus, he expanded the cost-of-carry theory by including the convenience of holding inventories, referred to as a convenience yield, which can be described as a liquidity premium for commodity inventories held to avoid the cost of interrupted production. Working also explained that marginal convenience yield should be a declining function of inventory levels—the convenience yield of each additional unit falls in proportion to rising inventory. Many studies tested this model: Brennan (1958), Telser (1958), Fama and French (1988), and Deaton and Laroque (1997), among others. In particular, Fama and French (1988) concluded that among agricultural commodities, futures prices varied less than spot prices when inventory was low. Pindyck (2001) developed a theoretical model showing how commodity market reaches equilibrium via equilibrium in two interconnected cash and storage market in response to a short-run shock and demonstrated the implication of the model in the crude oil market. We take this model as a base to verify our empirical results.

Many earlier empirical studies used standard techniques such as ordinary least squares and ignored the non-stationarity in series, which produced spurious results even though it is recognized that futures prices are non-stationary. However, as new time series analysis techniques emerged, many studies incorporated them to test relationships between commodity prices and inventories: Heaney (1998), Watkins and McAleer (2006), and Crompton and Xiarchos (2008). Watkins and McAleer (2006) found cointegration between spot, futures, interest rates, and inventory levels for seven metals. Crompton and Xiarchos (2008) confirmed the cointegration among inventories, cash, and futures prices, and found causality from inventories to prices for aluminum, copper, lead, and zinc.

Studies similar to ours have been carried out only by McMillan (2005), and Koussie (2008). McMillan (2005) applied an asymmetric threshold model to three metals (aluminum, copper, and zinc) and found non-linear cointegration relationships between spot and futures prices where more rapid adjustment to equilibrium occurred when futures prices are greater than spot prices. However, interest rate and inventory levels were not included in this model. Similarly, Kouassie (2008) examined the dynamic and asymmetric interaction between inventories and prices of six metals by using Threshold Autoregressive (TAR) model and momentum TAR where he found cointegration with asymmetric adjustment between price and stock for all metals in the sample. However, Kouassie (2008) employed monthly data and excluded the interest rate, which is essential to determine metal prices.

Our study offers a more comprehensive approach to understanding non-linear behavior of commodity—metal—prices depending on the level of inventories. We base our estimation on a theoretical framework which incorporates all of the components that determine the dynamics between spot and futures prices which were omitted in the earlier studies. Furthermore, in the current digital age, information transmission is very fast which enables market participants to take action quickly in response to the news on changes in inventories. Therefore, it is important to observe the changes in a higher frequency data set. Earlier studies employed monthly data which is a much lower frequency during which many changes take place. The results based on the monthly data may fail to reveal the responses of prices on immediate changes in the market.

2.3 Methodology

We employ two theoretical models in our analysis. The first model is a modified version of spot and futures price arbitrage framework in a way that incorporates inventories and provides a base for empirical testing. The second one is the theoretical model developed by Pindyck (2001) which we build our empirical hypothesis on. With these models, we aim to test asymmetries in commodity market reactions to temporary shocks; futures prices adjust to changes in inventory levels much slower when market is in contango with abundant inventories while it adjusts much faster when in backwardation with lower inventories.

2.3.1 Spot and Futures Price Arbitrage for Financial Assets

Before analyzing the dynamics of market adjustment, it is worthwhile reviewing the theory behind the relationship between spot and futures prices. In particular, the well-known arbitrage condition that determines the relationship between spot and futures prices for financial assets rarely holds for commodities. The role of commodities as consumption and processing goods, and the pivotal importance of physical inventories, among other factors, lead to a more complex and dynamic relationship. To elaborate, we first present the cost-of-carry relationship for a financial asset, ignoring coupon or dividend payments, in a market without frictions. This states that the price of a futures contract at time t which specifies delivery at $T > t$ denoted by $F(t,T)$ is equal to the current spot price $S(t)$ multiplied by the continuously compounded interest rate r for the period t to T:

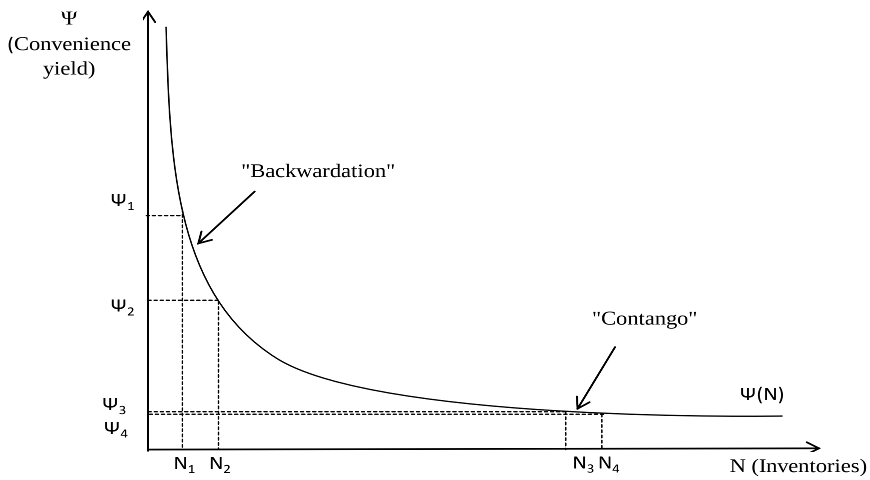
$$F(t,T) = S(t)\exp\left[r(T-t)\right] \tag{1}$$

2.3.2 Commodity Market Arbitrage between Spot and Futures

This relationship tends not to hold for commodities, for two main reasons. Spot and futures prices must take into account the costs of holding physical inventory, e.g., warehousing and insurance, which increases the “cost of carry” (which for financial assets includes only the interest rate). Also, market participants may hold physical inventory of a commodity for its value as a consumption good, rather than as a financial asset. The benefit that accrues to the inventory holder is often referred to as the "convenience yield".

We incorporate the physical storage costs, denoted by k, as a constant proportion of the spot price and this serves to create a small and—assuming that storage costs do not vary too much—a fairly stable wedge between the two sides of equation (1). The inclusion of the convenience yield for the marginal unit of inventory, denoted by ψ, leads to more profound changes. A number of theoretical models indicate that there should be a strong and non-linear relationship between the current and expected future level of inventories, which we denote by N, and the value of ψ. This nonlinearity reflects a declining marginal utility of inventories. In particular, as the level of current and expected future inventories falls, the probability of experiencing a physical "stock out" increases, and ψ should rise, at an increasing rate as inventories fall towards their zero bound (e.g., Deaton and Laroque, (1992) and Williams and Wright, (1991)). Stock outs can be very costly for the producers and users of the physical commodity as it can interfere with production and customer delivery schedules. This nonlinear relationship between convenience yield and current and future inventory levels (denoted by N) is summarized by Figure 2.2. This shows that the effect of a given change in inventories on the convenience yield is dependent upon the starting level of inventories:

Figure 2.2 Commodity Convenience Yield and Current and Expected Future Inventories



Incorporating these two features of commodity markets, storage costs and marginal convenience yields, into equation (1) obtains an arbitrage condition that is written as:

$$F(t,T) = S(t)\exp\left[\left(r + k - \psi(N)\right)(T - t)\right] \tag{2}$$

As described by Markert and Zimmermann (2006), these features of the commodity markets imply that there exists an arbitrage "upper bound" for commodity futures, when expressed in the form of standard financial asset interest rate arbitrage condition:

$$F(t,T) \leq S(t)\exp\left[r(T - t)\right] \qquad \text{where} \qquad \psi(N) - k \geq 0 \tag{3}$$

2.3.3 Price and inventory adjustment in backwardation

Equation (3) shows that current and expected future inventories play a key role in determining the shape of the futures curve. When inventories N are very low or expected to decline significantly and the probability of a physical stock out is relatively high, the marginal convenience yield ψ will be high. In other words, commodity producers, consumers, and processors will value highly the marginal unit of physical inventory. In this case, the futures curve may be in “backwardation”, with spot prices S higher than futures prices F. (When the spot price is higher than the futures price, the market is defined as “strongly backwardated”. When the spot price is below the futures price, but equation (3) holds as a strict inequality—i.e. the spot price is higher than the discounted value of the futures price—the market is defined as “weakly backwardated”.)

In a backwardated market, it is often assumed that the sensitivity of the marginal convenience yield net of storage costs (ψ-k) to changes, or expected changes, in inventories is very high (i.e. from Figure 2.2 we can see that $\partial\psi/\partial N$ is large). Starting from an initial condition of a tight physical market, with the inventory cycle near its low point (consistent with a backwardated market), small changes in expectations regarding the future path of inventories should have very large effects on the shape of the futures curve. In the case of a temporary supply shock which causes a large rise in the convenience yield and the spot price, expectations of a return to more “normal” physical market conditions should lead to a rapid reversal in these moves.

2.3.4 Price and Inventory Adjustment in Contango

When inventories are abundant and, conditional on demand projections, the probability of a physical stock out is low, the net marginal convenience yield (ψ-k) will be very low. In this case, assuming that physical storage costs are not too large, the spot price S will be lower than the futures price F and the futures curve will be in contango. As ψ reaches its zero lower bound, then interest rate arbitrage forces will limit the steepness of the curve. In particular, if S is lower than the discounted value of F, then the incentive and capacity to place an interest rate-based arbitrage trade will exist. Arbitrageurs will be able to take a long position in the spot market with a cost-of-carry equal to $r + k$ and take an offsetting short position in the futures markets, earning risk-free profits.[2]

In a contangoed market, the sensitivity of the net marginal convenience yield to changes, or expected changes, in inventories is very low (i.e. from Figure 2.2 we can see that the first derivative $\partial\psi/\partial N$ is small). Starting from an initial condition of a well-supplied physical market, with the inventory cycle near its high point (consistent with steep contango), even large changes in expectations regarding the future path of inventories should have relatively little effect on the shape of the futures curve. In this case, a temporary supply disruption would have only a modest effect on convenience yields and spot prices, as inventories would be sufficient to absorb the shock. In turn, the adjustment back towards equilibrium should also be more gradual.

2.3.5 A Nonlinear Price-Inventory Adjustment Model

In this section, we will propose an empirical model for this system of variables. The endogenous variables in our system, spot and futures prices and inventories, are all jointly determined and reflect current physical market conditions, but also expectations for the future. A natural question to ask is whether these variables share a stable long-run relationship; to put it differently, is there a futures market curve and level of inventories that together reflect "normal" or steady-state market conditions? During a normal market, it might be presumed that inventories, or stock-use ratios, are close to their average levels and the futures market curve reflects a steady-state perspective on the outlook, in particular with regard to the evolution of inventories in future periods. In other words, the system is anchored over the long-run by a steady-state level of inventories.

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[2] Mabro (2009) provides an example in oil markets where ample oil supplies in August 1997 and in 2008 moved the term structure of futures prices into a very steep contango. The increasing differential between spot and futures contracts gave sufficient incentives for traders to buy physical oil to add to inventories and sell a futures contract. This resulted in an inventory build-up subsequently pressuring prices flattening the term structure in 1998 and 2009, respectively.

We can test the hypothesis of long-run equilibrium existence by assessing evidence for a long-run cointegrating relationship between the endogenous variables *S*, *F*, and *N* and the exogenous variable that theory suggests should also determine curve slope, the interest rate *r*. We can write such a hypothesized relationship using the log-levels of each of these variables (with the exception of interest rates which are in levels) and normalizing with respect to the spot price *s* as:

$$s_t = \beta_1 + \beta_2 f_{t,T} + \beta_3 n_t + \beta_4 r_{t,T} + z_t \tag{4}$$

In (4), s_t is the log of the spot price, $f_{t,T}$ is the log of the futures price, n_t is the log of inventories, and r_t is the interest rate level. The constant β_1 can be interpreted approximately as a mean net marginal convenience yield and the unconditional expectation of *z* is zero. The β_1 can only be interpreted as an approximate mean net marginal convenience yield due to the presence of inventories on the right-hand side of equation (4).

How can we interpret the residual *z*? Comparing (4) with (2), it can be seen that the residual *z* is closely related to the concept of the net marginal convenience yield and, in our specification with current inventories as an explanatory variable, it approximately represents deviations from the average convenience yield. Because we have included current inventories on the right-hand side as an endogenous variable, this deviation in convenience yield arises from unobserved variables, principally expectations of future inventories and spot price volatility. The absolute values of the estimated coefficients may also diverge from unity, which means that a direct comparison with convenience yields cannot be made.

Equation (4) has implicitly assumed that the convenience yield over the long-run is a linear function of inventories; the nonlinearity in our model will instead emerge from the short-run dynamics of adjustment back to equilibrium. In particular, we test whether the initial level of *z* captures information regarding expected inventories and whether this in turn will affect how z converges back to zero. In other words, z is the self-exciting threshold process in this model.

2.3.6 Empirical Specification of the Nonlinear Adjustment

One way to model the potential nonlinearity of the process $\{z\}$ from equation (4) is suggested by Figure 2.2; that is, to follow Martens, Kofman, and Vorst (1998) and hypothesize that it might be described by a threshold autoregressive model, with the speed of adjustment determined by lagged values, such as:

$$z_t = \phi_0^{(j)} + \sum_{i=1}^{p} \phi_i^{(j)} z_{t-i} + \varepsilon_t^{(j)} \qquad k_{j-1} < z_{t-d} \le k_j \tag{5}$$

In this model, j indexes the thresholds separating regimes, d is the lag of z which determines the threshold, and k denotes the value of the thresholds. This specification provides a linear approximation for the adjustment process in each regime; in other words, in each regime it assumes a different linear adjustment process, characterized by varying autoregressive parameters ϕ and speeds of adjustment.

One of the hypotheses we wish to test is whether there is a band around the equilibrium (i.e. a “middle regime”) which is characterized by a random walk and two outer regimes in which the process converges back towards equilibrium. This is a common finding for financial assets and is often interpreted as a mispricing that is not sufficiently large and profitable to arbitrage away due to transaction costs (e.g., Martens, Kofman, and Vorst, (1998)).

A priori, we can only hypothesize about the value of the thresholds and the nature of the regimes; the thresholds will be estimated from the data. For now we assume that the forward curve process summarized by $\{z\}$ from equation (4) is subject to two thresholds and three regimes which are determined by the value of z itself (i.e., the threshold process is self-exciting). We hypothesize that these regimes are: (i) a lower regime, in which z is negative and the forward curve is upward sloping and steep (contango); (ii) a middle regime in which z is close to zero and the system is close to equilibrium; and (iii) an upper regime in which z is high and the forward curve is either relatively flat or inverted (backwardation). We can now write this model as:

$$z_t = \begin{cases} \phi_0^{(l)} + \phi_1^{(l)} z_{t-i} + \varepsilon_t^{(l)} & z_{t-1} < \underline{z} \\ \phi_0^{(m)} + \phi_1^{(m)} z_{t-i} + \varepsilon_t^{(m)} & \underline{z} \le z_{t-1} \le \bar{z} \\ \phi_0^{(u)} + \phi_1^{(u)} z_{t-i} + \varepsilon_t^{(u)} & z_{t-1} > \bar{z} \end{cases} \tag{6}$$

Where each of the regimes is listed respectively.

2.3.7 Applying a Threshold Vector Error-Correction Model

The system described by (6) allows us to test formally for the existence of nonlinearities, but it does not provide any guidance related to which variable (spot or futures prices or inventories) takes the burden of adjustment when the system deviates from equilibrium. A natural way to understand these features is by applying a threshold vector error model (T-VECM). In this model, global behavior is defined by the cointegrating vector and its residual z. Local behavior (or short-run dynamics) is described by the adjustment coefficient on the cointegrating vector and the coefficients on the lagged first-differences. This model can then be written as:

$$\Delta \mathbf{X}_t = \mathbf{A}_0^{(j)} + \sum_{k=1}^{K} \mathbf{A}_k^{(j)} \Delta \mathbf{X}_{t-k} + \boldsymbol{\beta}^{(j)} z_{t-1} + \sum_{l=0}^{L} \mathbf{C}_l^{(j)} r_{t-l} + \mathbf{E}_t^{(j)} \tag{7}$$

where: the superscript j indexes the regime, $\mathbf{X}$ is the (3x1) vector of endogenous variables, including the spot price, futures price, and inventories; Δ is the first difference operator; $\boldsymbol{\beta}$ is the (3x1) vector of adjustment coefficients; z_{t-1} is the lagged value of the variable described in equation (4); $\mathbf{C}$ is a (3x1) vector of coefficients on the exogenous interest rate r; and $\mathbf{E}$ is the (3x1) vector of reduced form residuals.

2.4 Data

The source of the base metals spot prices, futures prices, and inventories data is the London Metal Exchange (LME) which accounts for the largest share of trading in base metal spot and futures markets. For example, about 95 percent of the total world trade in copper futures occurs through the LME. The LME also provides storage facilities to make it possible for market participants to take or make physical delivery of metals. For futures prices we use two different contract maturities: three and six months. The interest rates are the three-month and six-month London interbank offered rates (Libor), as calculated by the British Bankers' Association. The sample period spans from July 23, 1997 to June 19, 2009. The start date is determined by the availability of all the data series at a daily frequency. The data were downloaded from Bloomberg L.P. Summary statistics are provided in Table 2.1. in which inventories are in metric tons and prices are in USD per metric tons. Prices of the base metals vary according to their rarity and extraction costs, ranging from around $15,000 per ton (nickel, tin), through $5,000 per ton (copper) down to around $1,500 per ton (aluminum, lead, zinc), observed in mid-2009.

Annual production of aluminum reached 38 million tons in 2008 which exceeds the output of all other industrial and precious metals combined. Copper, zinc and lead are the metals that are produced largest after aluminum; 18, 11 and 8.1 million tons, in 2008 respectively. The production of nickel and tin are much smaller in the same year than the previous four metals 1.4 and 0.4 million tons, respectively. The magnitude of production reflects the level of global demand. Aluminum, copper and zinc are the most commonly used base metals in various consumer products such as automobiles, building and infrastructure construction, electronics and packaging. Similar to production levels, volume of base metals traded on the LME is dominated by the aluminum, copper and zinc contracts, which combined represent around 85% of all turn over on the exchange. Aluminum is the most actively traded metal on the LME. The annual volume of LME aluminum trade in 2008 was 30 times the physical production. Although less than 1% of contracts are settled with physical delivery, all LME contracts are backed by physical metals, allowing those in the industry to sell excess stock in times of over-supply and source material in times of shortage. As a result, in order for this system to function efficiently, the LME has arranged a system for storing and delivering metals. The average level of LME inventories in Table 2.1 represents the overall magnitude of production for each metal. Average stocks can be ranked from the highest to the lowest as aluminum, copper, zinc, lead, nickel and tin. In addition to LME inventories, there are stocks held by the commercial companies but it is very hard to keep track of. Hence, the LME inventories are used in the market as a gauge of immediate availability of metals. Furthermore, unlike many commodities, the base metals show negligible seasonal variation in their supply, stock levels and only minor seasonal variation in demand. Due to high spread between spot and futures prices, investors went long and accumulated LME aluminum stocks which reached the record levels in 2009 and increased the average of stock figures further shown in Table 2.1.

As the initial step of our analysis, we assess the order of integration of the endogenous variables and interest rates using the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests. There are no theoretical reasons to suggest that the endogenous variables should be stationary. Interest rates should be expected to remain bounded over the very long run, but it is widely reported in the literature that interest rates follow integrated processes, a result which may be due in part to the low power of standard unit root tests in small samples (see Wu and Zhang, 1997). Overall, we were unable to reject the null that all of the log levels of each of these series, including interest rates, contain a unit root at standard levels of confidence, although there was clear evidence of stationarity for the first-differenced data (see Appendix Table 2.A.2). These results are consistent with those for base metal data as presented in McMillan (2005), Kouassie (2008), and Watkins and McAleer (2006).

Table 2.1 Base Metal Price and Inventory Series: Summary Statistics

	Levels				First differenced logs			
	Mean	Standard deviation	Skew	Kurtosis	Mean	Standard deviation	Skew	Kurtosis
Aluminum								
spot price	1,787	526	1.0	2.7	0.00	0.01	-0.30	5.92
futures price (3-month)	1,804	529	1.1	2.7	0.00	0.01	-0.30	6.28
futures price (6-month)	1,811	529	1.1	2.8	0.00	0.01	-0.38	6.42
inventories	935,013	597,629	3.3	15.9	0.00	0.01	4.63	47.40
Copper								
spot price	3,368	2,309	1.1	2.7	0.00	0.02	-0.12	7.84
futures price (3-month)	3,350	2,280	1.1	2.7	0.00	0.02	-0.13	8.01
futures price (6-month)	3,316	2,241	1.1	2.7	0.00	0.02	-0.13	8.40
inventories	402,435	285,122	0.4	1.8	0.00	0.01	5.18	91.29
Lead								
spot price	976	739	1.8	5.9	0.00	0.02	-0.18	6.84
futures price (3-month)	975	732	1.8	5.8	0.00	0.02	-0.21	7.53
futures price (6-month)	966	721	1.9	5.8	0.00	0.02	-0.25	8.12
inventories	101,671	50,669	0.3	1.9	0.00	0.02	10.04	240.87
Nickel								
spot price	13,515	10,151	1.7	5.6	0.00	0.02	-0.12	6.97
futures price (3-month)	13,367	9,817	1.6	5.2	0.00	0.02	-0.16	7.09
futures price (6-month)	13,123	9,449	1.6	5.0	0.00	0.02	-0.16	7.16
inventories	32,674	23,950	1.0	3.6	0.00	0.02	1.19	23.95
Tin								
spot price	8,022	4,522	1.6	5.1	0.00	0.02	-0.09	11.81
futures price (3-month)	8,011	4,511	1.6	5.1	0.00	0.02	-0.12	12.13
futures price (6-month)	7,979	4,478	1.7	5.2	0.00	0.02	-0.13	12.16
inventories	13,069	7,988	1.6	5.1	0.00	0.03	2.96	38.18
Zinc								
spot price	1,493	896	1.6	4.6	0.00	0.02	-0.37	7.19
futures price (3-month)	1,502	887	1.6	4.5	0.00	0.02	-0.32	7.15
futures price (6-month)	1,500	862	1.6	4.4	0.00	0.02	-0.30	7.04
inventories	385,746	208,802	0.3	1.8	0.00	0.01	6.21	92.51

2.5 Estimation and Results

Ideally, testing for cointegration and thresholds could be achieved using a single, consistent approach. However, as pointed out by Balke and Formby (1997), the threshold variable itself is determined by the cointegrating vector, which itself must be estimated. In other words, some of the alternative hypotheses have “nuisance” parameters—namely the thresholds—that do not form part of the null of no cointegration/linearity, which results in a nonstandard inference problem.

Consequently, we follow their suggestion to approach the analysis in two stages: first, an assessment of global behavior, with tests for cointegration; and second, assessing the local behavior of the time series, which tests for nonlinearity.

2.5.1 Testing for Cointegration

An inspection of Figure 2.2 suggests that a reasonable starting point is to assume that the spot price, futures price, relevant financing interest rate, and possibly the level of inventories, are cointegrated, in the form of equation (4). Although the relationship may change based on the shape of the futures curve—which could influence the local behavior of the equilibrium error *z*—the system should be eventually drift back towards equilibrium. There is no well-developed model that would suggest inventories should share a long-run linear relationship with the other variables; rather, a short-run nonlinear relationship is often suggested. For now, we include inventories in all of the cointegration tests to ensure our specification does not suffer from omitted variable bias.

We test for cointegration using the Philips-Perron and Engle-Granger tests based on the residuals from equation (4). Although the Johansen (1988) test has become the standard procedure for multivariate systems, Balke and Formby (1997) present evidence that this procedure may have particularly low power for asymmetric systems when compared to the Philips-Perron test. Enders and Siklos (2001) construct a direct test for asymmetry in a cointegrated system, but they acknowledge that this also suffers from particularly low power for a standard Threshold Autoregressive Model (TAR) model.

2.5.2 Strong Evidence in Favor of Cointegration

In fact, regardless of the tests used, we find strong evidence for cointegration (Appendix Tables 2.A.2 and 2.A.3). The estimates of equation (4) obtain coefficients that, in most cases, are statistically significant and close to what theory predicts based on equation (2) (Table 2.2). For example, after normalizing on the spot price the coefficients on the futures prices are close to one. The coefficients on interest rates are negative, but for the most liquid contracts (aluminum and copper) they are greater than one in absolute value. Inventory coefficients are negative, indicating that higher physical stocks are consistent with lower spot prices (keeping all else constant), although the economic significance of these coefficients is very low.

The constants in all cases (β_1 from equation (4)), except zinc are positive, which means the futures curve is flatter (steeper) when in contango (backwardation) than standard interest rate arbitrage relationships would predict. This reflects the constant component of the non-zero average convenience yield (net of storage costs) which is independent of inventories; even when inventories are high, there remains a non-zero probability of stock-outs and together with other utilities obtained from holding physical stocks.

Table 2.2 Long-Run Cointegrating Relationships between the System Variables

	Aluminum	Copper	Lead	Nickel	Tin	Zinc
			Three-month			
Constant	0.13***	0.31***	0.51***	0.14***	0.12***	-0.23***
	(0.01)	(0.005)	(0.01)	(0.01)	(0.01)	(0.01)
Futures	1.01***	0.99***	0.99***	1.00***	1.00***	1.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Inventories	-0.01***	-0.02***	-0.04***	-0.02***	-0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Interest rate	-1.44***	-1.12***	-1.16***	0.61***	-0.76***	0.64***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	0.99	1.00	1.00	1.00	1.00	1.00
Durbin-Watson stat	0.12	0.21	0.14	0.12	0.12	0.09
Observations	3108	3108	3108	3108	3108	3108
			Six-month			
Constant	0.30***	0.70***	0.98***	0.28***	0.20***	-0.58***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)
Futures	1.02***	0.98***	0.98***	1.01***	1.00***	1.05***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Inventories	-0.03***	-0.04***	-0.07***	-0.04***	-0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Interest rate	-1.38***	-0.97***	-0.93***	0.61***	-0.78***	0.91***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
R-squared	1.00	1.00	1.00	1.00	1.00	1.00
Durbin-Watson stat	0.03	0.06	0.06	0.05	0.05	0.03
Observations	3108	3108	3108	3108	3108	3108

Significance at the 1, 5, and 10 percent levels denoted by ***, **, and * respectively

2.5.3 Testing for and Locating Thresholds

Does the adjustment depend on the initial slope of the curve? In particular, we are interested in the speed with which the market adjusts to scarcity shocks, and which variables take the burden of adjustment. To achieve this, we implement the ordered autoregression described by Tsay (1989) in which the cases are arranged according to the values of a particular regressor.

To identify the appropriate autoregressive structure, we assessed both partial autocorrelation functions and information criteria and find that the AR process is strongly determined by the first lag (see Appendix Tables 2.A.5 and 2.A.6). This is not surprising given that commodity markets assimilate all new information quickly, weakening the influence of lags greater than one period. As a result, we assume no delay and a simple AR(1) process, which involves ordering the regressions according to the values of last period's equilibrium error, or z_{t-1}. This allows us ensure that the observations in a particular group follow the same AR process, conditional upon accurate identification of the thresholds.[3]

2.5.4 Strong Evidence in Favor of Nonlinearity

We conduct two tests for non-linearity of the ordered autoregressions: the Andrews-Quandt breakpoint test and the Tsay (1989) test.[4] We find clear evidence of at least one break in all of the commodity relationships and proceeding iteratively, we find evidence for two or more breaks (see Appendix sections 2.A.2 and 2.A.3 for detailed results). The evolution of the equilibrium error over time, and the location of the thresholds is shown in Figure 2.3 for the six-month relationships. These breaks indicate

[3] We also ran the threshold identification procedure for AR(3) processes, consistent with Akaike information criteria, and found that the results were mostly identical (or very close) to those obtained from an AR(1).

[4] We supplement this approach less formal analysis of AR(1) coefficient t-ratio scatter plots, obtained from recursive least squares regressions. This yielded less clear-cut conclusions, but tended to support the number and location of the thresholds obtained from the formal methods described. Details are available on request from the authors.

that the speed of adjustment back towards equilibrium is conditional upon the size and sign of the deviation itself (Table 2.3).

The threshold locations are similar across each of the metals and correlated significantly with the slope of the futures curve (Table 2.3). When the equilibrium error *z* is below the lower threshold, the market is very likely to be in contango, with the spot price below the futures price. In contrast, when *z* is above the upper threshold, the market is much more likely to be in backwardation, with spot prices above futures prices.

Table 2.3 Threshold Values and Curve Slope: Percent of Time in Contango[5]

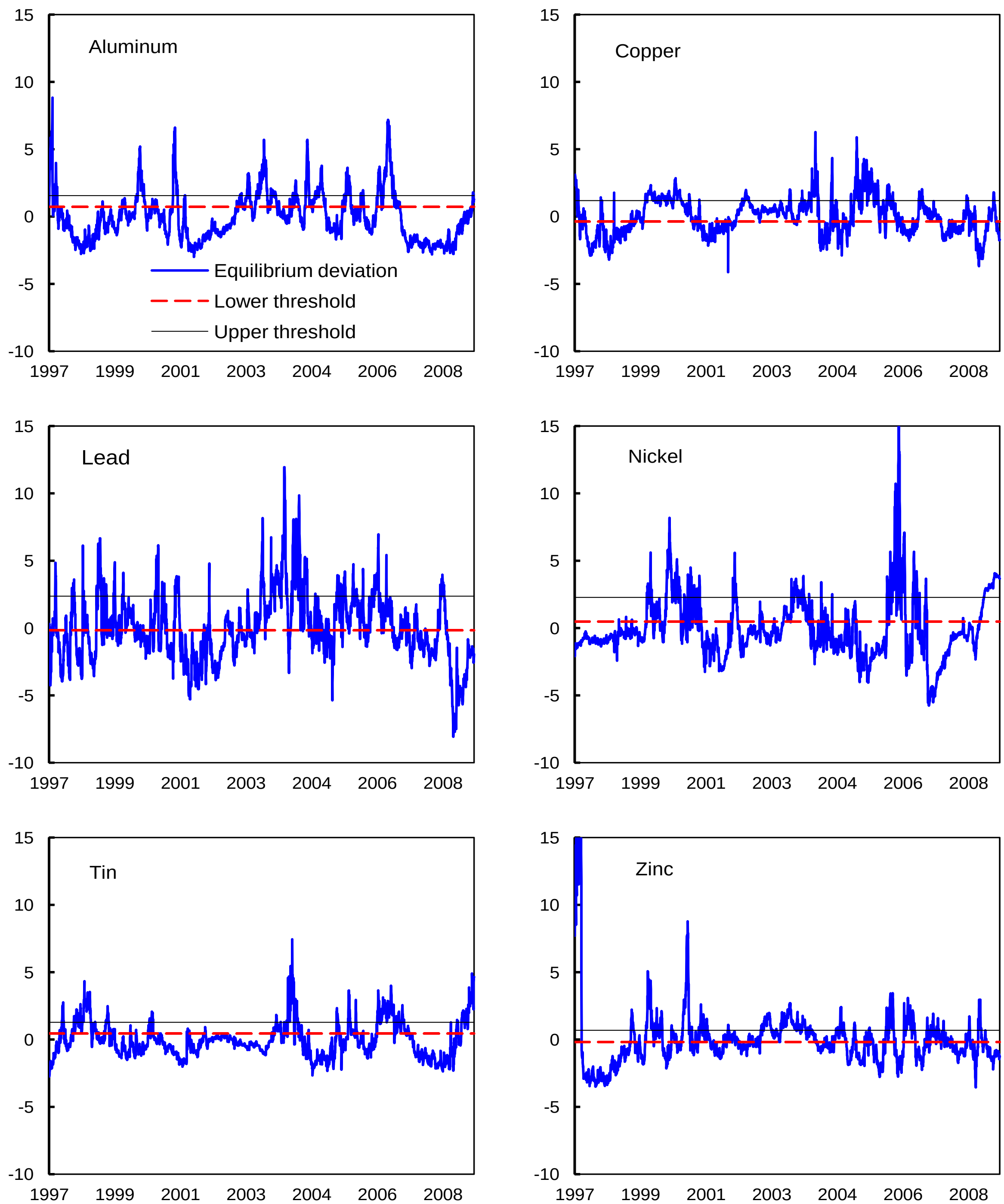
	When equilibrium error *z* is:			
	below lower threshold	between upper and lower	above upper threshold	Correlation of z with curve slope
Aluminum	100.0	94.7	22.1	0.91
Copper	74.5	59.4	48.1	0.42
Lead	88.3	69.9	13.8	0.65
Nickel	56.9	67.1	22.7	0.64
Tin	76.7	48.9	0.0	0.77
Zinc	94.6	88.2	46.9	0.89
Aluminum	96.6	55.6	8.2	0.85
Copper	65.3	56.8	42.7	0.36
Lead	73.2	35.3	3.2	0.61
Nickel	53.5	6.1	24.7	0.55
Tin	69.0	4.8	0.0	0.71
Zinc	88.3	77.7	48.8	0.76

We do not find evidence of a "no arbitrage" band in metals markets similar to that typically found for financial assets. The autoregressive structure of *z* is stable in all three regimes and the speed of convergence is typically faster in the middle regime which is closest to equilibrium. This indicates that transaction costs do not play a significant role in the commodity market adjustment. For the remainder of the analysis, we continue to divide the adjustment paths based on these three regimes, however. Assessing whether adjustment to temporary shocks is significantly different from when

[5] Defined as the futures price at the given maturity being above the spot price.

the market is initially close to equilibrium will provide an important insight into the nature of commodity market dynamics.

Figure 2.3 Deviations from Equilibrium and Identification of the Thresholds



2.5.5 Adjustment to Temporary Shocks

We assess how the system of spot and futures prices and inventories responds to temporary shocks by estimating separate VECM models for each of the three regimes. The cointegrating vector for each commodity (i.e., the coefficients on the level variables in the VECM) is the same in each regime, with the estimates taken from equation (4) we used to test for cointegration. We proceed to estimate the system (7), using the optimal lag lengths identified in Appendix Table 2.A.4. The results that follow use the six-month futures contract; the results with the three-month contract are qualitatively similar but less pronounced.

2.5.5.1 Describing the Curve Shock—a short-term spot price shock

Our main interest is in the behavior of the three variables when the relationship between them is in a disequilibrium caused by a temporary shock in the physical market; to create this condition, we apply a shock to the slope of the futures curve for the VECM in each regime. As discussed above, the most likely cause of a sharp and rapid change in the slope of the futures curve is a shift in actual or perceived short-term physical scarcity and a corresponding change in the marginal convenience yield. Interest rates and storage costs, the other two factors which explain the gradient, are unlikely to experience discrete jumps sufficient to match the observed volatility in curve slopes.

Why should the change in scarcity premium be confined to the short-term? If expectations of changing long-term scarcity emerged, then we should expect to see a permanent change in spot prices and, as a result, a shift across the entire futures curve. This would leave the slope constant (or at least little changed) and the system would remain in, or very close to, equilibrium.

The implication of these arguments is that these short-term futures curve shocks are most likely characterized by spot price shocks. Futures prices will be anchored by expectations that the supply shock should eventually dissipate and that market participants will be able to smooth the adjustment over time, in part by managing their inventories. Ideally, we would want to impose a structural spot price shock to the VECM system. One method would be to impose a Choleski ordering on the system, but this approach runs into some difficulties due to the challenges in disentangling spot and futures price shocks. The contemporaneous correlation between log changes in spot and futures prices is very high (above 0.9 for all metals), while the correlation when one of the price changes is lagged one period is very low and statistically insignificant. The correlation between the reduced form VECM residuals for the spot and futures price equations is also above 0.9 for all metals.

Alternative restrictions are suggested by theory and the nature of the data. For the system with four variables, we require at least $(n^2-n)/2 = 6$ restrictions. The first set of restrictions we apply is that interest rates are exogenous to all other variables in the system. The second set of restrictions is that there are no contemporaneous effects from inventories to prices (or *vice versa*). Inventory data, which may affect prices, are only available from the LME with a one day lag, while movements in physical inventories are unlikely to respond to price signals during the same day, in large part due to logistical constraints. One final restriction that we apply is that the futures curve moves in parallel in response to a futures price shock; in other words, the contemporaneous coefficient on the futures price change in the spot price equation is 1. The justification for this restriction is that the futures price can rise or fall as a result of changes in either the expected future spot price or the risk premium, which compensates the holder of the futures contract for holding the exposure to commodity price volatility. Arbitrage then links the spot price to the futures price, ensuring that these changes are reflected one-for-one in the spot price. For example, if the risk premium declines, leading to higher futures prices, then for unchanged carrying costs and convenience yield, the spot price must also increase by the same amount. This is because at the time of the futures contract's specified physical delivery; there is no difference between holding the spot or the future. Today's spot price can then be discounted back from the futures price by the carry cost and the convenience yield.

We apply a 1 percent positive shock to the spot price which, given the restrictions described above, implies shocks to the reduced form residuals in the spot and futures price equations of *1/(1-b)* and *b/(1-b).* The parameter *b* is the contemporaneous coefficient of the log change futures price on the log change spot price. For all commodities and all regimes, the estimate of this coefficient from the estimated VECM is between zero and one, implying that futures prices respond positively, but less than one-for-one to spot price shocks. In almost every case, the sensitivity of the futures to the spot price is highest in regime 1 when the curve is upward sloping (average 0.6) and lowest in regime 3, when the typical curve is backwardated (average 0.3). This difference likely reflects the dominant effects of the convenience yield on spot prices in backwardation.

2.5.5.2 A Theoretical Framework to Assess the Empirical Results

In this section, we compare the dynamics of adjustment as implied from our empirical approach to those of the theoretical model outlined by Pindyck (2001). Pindyck characterizes commodity market equilibrium as the outcome of interactions in the cash and storage markets. Total demand (denoted by *Q*) in the cash market is a function of the spot price (*P*), other demand shift variables z_Q (e.g., the effect of macroeconomic policies), and random shocks ε_Q (e.g., tastes and technologies). The supply of a commodity in the cash market (denoted by *X*) is also a function of the spot price, other variables affecting supply z_X (e.g., input costs), as well as random shocks ε_X, such as strikes or other unexpected supply disruptions. In equilibrium, net demand, which is the demand for production in excess of consumption, must equal the change in inventories ΔN by identity, so that we can write the cash market equilibrium as:

$$\Delta N_t = X\left(P_t; z_{Xt}, \varepsilon_{Xt}\right) - Q\left(P_t; z_{Qt}, \varepsilon_{Qt}\right) \tag{8}$$

The inverse net demand function can then be written as:

$$P_t = f\left(\Delta N_t; z_{Xt}, z_{Qt}, \varepsilon\right) \tag{9}$$

The inverse net demand function is upward sloping in ΔN; in other words, an increasing rate of inventory accumulation requires higher spot prices to increase supply and reduce demand.

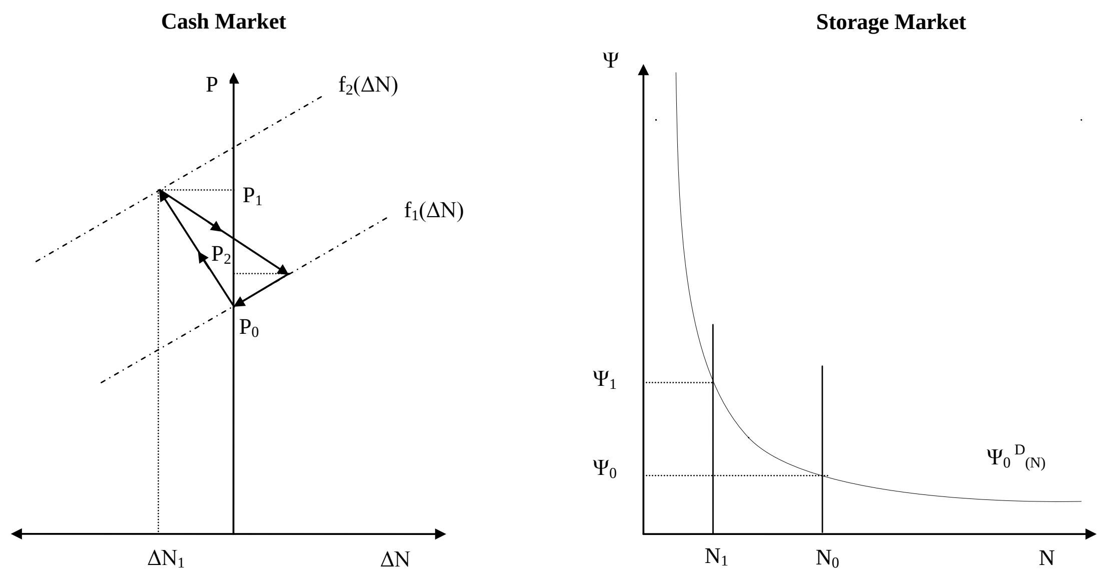
In storage market equilibrium, as described by Figure 2.2 above, the marginal convenience yield ψ is a function of inventory levels N and other variables, including price volatility σ, future and current consumption rates z_3 and random shocks ε_3. This can be written as:

$$\psi = g\left(N; \sigma, z_\psi, \varepsilon_\psi\right) \tag{10}$$

Given the values for σ and z_ψ equilibrium in the storage market gives ψ_t and N_t. Then given the values and N_{t-1}, z_X, and z_Q, we can find ΔN and solve for P.

What does the model predict in the event of a temporary supply shock? We will assume that a particular metal market is in a steady-state equilibrium with $\Delta N = 0$. Now consider that the effects of an unanticipated strike at a particularly large mine. This will decrease supply X and cause the net demand function to shift upwards and the spot price to rise (see Figure 2.4). Because the shock is seen as temporary, inventories will be run down, limiting the increase in spot prices, and the marginal convenience yield will increase. Futures prices will likely rise, but by less than the spot price, which will flatten or even invert the futures curve. Once the strike ends, the net demand curve will shift lower, but until the marginal convenience yield returns back to ψ_0, spot prices will fall but remain above the initial level to ensure that production exceeds consumption and inventories are rebuilt. The futures curve will move back towards its equilibrium slope as spot prices fall by more than futures prices.

Figure 2.4 Effect of Temporary Supply Shock



Source: Pindyck (2001)

2.5.5.3 Comparison between Theoretical Predictions and Empirical Results

How well does this theory predict the effects of short-term supply shocks in metal markets? Figure 2.5 presents the cumulative impulse responses from the estimated VECM models in each regime. A 1 percent spot price shock leads to a change in the log level of spot prices by more than the initial shock. This is because the spot price contemporaneously affects the futures prices, which in turn has feedback effects on the spot price, and so on. Initially, the curve flattens or inverts as spot prices increase by more than futures in each case, but the dynamics thereafter contrast sharply in each regime.

In many cases, the increase in spot and futures prices is gradually and partially reversed over time, as predicted by Pindyck's model. This pattern is strongest in regimes 2 and 3, where the market started out close to equilibrium or was already in a state of relative short-term scarcity. Inventories also tend to fall, as predicted, albeit more gradually than prices, as market participants run down stocks in response to scarcity in the physical market. In some respects, the empirical results confirm the predictions of the theoretical model, but there are three important discrepancies: the behavior of prices in steep contango (regime 1); the permanence of the effects on price and inventory levels of an initial spot price shock; and different outcomes for specific metals.

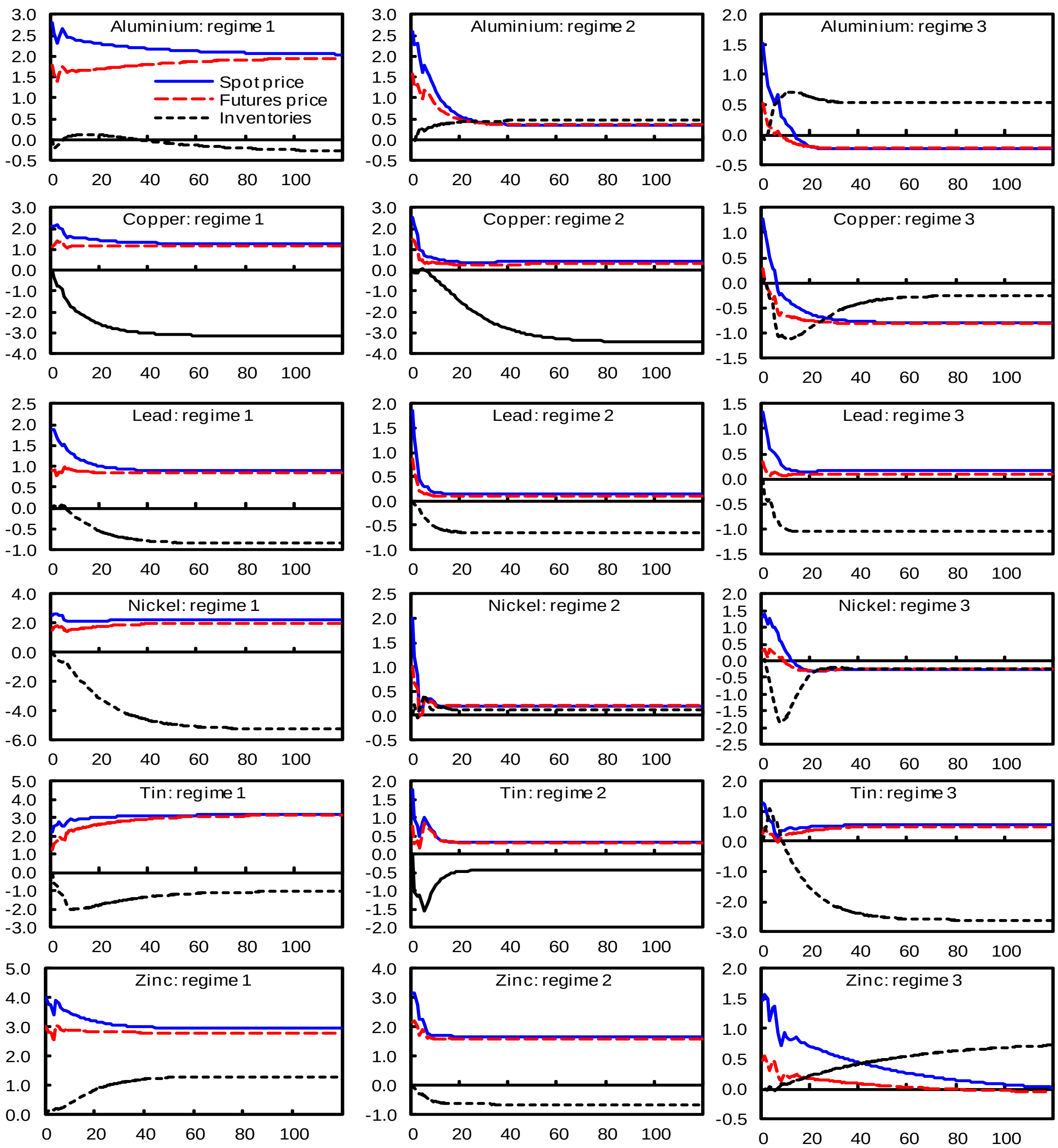
What can explain the apparent permanent change in spot and futures prices and inventories following a spot price shock? In our framework, we have interpreted an identified spot price shock as the result of a scarcity shock. This is an intuitive approach consistent with the predictions of most theoretical commodity price models for the instant response to a supply disruption. However, our results indicate that some of the effects from a spot price shock are permanent. In particular, in contango for many metals, a spot price shock leads to: a permanent shift higher across the futures curve; a modest flattening in the futures curve, with spot prices relatively higher than futures prices as compared to before the shock; and a compensating permanent decline in inventories. (In the long-run equations, the coefficient on inventories is small, which means that a relatively large decline is accompanied by only a small change in the slope of the futures curve.)

These results suggest that some spot price shocks have a permanent effect, perhaps due to learning over time. An initial supply disruption may, over time, be recognized as a more persistent impairment of supply capacity. Examples might include deteriorating ore quality in well-established mines or strikes which persist for months rather than weeks. In these cases, the market would learn gradually about the new supply environment, preventing a decline in prices to the levels which prevailed before the shock. This suggests that alternative identification methods may also be useful in exploring the effects of temporary scarcity shocks, including Blanchard-Quah decompositions.

When the futures curve is steeply upward sloping (regime 1), a spot price shock has relatively large effects on the futures price (albeit less than one-for-one). This means that given the same initial shock to the curve originating in the spot price, the entire curve shifts much higher than in other regimes. This suggests that in a market with abundant inventories and steep contango, markets perceive that spot price shocks are more likely to reflect longer-lasting changes in market conditions.

Figure 2.5 Impulse Responses from a Spot Price Shock

(Equivalent to a one percentage point futures price curve shock)



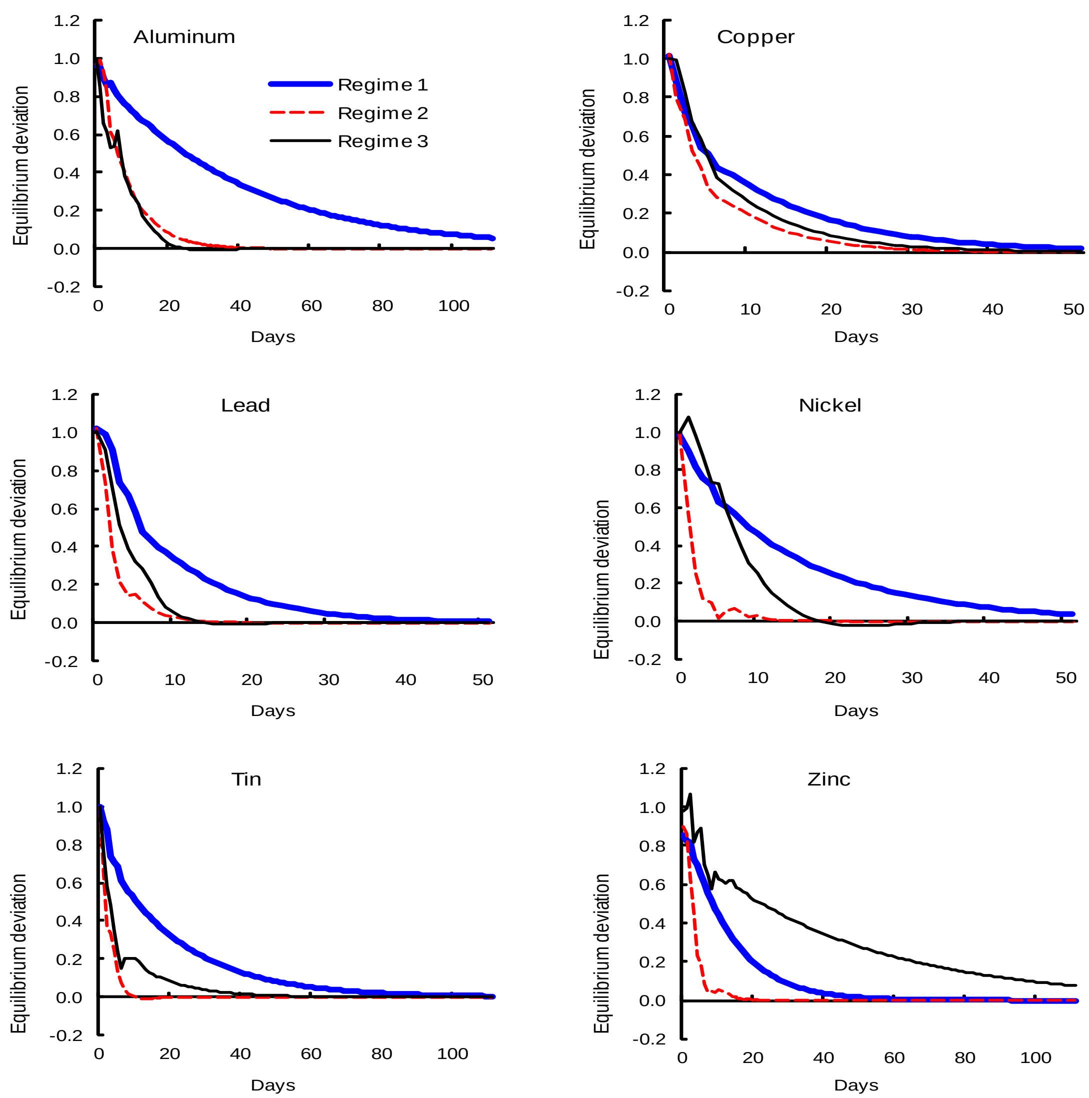
Second, the confidence intervals around impulse response estimates are much wider in regime 1 (contango) compared to regimes 2 and 3 (close to equilibrium and backwardation, respectively) for all commodities (Appendix figures 2.A.1 through 2.A.6). To generate standard errors for the impulse responses, we bootstrapped the residuals from each sample, produced 500 replications, and then calculated the standard deviation of the impulse responses from these estimations. These findings are less easy to interpret, but to some extent, they may reflect the large sample sizes for regime 1, with perhaps a greater range of conditions in this sample as compared to regime 3. A more detailed discussion of this particular results lies outside the scope of this chapter.

2.5.5.4 Different Pace of Adjustment in Each Regime

A key result from this chapter is that the adjustment path back towards equilibrium, for a given percentage point shock to spot prices, is generally more gradual when the futures curves is in contango and steeply upward sloping (regime 1). The adjustment is more rapid when the futures curve is relatively flat or inverted (regime 3). The most rapid adjustment occurs when the system is close to equilibrium (regime 2). This result holds especially for nickel in regime 3. The only metal for which this result does not hold is zinc (Figure 2.6). The different results on zinc may be due to a large outlier in the beginning of the data sample or the characteristics of the metal. Zinc can be substituted by aluminum or plastics. Rapid as opposed to expected gradual adjustment in contango can be a result of substituting other materials in place of zinc. Similarly, zinc spot prices may not go as high up during backwardation due to existing substitutes given that prices of substitutes would remain unchanged. In most cases, spot prices share much of the burden of adjustment and in backwardation, spot prices adjust particularly rapidly. This likely reflects the convexity of the marginal convenience yield with respect to inventories; in other words, when inventories are already low, the effect of supply disruptions on the marginal utility of inventories is significantly higher. A 1 percentage point shock to spot prices may reflect only a small supply disruption in terms of actual quantities, given the much higher sensitivity of the system to spot prices in backwardation. As inventories are rapidly drawn down, expectations for a more stable path for inventories allows the spot price to fall quickly and the futures curve to return to a more "normal" slope.

In contrast, a 1 percentage point spot price shock in a contangoed market may represent a very significant supply disruption since it will have little effect on the marginal convenience yield as inventories are already abundant. Inventories are drawn down more gradually and the price adjustment is slower. Mechanically, the adjustment coefficients for the VECMs in contangoed markets (regime 1) are much lower than in backwardation, which leads to a much more gradual error-correction process.

Figure 2.6 Adjustment Back to Equilibrium Following a 1% Spot Price Shock



2.6 Conclusions

In this chapter, we ask three questions: Is there such a thing as a "normal" commodity market, in which the relationship between spot and futures prices and inventories settles down to a long-run stable equilibrium? How does a commodity market adjust to a temporary scarcity shock which moves the price curve away from this equilibrium? How quickly do inventories and prices respond to such shocks?

Our answer to the first question is "yes". We find that the relationship between base metal spot prices, futures prices, inventories, and interest rates is cointegrating; to put it another way, it is possible to consider whether a commodity market is in "equilibrium" based on the relative values of each of these variables. When the system is away from equilibrium in response to a temporary shock, we should expect it to adjust back towards the steady state over time. The dynamics of this adjustment, however, vary across metals and depend on the initial state of the market.

To the second question, we find some evidence that a temporary scarcity shock, modeled as a spot price shock which changes the slope of the futures curve, does cause a reaction in commodity markets somewhat consistent with a theoretical model, such as Pindyck (2001). In particular, inventories are drawn down and spot prices gradually fall back towards their initial level. However, the initial state of the market is an important conditioning factor for the subsequent adjustment. In a contangoed market with abundant inventories, spot price shocks produce a much more gradual inventory response, while the effect on price levels can be permanent. In contrast, in a backwardated market the inventory drawdown occurs much faster and the rise in both spot and futures prices are temporary.

Our answer to the final question is that the adjustment of prices and inventories back towards equilibrium is much more gradual in a contangoed market. This may reflect the diminishing marginal utility of inventories and the resulting sensitivity of spot prices to supply disruptions in different initial states. For example, a 1 percentage point shock to spot prices may reflect only a small supply disruption in a tight, backwardated market, but a significant disruption when inventories are abundant and spot prices are much less sensitive to perceptions of scarcity. In summary, in a tight physical market, even a small supply disruption can have large price effects, but these typically prove to be short-lived.

These results are important for consumers, producers and inventory holders of commodities. In particular, they suggest that market participants should condition their response to market signals during periods of unusual conditions—or disequilibrium as we have defined it in this chapter—on the state of the inventory cycle, which is typically reflected in the slope of the futures curve.

2.A Appendix

Table 2.A.4 Interest Rate-adjusted Basis

	Mean	Std. Dev.	Skewness	Kurtosis	Observ.
Aluminum	0.95	0.47	-0.18	1.53	3108
Copper	0.96	0.46	-0.22	1.54	3108
Lead	0.96	0.46	-0.21	1.53	3108
Nickel	0.97	0.47	-0.17	1.55	3108
Tin	0.96	0.47	-0.18	1.52	3108
Zinc	0.95	0.47	-0.18	1.53	3108

Table 2.A.5 Unit Root Tests

	Log levels				First differenced logs			
	ADF		PP		ADF		PP	
	t-statistic	p-value	t-statistic	p-value	t-statistic	p-value	t-statistic	p-value
Libor interest rates								
3-month	-0.68	0.85	-0.54	0.88	-14.90	0.00	-43.89	0.00
6-month	-0.61	0.87	-0.61	0.86	-16.78	0.00	-48.70	0.00
Aluminum								
spot price	-1.38	0.59	-1.34	0.61	-57.49	0.00	-57.49	0.00
futures price (3-month)	-0.45	0.90	-0.52	0.89	-59.54	0.00	-59.41	0.00
futures price (6-month)	-0.60	0.87	-0.61	0.87	-53.92	0.00	-53.90	0.00
inventories	-1.14	0.70	-1.13	0.70	-55.37	0.00	-55.37	0.00
Copper								
spot price	-0.45	0.90	-0.39	0.91	-53.71	0.00	-53.72	0.00
futures price (3-month)	-1.12	0.71	-1.07	0.73	-57.64	0.00	-57.68	0.00
futures price (6-month)	-1.34	0.61	-1.34	0.61	-57.90	0.00	-57.90	0.00
inventories	-0.43	0.90	-0.51	0.89	-59.74	0.00	-59.60	0.00
Lead								
spot price	-0.51	0.89	-0.54	0.88	-54.20	0.00	-54.19	0.00
futures price (3-month)	-1.12	0.71	-1.11	0.71	-55.93	0.00	-55.95	0.00
futures price (6-month)	-0.39	0.91	-0.35	0.92	-53.77	0.00	-53.77	0.00
inventories	-1.09	0.72	-1.04	0.74	-57.94	0.00	-58.00	0.00
Nickel								
spot price	-1.26	0.65	-1.24	0.66	-57.63	0.00	-57.63	0.00
futures price (3-month)	-0.40	0.91	-0.49	0.89	-60.05	0.00	-59.89	0.00
futures price (6-month)	-0.44	0.90	-0.46	0.90	-54.29	0.00	-54.28	0.00
inventories	-1.08	0.73	-1.06	0.74	-56.01	0.00	-56.02	0.00
Tin								
spot price	-0.45	0.90	-0.39	0.91	-54.01	0.00	-54.03	0.00
futures price (3-month)	-1.03	0.74	-0.97	0.77	-57.85	0.00	-57.93	0.00
futures price (6-month)	2.27	1.00	1.56	1.00	-14.28	0.00	-50.45	0.00
inventories	-1.22	0.67	-1.23	0.66	-11.98	0.00	-57.17	0.00
Zinc								
spot price	-1.51	0.53	-1.71	0.42	-20.33	0.00	-51.57	0.00
futures price (3-month)	-1.18	0.69	-1.26	0.65	-20.01	0.00	-47.20	0.00
futures price (6-month)	-1.91	0.33	-1.90	0.33	-21.69	0.00	-48.60	0.00
inventories	-0.83	0.81	-0.90	0.79	-15.96	0.00	-53.62	0.00

ADF denotes Augmented Dickey-Fuller test and PP denotes the Philips-Perron test. Various lag lengths were used for the ADF tests and Table A1 show the results from tests with a lag length of six.

2.A.1 Cointegration Tests

For the Engle-Granger procedure, we tested the null hypothesis of no cointegration by estimating the following regression, using the residuals from equation (6):

$$\Delta\hat{\varepsilon}_t = a_1\hat{\varepsilon}_{t-1} + u_t \qquad \text{(A1)}$$

Table 2.A.3 presents the t-statistics from these regressions for each commodity using the 3-month and 6-month futures contract and interest rate, together with the 5 percent Engle-Granger critical values. In all cases, we were able to reject the null of no cointegration.

Table 2.A.6 Engle-Granger tests of Cointegrating Residuals

	Critical values	Test statistic	
		3-month model	6-month model
Aluminum	-4.12	-9.11	-4.88
Copper	-4.12	-12.73	-6.37
Lead	-4.12	-10.09	-6.91
Nickel	-4.12	-9.52	-6.71
Tin	-4.12	-8.25	-5.53
Zinc	-4.12	-8.00	-5.94

The null hypothesis is for a unit root in the residuals of the equation and no cointegration. The test statistic is calculated using the Philips-Perron procedure and the critical values are taken from MacKinnon (1991).

For the VECM estimations, we use the lag length identified by standard selection criteria for the VAR in log-levels for each commodity and based on the variables in equation (4) (Table 2.A.4).

Table 2.A.7 Vector Autoregression Lag Length Tests

	Akaike	Schwarz-Bayes	Hannan-Quinn
	Three-month model		
Aluminum	**7**	3	6
Copper	**8**	3	7
Lead	**7**	2	3
Nickel	**7**	2	4
Tin	**8**	2	3
Zinc	**11**	2	3
	Six-month model		
Aluminum	**7**	2	5
Copper	**7**	3	7
Lead	**7**	2	3
Nickel	**7**	2	3
Tin	**7**	2	3
Zinc	**7**	2	7

Information criteria include Aikaike (AIC), Schwarz-Bayesian (SIC), and Hannan-Quin (HQ). We base our decisions on the AIC.

2.A.2 Tsay's Test for Threshold Nonlinearity

The first stage is to assess the autoregressive structure of the equilibrium error. We find that partial autocorrelations decline rapidly after the first lag, although they remain statistically significant (Table 2.A.4). Although information criteria indicate that the optimal AR order varies between 2 and 5 (Table 2.A.5), running the threshold tests on AR(1) or these optimal AR orders produced either identical or very similar results, underscoring the dominant influence of the first lag.

Table 2.A.8 Partial Autocorrelation Functions for the Equilibrium Errors

	Lag order				
	1	2	3	4	5
			3-month		
Aluminum	**0.94**	**0.07**	**0.14**	0.03	**-0.06**
Copper	**0.89**	**0.09**	**0.11**	**0.04**	0.01
Lead	**0.93**	**-0.05**	**0.07**	0.03	0.04
Nickel	**0.94**	0.00	**0.05**	**0.05**	**-0.04**
Tin	**0.95**	0.02	**0.09**	0.01	0.00
Zinc	**0.97**	**-0.06**	**-0.14**	0.00	-0.03
			6-month		
Aluminum	**0.98**	**-0.04**	**0.06**	0.00	0.02
Copper	**0.97**	0.00	0.03	**0.04**	0.03
Lead	**0.97**	**-0.10**	**0.05**	**0.06**	0.03
Nickel	**0.97**	**-0.10**	0.01	0.00	0.00
Tin	**0.97**	0.03	**0.05**	0.01	**0.04**
Zinc	**0.98**	**-0.15**	**-0.12**	**0.05**	0.00

Autocorrelations significant at the 95 percent level.

Table 2.A.9 Information Criteria for Equilibrium Error AR(p) Equations

	AR order				
	1	2	3	4	5
			3-month		
Aluminum	-8.2896	-8.2942	-8.3125	-8.3123	**-8.3151**
Copper	-8.5228	-8.5309	-8.5431	**-8.5439**	-8.5430
Lead	-7.6642	-7.6653	-7.6689	-7.6691	**-7.6694**
Nickel	-7.9656	-7.9647	-7.9658	-7.9676	**-7.9682**
Tin	-9.2667	-9.2663	**-9.2733**	-9.2725	-9.2716
Zinc	-8.2470	-8.2505	**-8.2685**	-8.2682	-8.2685
			6-month		
Aluminum	-8.7211	-8.7229	-8.7271	-8.7271	**-8.7276**
Copper	-8.6499	-8.6498	-8.6526	**-8.6536**	-8.6534
Lead	-7.3551	-7.3640	-7.3653	-7.3683	**-7.3680**
Nickel	-7.7603	**-7.7702**	-7.7696	-7.7686	-7.7677
Tin	-8.7312	-8.7312	**-8.7330**	-8.7322	-8.7315
Zinc	-8.2937	-8.3254	-8.3421	-8.3624	**-8.3723**

Minimum criteria values in bold.

As a result, we arrange the data such that it is increasing in the value of the AR(1) regressor, in our case the equilibrium error in the previous period z_{t-1}. The least squares estimates of the AR(1) regressor in equation (5) will be consistent for each set of cases, if the value of the thresholds were known. Since the value of the thresholds is unknown, we proceed sequentially. The predictive residuals from equation (5) will be white noise asymptotically and orthogonal to the regressor until z_{t-1} reaches a threshold, at which point the predictive residual will be biased and a function of the regressor. To test this, we obtain the standardized predictive residuals from an ordered autoregression, where π_i is the time index of the tth smallest observation, and run the least squares regression:

$$\varepsilon_{\pi_t+1} = \omega_0 + \omega_1 z_{\pi_t} + v_{\pi_t+1} \tag{A1}$$

We do this for all sample periods $i = k + 1,\ldots,T - 1$, where k is the number of explanatory variable (on our case 1) and compute Tsay's statistic, which is the F-statistic of the resulting regression:

$$F(p,d)=\frac{\left(\sum\hat{\varepsilon}_t^2-\sum\hat{v}_t^2\right)/(p+1)}{\sum\hat{v}_t^2/(T-d-k-p-h)} \tag{A2}$$

In equation (A2), d is the delay parameter (in our case 1), p is the order of the autoregression, and h is obtained from max{1, p + 1}.This test statistic follows an F distribution with $p + 1$ and $T - d - k - p - h$ degrees of freedom. Implementing this procedure on the residuals from the cointegrating equations for each commodity obtains the following test statistics and p-values for the null hypothesis that the standardized recursive residuals are not a function of the regressor. Table 2.A.7 shows the results of these tests. In all cases (with the exception of 6-month zinc), it was possible to reject the null hypothesis of linearity at the 1 percent level of confidence. Although 6-month zinc was an exception, other tests for structural breaks suggested that there is a significant degree of nonlinearity.

2.A.3 Quandt-Andrews Tests for Structural Breaks

This procedure performs a Chow test at every observation between two dates, or observations. We then identify the maximum Wald F statistic from each individual Chow test and assess whether it is possible to reject the null of no structural break at the 95 percent confidence level. We then perform the same procedure for the largest remaining sub-sample to check for another breakpoint. In all cases, we found it was possible to reject the null hypothesis of no structural break at the 1 percent level for the overall sample and the sub-sample constructed by removing the smallest section of the sample split by the first threshold. We used these F statistic maxima to identify the threshold locations.

Table 2.A.10 Tsay's Nonlinearity Test Results

	3-month		6-month	
	Test statistic	p-value 1/	Test statistic	p-value 1/
Aluminum				
full sample	72.16	0.0000	32.2	0.0000
sub-sample	98.37	0.0000	161.4	0.0000
Copper				
full sample	300.36	0.0000	174.4	0.0000
sub-sample	11.52	0.0000	324.89	0.0000
Lead				
full sample	83.94	0.0000	29.31	0.0000
sub-sample	50.53	0.0000	16.41	0.0000
Nickel				
full sample	53.39	0.0000	13.07	0.0000
sub-sample	122.05	0.0000	177	0.0000
Tin				
full sample	27.64	0.0000	32.36	0.0000
sub-sample	14.16	0.0000	197.02	0.0000
Zinc				
full sample	6.01	0.0025	0.46	0.6313
sub-sample	74.2	0.0000	122.98	0.0000

Probability that the null hypothesis of linearity (no thresholds) is true.

Figure 2.7 Aluminum: Impulse Responses to 1 percent Spot Price Shock

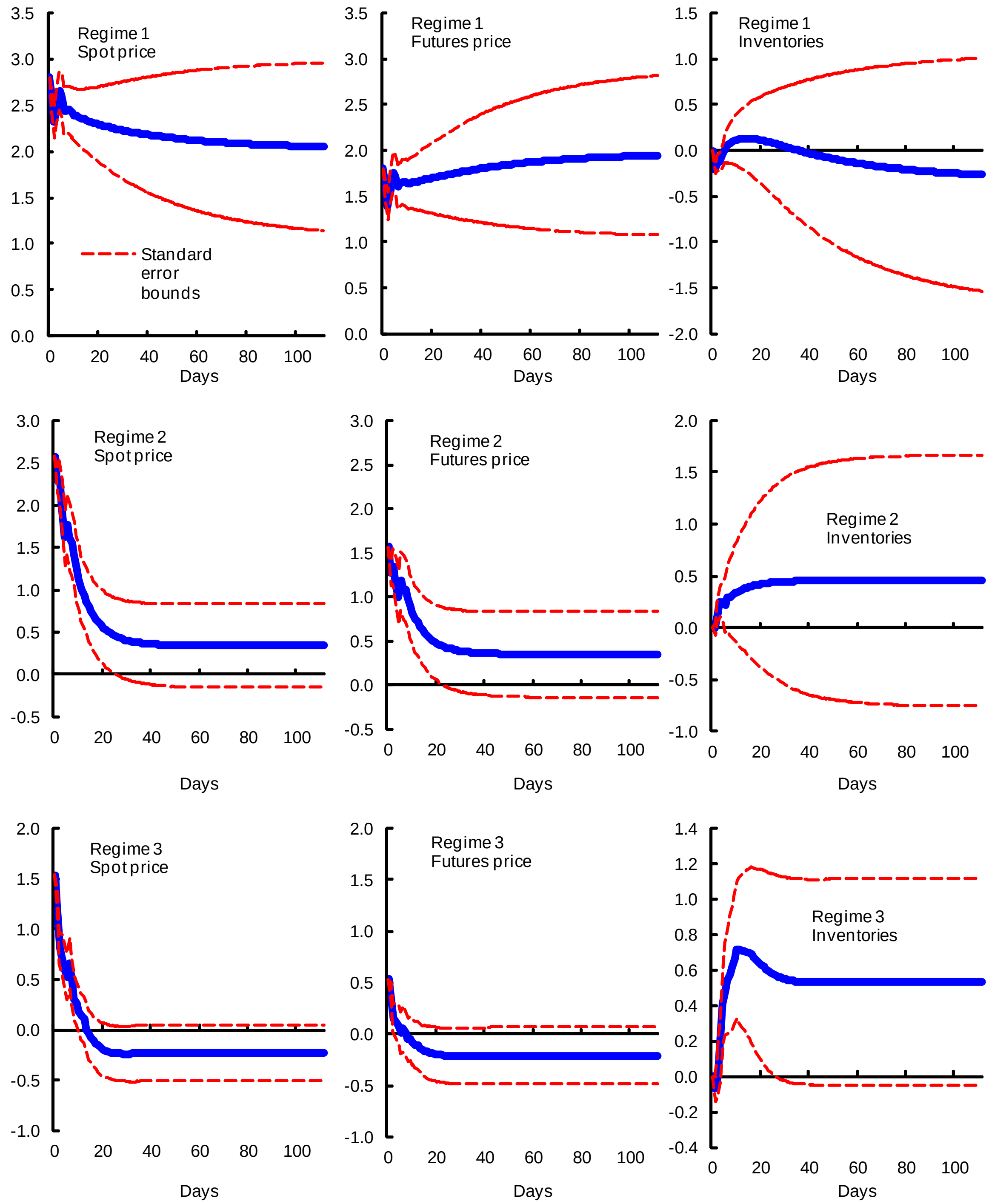


Figure 2.8 Copper: Impulse Responses to 1 percent Spot Price Shock

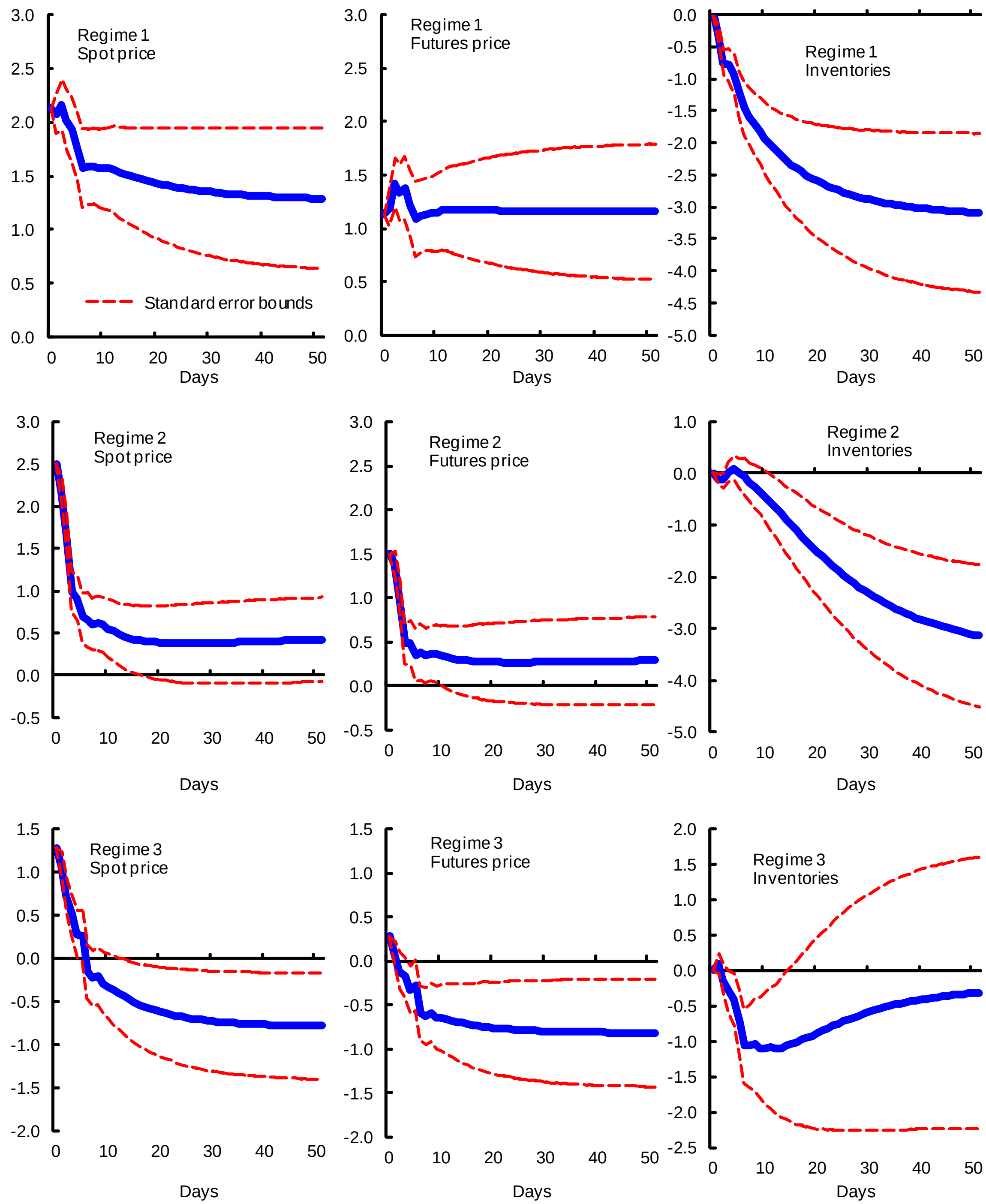


Figure 2.9 Lead: Impulse Responses to 1 percent Spot Price Shock

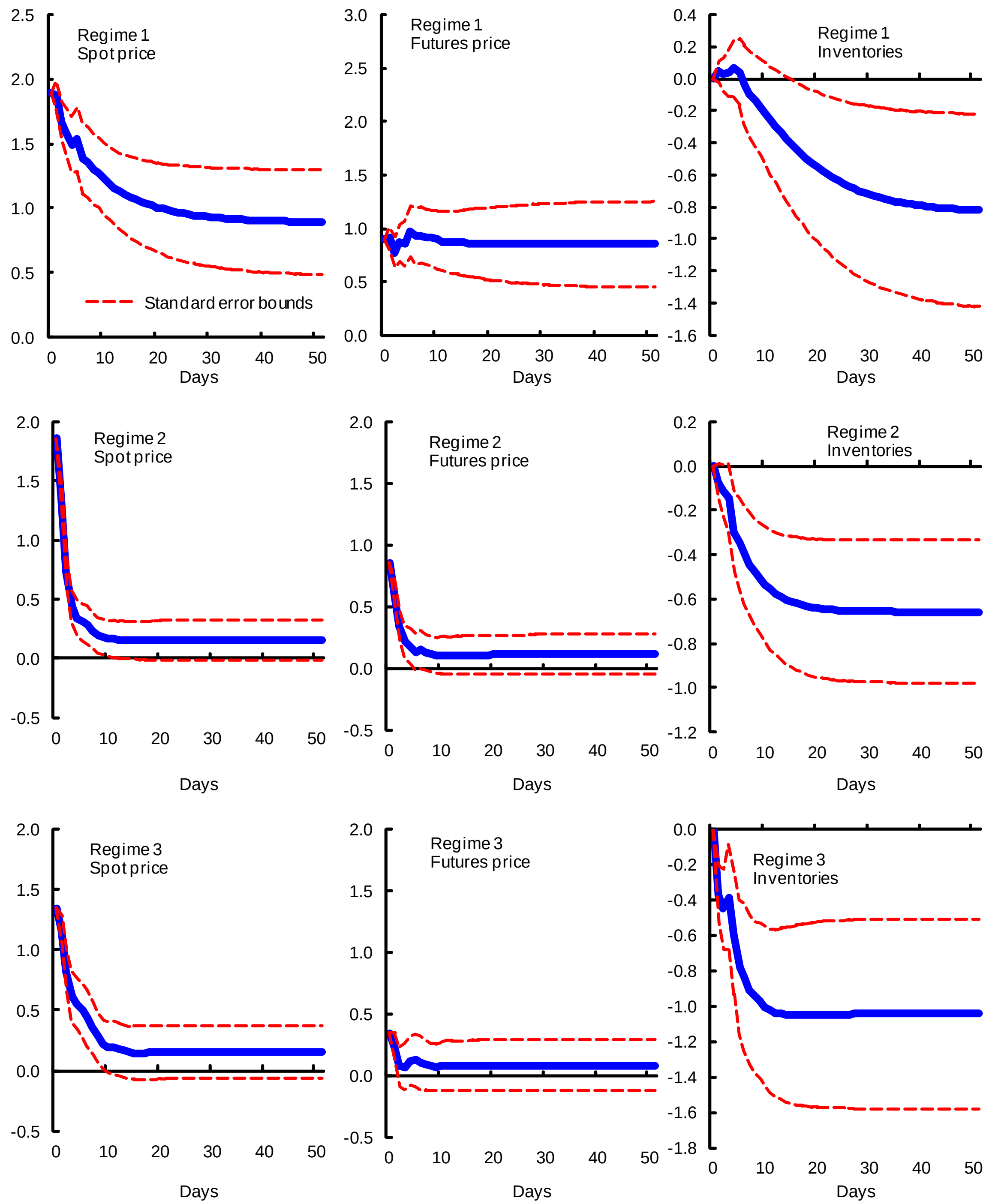


Figure 2.10 Nickel: Impulse Responses to 1 percent Spot Price Shock

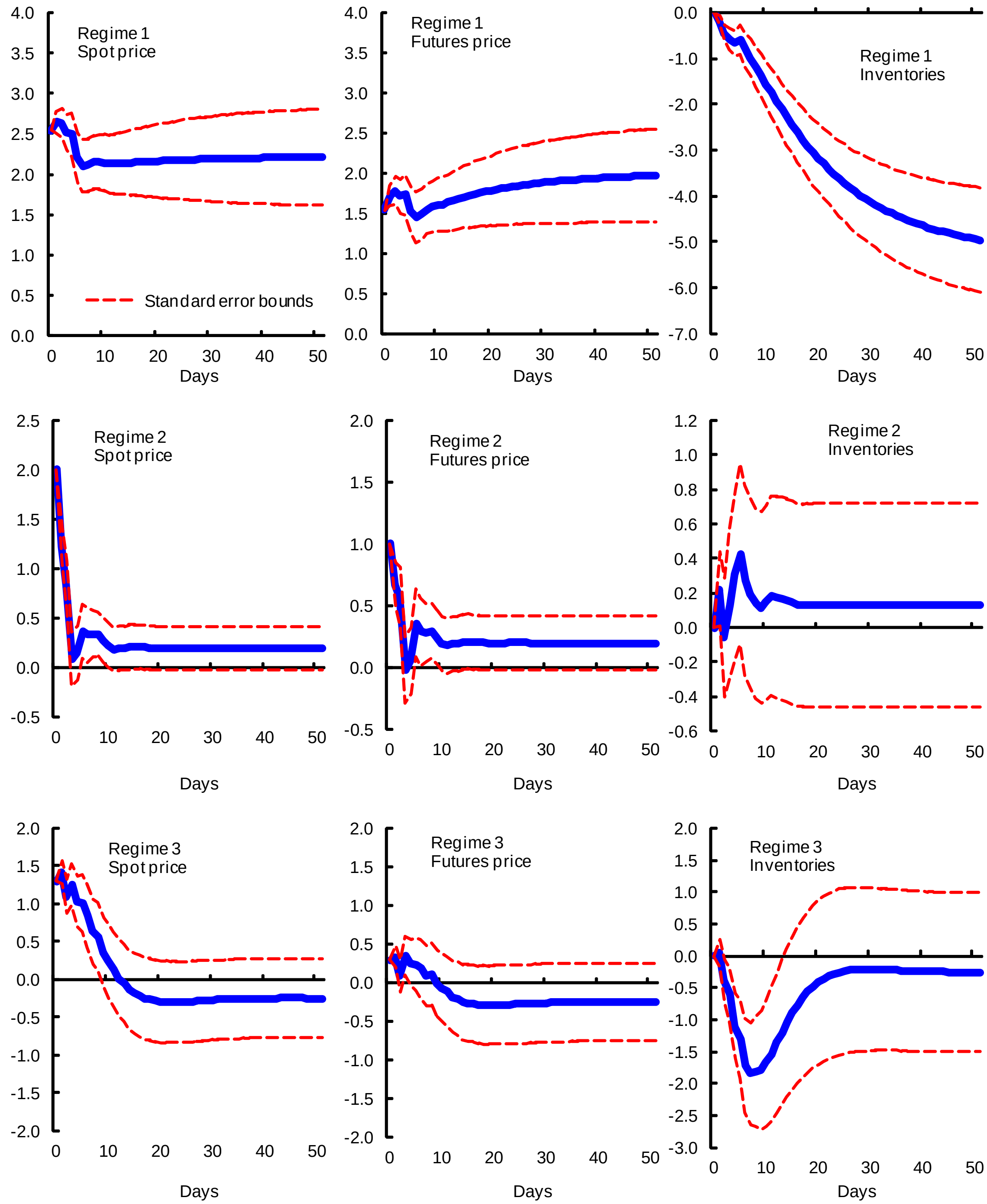


Figure 2.11 Tin: Impulse Responses to 1 percent Spot Price Shock

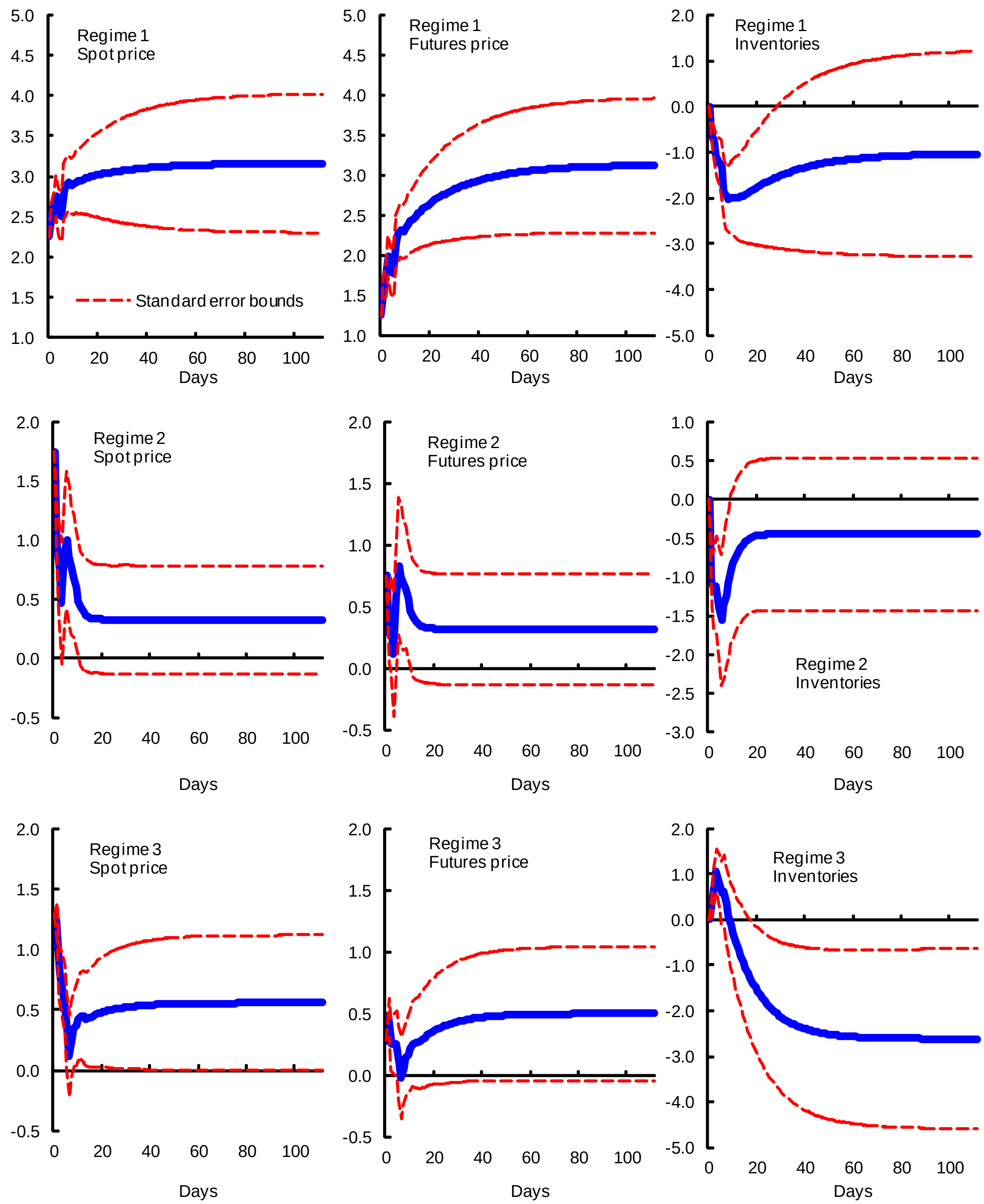
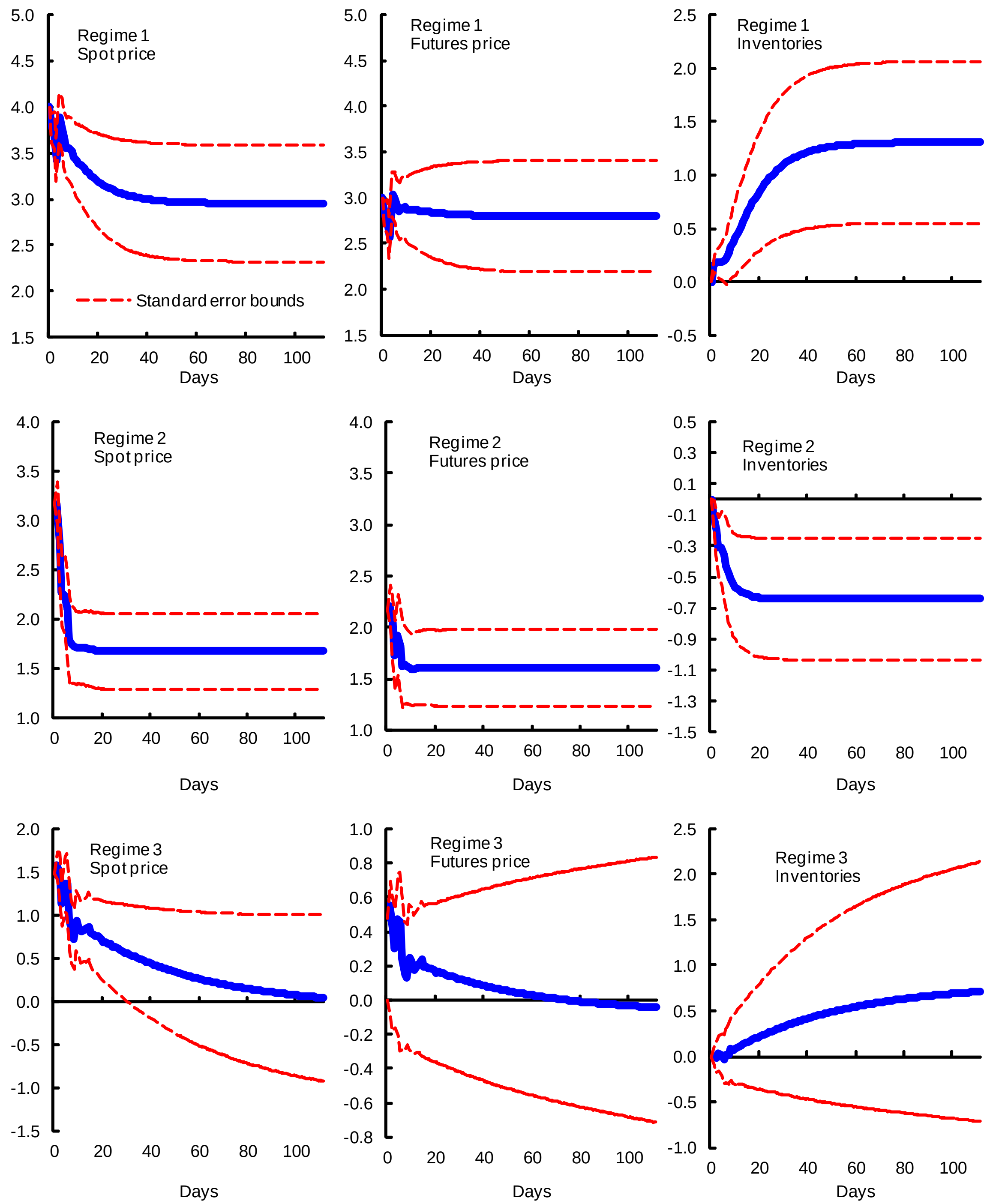


Figure 2.12 Zinc: Impulse Responses to 1 percent Spot Price Shock



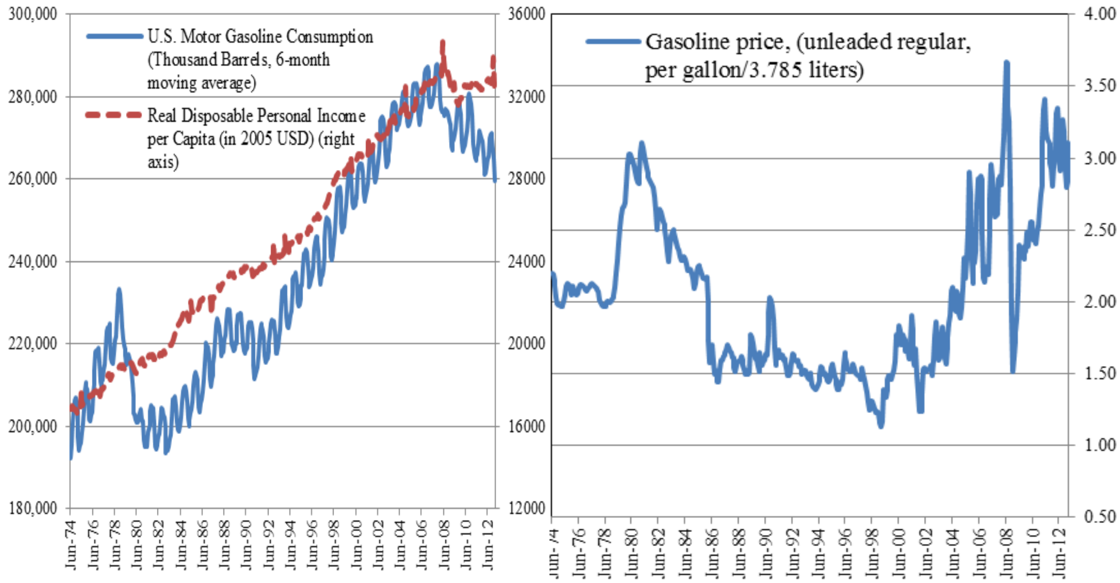
3 Price and Income Elasticity of the U.S. Gasoline Demand

3.1 Introduction

Crude oil and gasoline play an important role in the U.S. economy. The U.S. is the largest crude oil consumer in the world making up 21% of total oil consumption. Gasoline accounts for over 50 percent of U.S. oil consumption. Understanding the role of income and gasoline prices on demand is an integral part of effective fiscal, tax and environmental policy-making in the U.S. and has been studied extensively in the 1970s and the early 1980s when prices were very high and supplies were tight. In recent years, there is a renewed interest in price-based policies such as gasoline or carbon taxes, as pressures increase to reduce greenhouse gas emissions produced by transport sector. In this context, it is important to review whether gasoline demand elasticities have changed by incorporating recent developments using the latest data.

From the mid-2000s to 2008 commodity prices in general and gasoline prices in specific increased continuously reaching record levels in real and nominal terms. In the U.S., gasoline prices exceeded unprecedented levels of 4 dollars per gallon in mid-2008 (right panel of Figure 3.1). High commodity prices were a result of increased world demand in the 2000s during which the U.S. as well as other advanced and emerging economies experienced high level of economic growth and wealth. The rise in income increased automobile ownership and demand for gasoline. The left panel of Figure 3.1 illustrates the steep climb in real disposable income since the early 2000s and increase in motor gasoline consumption in the U.S. With the onset of financial crisis in the second half of 2008, gasoline prices, income and gasoline consumption fell sharply. Gasoline prices started to recover in 2009, but they did not revert back to the levels of 2008. Despite recovery in real disposable income in the last few years, gasoline consumption continues to fall (left panel).

Figure 3.1 Gasoline Consumption, Disposable Income and Real Gasoline Prices



Source: U.S. Energy Information Administration and the Bureau of Labor Statistics.

In addition to rising income levels, low interest rates during the 2000s enabled many U.S. consumers to gain access to cheap credit to purchase new vehicles--especially large size vehicles which consume more fuel--increasing the total number of motor vehicles to record levels in 2007 as well as the demand for gasoline. Left panel of Figure 3.2 illustrates the number of motor vehicles per 1000 people in the U.S. which is highest in the world. The number has come down as income fell and unemployment increased with the start of financial crisis in 2008. However, the U.S. still remains a country with the highest transportation fuel consumed per capita and the lowest fuel tax and prices in the OECD countries as shown in the right panel of Figure 3.2.[6] Per capita miles travelled in European countries are between 35 to 45 percent of U.S. miles travelled.[7] Great distances between cities, disbursed urbanization and limited public transportation services make the U.S. citizens rely heavily on

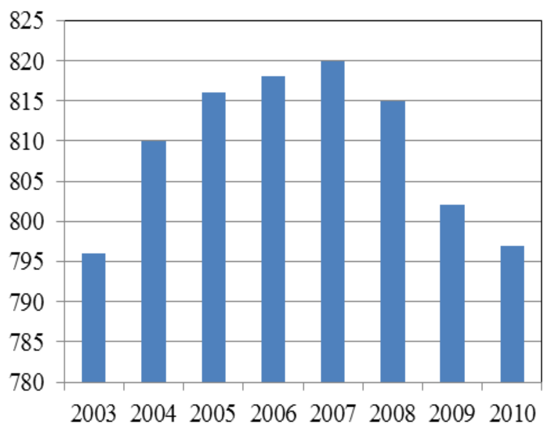
[6] Size of the circle is proportional to population. The line is fitted value from a regression of the log of consumption on the log price. This chart is taken from Knittel (2012).

[7] Knittel (2012).

automobiles as means of transport. Polzin and Chu (2005) find that the share of transit passenger miles traveled relative to other types of transportation has steadily decreased over the past thirty years suggesting that U.S. consumers may be more dependent on automobiles than in previous decades.

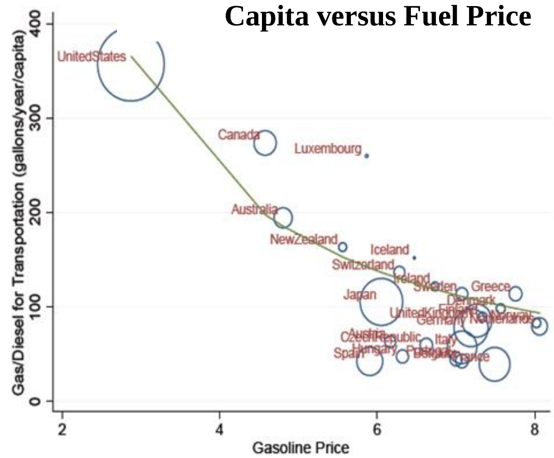
Figure 3.2 Motor Vehicles and Transportation Fuel in the US

Motor Vehicles (per 1,000 people)



Source: World Bank, World Indicator Database

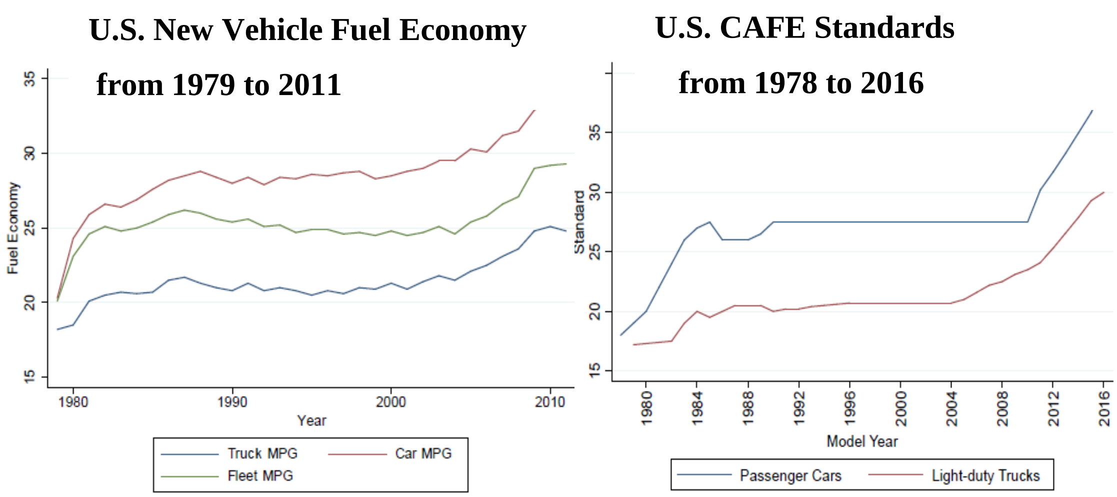
Transportation Fuel Consumption per Capita versus Fuel Price



Source: World Bank

The heavy usage of motor vehicles in the U.S. causes high amount of carbon dioxide emission. The 33.8% of total carbon dioxide emissions are derived from the transportation sector in the U.S. Shortly after the oil prices shocks of the 1970s, the U.S. adopted Corporate Average Fuel Economy (CAFE) standards, which set minimum average fuel economy thresholds for the new vehicles sold by an automaker in a given year. As the left panel of Figure 3.3 shows, there was a small improvement on the average fuel economy of new fleet vehicles in the past two decades up until the run-up in gasoline prices beginning in 2005, fleet fuel economy increased however, this rise appears to have subsided by 2010. Overall miles-per-gallon standards in the U.S. are not as high as in other OECD countries. After accounting for differences in the testing procedures, the United Nation estimated that the European Union standard was roughly 17 miles-per-gallon more stringent in 2010 than the U.S. standard (An et al., 2011). A new Corporate Average Fuel Economy standard in place for 2011 seeks to increase average fuel economy further by 2016 (right panel in Figure 3.3). In addition, new standards will evaluate the mileage standards based on the greenhouse gas emissions of the vehicle and on the area of the footprint of its tires.

Figure 3.3 U.S. Vehicle Fuel Economy and CAFE Standards



This chapter examines the price and income elasticities of gasoline demand in the U.S. from 1975 to 2013 based on the methodologies in Hughes et al. (2008) and in Davis and Kilian (2010). Hughes et al. (2008) estimate the short-run elasticities in two different periods: 1975-1980 and 2001-2006 during which gasoline prices were high.[8] Since elasticity estimates vary according to data type and empirical model specification, they use a consistent set of data and models between the two periods to make the elasticities comparable over time. They show that the short-run gasoline price elasticity declined over time compared to the results of earlier studies. They attribute this change to structural and behavioral changes occurred in the U.S. gasoline market. We also estimate the elasticities in these two periods but include a third sample period from October 2008 to February 2013 during which the U.S experienced a severe recession while gasoline prices remained high. It is imperative to examine the

[8] Goodwin et al. defines the short term 1 year and long term as the asymptotic end state when responses are completed, for much of the transport literature, periods of 5–10 years are estimated empirically, within which the greatest part of the response is in the first 3–5 years.

elasticities and consumer behavior during this most recent yet difficult period for consumers in terms of determining the future tax and environmental policies. In addition to three subsamples, we also estimate the models using the full sample to study the long-term behavior of elasticities. Elasticities are estimated using several simple econometric models similar in form to those used in previous studies of gasoline demand including Hughes et al. (2008). These are OLS, partial adjustment dynamic model where we include a lagged dependent variable to allow slow adjustment to the equilibrium level, Instrumental Variable (IV) to correct for the endogeneity between gasoline price and consumption.

In addition to the simple econometric models, we explore a dynamic time series approach involving a bivariate vector autoregression (VAR) developed by Davis and Kilian (2011) to estimate the short-run price elasticity of gasoline demand and handle the endogeneity between gasoline price and gasoline consumption. The increases in the demand for gasoline cause the price of gasoline to increase, resulting in a spurious correlation between the price and the regression error producing biased estimates. The endogeneity can be addressed with the right instrumental variables. However, finding the proper instruments is always a challenge. Instead of using instruments in identifying exogenous movements in gasoline prices, we focus on unpredictable changes in gasoline prices and measure responses of gasoline demand employing the VAR model in which the percent change in gasoline prices is ordered first and the percent change in gasoline consumption is ordered second. This ordering implies that gasoline prices do not react to gasoline consumption shocks within the same month but with one month delay while gasoline demand responds to gasoline price shocks immediately. The response of gasoline consumption to 1% shocks to gasoline prices within 12 months can be interpreted as short-run price elasticity of gasoline demand. The disadvantage of this approach, however, is that since income changes very slowly over time, it is very difficult to estimate the income elasticity in this specification. Hence, we only estimate the price elasticity using this model on three sample periods as well as on the full sample as is done with the simple models explained earlier.

The contribution of this study to literature is to include the latest period of data and use a number of various models to estimate the gasoline demand responsiveness to price and income changes in the U.S. and compare the results to draw policy implications.

The plan of the chapter is as follows. In the next section, we present a brief literature review followed by the section 3 which includes the description of data to be used in estimations. In section 4, we discuss the methodology and description of the models. Section 5 covers the estimation results and discussion of the results. Finally, we conclude and offer policy implications in section 6.

3.2 Literature Survey

A large body of econometric studies focused on understanding gasoline demand during the 1970s and the early 1980s when fuel prices were high and concerns about energy conservation and energy security were at peak. Sterner and Dahl (1992), Dahl (1995), Espey (1998) and more recently Graham and Glaister (2002) provide thorough reviews based on a large number of gasoline demand studies.

Dahl and Sterner (1991 and 1992) first, examine nearly 300 studies and classify them by the type of model and report the price and income elasticities of gasoline demand for OECD countries over the period 1960-1985. The short run price elasticity of gasoline demand varies between -0.10 to -0.24 depending on the model estimated. The equivalent long run figure is between -0.54 and -0.96. Averaging these estimates gives a short run value of -0.23 and a long run figure of almost three and half times as large, -0.77. The average income short run elasticity is given as 0.39 and the long run as 1.17. Dahl and Sterner note the higher absolute value of income elasticity than the value of price elasticity suggests that gasoline prices must rise faster than the rate of income growth if gasoline consumption is to be stabilized at existing levels.

Second, they compare dynamic, static and pooled model estimates of long-run elasticities by testing the models with the same data set, since different model specifications may give very different estimates. The dynamic models give estimated price elasticities within the range -0.80 to -0.95, and income elasticities of between 1.1 and 1.3. Static models for cross-section data give roughly unitary elasticities for both price and income. Pooled data model estimates price elasticities as high as -1.3 or -1.4.

Dahl (1995) moves the review period further and focuses on a number of gasoline demand surveys conducted since 1977 on the U.S. to explore if and how the magnitude of elasticities have changed. She finds that static models estimate long run price and income elasticities of –0.16 and 0.46 from studies based on recent data, somewhat smaller in magnitude compared to previous estimates of –0.53 and 1.16. The review of dynamic models shows no substantial reduction in the magnitude of the elasticity estimates. Dahl (1995) argues that elasticities have become smaller in magnitude over time, particularly for income. While previous studies show long run price and income elasticities of around –0.8 and 1.0, recent studies suggest a price response of around –0.6 and a slightly inelastic income response.

Espey (1998) carries out ‘meta-analyses’ of international gasoline demand elasticities to explain the variation in the magnitude of estimated price and income effects. This work makes a novel contribution to the literature since it examines and explains empirically why variation in estimates exists, whereas the major other reviews identify the variation. Espey’s study is based on an extensive review of articles published between 1966 and 1997 which gave 277 estimates of long run price elasticity, 245 estimates of long run income elasticities, 363 estimates of short run price elasticity, and 345 estimates of the short run income elasticity. The author shows that variation in the short and long run income and price elasticities can be explained by demand specification, data characteristics, ‘environmental’ characteristics (i.e. the level of the data, the setting, time span analyzed etc.) and the estimation method.

Espey’s (1998) results show that elasticity estimates are sensitive to a number of different aspects of model structure. In terms of price effects, the inclusion of vehicle ownership and fuel efficiency variables serves to lower estimates of the short, but not the long-run price elasticity. Static models tend to produce larger short run price elasticities and lower long run price elasticities. No differences are found for price elasticities across different dynamic specifications, nor are differences in long run price elasticity estimates found among time series, cross-sectional and cross-sectional-time series studies.

As regards income effects, Espey's (1998) analysis finds that the inclusion of vehicle ownership and vehicle characteristics substantially influences results. Models that include some measure of vehicle ownership estimate significantly lower short and long run income elasticities. No statistically significant differences are found for long run estimates between static and dynamic models, or between different dynamic specifications.

There are studies that examine disaggregated household data to measure the impact of fuel price changes on consumption. Puller and Greening (1999) is a good example of such studies which reviews short run estimates of price elasticities of gasoline demand from a number of studies that are conducted from 1980 to 1995 based on dissagregated household data. They summarize the short run price elasticities that range from -0.67 to -0.43. In addition, the authors construct a panel of US households over 9 years to examine household adjustment to changes in the real price of gasoline. They apply a variety of estimation techniques and lag structures to their data which are different from the studies they reviewed to estimate the short-run price elasticity of gasoline around –0.35, a figure they believe to be consistent with estimates from the literature.

Kayser (2000) estimates household demand for gasoline and the corresponding price and income demand elasticities by using household level data from the 1981 Panel Study of Income Dynamics PSID which include the living environment of the household such as living in rural or urban area and availability of public transportation to commute to work. Economic factors are the household's income, the price of gasoline for the household, and the employment status of the head of the household.

Gasoline demand is calculated by deflating the reported miles traveled by the imputed household-specific fuel efficiency.

Kayser's empirical results from a selection corrected gasoline demand regression suggest low short-run price (-0.23) and income (0.48) elasticities and clear differences in gasoline demand across the population. The living environment has a significant effect on gasoline consumption; living in the presence of good public transportation tends to significantly lower gasoline consumption. On the other hand, living in a rural setting increases gasoline consumption. As for income, the results indicate that households with higher incomes tend to consume more gasoline but that the additional consumption comes at a decreasing rate.

Kayser uses an interaction term between the price of gasoline and income which implies that the income elasticity is lower when prices are higher, and that the price elasticity is greater at higher levels of income. The coefficient of the interaction terms indicates that households with lower incomes do not respond as much to higher gasoline prices as wealthier households. It is not unreasonable to assume that low income households cannot reduce their driving and gasoline consumption further in response to increasing prices as their driving and consumption is at the level of necessity where there is very little room for significant decline. The wealthier households on the other hand are probably able to reduce some of the consumption which is less of a necessity. Furthermore, the fuel efficiency regression shows that income is a significant explanatory variable for the fuel efficiency of a household's car fleet. Also there is a consistently positive relationship between income and fuel efficiency for each of the chosen subgroups. It appears that higher income allows households to purchase newer cars that will on average be more fuel-efficient because cars in 1981 are subject to the corporate fuel efficiency standards. Overall results suggest that a gasoline tax is not likely to result in large decreases in gasoline consumption.

Nicol (2003) estimates gasoline demand elasticities for six different household groups varying by family size and housing tenure status, for different regions in Canada and the United States. The results show that gasoline demand is generally more responsive to price and income changes in Canada, but this is not universally true for all household types. Also, while regional differences in elasticities are observed in both Canada and the United States, family size and housing tenure status have larger impacts on differences in elasticities across households.

In their review of studies on gasoline price elasticities, Graham and Glaister (2002) conclude that the consensus from the studies that use disaggregated household data is that short term price elasticity effects do exist and are of the order of magnitude suggested by the majority of the articles. There is evidence, however, that income effects are more difficult to determine in the short run.

Graham and Glaister (2002) review fuel elasticity studies which are conducted until early 2000's. They admit that the use of specific data or methodological approaches in addition to geographical area of study can create crucial differences in the magnitude of elasticity estimates. However the overwhelming evidence from their survey suggests that long run price elasticities typically tend to fall in the –0.6 to –0.8 range. Specifically the long-run elasticity in the US ranges from –0.23 to –0.8, and within the OECD ranges from –0.75 to –1.35. In many cases authors explicitly claim to find similarities and not differences between countries in the size of long run price elasticities. Individual studies, which apply a variety of different estimation techniques to the same data, also produce long run estimates within the same range. These same studies show that short run price elasticities normally range from –0.2 to –0.3. Again, this is fairly consistent across different empirical studies.

As for income elasticity, the long run income elasticity of fuel demand is typically found to fall in the range 1.1 to 1.3. Short run income elasticities are in the range 0.35 to 0.55. Overall, studies find that the U.S. has lower fuel consumption elasticities than Europe with respect to both price and income. Graham and Galister summarize the elasticity results as in the Table 3.1 below.

Table 3.1 Summary of Elasticities across Studies

	Price elasticity		Income elasticity	
	Short	**Long**	**Short**	**Long**
Fuel Consumption	-0.2 to -0.3	-0.6 to -0.8	0.35 to 0.55	1.1 to 1.3

They confirm and conclude that as fuel prices rise, abstracting from other changes, fuel consumption will fall by a less than proportionate amount. As economic activity and real incomes increase, abstracting from other changes, fuel consumption will increase by a slightly greater proportion. In all cases it takes time for people to adjust, so the initial impact effects are smaller than effects in the long term. Improvements in the fuel efficiencies of vehicles have significantly changed fuel consumed and the fuel costs of travelling a given distance. Fuel taxation can play a significant part in fuel consumption and the volume of emissions, especially over the long term. However, as several of the authors surveyed point out, an implication of the relative magnitudes is that real fuel prices would have to rise faster than real incomes in order to offset their effect.

Small and Van Dender (2007) investigate the short and long run price elasticities of gasoline demand by factoring in the endogenous changes in fuel efficiency and using annual cross-sectional time-series data at the U.S. state-level from 1966 to 2001. The authors model explicitly the simultaneous aggregate demand for vehicle miles traveled, vehicle stock and fuel economy. They distinguish between the cost per mile of travel and the cost per gallon of fuel and therefore can estimate the price elasticity of gasoline in addition to exogenous and endogenous changes in fuel efficiency. In general, as energy efficiency improves, the cost of consumption becomes cheaper, thereby providing an incentive to increase its use. Thus total energy consumption changes less than proportionally to changes in physical energy efficiency. For the full sample, they find the short run elasticities at -0.05 and long run elasticities at -0.22. Their estimates for short and long run elasticities decline to -0.02 and -0.11, respectively when 1997 – 2001 data period is tested. They attribute the decline in elasticities in the last five years of the sample to rising real income and lower real fuel prices. The decline in consumption as a result of efficiency gains gets smaller as income increases. They conclude that the responses of gasoline demand to increases in prices are considerably smaller than values typically assumed for policy analysis.

Hughes *et al.* (2008) estimate the average per capita demand for gasoline in the U.S. for the period from 1974 to 2006. They investigate two periods (1975 -1980) and (2001-2006) which have similar gasoline price increases to demonstrate changes in short-run elasticities over time. They find that the majority of literature overestimates gasoline demand elasticities for the past decade. They show that the short-run gasoline price elasticity shifted down considerably from a range of −0.21 to −0.34 in the late 1970s to −0.034 to −0.077 in the early 2000s. They argue that the change in price elasticity of demand is likely due to structural and behavioral changes in the U.S. since the 1970s which might include the implementation of Corporate Average Fuel Economy program (CAFE), changing land-use patterns, growth in per capita and household income and an increase in public transportation. Hughes *et al*. (2008) suggest that it is likely that long-run elasticities have decreased over time in contrast to Espey (1998) who argues that short-run elasticities have increased over time.

Wadud *et al.* (2009) assess the cointegration between gasoline consumption, gasoline price and income in US data using an annual time-series from 1949 to 2004. The results indicate that no stable and meaningful long-run relationship exists between these three variables for the whole period. Dividing the sample into two subsets, pre-1974 and post-1978, similar tests indicate that cointegration exists between the three variables for the post-1978 sub-sample, but not for the pre-1974 sub-sample which may suggest that there may have been a structural break in the data between 1974 and 1978, coinciding with the oil supply and price shocks, as well as introduction of fuel economy standards in the US.

Davis and Kilian (2010) examine the impact of a gasoline price tax increase on the gasoline consumption in the U.S. at the state and national level using monthly data from 1998 to 2008. They first estimate the price elasticity of gasoline demand deploying a single-equation specification to find a price elasticity of -0.10 at the national level. Second, they model gasoline consumption at the state level using panel data methods which help overcome the price endogeneity with respect to quantity. With this specification they find a price elasticity of -0.19. Third, they construct an instrument variable by using changes in gasoline taxes by state and month to tackle further the endogeneity issue. The resulting panel IV estimates are substantially larger than the OLS panel estimates. They find that a 10 cent tax increase would be associated with a 3-4% decrease in gasoline consumption. Finally, they implement a bivariate vector autoregression (VAR) model to measure the response of gasoline demand to the shock to percent change in gasoline prices as price elasticity of demand. The authors find a one-year price elasticity in the range of -0.07 to -0.12, implying that a 10 cent tax increase would be associated with a reduction in gasoline consumption between -0.22 and -0.37. If the change in prices in this VAR model is replaced with the change in taxes, however, that estimate increases to between -3.39 and -3.91, similar to the panel IV estimate.

Overall, the results of Davis and Kilian (2010) suggest that gasoline consumption is more sensitive to increases in gasoline taxes than to increases in the gasoline prices due to the fact that changes in taxes are much more persistent than typical changes in prices. However, gasoline tax increases of the magnitude that have been discussed would have only a moderate impact on total U.S. gasoline consumption and carbon emissions based on the estimates. In addition, the adjustment to tax increase takes very long time and the reduction achieved with it is very small to make a big impact on U.S. carbon emissions which falls far short of the emissions reductions targets. They conclude that there is no statistical evidence to suggest that a gasoline tax increase of the magnitude considered by policymakers would reduce carbon emissions enough to have a substantial effect on global warming.

Lin and Prince (2013) follow similar approach to Hughes *et al*. (2008) to examine the price elasticity of gasoline demand but include gasoline price volatility into static and dynamic models. They split the sample into periods by price volatilities and observe how gasoline price volatility impacts consumers' price elasticity of demand for gasoline. Their results show that volatility in prices decreases consumer demand for gasoline in the intermediate run. They also find that consumers appear to be less elastic in response to changes in gasoline price when gasoline price volatility is medium or high, compared to when it is low. Moreover, the authors find that when controlled for variance in the econometric model, gasoline price elasticity of demand is lower in magnitude in the long run.

The methodology in this chapter is built on the methodologies from the earlier studies to examine the elasticity of gasoline demand in the U.S. We employ a cross-sectional as well as a time-series analysis and take endogeneity problem into account. The most of studies use either cross-sectional or time series analysis and may not address the endogeneity issue properly which may undermine the results.

3.3 Data

The data used in the analysis are U.S. aggregate monthly data reported by several U.S. government agencies for the period from January 1975 to February 2013. Gasoline consumption is approximated as monthly "product supplied" reported by the U.S. Energy Information Administration, which is calculated as domestic production plus imports, less exports and changes to stocks. Gasoline prices are U.S. city average prices for unleaded regular fuel and are converted to real values by using Consumer Price Index (All Urban Consumers, U.S. city average 1982-84=100) which was re-indexed to 2005 to be consistent with the real income series. The data source is the U.S. Bureau of Labor Statistics for both series. Real Personal disposable income (based in 2005 prices) is from the U.S. Bureau of Economic Analysis, National Economic Accounts. Total gasoline consumption and income are converted to per capita by dividing them by mid-year total population, which is from the Census Bureau's Population Estimates Program (PEP). As for macroeconomic variables; unemployment rate is from the U.S. Bureau of Labor Statistics, 1 and 10-year interest rates are 1 and 10-Year Treasury Constant Maturity Rate from the Board of Governors of the Federal Reserve System.

3.4 Model Specifications

3.4.1 Basic Model

The basic model is based on the previous studies including Hughes *et al*. (2008) which is in double-log form and assumes that the elasticity is constant over each analysis period.

$$\text{In } G_{jt} = \beta_0 + \beta_1 \ln P_{jt} + \beta_2 \ln Y_{jt} + \varepsilon_j + \varepsilon_{jt} \qquad (1)$$

where Gjt is per capita gasoline consumption in gallons in month j and year t, Pjt is the real retail price of gasoline in month j and year t, Yjt is real per capita disposable income in month j and year t, ε_j represents unobserved demand factors that vary at the month level and ε_{jt} is a mean zero error term. Both Yjt and Pjt are in constant 2005 dollars. We model the ε_j's as fixed month effects to capture the seasonality present in gasoline consumption. The price and income elasticities are β_1 and β_2 .

$$\frac{\delta \text{ In } G_{jt}}{\delta \text{ In } P_{jt}} = \beta_1 \quad \text{and} \quad \frac{\delta \text{ In } G_{jt}}{\delta \text{ In } Y_{jt}} = \beta_2$$

In this set up, since there are no lags included, the elasticity estimates only account for adjustments in the current time period and produce short-run estimates.

Although some, including Hsing (1990), have rejected the double-log functional form, it is a common specification used in a large number of previous studies. It is adopted here as it provides a good fit to the data and allows for direct comparison with previous results from the literature. Regardless, we also present results for linear and semi-log specifications.

3.4.2 Alternative Specifications

We use a number of alternate model specifications to check for robustness of the price and income elasticities that are estimated by the basic model. In addition, by factoring in other variables such as macroeconomic variables, we check whether there is omitted variable bias. With this robustness check, we attempt to verify the changing value of elasticities in the early and recent periods.

3.4.2.1 Recession and Estimation with Macroeconomic Variables

We examine the possibility that elasticity estimates are biased upward because of omitted variables. The period of high gasoline prices from 1975 to 1980 and 2008 to 2013 coincided with an economic recession in the United States. It is important to account for macroeconomic conditions in our elasticity estimates as factors such as high unemployment and inflation may have contributed to changes in gasoline consumption during these periods. Following the specification in Hughes et al. (2008), we use the basic double-log model and estimate price and income elasticities including explanatory variables that represent macroeconomic variables such as unemployment rate (*UNEMP*), interest rate (*INT*) and inflation rate (*INF*) in addition to real price, income and fixed month effects. If the economic recession contributed to a decrease in gasoline consumption during the period from 1975 to 1980 and 2008 and 2013, failure to account for this effect would artificially inflate the estimated price elasticity.

3.4.2.2 Price Income Interaction Parameter Model

We specify a simple interaction model of the form (2) to examine the interaction between the price elasticity of demand and income. We use the interaction term, $\ln P_{jt} \ln Y_{jt}$ which measures the responsiveness of consumers to price changes in the event of income changes.[9] Namely, whether the responsiveness of gasoline

[9] We use a linear interaction term as multicollinearity is lower. Hughes *et al.*(2008) finds that using a quadratic interaction term was impossible as $\ln P_{jt}(\ln Y_{jt})^2$ due to high collinearity between $\ln Y_{jt}$ and $(\ln Y_{jt})^2$.

consumption will increase or decrease in case of a price change when income rises. In this specification, the price elasticity of gasoline demand is equal to $E_p = \beta_1 + \beta_3 \ln Y_{jt}$. Since the price elasticity is less than zero, a positive coefficient β_3 on the interaction term indicates a decrease in the price response as income rises. That is, price elasticity will be more inelastic as income increases.

$$\text{Ln } G = \beta_0 + \beta_1 \ln P_{jt} + \beta_2 \ln Y_{jt} + \beta_3 \ln P_{jt} \ln Y_{jt} + \varepsilon_j + \varepsilon_{jt} \quad (2)$$

3.4.2.3 Simultaneous Equations (Instrumental Variable) Models

It is well known that demand equation estimates are prone to the endogeneity issue as price and quantity are jointly determined through shifts in both supply and demand resulting in biased and inconsistent parameter estimates. The major challenge in these cases is to find appropriate instruments. An ideal instrumental variable for determining gasoline demand is one that is highly correlated with the price of gasoline (the endogenous variable) but not with unobserved shocks to gasoline demand. It is even more challenging in our case as we try to compare the elasticities in three different periods.

Ramsey *et al.* (1975) and Dahl (1979) used the relative prices of refinery products such as kerosene and residual fuel oil as instrumental variables. The problem with this approach is that the relative prices of other refinery outputs are likely to be correlated with gasoline demand shocks. Since gasoline demand and oil price are correlated, gasoline demand is likely correlated with the prices of other refinery outputs via the price of oil. Hughes et al. (2008) use two types of instrumental variables: crude oil quality and crude oil production disruptions. Crude oil production disruptions are represented for three countries, Venezuela, Iraq and the United States. Because each country has had its production of crude oil that are affected by external shocks that are unlikely to be related to gasoline demand shocks. Unfortunately, crude oil quality does not prove to be an appropriate instrumental variable, as the coefficients on sulfur content and specific gravity are not significant. As for the production disruption, only disruptions in U.S. production were significant.

Davis and Kilian (2010) use changes in gasoline taxes by state and month as an instrument. Even though tax legislation may respond to current prices, the implementation of tax changes typically occurs with a lag making it reasonable to believe that changes in tax rates are uncorrelated with unobserved changes in demand. In constructing the instrument they exclude ad valorem gasoline taxes (used in many states) because they are functionally related to price, violating the endogeneity assumption. For the national data the instrumental variable (IV) estimates rely on the historical variation in gasoline taxes over time. They find a price elasticity that is much larger, but not statistically distinguishable from zero, even after accounting for weak instruments.

The results of previous studies show that the challenge of finding a robust instrument remains. We try a different variable as an instrument in this study which has not been used before which is the change of the cost of crude oil to the refineries. In general gasoline price is linked to crude oil price as it is the raw material to produce gasoline. However, the monthly change in the cost can also be related to the refinery specific problems which will determine the gasoline price in the short-run. Furthermore, gasoline demand would not be correlated with the cost of crude oil in the short-run as refineries plan the production of gasoline for a medium or long term following the trend of consumption.[10]

3.4.2.4 Dynamic Lag Model (or Partial Adjustment Model)

Another common approach to modeling gasoline demand is through the use of a dynamic lag or partial adjustment model (Houthakker *et al*. (1974), Basso and Oum (2007) and Lin and Prince (2013)). This model includes a lagged dependent variable

[10] Borenstein and Shepard (2002); refineries operate most efficiently when the product and input mixes are constant over planned period of time since adjusting output proportions is costly. For example, from May until September more gasoline is produced during high driving summer months. From September onwards, more heating oil is produced during the winter months. Although refinery output might be tweaked slightly in response to price changes, refiners spread substantive adjustments in production over time.

(gasoline demand) which represents the desired change necessary for the adjustment back to the equilibrium level in case of a shock to gasoline demand. In this chapter, we estimate models with both 1-month (*t* - 1) and 12-month (*t* - 12) lags with and without fixed month effects. In this specification, the short-run price and income elasticities are given by the coefficients β_1 and β_2, respectively.

$$\text{In } G_{jt} = \beta_0 + \beta_1 \ln P_{jt} + \beta_2 \ln Y_{jt} + \beta_3 \ln G_{jt-1} + \varepsilon_{jt} \quad (3)$$

The fully adjusted coefficients on the price and income terms, $\beta_1/1-\beta_3$ and $\beta_2/1-\beta_3$ are generally interpreted as long-run elasticities. The speed of adjustment ($1/1-\beta_3$) depends on the magnitude of β_3. A large β_3 implies a slower, while a small β_3 indicates a faster adjustment.

3.4.2.5 Vector Autoregressive Models (VAR)

A bivariate VAR model is an effective way of circumventing the endogeneity between gasoline prices and consumption of gasoline. In this specification, changes in gasoline prices are assumed to be predetermined with respect to the factors that drive gasoline consumption and the response of gasoline consumption to such changes in gasoline prices can be estimated as elasticity. This approach is especially appealing when working with high frequency data such as monthly data, as we do in this chapter, but less suitable for data measured at lower frequency such as annual. The VAR models are widely used for measuring dynamic short-run responses of model variables to structural shocks to the model. As we examine the short-run elasticities of gasoline demand, the VAR method comes especially handy to obverse the response of gasoline demand to a given one-time structural shock to prices in several months up to 12 months.

Let Δp_t denote the percent change in real gasoline prices of gasoline and Δg_t the percent change in real gasoline consumption. Consider the model

$$\Delta p_t = \theta\, \Delta g_t + \epsilon_{1t} \qquad \Longleftrightarrow \qquad \underbrace{\begin{bmatrix} 1 & -\theta \\ -\delta & 1 \end{bmatrix}}_{A_0} \underbrace{\begin{pmatrix} \Delta p_t \\ \Delta g_t \end{pmatrix}}_{X_t} = \underbrace{\begin{pmatrix} \epsilon_{1t} \\ \epsilon_{2t} \end{pmatrix}}_{\epsilon_t}$$

$$\Delta g_t = \delta\, \Delta p_t + \epsilon_{2t}$$

where ε_{1t} and ε_{2t} are mutually uncorrelated errors. In this representation, all deterministic terms and the dependence of both variables on lagged observations are suppressed. Predeterminedness in this model means that $\theta = 0$[11], implying no contemporaneous feedback from gasoline demand Δg_t to gasoline price Δp_t. This is only possible; when gasoline supply curve is assumed to be flat; perfectly elastic i.e. gasoline price is determined only when gasoline supply curve shifts in the same month and responds to gasoline demand with a delay of one-month. In addition, it is assumed that there are no other exogenous innovations outside of the model that are correlated with the innovation in the real price of gasoline. Then the coefficient δ may be interpreted as the contemporaneous causal effect of the price innovation on real gasoline consumption.

The same logic applies in the more general VAR(p) model that allows for additional unrestricted delayed feedback between real gasoline consumption growth and real gasoline price changes up to some lag order p. If $x_t \equiv (\Delta p_t \quad \Delta g_t)'$ and $\epsilon_t \equiv (\epsilon_{1t} \quad \epsilon_{2t})'$, then the structural representation of the VAR(p) model would be

$$A_0\, x_t = \sum_{i=1}^{p} A_i\, x_{t-i} + \epsilon_t$$

The lag order for each sample period is selected by the Akaike Information Criterion (AIC). Predeterminedness in this VAR model implies an exclusion restriction on the upper right element of A_0. The reduced form representation of this model is

[11] See, for example, Cooley and LeRoy (1985).

$$x_t = \sum_{i=1}^{p} B_i x_{t-i} + e_t \,, \qquad (4)$$

where $B_i = A_0^{-1} A_i$, $i=1,\ldots,p$ and $e_t = A_0^{-1}\epsilon_t$

The reduced form may be estimated by the least squares method. Applying a lower triangular Cholesky decomposition to the estimate of the 2 × 2 variance-covariance matrix $\Sigma\ e_t = A_0^{-1}\ A_0^{-1'}$ of the reduced form VAR errors allows us to estimate A_0^{-1} subject to the identifying restriction of predetermined changes in gasoline prices. Given an estimate of A_0^{-1}, it is straightforward to construct the dynamic responses of gasoline consumption to an exogenous change in the price of gasoline from this model.[12]

The structure of VAR model—the identifying assumption of predeterminedness of gasoline prices and the order of the variables-- comes from the economic argument related to this specification. A recursive ordering provides sufficient restrictions on the contemporaneous relationships between the variables to exactly identify the structural shocks from the reduced-form residuals. The order of the variables in the VAR; changes in gasoline price being first and changes in gasoline demand being second mean that while unanticipated shifts in gasoline demand in the model do not move the price of gasoline instantaneously, they are allowed to affect the price of gasoline with a delay of one month. The reasoning behind this assumption is the difficulty of distinguishing a temporary variation in gasoline demand from a change in long-term trend. Only if a change in demand is sustained and hence is expected to persist, will a gas distributor respond by raising the price of gasoline. Recognizing such persistent shifts in expected demand by construction requires time, justifying the delayed price response.

[12] This is an identification strategy widely used in literature as in Edelstein and Kilian (2007) and Hamilton (2009).

The price of gasoline reflects gasoline supply shocks immediately either arising at the refining stage or changes in the price of imported crude oil representing costs shocks for U.S. refiners. The model assumes that the retail supply curve for gasoline is perfectly elastic in the short run due to existing inventories. Refineries plan their production based on the consumption trend and keep extra supplies in inventories. Under these assumptions, the model can estimate the elasticity as dynamic response of U.S. gasoline consumption to a 1% gasoline price increase, as discussed above.

Davis and Kilian (2010) argues that the inclusion of U.S. macroeconomic variables is not required for the identification of the gasoline price shock, as long as changes in gasoline prices are predetermined with respect to all omitted variables. Kilian and Vega (2011) have recently shown using daily data that there is no evidence of feedback from exogenous U.S. macroeconomic news to the U.S. retail price of gasoline or the price of crude oil within one month of such shocks, suggesting that the assumption that U.S. gasoline prices are predetermined with respect to U.S. macroeconomic aggregates. Furthermore there is no loss of generality in restricting the analysis to a bivariate model in prices and quantities, as U.S. gasoline prices are predetermined with respect to these macroeconomic aggregates. Because we can view the bivariate model as a marginalized representation in which all additional variables other than the percent change in gasoline consumption have been integrated out.

3.5 Estimation Results and Discussions of the Results

The descriptive statistics of the variables are presented in Table 3.2.

Before we move on to present the estimation results, we first check the existence of unit roots and present them in Table 3.3. Overall, we were unable to reject the null that the log levels of each of these series contain a unit root at standard levels of confidence, except for gasoline consumption per capita which may not have a unit root at 10% level, although there was clear evidence of stationarity for the first-differenced data. Since gasoline consumption is at the border line, we can still treat it as it has a unit root as other variables.

Table 3.2 Descriptive Statistics

Variables	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	# of Obs.
Levels								
Gasoline consumption per capita	0.91	0.91	1.10	0.72	0.06	-0.08	3.26	458
Real gasoline price	2.03	1.97	3.67	1.13	0.56	0.66	2.45	458
Real income per capita	25441	24446	34648	16573	5201	0.04	1.65	458
Unemployment rate	6.52	6.10	10.80	3.80	1.61	0.53	2.50	458
1-year treasury bill rate	5.75	5.59	16.72	0.10	3.61	0.52	3.18	458
10-year treasury bill rate	6.97	6.80	15.32	1.53	2.97	0.55	2.88	458
Inflation	4.16	3.30	14.80	-2.10	2.94	1.53	5.33	458
Cost of oil production	32.91	23.75	129.03	9.48	26.15	1.71	5.02	458
Logs								
Gasoline consumption per capita	-0.10	-0.09	0.09	-0.33	0.07	-0.30	3.38	458
Real gasoline price	0.67	0.68	1.30	0.12	0.27	0.28	2.02	458
Real income per capita	10.12	10.10	10.45	9.72	0.21	-0.17	1.74	458
Unemployment rate	1.84	1.81	2.38	1.34	0.24	0.09	2.20	458
1-year treasury bill rate	1.37	1.72	2.82	-2.30	1.13	-1.63	4.97	458
10-year treasury bill rate	1.84	1.92	2.73	0.43	0.47	-0.59	3.25	458
Cost of oil production	3.26	3.17	4.86	2.25	0.65	0.71	2.63	458

Table 3.3 Augmented Dickey-Fuller Unit Root Tests

	Log levels		First differenced logs	
	t-statistics	p-value	t-statistics	p-value
Gasoline consumption per capita	-2.61	0.09	-15.62	0.00
Real gasoline price	-1.97	0.30	-15.52	0.00
Real income per capita	-1.48	0.54	-16.75	0.00
Unemployment rate	-2.30	0.17	-7.75	0.00
Inflation	-1.45	0.56	-7.90	0.00
Cost of oil production	-1.49	0.54	-12.29	0.00
10-year treasury bill rate	0.02	0.96	-15.71	0.00
1-year treasury bill rate	0.76	0.99	-13.99	0.00

It is common to find that demand, income, and price in Eq. (1) are all nonstationary, they are integrated of order 1, i.e. I(1). If all variables in the model are integrated of the same order, then a linear combination of non-stationary variables may be stationary (they become I(0)), such that co-integration exists. As autocorrelation plots in Figure 3.4 suggest the residuals are stationary, smaller than 1, only the residuals of the full sample are slightly higher than that of the other samples but even those residuals are less than 1.There is little evidence in these figures to suggest existence of non-stationarity so we reject a unit root in residuals for all samples. Based on these results, our demand model can be viewed as a cointegrating regression model.

3.5.1 Basic Model Results

The basic double-log model as specified in equation (1) along with 11 monthly seasonal dummies is estimated for each period using Ordinary Least Squares (OLS). The summary of estimated parameters for three sample periods: 1975-1980, 2001-2008 and 2008-2013 as well as for the full sample is presented in Table 3.4 with heteroskedasticity and autocorrelation corrected Newey-West standard errors. The model provides a good fit for the three sub-samples with R-squares of 0.88, 0.89 and 0.90 and small sum of squared residuals. However, the fit for the full sample is weaker with R-squares of 0.54 and a large sum of squared residuals. The monthly fixed effects demonstrate the strong seasonality present in the demand for gasoline. Normally gasoline demand increases in the summer months after schools close in June and stays high until schools re-open early September. Positive signs in coefficients for the high demand months are consistent with the expectation of high gasoline demand. Similarly, months of expected low demand have negative signs. The magnitudes of seasonal effects are similar between the three periods although the winter effect is somewhat smaller in the last two periods than the earlier period. Also summer effect seems to have increased in the later periods especially in the last sub-sample (2008-2013).

Figure 3.4 Autocorrelation Plot for Residuals of the Basic Double-Log Model

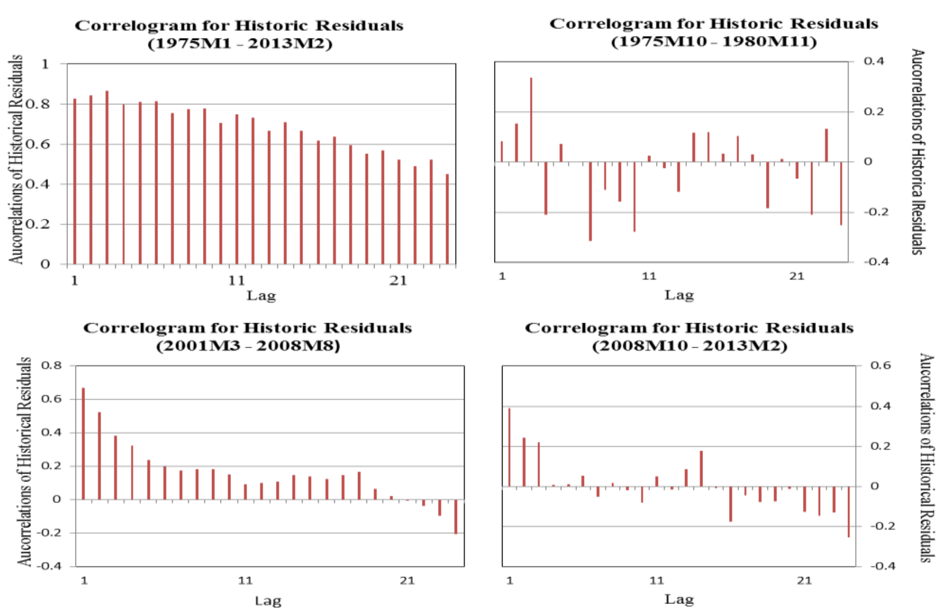


Table 3.4 OLS Regression Results-Double-Log Basic Model
Dependent variable: Log gasoline demand; $\ln(G_t)$

	1975-2013	1975-1980	2001-2008	2008-2013
β_0	0.17	-3.90***	-3.19***	5.33*
	(0.28)	(1.25)	(0.93)	(3.16)
ln(P)	-0.04***	-0.36***	-0.05**	-0.10***
	(0.01)	(0.04)	(0.02)	(0.02)
ln(Y)	-0.02	0.42***	0.31***	-0.52*
	(0.03)	(0.13)	(0.09)	(0.30)
Jan	-0.08***	-0.08***	-0.05***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Feb	-0.14***	-0.13***	-0.13***	-0.11***
	(0.01)	(0.02)	(0.01)	(0.02)
Mar	-0.02**	-0.02***	-0.02**	0.01
	(0.01)	(0.01)	(0.01)	(0.01)
Apr	-0.03***	-0.03	-0.04***	0.00
	(0.01)	(0.02)	(0.01)	(0.01)
May	0.01	0.01	0.02**	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Jun	0.00	0.01	-0.01	0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Jul	0.03***	0.03*	0.03***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Aug	0.04***	0.04***	0.03***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)
Sep	-0.04***	-0.03***	-0.04***	-0.02
	(0.01)	(0.01)	(0.01)	(0.01)
Oct	0.00	0.00	0.00	0.02
	(0.01)	(0.01)	(0.01)	(0.02)
Nov	-0.05***	-0.06***	-0.04***	-0.03***
	(0.01)	(0.02)	(0.00)	(0.01)
R-squared	0.54	0.88	0.89	0.90
S.E. of regression	0.05	0.03	0.02	0.02
Durbin-Watson stat	0.34	1.74	0.54	1.04
Sum squared resid	0.91	0.03	0.02	0.01
Number of obs.	458	63	91	91

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

We present the results from two alternative functional forms together with double-log functional form in Table 3.5. The monthly seasonal dummy variables have been excluded to simplify the presentation of the results. The coefficients on price and income are significant for the first (1975 – 1980) and the second (2001–2008) samples in the linear and double-log form estimations. The R-squares are high. The Durbin-Watson statistics for the later sample is lower suggesting positive serial correlations in residuals. Only the price elasticity in the full and the last (2008-2013) samples is significant in three models. Overall the fit of the full sample is much weaker compared to the other sample periods indicating changing market structure in the time period starting in the mid-1970's, therefore varying coefficients. As a result, the R-squared is lower and the Durbin-Watson statistics is close to zero which is an indication of positive autocorrelation in residuals.

Table 3.5 OLS Regression Results – Basic Model

	Basic Model:Linear				Basic Model:Semi-Log				Basic Model:Double-Log			
	1975-2013	1975-1980	2001-2008	2008-2013	1975-2013	1975-1980	2001-2008	2008-2013	1975-2013	1975-1980	2001-2008	2008-2013
β_0	0.98***	0.88***	0.63***	1.34***	-0.02	-0.12	-0.40	0.41	0.17	-3.90***	-3.19***	5.33*
	(0.03)	(0.13)	(0.08)	(0.28)	(0.03)	(0.13)	(0.08)	(0.32)	(0.28)	(1.25)	(0.93)	(3.16)
P	-0.02***	-0.14***	-0.03***	-0.04***	-0.02***	-0.15***	-0.03	-0.04***				
	(0.006)	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)				
Y	4.91E-07	2.34E-05***	1.25E-05***	1.15E-05	-4.25E-07	2.37E-05***	1.34E-05	-1.34E-05				
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)				
ln(P)									-0.04***	-0.36***	-0.05**	-0.10***
									(0.01)	(0.04)	(0.02)	(0.02)
ln(Y)									-0.02	0.42***	0.31***	-0.52*
									(0.03)	(0.13)	(0.09)	(0.30)
R-sq	0.53	0.87	0.91	0.90	0.55	0.88	0.91	0.90	0.54	0.88	0.89	0.90
S.E. of reg.	0.04	0.03	0.01	0.02	0.05	0.03	0.01	0.02	0.05	0.03	0.02	0.02
Durbin-Watson st.	0.33	1.70	0.67	1.06	0.34	1.72	0.69	1.07	0.34	1.74	0.54	1.04
Sum squared resid	0.76	0.03	0.01	0.01	0.90	0.04	0.02	0.01	0.91	0.03	0.02	0.01

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3.6 summarizes the elasticities estimated by the three models. The price and income elasticities for the linear and semi-log models are calculated by using the coefficients from the estimations presented in Table 3.5. The coefficient in the linear model denotes the change in demand in response to change in price or income. Hence to calculate the elasticities, the respective coefficient is multiplied by the ratio of price to either demand or income; namely price/demand or price/income. For the semi-log model, the estimated coefficient for the price can be shown as $\beta = \frac{d \log G}{dP} = \frac{dG/G}{dP} = \frac{dG}{G}\frac{1}{dP}$. To calculate the price elasticity of demand we multiply it by the price level as: $E_p = \frac{dG}{dP}\frac{P}{G}$.

Table 3.6 Price and Income Elasticities – Basic Model

	Basic Model							
	1975-2013		**1975-1980**		**2001-2008**		**2008-2013**	
	Ep	**Ei**	**Ep**	**Ei**	**Ep**	**Ei**	**Ep**	**Ei**
Linear	-0.041	-0.014	-0.337	0.447	-0.073	0.419	-0.113	-0.431
	(0.001)	(0.000)	(0.009)	(0.005)	(0.002)	(0.003)	(0.003)	(0.003)
Semi-Log	-0.042	-0.011	-0.335	0.434	-0.073	0.419	-0.112	-0.435
	(0.001)	(0.000)	(0.007)	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)
Double-Log	-0.038	-0.022	-0.359	0.425	-0.053	0.307	-0.100	-0.517
	(0.015)	(0.028)	(0.038)	(0.127)	(0.021)	(0.091)	(0.017)	(0.305)

Standard errors in parentheses

The price elasticity of gasoline demand ranges from -0.36 to -0.34 consistently across the three different specifications in the period 1975-1980 which is slightly higher than the estimates of Hughes *et al.* whose findings range from -0.31 to -0.33. The elasticity declines in the next period (2001–2008) to a range of -0.073 to -0.053 and increases to about -0.11 in the last sample period. Hughes *et al.* (2008) find a price elasticity of -0.042 for the sample 2001-2006. Their elasticity during this period may be smaller because their sample period excludes the record high gasoline prices. The elasticity in the full sample is lower than the elasticities in the sub-samples; ranging from -0.042 to -0.038. Income elasticity of gasoline demand is positive and around 0.43 across specifications in two sub-samples: 1975-1980 and 2001-2008. However, the sign turns negative in both the last sample (2008-2013) and the full sample. Negative income elasticity in the sub-sample of 2008-2013 may reflect the energy saving efforts with increasing fuel efficient vehicles as shown in the left panel of Figure 3.1, gasoline consumption continues to decline although income steadies and then increases slowly in 2012 onwards.

In order to test whether the subsamples from each period are independent, we perform a Student's t-test on the estimation of price and income elasticities for each model between subsamples and present the results in Table 3.7. We calculate the t-statistics as between two periods as: $\frac{E_p^{1975-1980} - E_p^{2001-2006}}{\sqrt{(s_p^{1975-1980})^2 + (s_p^{2001-2006})^2}}$. We reject the null hypothesis that the elasticities are the same in the two periods for all periods and models except for two cases with double-log estimations. The first one is when the t-statistics is 2; we fail to reject the null that the price elasticities between the periods 2001-2008 and 2008-2013 are the same. We cannot reject the null hypothesis of the same income elasticities between 1975-1980 and 2001-2008, for which the t-test value is 1.

Table 3.7 The Student t-tests on the Elasticity Estimates[13]

	t_p				t_i		
	1st and 2nd	2nd and 3rd	1st and 3rd		1st and 2nd	2nd and 3rd	1st and 3rd
Linear	-28	10	24		5	200	-154
Semi-Log	-38	11	31		6	432	-448
Double-Log	-7	2	6		1	3	-3

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

3.5.2 Alternative specifications

We employ a number of alternative model specifications to test the robustness of the price and income elasticity estimates produced by the basic model. We present the results in the sections a through d and discuss the results in section e.

3.5.2.1 Recession and Estimation with Macroeconomic Variable

In this section we include some macroeconomic variables in the basic-log model to investigate whether there was an upward bias in the elasticity estimations because of omitted variables especially during the periods when high gasoline prices

[13] 1st period refers to 1975-1980, 2nd period refers to 2001-2008 and the 3rd period refers to 2008-2013.

coincided with an economic recession in the United States. It is important to include such macroeconomic factors because as a result of recession, high employment and inflation may contribute to changes in gasoline demand. These recession periods are the first (1975-1980) and the last (2008-2013). Nevertheless we conduct the tests for the other periods as well as for the full sample for comparison purposes. We estimate price and income elasticities by including unemployment rate, interest rate and inflation rate in addition to real price, income and fixed month effects. We repeat the tests with the 1-year and 10-year interest rates. If the economic recession has a significant effect and decreases the gasoline consumption during the recession periods, we would expect smaller elasticities because in the original form, without the macroeconomic factors, model would artificially inflate the estimated price elasticity.

Results presented in Table 3.8 indicate that only inflation rate is statistically significant at 1% in the full and first sample when regressed with 1-year and 10-year interest rates. It is also significant at 10% in the last sub-sample when regressed with 10-year interest rate. Unemployment rate is only significant in the full and first sample when regressed with 10-year interest rate. Coefficients of both unemployment and inflation rate are negative which is expected as both high unemployment and inflation reduce gasoline demand due to declined purchasing power. Only 1-year interest rate coefficient is significant at 10% in the full sample. Overall interest rate coefficients are small and close to zero. However, the high F-statistics in each regression implies that the variables are jointly significant.

Our results are comparable to those estimated by Hughes *et al*. for the period of 1975-1980 as they only test this sample. Their price elasticities become more inelastic; -0.22 and -0.21 for the 1-year and 10-year interest rate models, respectively. The estimated income elasticities are also more inelastic at 0.33 and 0.38. The price elasticities we obtain for the same period are close to their values (-0.21 and -0.23). However, our income elasticities were smaller than their estimations which are 0.20 and 0.31, respectively. Nevertheless they are still lower than the estimated values without macroeconomic variables. The elasticities in the other recession period (2008-

2013) also decline with macroeconomic variables. We compare the elasticities in Table 3.9.

In the other recession period (2008-2013) both price and income elasticities become more inelastic. The elasticities in the non-recession period (2001-2008) nearly remained unchanged, except for the price elasticity estimate with 10-year interest rate which declined. This supports the idea that during the recession periods macroeconomic factors have a dampening effect on gasoline demand, whereas during growth periods their impact is subdued. The price elasticity in the full sample estimate remains unchanged however income elasticity gets larger.

Table 3.8 OLS Regression Results – Macroeconomic Variables[14]

	Regression with 10-year U.S. Treasury Bonds				Regression with 1-year U.S. Treasury Bonds			
	1975-2013	**1975-1980**	**2001-2008**	**2008-2013**	**1975-2013**	**1975-1980**	**2001-2008**	**2008-2013**
β_0	-5.68***	-1.39	-3.15***	4.64	-5.52***	-2.53	-2.84**	5.38
	(0.54)	-2.83	-1.58	(4.01)	(0.61)	(2.13)	(1.20)	(3.80)
ln(P)	-0.04***	-0.21***	-0.06	-0.01	-0.04***	-0.23***	0.01	-0.02
	(0.01)	(0.06)	(0.04)	(0.02)	(0.01)	(0.05)	(0.03)	(0.03)
ln(Y)	0.72***	0.20	0.31***	-0.18	0.71***	0.31	0.27**	-0.20
	(0.06)	(0.28)	(0.15)	(0.30)	(0.07)	(0.21)	(0.12)	(0.28)
ln(UNEMP)	-0.03	-0.14	-0.05	-0.02	-0.04***	-0.10*	0.02	-0.06
	(0.02)	(0.08)	(0.06)	(0.05)	(0.01)	(0.06)	(0.02)	(0.04)
ln(INF)	-0.39***	-0.06***	0.00	-0.60	-0.38***	-0.05***	-0.01	-0.68*
	(0.03)	(0.04)	(0.01)	(0.27)	(0.03)	(0.02)	(0.01)	(0.39)
ln(Int1)	0.01*	-0.01	0.00	0.01				
	0.00	(0.03)	(0.01)	(0.01)				
ln(Int10)					0.01	-0.02	-0.02	0.01
					(0.01)	(0.06)	(0.02)	(0.02)
R-squared	0.88	0.89	0.90	0.94	0.88	0.90	0.96	0.94
S.E. of regression	0.02	0.03	0.02	0.01	0.02	0.03	0.01	0.01
Durbin-Watson stat	1.34	2.06	0.54	1.69	1.33	1.96	1.48	1.72
Sum squared resid	0.24	0.03	0.02	0.01	0.24	0.04	0.01	0.01
F-statistic	204.13	23.64	39.48	38.14	202.13	29.46	90.53	36.96
Number of obs.	458	62	90	53	458	62	90	53

Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

[14] Inflation rate was negative in 9 months of 2009. So instead of the log value of inflation, the inflation rate is used in samples include 2009.

3.5.2.2 Price Income Interaction Parameter Model

The regression results of the price-income interaction model are presented in Table 3.9. The price and income elasticities are calculated based on the coefficients from the regressions as

$$Ep= \beta_1 + \beta_3 \ln Y_t \quad \text{and} \quad Ei= \beta_2 + \beta_3 \ln P_t$$

and presented in Table 3.12 along with the elasticities produced by the other alternative specification models. The elasticities are close to the values of Hughes *et al*. in the subsample of 1975-1980. Our price and income elasticities are much more inelastic than their elasticities in the second subsample but again their sample ends in 2006 while ours include months until 2008. All of the coefficients are statistically significant at 1% in the period 2001-2008 during which the U.S. economy witnessed a strong income growth.

If increasing income results in a decrease in the consumer response to gasoline price changes, we would expect a positive coefficient on the interaction term of the model. However, in all periods, we find the sign of coefficient on the interaction term is negative suggesting that on average, gasoline consumption is more sensitive to price changes as income rises. This somewhat counterintuitive result is supported by the findings of Hughes *et al.* and Kayser (2000). There are a few hypothesis offered in literature. First, Kayser (2000) argues that for high income households a greater proportion of automobile trips are discretionary which potentially can be reduced. Low-income households, however, are not able to reduce their consumption and amount of travel further as they already it to the minimum leaving little room for adjustment to higher prices. Second, Kayser (2000) also states that in response to increasing gasoline prices, high-income households can afford to purchase newer cars that will on average be more fuel-efficient. Along the same line, another explanation is that the number of vehicles per household increases with income. When the number of household vehicles exceeds the number of drivers, there is the possibility for drivers to shift to more fuel efficient vehicles within the household stock as gasoline prices rise. Whatever the explanation, the overall decrease in price elasticity despite growth in incomes suggests that these effects are relatively small compared to other factors affecting gasoline demand.

Table 3.9 OLS Regression Results- Interaction Variable

	1975-2013	1975-1980	2001-2008	2008-2013
β_0	-0.02	-31.31*	-11.39***	-15.87
	(0.90)	(16.37)	(1.51)	(13.87)
ln(P)	0.19	36.27	11.28***	23.68
	(0.97)	(22.01)	(1.43)	(16.71)
ln(Y)	0.00	3.21*	1.10***	1.52
	(0.09)	(1.66)	(0.15)	(1.33)
ln(P) * ln(Y)	-0.02	-3.72	-1.09***	-2.29
	(0.09)	(2.24)	(0.14)	(1.61)
R-squared	0.54	0.88	0.95	0.90
S.E. of regression	0.05	0.03	0.01	0.02
Durbin-Watson stat	0.34	1.83	1.31	1.14
Sum squared resid	0.91	0.03	0.01	0.01
F-statistic	37.42	25.62	96.16	25.17
Included observations	458	62	90	53

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

3.5.2.3 Dynamic Lag Model (or Partial Adjustment Model)

We estimate the equation (2) including 1-month and 12-month lags of gasoline demand separately along with the monthly seasonal dummies. As results show in Table 3.10, the price elasticity is significant at 1% in all samples; the income elasticity is significant only in two subsamples. The magnitudes of the elasticities are smaller than the values in basic log model. The coefficients of the lagged dependent variable are significant in both set of estimations for all samples. Usually including a lagged dependent variable as a regressor increases the risk of serial correlation in error terms. Since the Durbin-Watson test is not an appropriate test when lagged dependent variables included, we perform a Breusch-Godfrey Lagrange-Multiplier (LM) test for serial correlation up to order 12 (end of Table 3.10). We are able to reject the null hypothesis of serial correlation for the three subsamples, except for the full sample, in the estimation with 1-month lag. For the 12-month estimation we are able to reject the null of serial correlation for the first (1975-1980) and last sample (2008-2013).

Table 3.10 OLS Regression Results- Dynamic Lag

	1-moth Lag w/ Month Dummies				12-moth Lag w/ Month Dummies			
	1975-2013	**1975-1980**	**2001-2008**	**2008-2013**	**1975-2013**	**1975-1980**	**2001-2008**	**2008-2013**
β_0	0.08	-3.25***	-1.10**	3.42	0.13	-1.69	-2.71***	5.21**
	(0.06)	(1.16)	(0.55)	(2.66)	(0.14)	(1.65)	(0.89)	(2.16)
ln(P)	-0.01***	-0.31***	-0.02***	-0.06***	-0.05***	-0.34***	-0.05**	-0.07***
	(0.00)	(0.05)	(0.01)	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)
ln(Y)	0.00	0.36***	0.11**	-0.33	-0.01	0.20	0.26***	-0.51**
	(0.01)	(0.12)	(0.05)	(0.26)	(0.01)	(0.17)	(0.09)	(0.21)
ln(G_{t-1})	0.83***	0.14***	0.73***	0.42*				
	(0.03)	(0.11)	(0.12)	(0.12)				
ln(G_{t-12})					0.78***	0.28**	0.35*	0.32**
					(0.07)	(0.14)	(0.20)	(0.14)
R-squared	0.86	0.88	0.95	0.91	0.82	0.89	0.90	0.91
S.E. of regression	0.03	0.03	0.01	0.02	0.03	0.03	0.02	0.02
Durbin-Watson stat	2.83	2.06	2.17	1.89	1.17	1.93	0.76	1.26
Sum squared resid	0.29	0.03	0.01	0.01	0.36	0.03	0.02	0.01
F-statistic	188.48	24.77	93.01	28.95	142.55	27.45	47.25	28.52
Breusch-Godfrey Serial Correlation LM Tests								
F-statistic	33.66	1.61	0.66	0.50	30.75	1.07	4.23	0.94
Prob. F-Stat	0.00	0.13	0.79	0.89	0.00	0.41	0.00	0.52

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

3.5.2.4 Simultaneous Equations (Instrumental Variable) Models

We estimate the basic-log model using the log of crude oil cost to the refinery and its second lag via two-stage least square (2SLS). We test the equation with different lags of oil cost as well as changes in crude oil cost but the second lag produced slightly better results which are presented in Table 3.11. Yet, they fail to produce much improvement. Only significant price elasticity at 1% is for the 1975-1980 period. Both the price and income elasticities are significant at10% for 2001-2008 sample but with the wrong signs. Overall the R-squares are low indicating a poor fit. This again proves the difficulty of finding a good instrument for the gasoline price.

Table 3.11 2SLS Regression Results - Instruments: loilcost and loilcost(-2)

	1975-2013	1975-1980	2001-2008	2008-2013
β_0	7.07	-8.14	9.33*	5.89
	(5.39)	(12.32)	(5.12)	(7.74)
ln(P)	0.47	-0.41***	0.14*	-0.07*
	(0.41)	-0.19	(0.07)	(0.04)
ln(Y)	-0.74	0.86	-0.92*	-0.57
	(0.56)	(1.27)	(0.50)	(0.74)
R-squared	-9.45	0.37	-0.20	0.12
S.E. of regression	0.21	0.06	0.05	0.05
Durbin-Watson stat	0.11	1.30	1.57	1.28
Sum squared resid	20.74	0.18	0.20	0.12

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

3.5.2.5 Summary of Alternative Specifications Results

The estimated price and income elasticities of gasoline demand for alternative model specifications as well as the basic model are presented in Table 3.12. From all alternative model results, the price elasticities range from -0.41 to -0.21 in 1975-1980 and from -0.004 to -0.06 in 2001-2008 and from -0.07 to -0.11 in 2008-2013. There are positive price elasticities from the estimations with the macroeconomic variables with 10-year bond and from the IV estimations. The elasticity remains small in the full sample from -0.04 to -0.01 with the exception of IV estimation. The income elasticity is positive and varies from 0.18 to 0.86 in 1975-1980, from 0.11 to 0.31 in 2001-2008. However, it turns negative consistently across all models in 2008-2013 period which can be explained by the sharp drop in income due to financial crisis coincided with fuel efficiency efforts as a result of record high prices. The estimated elasticities are consistent with the finding of Hughes *et al*. for the common sample periods. Despite the best efforts, however, the endogeneity issue in estimating demand curve remains a challenge which may undermine the reduced elasticity estimation results especially for the recent years presented in the Table 3.12. The one of the causes of recent commodity boom is the increase in global demand for commodities including gasoline. The impact of endogeneity increases, i.e. elasticity gets smaller, if price changes are caused by demand shocks rather than supply shocks.

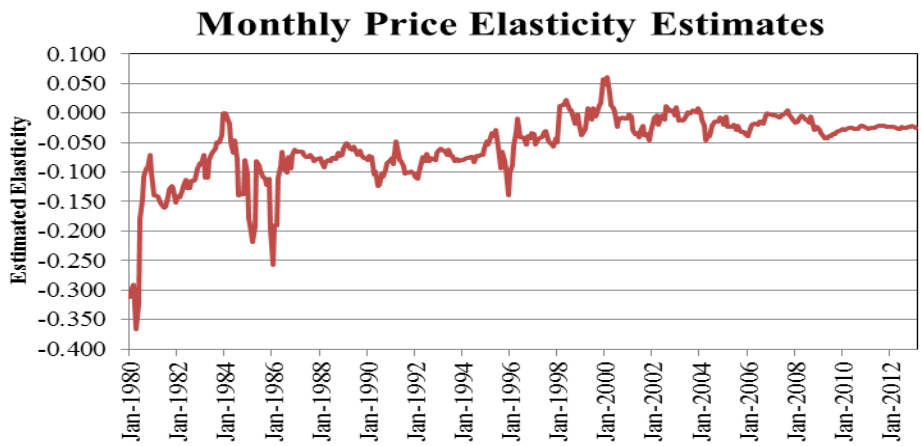
Table 3.12 Price and Income Elasticities – Alternative Specifications

	1975-2013		1975-1980		2001-2008		2008-2013	
	Ep	**Ei**	**Ep**	**Ei**	**Ep**	**Ei**	**Ep**	**Ei**
Basic	-0.04***	-0.02	-0.36***	0.42***	-0.05***	0.31***	-0.10***	-0.52*
Macroeconomic variables 1-year Interest rate	-0.04***	0.72***	-0.21***	0.20	-0.06	0.31***	-0.01	-0.18
Macroeconomic variables 10-year Interest rate	-0.04***	0.71***	-0.23***	0.31	0.01	0.27**	-0.02	-0.20
Price-Income Interaction	-0.01	-0.01	-0.21	0.18*	-0.004***	0.31***	-0.11	-0.68
Dynamic-lag model with 1 month lag	-0.01***	0.00	-0.31***	0.36***	-0.02***	0.11**	-0.06***	-0.33
Dynamic-lag model with 12 month lag	-0.05***	-0.01	-0.34***	0.20	-0.05**	0.26***	-0.07***	-0.51**
IV estimations	0.47	-0.74	-0.41***	0.86	0.14*	-0.92*	-0.07*	-0.57

3.5.3 Stability of the Estimated Price Elasticity over Time

The underlying assumption in the basic-log model is that the elasticities are constant over the estimated sample. However, the level and change in gasoline prices as well as the regulatory implementations such as the Corporate Average Fuel Economy (CAFE) program may cause shifts in price elasticities during different periods. To examine whether price elasticity varies over time, Equation 1 is estimated on a 61-month period and estimation period is rolled one-month at a time. We include the macroeconomic variables in the estimation as there are several recession periods during the full sample. The Figure 3.5 plots the estimated price elasticities for the entire period from January 1980 through February 2013. Gasoline demand is more elastic in the early and late 1980s. It becomes inelastic briefly in the mid-1980s possibly as a result of declining gasoline prices and increases in the fuel economy due to CAFÉ standards. In the 1990s it remains in a narrow band between -0.05 and -0.10 until the 2000s. In the early 2000s it moves up and remains positive briefly before it settles in a narrow range between -0.05 and 0. From the plot, we can infer that gasoline demand has become more inelastic over the years and even more permanently inelastic in the past decade.

Figure 3.5 Rolling Monthly Price Elasticity Estimates Jan. 1975 - Feb. 2013



3.5.4 Vector autoregressive model (VAR)

We first start with determining the lag length in VAR model for each sample period. Allowing for up to 12 lags, we estimate the VAR model and select 2, 3, 12 and 12 lags for 1975-1980, 2001-2008, 2008-2013 and 1975-2013 samples, respectively based on the AIC. The model including seasonal dummies and the changes in gasoline price and demand with the respective lags are re-estimated. The impulse response coefficients have been normalized such that the coefficient estimates can be interpreted as elasticities which are displayed in Table 3.13 up to 12 months. The Figure 3.6 shows the time path of 12-month of the response of gasoline consumption to a 1% increase in gasoline prices in each sample period.

A shock to the real gasoline price has a large and statistically significant impact on gasoline demand for the sample period 1975-1980 as shown in Table 3.13 and Figure 3.6. Except for the first two months, all other months have statistically significant coefficients. The elasticity is -0.19 in the first month but increases in magnitude through the months and reaches -0.82 in one year which is larger than the elasticity calculated by the OLS models. Although they are not statistically significant, the elasticity estimates in the sample 2001-2008 are fairly consistent and vary between -0.04 to -0.05 and similar in magnitude to the estimate of the basic log model. The elasticity estimates in 2008-2013 seem to be more volatile across the months and vary from -0.22 to 0.39. For the full sample, the elasticity is -0.10 and is statistically significant in the second month and reaches -0.11 in one year. Davis and Kilian (2010) also find the one-year elasticity of -0.12 for a sample period of 1989-2008 using a similar VAR model.

For robustness check we relax the assumption of perfect elastic supply curve (θ=0) in the VAR identification restriction matrix (A_0) and allow for a various degree of feedback from demand shifts to the price of gasoline. We impose a value for θ that is greater than zero and solve numerically for the remaining unrestricted parameter of A_0 conditional on that identifying assumption. The choice of θ has implications for the supply curve. For $\theta > 0$ the supply curve is upward sloping. Relative to the benchmark of no feedback, the one-year price elasticity is remarkably robust to these alternative assumptions. We replace the zero value of θ with 0.1, 0.3 and 0.5 and find that the elasticities are not different from the ones obtained by the original assumption of flat supply curve.

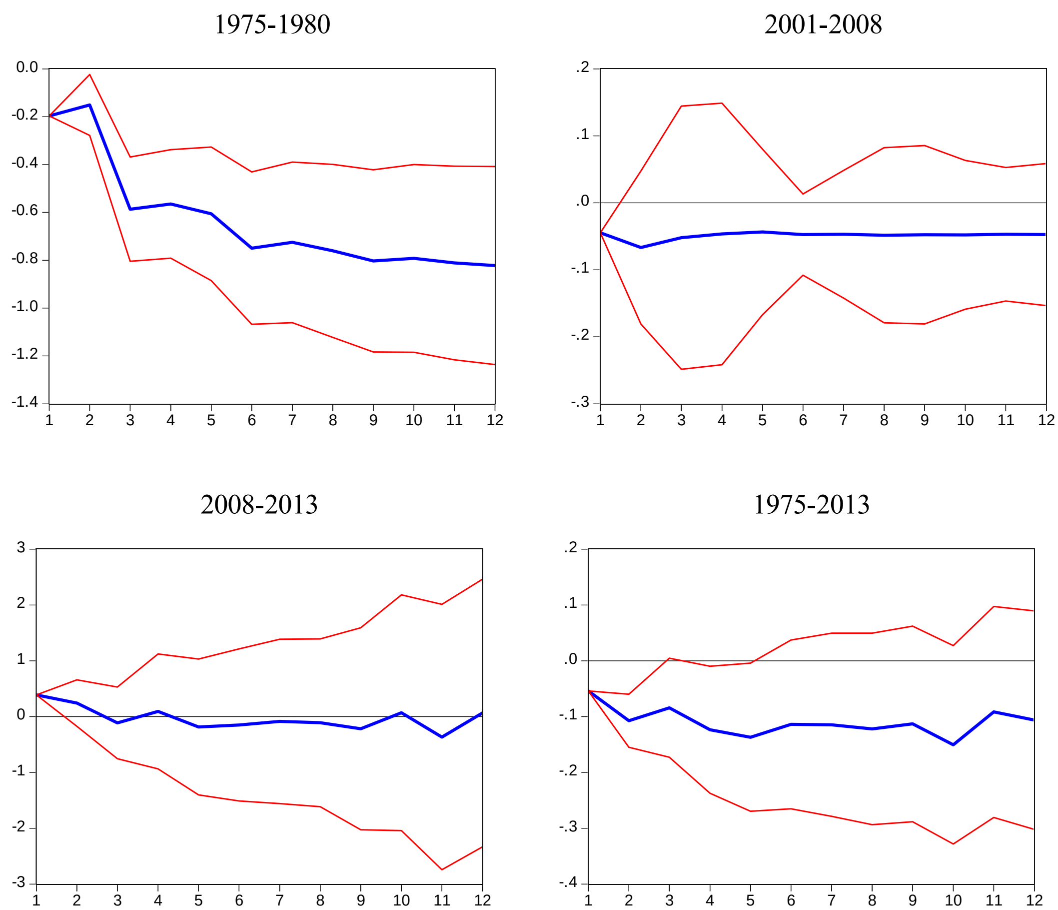
Table 3.13 Impulse Response Coefficients

(Elasticities estimated with the VAR model)

months	1975-2013	1975-1980	2001-2008	2008-2013
1	-0.054	-0.197	-0.045	0.389
	(0.000)	(0.000)	(0.000)	(0.000)
2	-0.108**	-0.151	-0.067	0.241
	(0.047)	(0.127)	(0.114)	(0.416)
3	-0.084	-0.587***	-0.052	-0.114
	(0.089)	(0.218)	(0.196)	(0.643)
4	-0.124	-0.565***	-0.046	0.092
	(0.114)	(0.227)	(0.195)	(1.030)
5	-0.137	-0.606**	-0.044	-0.186
	(0.133)	(0.279)	(0.124)	(0.133)
6	-0.114	-0.750**	-0.047	-0.151
	(0.151)	(0.318)	(0.061)	(1.362)
7	-0.115	-0.725**	-0.047	-0.086
	(0.172)	(0.361)	(0.131)	(1.502)
8	-0.122	-0.761**	-0.048	-0.111
	(0.178)	(0.392)	(0.111)	(2.111)
9	-0.113	-0.803**	-0.048	-0.219
	(0.175)	(0.381)	(0.133)	(1.809)
10	-0.151	-0.792**	-0.048	0.068
	(-0.948)	(-2.694)	(-0.265)	(-0.177)
11	-0.092	-0.812**	-0.047	-0.367
	(-1.033)	(-2.170)	(-0.353)	(-0.153)
12	-0.106	-0.822**	-0.047	0.065
	(0.196)	(0.414)	(0.106)	(2.397)

Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Figure 3.6 Cumulated Responses to 1% Structural Shocks with 1-Std Error Confidence Bands



3.6 Conclusions and Policy Implications

In this chapter we thoroughly examine the price and income elasticities of gasoline demand in the U.S. from 1975 to 2013 using various simple econometric techniques in addition to a dynamic VAR time series model. We split the full sample into several subsamples during which gasoline prices were high to make the results comparable to previous studies as well as to observe the elasticities in a similar price environment. Our results are comparable to the results of the recent studies. The estimated price elasticities in 1975-1980 seem to be more robust and range from -0.41 to -0.21, however, they decline and become more inelastic in the following two subsamples (a range of -0.004 to -0.11). Similarly, the full sample results are weighed by the impact of the recent periods and also reveal more inelastic values of around -

0.04. The estimation of elasticities in a 61-month window by rolling one month from 1975 to 2013 confirms the varying and declining price elasticities over time. However, estimated smaller elasticity could be partly also due to endogeneity between demand and supply shocks determining the prices. If price changes are as a result of demand shocks instead of supply then endogeneity would reduce the size of the elasticity further.

The VAR elasticity estimates of 1975-1980 period show significant and higher elasticity of -0.82 in one year. The sub-sample 2001-2008 has lower but not significant elasticity estimation of -0.05. The elasticities in 2008-2013 seem to be more volatile and insignificant. The full sample estimation with VAR model reveals a lower price elasticity of demand at -0.11.

The income elasticity results are more consistent. They are positive and around 0.36-0.42, 0.26-0.31 and 0.71-0.72 in 1975-1980, 2001-2008 and 1975-2013 samples, respectively. The income elasticity in the most recent sub-sample is estimated to be around -0.51 which seems puzzling at first but given the persistent high prices combined with fuel efficiency efforts and recovery in income level after a deep recession produces a negative income elasticity implying gasoline demand declines as income rises. Compared with the price elasticities, income elasticities appear to be declining but somewhat more stable, excluding the latest sample (2008-2013).

Significantly declining price elasticities found in recent decades support the idea of structural change in demand for gasoline. The results suggest that on average, U.S. drivers appear less responsive in adjusting to gasoline price increases than in previous decades because of a structural change in the U.S. market for transportation fuel and may reflect changes in demographics, social or vehicle characteristics during the past several decades.

There may be a number of potential explanations. First, the U.S. consumers have grown more dependent on automobiles for daily transportation than during the

1970’s and 1980’s and as a result, are less able to reduce vehicle miles traveled in response to higher prices. This could mean that drivers have less ability to respond to price changes because greater distances decrease the sustainability of non-motorized transportations. In addition, when demographic development patterns increase the distance between home and non-discretionary destinations such as the workplace, a greater share of the total vehicle miles traveled are fixed and cannot be reduced. An increase in multiple income households would further decrease flexibility if a greater share of the population requires a daily work commute. Finally, these effects are compounded if the availability of public transit is less than in earlier decades.

Second, with the record gasoline prices, drivers may change their driving behaviors in the short-run to save fuel and may switch to more fuel efficient vehicles in the medium to long term. A driver’s response to higher prices is largely composed of a reduction in the amount of driving (vehicle miles traveled) and an increase in the fuel efficiency of driving. The fuel efficiency of driving can be increased through, for example, improved vehicle maintenance or changes in driving behavior such as slower acceleration or reduced vehicle speed. In addition, purchasing more fuel efficient vehicles by consumers may contribute to decline in low elasticities.

Third, with the increasing income and wealth especially in the past decade, the share of gasoline consumption in total income has declined over the years, reducing the impact of an increase in gasoline prices on budget and making the consumers less sensitive to price increases.

Finally, the overall improvement in vehicle fleet average fuel economy since the late 1970’s and early 1980’s may have also contributed to a decrease in the elasticity of price on gasoline demand. As a result of the U.S. (CAFE) standard, the U.S. fleet average fuel economy improved from the 1980’s. Because the vehicle fleet has become more fuel efficient, a decrease in miles traveled today has a smaller effect on gasoline consumption which means if, for example, discretionary travel is diminished, the resulting reduction in gasoline consumption today is less than in the 1980's because today's vehicles burn less fuel per mile driven.

Fuel taxation can also play a significant role in fuel consumption and in reduction of greenhouse gas emissions, especially over the long term. However, for gasoline tax increases to be effective, the real fuel prices would have to rise faster than real incomes in order to offset their effect. Given the lower price elasticity of demand compared to the elasticity in previous decades, smaller reductions in gasoline consumption will occur for any given gasoline tax level. As a result, a tax would need to be significantly larger in order to achieve an equivalent reduction in gasoline consumption (Davis and Kilian (2010)). In the U.S., gasoline taxes have been politically difficult to implement. If imposing gasoline tax may not appear to be viable then it is very important to invest in research and technologies to improve vehicle fuel economy. An alternate measure to promote fuel efficiency would be an increase in the CAFE standard to achieve desired reductions in gasoline consumption which may compel the production of fuel efficient vehicles by auto makers and purchase of fuel efficient vehicles by private, business and public entities. Another alternative public policy would be to improve the network of public transportation in the areas where limited transportation exists and encourage the utilization of public transport.

3.A Appendix

3.A.1 Data Sources

Gasoline Consumption: MGFUPUS1, U.S. Product Supplied of Finished Motor Gasoline (Thousand Barrels), from the U.S. Energy Information Administration, which is calculated as domestic production plus imports, less exports and changes to stocks.

Real total disposable income: Disposable personal income: Total, billions of chained (2005) dollars, the U.S. Bureau of Labor Statistics, National Economic Accounts.

Gasoline price: Unleaded Regular Gasoline, U.S. City Average Retail Price, (Dollars per Gallon Including Taxes), Gasoline, unleaded regular, per gallon/3.785 liters, the U.S. Bureau of Labor Statistics.

CPI: CUSR0000SA0, Consumer Price Index - All Urban Consumers, U.S. city average,

1982-84=100, from the U.S. Bureau of Labor Statistics, re-indexed to 2005.

Inflation: Annual inflation is calculated using the CPI.

Population: The Census Bureau's Population Estimates Program (PEP).

1 and 10 year interest rates: 1 (GS1) and 10-year (GS10) Treasury Constant Maturity Rate: the Board of Governors of the Federal Reserve System.

Unemployment: LNS14000000, Labor Force Statistics from the Current Population Survey, the U.S. Bureau of Labor Statistics

Instrumental Variable: Refinery cost of crude oil: Refiner Acquisition Cost of Crude Oil, Composite (Dollars per Barrel), the U.S. Energy Information Administration

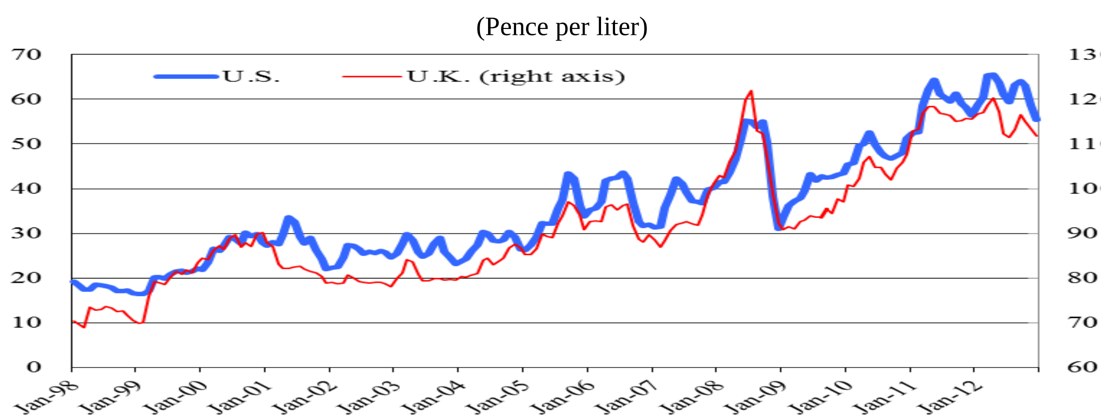
4 DEMAND AND SUPPLY SHOCKS IN THE U.S. AND U.K. GASOLINE MARKET

4.1 Introduction

This chapter is an extension of Chapter 3 in which we aim to identify the underlying demand and supply shocks in gasoline markets in two structurally different countries: the U.S. and U.K. Understanding the source of gasoline price changes and the response of demand and supply to price changes would help formulate policy responses. Similar to other commodity prices, the level and volatility of motor gasoline prices have risen in the U.S. and U.K. in the past decade. It is widely accepted that this surge in gasoline prices was part of a larger commodity price boom and caused by a sharp demand increase due to high global economic activity, while supply constraints had a limited effect on the prices. Both Hamilton (2009) and Kilian (2009) state that previous oil price shocks were primarily caused by physical disruptions of supply, but the record prices in 2008 were caused by strong demand coupled with stagnating world production.

Figure 4.1 illustrates the real gasoline price development in the U.S. and U.K. Overall both prices seem to follow a similar trend with the exception of small local price deviations and divergence. The level of price difference is striking; the price of one liter gasoline in the U.K. is nearly double the price of one liter in the U.S. In 2012, the real U.S. gasoline price in British pound pence seems to exceed the record levels reached in 2008.

Figure 4.1 Real Gasoline Prices



Source: The U.K. Department of Energy and Climate; the U.S. Energy Information Administration.

There are some similarities on the supply side in the U.S. and the U.K.; both extract and refine crude oil to produce gasoline and both are nearly self-sufficient in terms of production but they differ significantly in market and consumption structure. The U.K. has the highest excise tax rate among industrial countries and the U.S. has the lowest.[15] Public transportation is widely available in the U.K. while it is essential to own and drive a car in the U.S. to be mobile. The most of the vehicle run on gasoline in the U.S. while the diesel fuel usage is higher than gasoline usage in the U.K. where diesel car sales doubled since the 2000's increasing demand for diesel. Finally, in terms of volume of consumption, the U.S. consumes more than 10 times the amount that the U.K. consumes.

These differences are reflected in the gasoline consumption patterns which are shown in Figure 4.2. The volume and share of gasoline in total petroleum products consumed has been steadily declining in the U.K. since the early 2000s, due to an increase in usage of diesel. The financial crisis in 2008 followed by a recession did not make any changes on the down-trend. The actual volumes consumed in the U.S. have risen steadily since the 1990's before dropping in 2008. Similarly, the share of gasoline consumption started to climb in the 2000s, before falling in 2008. However, both the share and volume began to recover in recent years, albeit at a slower pace. Because of these structural dissimilarities, the determinants of gasoline prices and the dynamics of supply and demand conditions would likely to be also different in these two markets.

There is a large body of work on gasoline markets which mainly focuses on determining the short or long term sensitivity of gasoline consumption to changes in prices or income. There have been some studies such as Borenstein *et al*. (1997) attempting to link movements in crude oil and gasoline prices. A small number of research focused on the effect of retail energy price shocks on the economy (Edelstein and Kilian (2009)). However, none of these studies includes the supply conditions and

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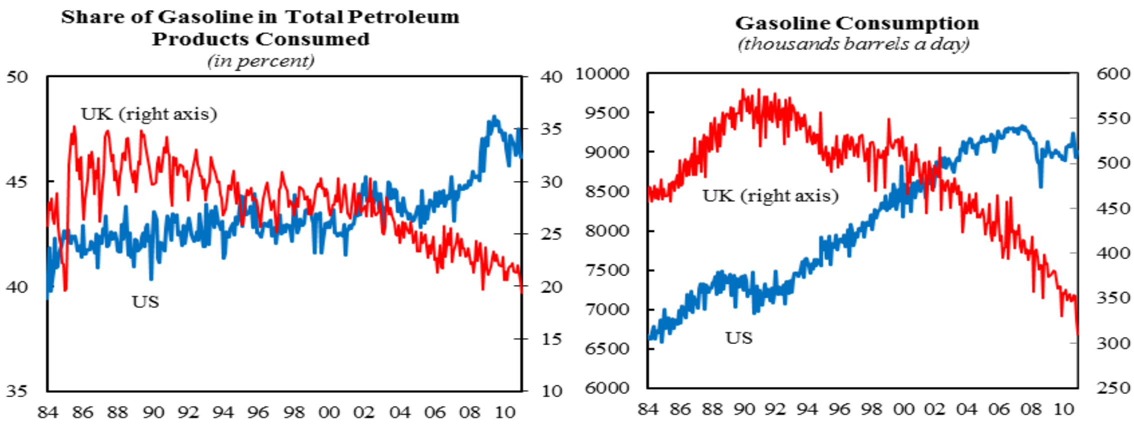
[15] From January 4, 2011, the UK duty rate for the road fuels unleaded petrol, diesel, biodiesel and bioethanol is GB£ 0.5895 per liter (£2.20 per U.S. gallon or about $3.56). In the US, the federal excise tax on gasoline is 18.4 cents per gallon. In January 2011, motor gasoline taxes averaged 48.1 cents per gallon nationwide.

examines the effect of demand or supply shocks on gasoline prices or the reverse; effect of price changes on demand/supply in a dynamic framework until Kilian (2009) and Kilian (2010) developed two related structural VAR models.

Figure 4.2 Gasoline Consumption in the U.S. and U.K.[16]



Source: International Energy Agency.

In the first model, Kilian (2009) constructs a structural VAR model of the global crude oil market in which he includes three variables: global oil production, global demand and oil price and measures the response of each variable to the shocks to the system. The second model Kilian (2010) built is an extension of the first in which the U.S. retail gasoline market is linked to the imported crude oil dynamics. This joint structural VAR model includes five variables: global oil production, real global economic activity, real price of imported oil, the real price of gasoline and finally the U.S. gasoline consumption. With this framework, he aims to understand the evolution of gasoline prices that includes both the crude oil demand and supply shocks that drive the global price of crude oil and the additional gasoline demand and supply shocks that affect the domestic retail gasoline market by allowing for feedback between these markets. The joint VAR model was useful to differentiate the global or local impact on

[16] Series are seasonally adjusted to exhibit the trend.

the gasoline prices. In both study, he argues that prices respond to demand and supply shocks differently in magnitude, pattern and persistence.

In this chapter, we take the structural VAR model that was developed for the crude oil in Kilian (2009) and apply to the gasoline markets. Instead of linking the gasoline to crude oil market, we focus to understand the domestic gasoline fundamental dynamics in the U.S. and the U.K. In this set-up, not explicitly but the price and supply of crude oil are included indirectly through gasoline supply, since gasoline production depends on crude oil and its availability. Any shock to crude oil supply or price would impact gasoline supply. Hence, we include the gasoline market fundamentals: supply, demand and prices in the VAR specification and then decompose the real price of gasoline into three fundamental components: supply shocks, global demand shocks and gasoline specific demand shocks and measure the responses of each variable. These responses would help us explain the fluctuations in the price of gasoline, but also understand how consumers react to gasoline price fluctuations.

This chapter contributes to the empirical literature by attempting to explain the dynamic effects of shocks on gasoline markets in two distinctly different markets; the U.S. and U.K. during 1983-2010 and 1998-2010, respectively. Other than Kilian's work on the gasoline and crude oil prices in the U.S., there is no study which applied this framework on any other country and compared the results. Applying the same model to the U.S. and U.K. will be helpful to observe the different market dynamics and draw some policy conclusions in two structurally distinct markets.

The plan of this chapter is as follows. Section 2 presents a brief literature survey, section 3 explains the model that will be used for the estimations. Section 4 describes the data. Section 4 presents the estimation results. Section 5 provides concluding remarks.

4.2 Literature Survey

There is a large literature on price and income elasticities of gasoline demand across countries and time period. More recent studies, such as Hughes *et al* (2008) argue that structural change in the gasoline market in the U.S. caused insensitivity of gasoline demand to price changes in the last decade. Lin and Prince (2013) find that consumers appear to be less elastic in response to changes in gasoline prices when gasoline price volatility is medium or high, compared to when it is low. However, these studies focus only on response of demand to changes in price without investigating the possible changes in supply condition or dynamic interactions between supply, demand and price. This type of analysis usually suffers from endogeneity which undermines the estimated results. To circumvent the endogeneity problem and examine the dynamic interaction among supply, demand and price, we adopt a structural VAR framework which was developed in Kilian (2009) and Kilian (2010). We briefly review these two models before we lay out our framework for empirical analysis.

In Kilian (2009), a structural VAR model of the global crude oil market is constructed to identify the underlying demand and supply shocks in the global crude oil market. The structural VAR representation is as follows:

$$A_0\, z_t = \sum_{i=1}^{24} A_i\, z_{t-1} + \varepsilon_t$$

where ε_t denotes the vector of serially and mutually uncorrelated structural innovations. A_0^{-1} has a recursive structure such that the reduced-form errors e_t can be decomposed according to $e_t = A_0^{-1}\, \varepsilon_t$:

$$e_t \equiv \begin{pmatrix} e_t^{\Delta production} \\ e_t^{real\ economic\ index} \\ e_t^{real\ oil\ price} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{oil\ specific-demand\ shock} \end{pmatrix}$$

The three variables that are jointly determined are the percent change in global crude oil production, the index of real economic activity (proxy for aggregate demand) and the real price of oil. These variables are driven by three demand and supply shocks in the order as defined above: shocks to the current physical availability of crude oil (oil supply shocks), shocks to the current demand for crude oil driven by fluctuations in the global business cycle (aggregate demand shocks); and shocks driven by shifts in the precautionary demand for oil (precautionary demand shocks). Precautionary demand arises from the uncertainty about shortfalls of expected supply relative to expected demand.

Based on these structural shocks, he finds that source of oil price increases may have very different effects on the real price of oil, depending on the underlying cause of the price increase. For example, an increase in precautionary demand for crude oil causes an immediate, persistent, and large increase in the real price of crude oil; an increase in aggregate demand for all industrial commodities causes a somewhat delayed, but sustained, increase in the real price of oil that is also substantial; and crude oil production disruptions cause a small and transitory increase in the real price of oil within the first year.

Kilian argues that decompositions of fluctuations in the real price of oil show that oil price shocks historically have been driven mainly by a combination of global aggregate demand shocks and precautionary demand shocks, rather than oil supply shocks. For example, the surge in the price of oil after 2003 was driven primarily by the cumulative effects of positive global demand shocks. Likewise, the increase in the real price of oil after 1979 was driven by the superimposition of strong global demand driven by a booming world economy and a sharp increase in precautionary demand. Typically, disruptions of crude oil production play a less important role. When exogenous political events do affect oil prices, it is less the physical supply disruptions than the increased precautionary demand for oil triggered by increased uncertainty about future oil supply shortfalls that drives the price of oil.

In his second paper, Kilian (2010) uses a joint structural VAR model of the global market for crude oil and the U.S. market for gasoline during the sample period of 1975-2008 and 2002-2008. The VAR specification is the same as the one in Kilian (2009) and jointly explains the evolution of the five variables: the growth of world production of crude oil, the measure of global real economic activity, the real price of imported crude oil, the real price of gasoline in the U.S., and the growth of the quantity of gasoline consumed in the U.S. These five variables are driven by five structural shocks: (1) crude oil supply shocks (oil supply shocks); (2) shocks to the demand for all industrial commodities in global markets (aggregate demand shocks); (3) demand shocks that are specific to the global crude oil market (oil-market specific demand shocks); (4) shocks to the supply of gasoline in the U.S. (exemplified by refinery shocks); and (5) shocks to the U.S. demand for gasoline (gasoline demand shocks). The ordering and feedback structure of the VAR are shown below.

$$e_t \equiv \begin{pmatrix} e_t^{\Delta\, global\ oil\ production} \\ e_t^{global\ real\ economic\ activity} \\ e_t^{real\ price\ of\ crude\ oil} \\ e_t^{real\ U.S.\ price\ of\ gasoline} \\ e_t^{U.S.\ gasoline\ consumption} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 & 0 & 0 \\ a_{21} & a_{22} & 0 & 0 & 0 \\ a_{31} & a_{32} & a_{33} & 0 & 0 \\ a_{41} & a_{42} & a_{43} & a_{44} & 0 \\ a_{51} & a_{52} & a_{53} & a_{45} & a_{55} \end{bmatrix} \begin{pmatrix} \varepsilon_t^{oil\ supply\ shock} \\ \varepsilon_t^{aggregate\ demand\ shock} \\ \varepsilon_t^{oil-market\ specific\ demand\ shock} \\ \varepsilon_t^{refinery\ shock} \\ \varepsilon_t^{gasoline\ demand\ shock} \end{pmatrix}$$

He shows that, in the short run, 80% of the fluctuations in the real price of gasoline are determined by refining shocks and 20% by oil market specific demand shocks. In the long run, 54% of the variation in the real price of gasoline in the U.S. is driven by oil-market specific demand shocks, 41% by shocks to the global business cycle, and 4% by refining shocks with basically no role for domestic gasoline demand shocks or global oil supply shocks. Gasoline consumption shows a somewhat different picture. In the short run 96% of the variation in the growth rate of U.S. gasoline consumption is driven by gasoline demand shocks and 2% by shocks at the refining stage. In the long run, 83% of the variation in the growth rate of U.S. gasoline consumption is driven by domestic gasoline demand shocks, 3% by refining shocks, 4% by demand shocks specific to the crude oil market, 4% by shocks to the global business cycle, and 6% by oil supply shocks.

The main conclusion of Kilian's analysis is that each demand and supply shock has distinct dynamic effects on the real price of imported crude oil and on the retail price of gasoline in the U.S. He concludes that the origin of the shocks mattered in assessing the responses of prices and consumption as they responded differently in magnitude, pattern and persistence to each demand and supply shock. He also showed that the surge in the gasoline price in the U.S. between 2002 and mid-2008 was due to positive demand shocks in global commodity market.

For our analysis in this chapter, we adopt the VAR model that is developed in Kilian (2009) for crude oil market to gasoline market, instead of using Kilian (2010) which links the gasoline prices to crude oil prices. We choose to concentrate on the dynamics of gasoline demand, supply and prices, rather than examining the interaction between gasoline and crude oil markets. Because gasoline production and prices depend on crude oil supply and prices, any shock to crude oil price will affect the gasoline prices. The distinction of the source of crude oil price shock whether it is due to shortages of crude oil or increase in demand for crude oil is not the focus of our analysis. In the next section, we will lay out the specifications of VAR model for empirical testing.

4.3 Methodology

We employ the reduced form VAR with recursive shock identification as specified in Kilian (2009) to disentangle the shocks to the gasoline prices. There are three variables in the model: total gasoline supply, industrial production as a proxy for a measure of global real economic activity and the real price of gasoline. The VAR representation is as follows:

$$A_0 z_t = \alpha + \sum_{i=1}^{n} A_i z_{t-i} + \varepsilon_{t,} \qquad (1)$$

where n is the lag order, ε_t represents the vector of serially and mutually uncorrelated structural innovations. A_0^{-1} has a recursive structure such that the reduced-form errors e_t can be decomposed according to $e_t = A_0^{-1}\ \varepsilon_t$

The recursive shock identifications are proposed as below

$$e_t = \begin{pmatrix} e_t^{\text{gasoline production}} \\ e_t^{\text{global real economic activity}} \\ e_t^{\text{real gasoline price}} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{pmatrix} \begin{pmatrix} \varepsilon_t^{\text{gasoline supply shock}} \\ \varepsilon_t^{\text{aggregate demand shock}} \\ \varepsilon_t^{\text{gasoline specific shock}} \end{pmatrix}$$

It is proposed that these three variables are driven by three structural shocks: (1) shocks to the current physical availability of gasoline (supply shocks), (2) shocks to the current aggregate demand for all industrial materials including gasoline driven by fluctuations in the global business cycle (aggregate demand shocks); and (3) shocks driven by shifts in consumer demand in U.S. or U.K. (gasoline specific demand shock).

With the ordering of these shocks, three restrictions are imposed on A_0^{-1}.

The first restriction is that the short-run gasoline supply curve is very steep so that shifts in the demand curve do not produce immediate changes in supply. The rationale for this assumption is that changing gasoline production is costly, because the production of gasoline involves two constraints: crude oil and refineries. Both oil producers and refineries set production based on expected trend growth in demand not to unexpected variation in demand. So gasoline price responds immediately to a shift in demand to clear the market. If the demand shock persists then the supply response will lag by at least one month. Example of gasoline supply shocks are supply shocks to price or supply of crude oil in addition to refinery problems that shut down the operation of refiners and reduce the domestic supply of gasoline or changes in regulation that restrict gasoline output. A distinction between the effect of a crude oil or refineries shock will not be made in this model. Both will be considered as a shock to supply of gasoline.

The second restriction is related to the effect of shocks to the industrial or economic activity in the U.S. or U.K. and the rest of the world. This shock is interpreted as a shock to global precautionary demand; in other words, the change in price is driven by market participants to increase their inventories, reflecting expectations of tighter commodity supply markets in the near future. During the recent commodity boom, almost all commodity prices rose in tandem as a result of a surge in global demand. So it can be argued that the commodity markets are globally integrated and a global demand shock should have approximately the same impact on gasoline as on other commodities regardless of its origin. With this assumption, it is assumed that country's industrial production will not respond immediately to the real gasoline price shocks but will respond with a lag.

Finally, the third source of shocks is represented by the gasoline specific shocks which reflect shifts in consumer preferences, changes in demographic structure and the degree of urbanization and other shifts in gasoline demand for a given real price of gasoline. Any unanticipated shifts in gasoline supply or economic activity will result in an immediately response of the real price of gasoline.

4.4 Description of Data

The details on data and data sources are listed in Appendix 4.A.1. The data are monthly from January 1983 to December 2012 for the U.S. and from January 1998 to December 2012 for the U.K. As a proxy for global economic activity, Industrial Production is used. But we also try the domestic demand to examine whether the results would differ. The gasoline prices are converted to real by using respective CPIs for both countries. Gasoline supply is domestic production plus imports, minus exports and changes to stocks. All variables are in logarithms. Summary statistics for the variables used in the estimations are provided in appendix Table 4.A.1. The graphical representation of variables is presented in Figure 4.3 and 4.4. Both the demand and supply series exhibit a clear seasonal pattern. The VAR tests conducted with the non-seasonally adjusted series along with 11 monthly dummies are presented in the text; the estimation results with seasonally adjusted series are included in Appendix. The unit root tests of seasonally adjusted series are also included in Appendix. The graphs show that most of the series have an apparent trend and are non-stationary. All series except for demand in the U.S. are I(1) as the ADF test results presented in Table 4.1 In contrast, the first difference of the logs of all variables shows clear evidence of stationary in ADF and in Philips-Peron tests. However, Philips-Peron tests results reveal that the logs of demand and supply in the U.S. and supply in the U.K. turn to be I(0) .

Table 4.1 Unit Root Tests

	U.S.			
Logs	**Augmented Dickey Fuller**		**Phillips-Perron**	
	t-statistics	**Probablity**	**t-statistics**	**Probablity**
	Lag length=6			
Supply	-1.70	0.43	-3.16	0.02
Price	-2.01	0.28	-1.65	0.46
IP	-1.51	0.53	-2.00	0.29
Log Differences				
	t-statistics	**Probablity**	**t-statistics**	**Probablity**
	Lag length=6			
Supply	-15.71	0.00	-43.15	0.00
Price	-13.40	0.00	-10.36	0.00
IP	-4.93	0.00	-17.84	0.00
	U.K.			
Log	**Augmented Dickey Fuller**		**Phillips-Perron**	
	t-statistics	**Probablity**	**t-statistics**	**Probablity**
	Lag length=6			
Supply	-2.07	0.26	-4.41	0.00
Price	0.11	0.97	-0.09	0.95
IP	-1.75	0.40	-1.50	0.53
Log Differences				
	t-statistics	**Probablity**	**t-statistics**	**Probablity**
	Lag length=6			
Supply	-13.74	0.00	-19.92	0.00
Price	-16.35	0.00	-16.24	0.00
IP	-9.63	0.00	-9.65	0.00

Figure 4.3 U.S. Gasoline Fundamentals

(January 1983 – December 2012)

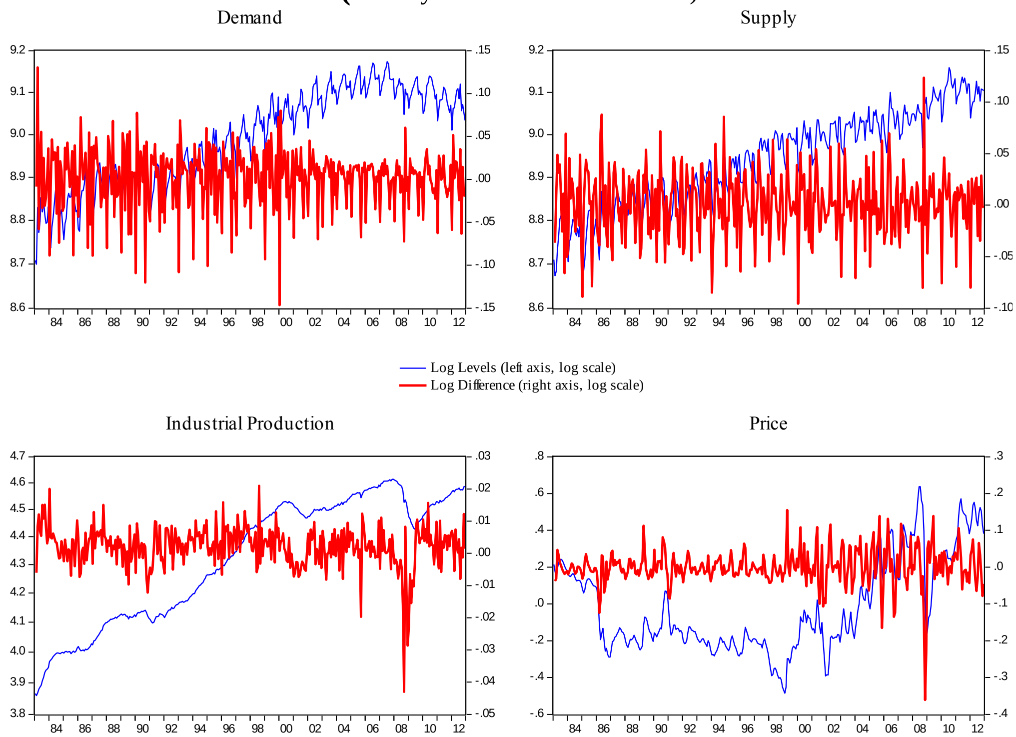
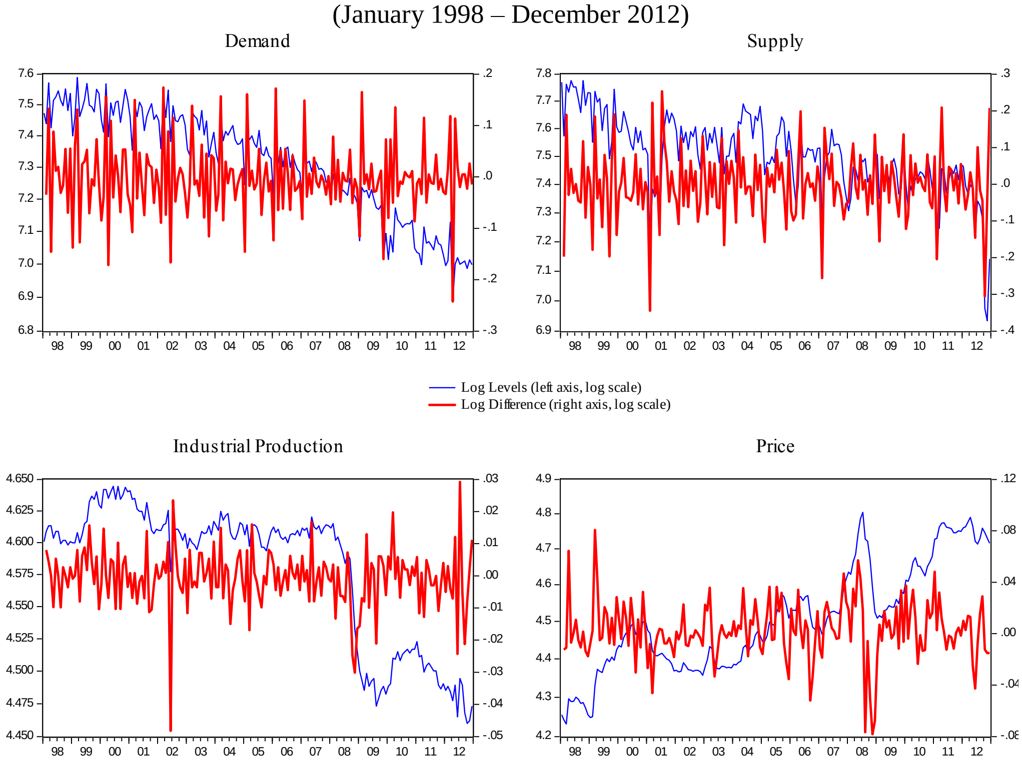


Figure 4.4 U.K. Gasoline Fundamentals

(January 1998 – December 2012)



4.5 Estimation Results and Discussions

Three variables are used in the estimation: gasoline supply, industrial production as proxy for global economic activity or aggregate demand and gasoline price. We also replace the industrial production with domestic demand to examine whether the results will differ. The lag length in each VAR specification is calculated and included in the relevant table. The lag lengths were based on the results from Akaike information criteria (AIC). Due to high seasonality in the data, 11 monthly dummies are included in the regressions for the U.S. but not in the regressions for the U.K. as they did not make much difference in the results. The same tests are repeated with seasonally adjusted series and included in the Appendix. The industrial production and price series are expressed in log differences in the estimations for both the U.S. and U.K. The supply series showed sign of I(0), so we performed the tests using both in log levels and in the log differences. However, supply in log level is not responsive to the shocks and makes the interpretation and comparison difficult. Therefore we include the results of estimation with the log difference of supply in the text. We add the results with supply log levels in Appendix. The order of variables in each of VAR estimation is explained in the methodology section. The covariance matrix of reduced form residuals from estimated VAR models reveal that the correlation of residuals of variables are quite small indicating that the order would not make a big difference in the VAR results.[17]

Each row in Figures shows the cumulated response of each variable to one percentage point shock to each one of three variables for a horizon of up to 24 months. All of these shocks are applied in a way that gasoline price will increase. Namely, the supply shock was normalized to represent a crude oil or refinery disruption, i.e. one percent point decline in supply. The demand shock or economic activity shock was

[17] In fact, VARs estimated with a different ordering of the variables (industrial production, supply and price), the results did not differ much.

normalized to represent a demand expansion (one percent point increase in aggregate demand).

Figure 4.4 illustrates the cumulated responses of each variable for the U.S. The first row shows the responses of supply to shocks to all variables in the model. The first graph displays an unanticipated shock to gasoline supply persists for a long time and does not return to original levels. This result is statistically significant and reflects s slow adjustment in gasoline production in case of a disruption due to refinery outages. If it is not planned refinery maintenance then it is likely to take longer time to fix and bring the refinery back to the original level of production. The initial response of supply to an increase to in global growth is to rise but then to decline in 3-4 months. It goes back to the original levels in two years. The effect of a gasoline demand shock on supply is less dramatic and shows a slow adjustment. However, these results statistically insignificant. Also the seasonality in supply data is evident in these responses.

In the second row, the responses of aggregate demand are presented where results are not statistically significant and standard errors are large. In the last row, the responses of gasoline prices to shocks to all three variables in the model are exhibited. All of the results are statistically significant. Gasoline price increases and reaches a peak after two quarters in response to a negative supply shock. It declines and settles at a level slightly lower than the original level after 24 months. The highest impact on gasoline price comes from a shock to the aggregate demand. It increases by almost 4 percent in about a year in response a one percent increase in economic activity. The effect declines yet remains high and becomes permanent after 2 years. Gasoline prices increase in the first quarter after a shock to gasoline demand but the effect dies down and the level goes back to the original level after two years.

Overall, these results suggest that gasoline price in the U.S.is fairly responsive to supply and aggregate demand shocks. The responses of the seasonally adjusted price series are similar to the non-seasonally adjusted series, they only look smoother and the magnitudes of the responses are somewhat smaller (Figure 4.A.3).

Figure 4.6 exhibits the accumulated responses to one percentage shocks of each variable in the U.K. gasoline market. In all cases the impact becomes permanent and the series do not go back to the original levels for the U.K. Also the adjustments to shocks are rather fast due to short lag length in VAR estimation. Gasoline supply recovers in a quarter after a negative supply shock. The supply also responds an aggregate demand shock by rising first then settling at a higher level than the original level. The result is statistically significant. Supply increases and reverts to the original levels after a shock to gasoline demand. In the next row, industrial production, or aggregate demand, is unresponsive to shocks to supply or gasoline demand and results are insignificant. The most interesting result is the response of gasoline prices to aggregate demand. The prices rise and remain higher than the original level and statistically significant. A shock to supply does not create any permanent or significant impact on the price. The graphs of responses with the seasonally adjusted series are included in appendix Figure 4.A.4 which shows similar results. There are more fluctuations in the series since the lag length turned to be for 4. Overall, supply and gasoline prices are more responsive to aggregate shocks in the U.K.

The data sample for the U.S. cover longer period than that of the U.K.. So to make the results comparable, the VAR estimations are conducted with the same time period for the U.S. (1998-2012). The results are presented in Figure 4.7. There are more fluctuations in the responses to shocks as the lag length is 12. The results are similar to the results of full sample except for the response of price to supply shocks and aggregate demand shock. Gasoline price jumps in response to a supply shock and goes back to the original level in 24 months, in the full sample estimation; it remained below the initial levels. The most notable result is the response of price to a shock to aggregate demand growth which is statistically significant and even higher in terms of magnitude (8%) than the results with the longer sample period. Furthermore, the response of gasoline price to a shock to the aggregate demand is four times higher than the response of gasoline price to a supply shock. This result confirms the argument that the increase in gasoline price was part of a larger commodity price boom and caused by a sharp demand increase due to high global economic activity, while supply constraints had a limited effect on the prices.

To summarize, the VAR estimation results imply that the gasoline price in the U.S. is more responsive to aggregate demand and supply shocks. The response of gasoline price to aggregate demand is much larger than the response to supply shocks. The gasoline price in the U.K., however, seems to respond only to aggregate demand changes. The response of the U.S. gasoline price to growth in aggregate demand is nearly four times higher than the response of gasoline price in the U.K. to an aggregate shock.

Figure 4.5 U.S. Cumulated Responses 1% Point Shock with 1-Std Error Confidence Bands

(Jan. 1983 – Dec. 2012, order: dlsupply dlip dlp, 11 monthly dummies Lag length=6)

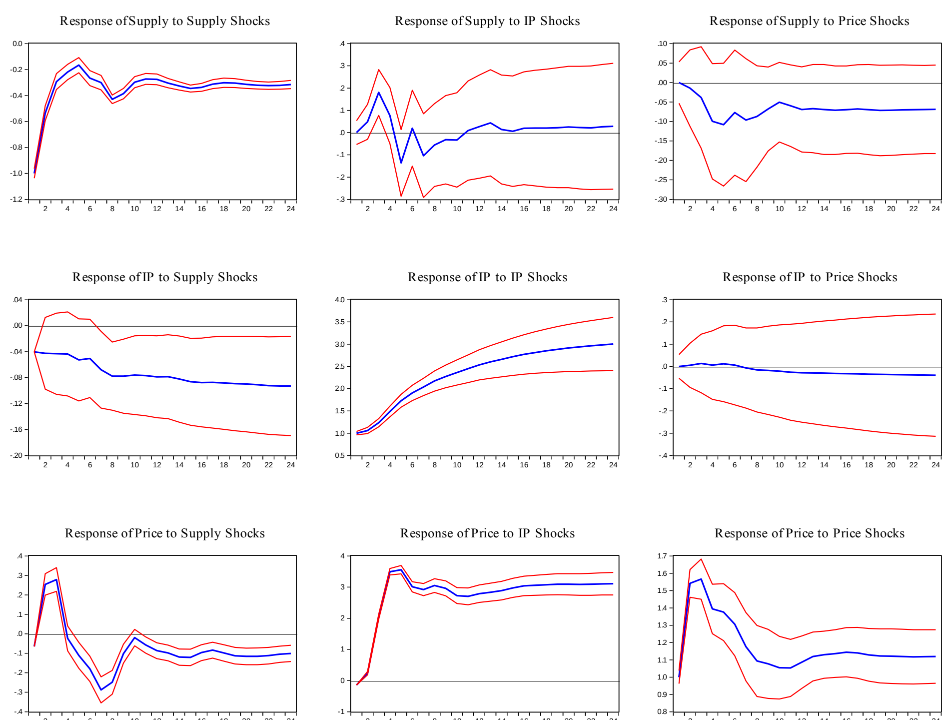


Figure 4.6 U.K. Cumulated Responses

(Jan. 1998 – Dec. 2012, order:dlsupply dlip dlp, Lag length=2)

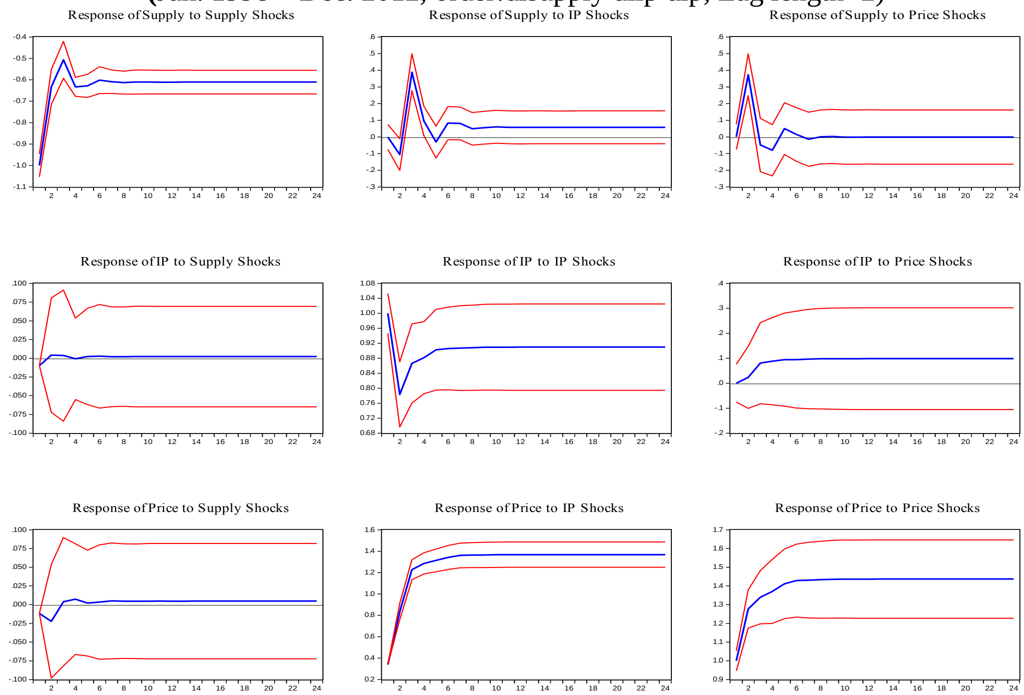
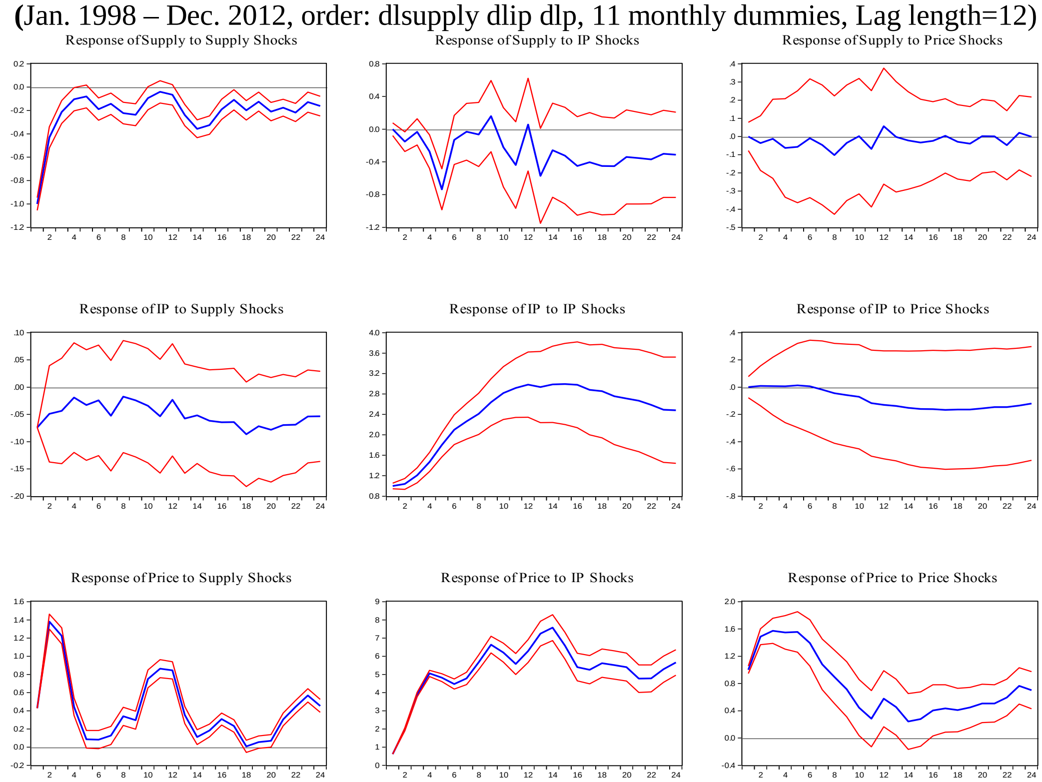


Figure 4.7 U.S. Cumulated Responses to 1% Point Shock with 1-Std Error Confidence Bands

(Jan. 1998 – Dec. 2012, order: dlsupply dlip dlp, 11 monthly dummies, Lag length=12)



How much of the variation in U.S. and U.K. gasoline prices can be attributed to each demand or supply shock? This can be answered with the error variance decompositions based on the estimated VAR model. Table 4.2 reports the average contribution of each shock to the total variation in the real price of gasoline in percentage terms. The variation in price in the U.K. seems to be mainly determined by the gasoline demand and the aggregate demand, whereas supply has a very small impact. The price variation in the U.S. however appears to come from all three; the gasoline demand, supply and aggregate demand, the impact of aggregate demand being slightly higher than that of supply in the earlier months of a shock. In addition, the share of the supply and aggregate demand is much higher than that of the U.K.. This confirms the argument that the increase in gasoline prices was partly due to the increase in global demand for commodities, while the share of the supply remained limited.

Table 4.2 Variance Decomposition for Gasoline Price

	US			UK		
	Supply	**IP**	**Price**	**Supply**	**IP**	**Price**
1 quarter	8.84	10.31	80.85	1.29	7.90	90.81
	(3.75)	(4.85)	(6.11)	(1.95)	(4.16)	(4.58)
2 quarter	14.90	15.28	69.82	1.34	7.94	90.71
	(4.99)	(5.85)	(6.93)	(2.01)	(4.19)	(4.63)
4 quarter	15.84	15.69	68.47	1.35	7.95	90.70
	(5.34)	(6.06)	(6.88)	(2.02)	(4.20)	(4.64)
8 quarter	15.87	15.72	68.41	1.35	7.95	90.70
	(5.48)	(6.14)	(7.01)	(2.02)	(4.20)	(4.64)

Standard errors in parentheses.

4.6 Conclusions

In this study we employed a structural VAR model to measure the response of gasoline prices to aggregate demand and supply shocks as well as to examine the responses of demand and supply to gasoline price shocks. We attempted to determine the source of gasoline price increases in the U.S. and U.K.

The results for the U.S. in this chapter are comparable to the results in Kilian (2010). All of the factors; supply, both aggregate and gasoline demand play a role determining the price of gasoline in the U.S. but the impact of a positive aggregate demand shock is larger than that of the others. For the U.K., the impact of aggregate and local gasoline demand are important to determine the gasoline price but supply does have a limited effect.

Our results also show that gasoline price increases were partly driven by the increase in demand for commodities due to the expansion in global economy which may also imply that gasoline prices, to some extent, are determined globally through the price of crude oil. Despite the differences in structure of the market, the gasoline prices in the U.K. and the U.S responded to aggregate demand shocks at a varying degree. The gasoline price in the U.S. seems to be more responsive to aggregate demand and supply shocks. The response of gasoline price to an aggregate demand shock is much larger than the response to supply shocks. The gasoline price in the U.K., however, seems to respond only to aggregate demand changes, as the U.K. is a smaller country compared to the U.S. Furthermore, the crude oil and subsequent gasoline production has been declining in the U.K. and fuel imports have been increasing. Increasing dependency on imports provides a channel for transmitting the changes from the global into the domestic market. The response of U.S. gasoline price to an increase in aggregate demand is nearly four times higher than the response of gasoline price in the U.K. to an aggregate shock.

4.A Appendix

4.A.1 Data Sources

U.S.

The CPI and IP are from Haver Analytics.

Consumer Price Index: CPI-U: All Items (SA, 1982-84=100), PCU@USECON

Industrial Production: Industrial Production excluding Construction (SA, 2007=100), S111D@G10

Data on gasoline are from the U.S. Energy Information Administration

http://www.eia.doe.gov/dnav/pet/pet_cons_psup_dc_nus_mbbl_m.htm

Demand: MGFUPUS2: U.S. Product Supplied of Finished Motor Gasoline (Thousand Barrels per Day)

Supply: MGFRPUS1: U.S. Refinery and Blender Net Production of Finished Motor Gasoline (Thousand Barrels) divided by the number of days in each month

Gasoline Prices: A103600002: U.S. Total Gasoline Retail Sales by Refiners (Cents per Gallon)

U.K.

The CPI and IP are from Haver Analytics.

Consumer Price Index: All Items (NSA, 2005=100), D7BT@UK

Industrial Production: Production Industries (SA, 2006=100), CKYW@UK

Data on gasoline are from the Department of Energy and Climate Change (DECC)

http://www.decc.gov.uk/en/content/cms/statistics/source/oil/oil.aspx

Demand: Table 3.13 Deliveries of petroleum products for inland consumption

Supply: Table 3.12 Refinery throughput and output of petroleum products

Gasoline Prices: Table 4.1.1 Typical retail prices of petroleum products and a crude oil price index (the price average of two different grades are taken (super and premium unleaded).

Table 4.A.3 Summary Statistics

U.S.

	Mean	Median	Std. Dev.	Skewness	Kurtosis	Obs.
Levels						
Supply	7691	7741	835	-0.02	2.06	360
Price	1.02	0.88	0.28	1.08	3.28	360
IP	77.5	83.6	16.2	-0.21	1.50	360
Log Levels						
Supply	8.94	8.95	0.11	-0.20	2.14	360
Price	-0.02	-0.13	0.25	0.69	2.49	360
IP	4.33	4.43	0.22	-0.37	1.65	360
Log Differences						
Supply	0.001	0.002	0.032	-0.09	3.65	359
Price	0.000	-0.003	0.050	-1.17	12.23	359
IP	0.002	0.003	0.006	-1.47	11.06	359

U.K.

	Mean	Median	Std. Dev.	Skewness	Kurtosis	Obs.
Levels						
Supply	1838	1819	242.4	-0.13	3.51	180
Price	91.8	89.2	13.61	0.56	2.31	180
IP	97.6	100.1	5.17	-0.88	2.17	180
Log Levels						
Supply	7.32	7.35	0.17	-0.50	2.14	180
Price	4.51	4.49	0.14	0.33	2.21	180
IP	4.58	4.61	0.05	-0.91	2.20	180
Log Differences						
Supply	-0.004	-0.007	0.09	-0.25	4.42	179
Price	0.003	0.001	0.02	-0.25	5.28	179
IP	-0.001	0.000	0.01	-0.82	7.27	179

Table 4.A.4 Unit Root Tests for Seasonally Adjusted Series

U.S. Seasonally Adjusted Series

Logs	**Augmented Dickey Fuller**		**Phillips-Perron**	
	t-statistics	**Probablity**	**t-statistics**	**Probablity**
	Lag length=6			
Supply	-1.23	0.66	-1.73	0.41
Price	-0.79	0.82	-1.12	0.71
IP	-1.51	0.53	-2.00	0.29
Log Differences				
	t-statistics	**Probablity**	**t-statistics**	**Probablity**
	Lag length=6			
Supply	-8.23	0.00	-3.33	0.01
Price	-8.25	0.00	-3.18	0.02
IP	-4.93	0.00	-17.84	0.00

U.K. Seasonally Adjusted Series

Log	**Augmented Dickey Fuller**		**Phillips-Perron**	
	t-statistics	**Probablity**	**t-statistics**	**Probablity**
	Lag length=6			
Supply	0.38	0.98	-0.09	0.95
Price	-1.33	0.62	-1.27	0.64
IP	0.11	0.97	-0.09	0.95
Log Differences				
	t-statistics	**Probablity**	**t-statistics**	**Probablity**
	Lag length=6			
Supply	-4.98	0.00	-4.16	0.00
Price	-5.40	0.00	-3.85	0.00
IP	-16.35	0.00	-16.24	0.00

Figure 4.A.8 U.S. Cumulated Responses to 1% Point Shock of with 1-Std Error Confidence Bands

(Jan. 1983 – Dec. 2012, order: lsupply dlip dlp, 11 monthly dummies, Lag length=12)

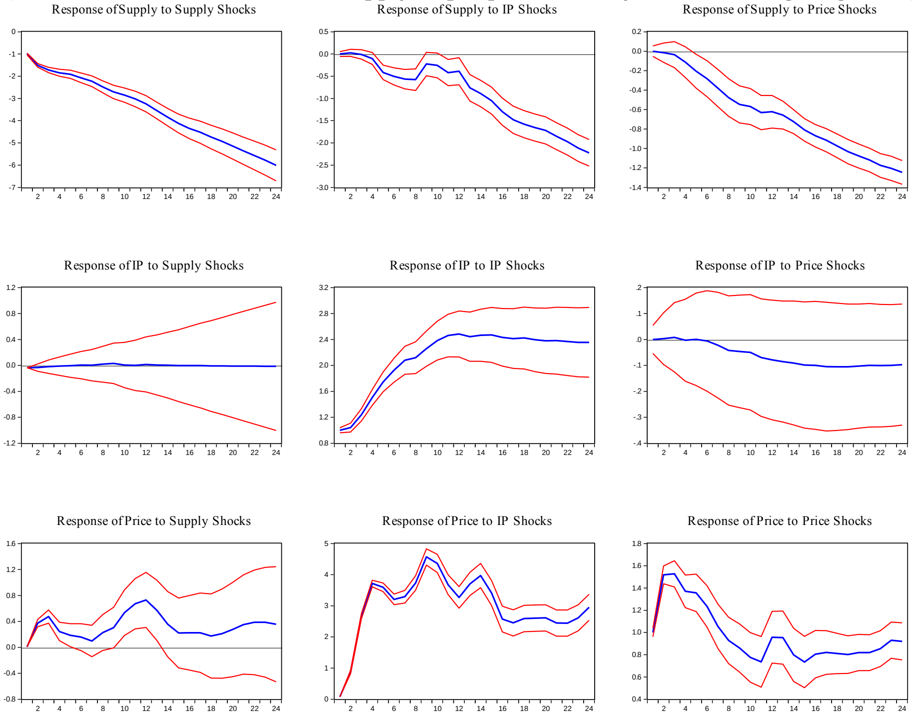


Figure 4.A.9 U.K. Cumulated Responses

(Jan. 1998 – Dec. 2012, order: lsupply dlip dlp, Lag length=1)

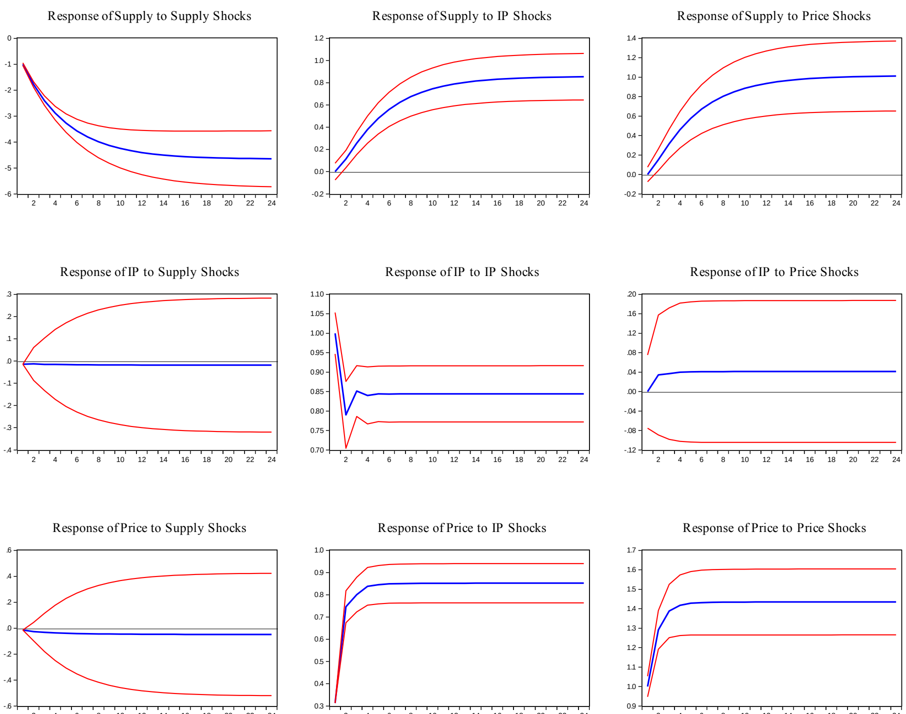


Figure 4.A.10 The Impulse Response Functions for the U.S. with Seasonally Adjusted Supply and Price Series with 1-Std Error Confidence Bands
(Jan. 1983 – Dec. 2012, dlsupply dlip dlp, Lag length=6)

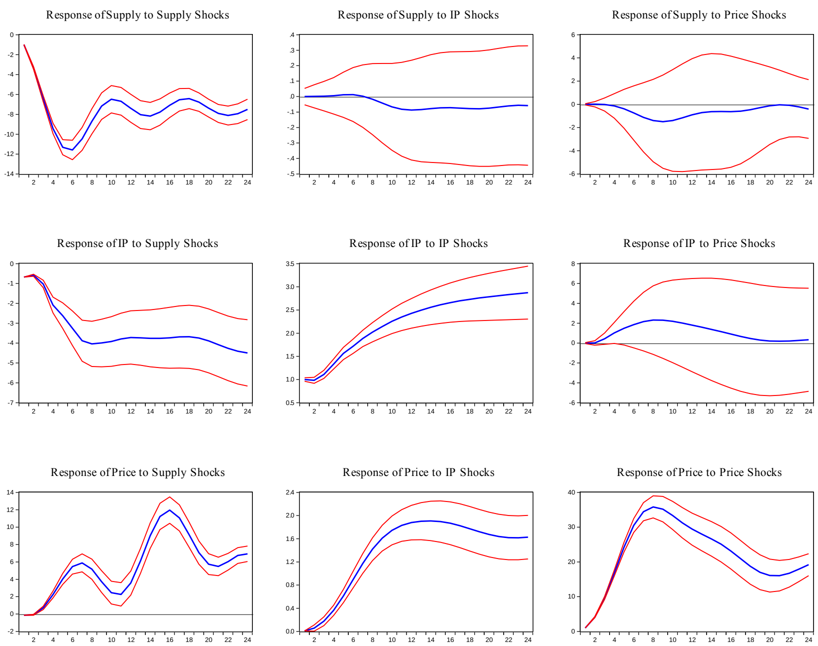
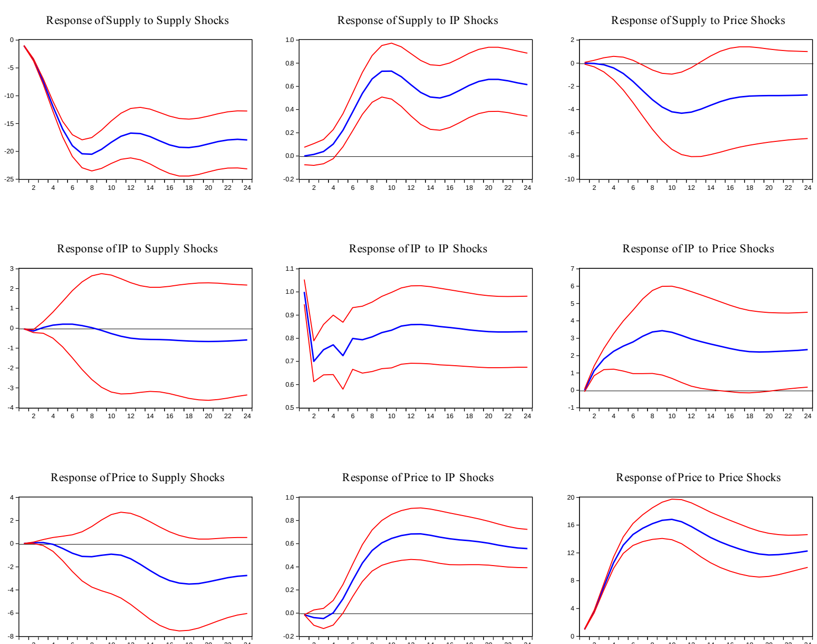


Figure 4.A.11 The Impulse Response Functions for the U.K. with Seasonally Adjusted Supply and Price Series with 1-Std Error Confidence Bands
(Jan. 1998 – Dec. 2012, dlsupply dlip dlp, Lag length=4)

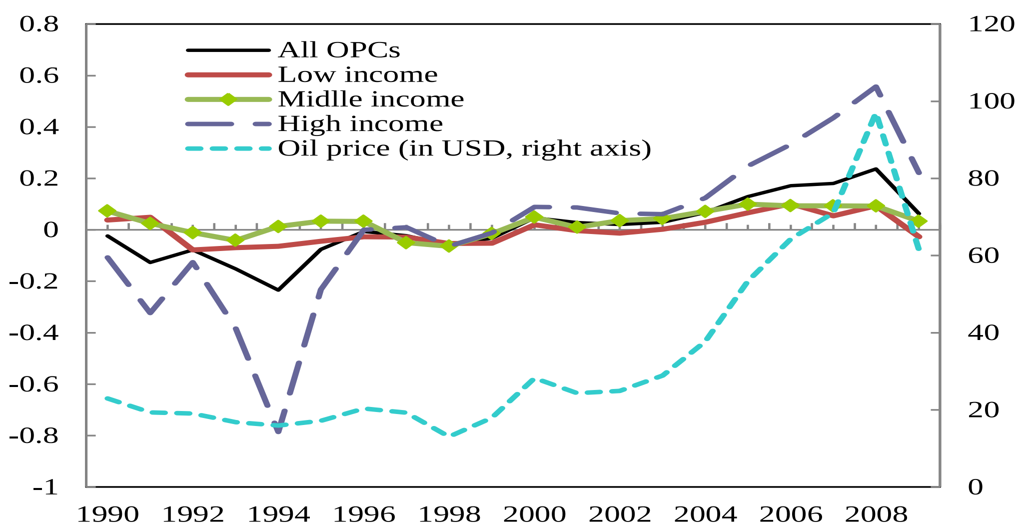


5 PROCYCLICALITY OF FISCAL POLICIES IN DEVELOPING OIL-PRODUCING COUNTRIES

5.1 Introduction

Oil price volatility has increased in recent years. Large, unpredictable swings have a major impact on fiscal balances in developing oil-producing economies (Figure 5.1).[18] Even a small fall in prices, for example, may lead to a substantial increase in financing needs, as the exports of these countries are not diversified and oil revenue accounts for a large portion of total revenue. The political, institutional, or budget structure of these countries, as well as their inability to accumulate financial assets or to gain access to credit markets, forces governments to react to oil price volatility by conducting procyclical fiscal policies. A large number of studies show that procyclical fiscal policies have harmful implications for developing countries.[19] When governments cut expenditure in response to a fall in oil revenue, the poor get hurt because of the weak safety net, and long-term growth is hampered as governments cut capital expenditure and withdraw resources from productive projects.

Figure 5.1 Oil Price and Overall Fiscal Balance in Percent of GDP in Oil Producing Countries[20]



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[18] Throughout this chapter, the term “oil” is used to refer to “hydrocarbon” or “petroleum” because gas is also an important resource in several countries (e.g., Algeria and Qatar).

[19] See Lane (2003) who reviews neoclassical and Keynesian arguments related to optimal cyclicality in fiscal policy.

[20] Simple averages.

This chapter examines whether fiscal behavior is indeed procyclical in 28 developing oil- producing countries (OPCs) (Table 5.1) by employing rigorous econometric tests. Although there is a growing number of studies on the topic, few have thoroughly studied the procyclicality of fiscal policies, particularly during the recent period of high oil prices. With this analysis, the chapter contributes to the literature in three ways.

Table 5.1 OPCs Classified by Income Level

Low income		Middle income	High income
Algeria	Angola	Gabon	Bahrain
Azerbaijan	Cameroon	Kazakhstan	Brunei
Chad	Congo	Libya	Equatorial Guinea
Ecuador	Indonesia	Mexico	Kuwait
Iran	Nigeria	Russia	Qatar
Sudan	Syria	Venezuela	Saudi Arabia
Vietnam			Trinidad & Tobago
Yemen			UAE

Based on 2009 World Bank country classification (nominal GNI per capita).

First, fiscal behavior is studied among different groups of OPCs by breaking down the country sample into three subgroups according to their level of development and conducting the cyclicality tests on the full sample, as well as on the subsamples. Since the OPCs are not a homogenous group, their fiscal policies are likely to respond differently to oil price shocks due to significant variations in the extent of their dependency on oil revenue, economic development, political and institutional structure, financial positions, the level of existing oil reserves, and the degree of maturity in oil production.[21] Due to these differences, it is important to study the fiscal behavior not only in a large group but also in smaller groups, to see whether countries with certain characteristics show consistent fiscal policy patterns; this, in turn, may be useful for designing effective policies. Indeed, this study finds that the results are not uniform across income groups. Total expenditure is highly procyclical in the low and middle-

[21] There is a noteworthy negative correlation between the use of the additional fiscal oil revenue and the income or development level of OPCs (Davis, Ossowski, and Fedelino, 2003).

income groups, while it is countercyclical in the high-income countries. In addition, the estimation results show that political and institutional factors, as well as financing constraints, play a role in the cyclicality of fiscal policies in the OPCs, especially in the low-income group.

Second, the cyclical behavior of several fiscal policy variables is tested: total expenditure and its components, public consumption and investment; the non-oil primary balance; and non-oil revenue. Most studies use either expenditure or consumption as a dependent variable. However, this chapter examines total government expenditure as well as its components, which will be a key contribution of the chapter for the following reason. Focusing only on aggregates can be misleading if their subcomponents move in offsetting ways. Thus, looking at the subcomponents separately may further explain the preferred direction of fiscal policy and reveal important policy implications; for example, a government may change either consumption or investment more in response to a change in output. In fact, the estimation results in this chapter show that expenditure is countercyclical for the high-income group, but its components move in different directions: consumption is procyclical while capital expenditure is countercyclical. Similarly, Villafuerte and Lopez-Murphy (2010) and Arezki and Ismail (2010) indicate that, during oil price declines, governments reduce capital expenditure more than they reduce government consumption. Furthermore, the non-oil primary balance as a dependent variable will measure the injection/use of oil revenue in the economy and the overall level of fiscal effort. Finally, non-oil revenue will be a useful measure of the tax collection mechanism. All of these five fiscal variables show strong procyclical behavior in the full sample of OPCs.

Third, there have been only a few econometric studies on the procyclicality of OPCs. In this chapter, not only are various econometric methods employed to test procyclicality, but the possibility of reverse causality between output growth and the fiscal variable is taken into account. Pooled ordinary least squares (OLS), fixed-effect, instrument variables (IV), and general methods of moments (GMM) estimations are used and their results compared.

The plan of the chapter is as follows. In the next section, some special characteristics of OPCs that are relevant to the analysis will be discussed. In Section 3, the empirical specification and the data will be described. In Section 4, the results will be presented, and Section 5 will conclude.

5.2 Literature Survey

Both the neoclassical and Keynesian theories support the idea that effective fiscal policy should smooth the volatility of output during the business cycle. Barro's (1973) "tax-smoothing" hypothesis of optimal fiscal policy suggests that, for a given path of government expenditure, tax rates should be held constant over the business cycle, and the budget surplus should move in a procyclical fashion. According to the Keynesian approach, however, if the economy is in recession, policy should increase government expenditure and lower taxes to help the economy out of the recession. During economic booms, the government should save the surpluses that emerge from the operation of automatic stabilizers and, if necessary, go further with discretionary tax increases or spending cuts. As a result, fiscal policies are expected to follow countercyclical patterns through automatic stabilizers and discretionary channels. In other words, one would expect a positive correlation between changes in output and changes in the fiscal balance or a negative correlation between changes in output and changes in government expenditure. However, empirical studies show that fiscal policies are procyclical in developing countries and in OPCs.[22] They increase spending with an increase in oil revenue during an oil price boom. They are forced to reduce spending because of a revenue decline as a result of a drop in oil prices. Since, in general, these countries are not able to accumulate savings in years with high oil

[22] Gavin and Perotti (1997) find total spending and its components are highly procyclical in Latin America. Kaminsky, Reinhart, and Végh (2004) find that fiscal policy is procyclical in their subsample of 83 low- and middle-income countries.

revenues, they can only finance deficits by cutting expenditure during revenue shortfalls. Fouad and others (2007), Abdih and others (2010), and Villafuerte and Lopez-Murphy (2010) find that oil-producing countries followed procyclical fiscal policies during the recent oil price cycle. Baldini (2005) and De Cima (2003) also present evidence for the procyclicality of fiscal policies in two oil-producing countries, Venezuela and Mexico. More recent studies, e.g. Ilzetzki and Vegh (2008), find, using instrumental variable regression, strong evidence of procyclical fiscal policy in developing countries.

Two broad arguments that have been proposed as an explanation for procyclical policies in developing counties also apply to OPCs: constraints on financing (or limited access to credit markets) and factors related to the structure of the economy (the budget, political, power, and social structure, and weak institutions). In general, these factors are presented separately but they go together and are likely to reinforce each other. For example, weak institutions, the budget structure, or a corrupt government may hinder prudent fiscal policies, which may, in turn, affect fiscal sustainability and creditworthiness by amplifying the financing constraints.

Liquidity and borrowing constraints emerge when a developing country needs financing the most--during a downturn--and that is when it is least likely to be able to obtain it. Many countries do not have significant foreign assets or developed domestic financial markets to raise funds. When these countries face large terms of trade shocks (i.e., a sharp fall in oil prices in the case of OPCs), investors may lose confidence and be less likely to lend, because they fear that the lack of policy credibility and discipline may force the government to run up large budget deficits and to default.[23] Governments in this situation will also experience recurring credit constraints in world capital markets (“sudden stops,” as explained in Calvo and Reinhart (2000)), which hamper their ability to conduct countercyclical policies.

[23] Reinhart, Rogoff, and Savastano (2003), Caballero and Krishnamurthy (2004), and Haussmann and others (1996).

Oil stabilization funds have been increasingly used by OPCs as an instrument to cope with oil revenue volatility. These funds are aimed at stabilizing budgetary revenues: when oil revenues are high, some portion of the revenue would be channeled to the stabilization fund; when oil revenues are low, the stabilization fund would finance the shortfall. However, the creation of such funds is found to have no impact on the relationship between oil export earnings and government expenditure in countries where no sound and transparent fiscal and macroeconomic policies were implemented.[24] Moreover, some oil funds have operated outside existing budget systems and are often accountable to only a few political appointees. This makes such funds especially susceptible to abuse and political interference. Therefore, stabilization funds should not be regarded as a substitute for sound fiscal management.

The other argument proposed to explain the difficulty in implementing countercyclical policy focuses on procyclical government spending due to three aspects of the economy and the government: the budget structure, the weak political structure and institutions, and corruption in government.

First, developing countries run procyclical fiscal policies because of their budget structure. These countries have a few automatic stabilizers built into their budgets. As a result, government spending in developing and emerging countries displays less of a countercyclical pattern than in industrial countries. For example, Gavin and Perotti (1997) note that Latin American countries spend much less on transfers and subsidies than do richer OECD economies (24 percent of total government spending, compared with 42 percent in the industrial countries). Furthermore, most developing countries and OPCs cannot raise revenue effectively through taxes since they usually suffer from inefficient tax collection systems, owing to the low level of compliance with tax laws, insufficient political commitment, and a lack

[24] Davis, Ossowski, and Fedelino (2003), Fasano-Filho (2000), and Ossowski and others (2008).

of capacity, expertise, and resources.[25] Additionally, non-oil tax bases in these countries are in general very low.[26]

Second, weak institutions and political structure encourage multiple powerful groups in a society to attempt to grab a greater share of national wealth by demanding higher public spending on their behalf. This behavior, called the “voracity effect” by Tornell and Lane (1999), results in fiscal procyclicality arising from common pool problems, whereby a positive shock to income leads to a more than proportional increase in public spending, even if the shock is expected to be temporary. This is discussed extensively in “resource curse” literature as a reason for low economic growth in resource-rich countries.[27] Moreover, fiscal policies are more intense in countries with political systems having multiple fiscal veto points and higher output volatility (Stein, Talvi, and Grisanti, 1998;and Talvi and Végh, 2000). Similarly, Lane (2003) and Fatas and Mihov (2001) find that countries with power dispersion are likely to experience volatile output and procyclical fiscal behavior.

Lastly, Alesina and Tabellini (2005) argue that a more corrupt government displays more procyclical fiscal policies as voters, who do not trust the government, demand higher utility when they see aggregate output rising. This behavior would be more prevalent in democracies since a corrupt government is accountable to the voters, whereas, in a dictatorship, the government would not be accountable and, even if corruption were widespread, voters could not influence fiscal policy. Alesina and Tabellini conclude that corrupt governments in democracies, rather than credit market imperfections, are the underlying cause of procyclical fiscal policy.

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[25] Davis, Ossowski, and Fedelino (2003). Furthermore, some countries until recently did not have even a full-fledged modern value-added tax (VAT) system. See Crandall and Bodin (2005).

[26] Most OPCs have quasi-fixed exchange rate regimes, which, coupled with high international capital mobility, limit the role of monetary policy.

[27] Collier (1999), Sachs and Warner (1995), and Klare (2001).

This study is very through in understanding the fiscal behavior in crude oil producing countries and differs from the earlier ones for a number of reasons. First, there are not many studies that investigated the political and institutional aspects of fiscal policies in oil producing countries by looking at a wide range of political and institutional factors. Second, fiscal behavior is studied among different groups of OPCs by breaking down the country sample into subgroups according to their level of development and conducting the cyclicality tests on the full sample, as well as on the subsamples. This approach may reveal general characteristics of oil producing countries as well as specifics to subgroups. Previous studies normally looked at one set of countries. The second, the aggregate as well as the component of the fiscal indicators are tested to observe whether individual components' movement offsets each other. Most studies only investigated the aggregate components such as total expenditure or primary balance. Finally, various techniques have been applied to tackle the endogeneity as it was ignored in some of the earlier empirical studies.

5.3 Methodology and Data

5.3.1 Methodology

The specification for estimation is based on the following framework which has been widely used in the literature where changes in fiscal balance reflects changes in output, terms of trade cycles (particularly in the case of commodity producing small open economies), changes in its own lagged value (a term that limits the long-run movement of the balance from its initial equilibrium) and other political and institutional control variables that have been shown or would be tested in this study for having an impact on the fiscal policy.[28]

[28] Gavin and Perotti (1997), Alesina and Tabellini (2005) and Lledo, Yackovlev, and Gadenne (2009).

$$\Delta(\log(\text{Fiscal}_t)) = \alpha + \beta\,\Delta(\log(\text{non-oil GDP}_{it})) + \theta\,\Delta(\log(\text{TOT}_{it})) + \delta\,\Delta(\log(\text{Fiscal}_{it-1})) + \delta Z_{it} + \eta_i + e_{it} \qquad (1)$$

$t=1,\ldots T, \quad i=1,\ldots,N,$

where Fiscal represents a fiscal variable. The independent variables on the right-hand side are non-oil GDP, an index of the country's terms of trade, TOT, the lagged fiscal variable, a set of other control variables as Z, fiscal shocks as e_{it} and η_i as an unobserved, country fixed effect. The i and t denote the country and the time period, respectively.

Equation (1) is a fiscal reaction function where fiscal policy responds to contemporaneous output changes, terms of trade, the lagged fiscal variable, other control variables, and fiscal shocks (e_{it}). The variables included in equation (1) are in in growth rate while other papers scale the variables in total GDP or take the deviations of GDP and fiscal variables from their long-run trends by using the Hodrick-Prescott (HP) filter. However, both transformations have shortcomings. In the former, the cyclical stance of fiscal policy may be dominated by the cyclical behavior of total output. In the later, the HP-based measures of cyclicality produce misleading results when samples have different levels of volatility. Furthermore, de-trending is not necessary in this study because it does not attempt to differentiate between discretionary fiscal policy and automatic stabilizers (likely very small in OPCs) and focuses on the evolution of actual fiscal balances (rather than the cyclically adjusted balances, which better reflect discretionary behavior).

The terms of trade variable is important for developing countries in general but especially for OPCs, as their fiscal balances and economies are highly prone to terms of trade shocks, which usually originate from outside the domestic economy. Each individual country does not have control over the oil price; thus, including TOT provides a control for external shocks to the economy. Furthermore, the shocks to the fiscal balance or policy decisions in the previous year may have lasting effects on the following period, so the lagged dependent variable is included in the specification to allow for long-term mean reversion in fiscal behavior.

The cyclicality of fiscal policy is determined by gauging the sign and the size of coefficient β, which measures the elasticity of the fiscal variable with respect to output growth. When fiscal policy is procyclical, a positive β for most of the fiscal measures, except for the non-oil primary balance, is expected. Government expenditure, consumption, revenues, and investment should move in the same direction as output. If output increases during booms, the fiscal variables also increase, while the opposite happens in recessions. An estimated β value above 1 implies a more-than-proportionate response of the fiscal variable to output fluctuations.

The issue of endogeneity needs to be addressed with equation (1) which emerges from three different channels.

The first is the endogeneity of the output growth with respect to contemporaneous fiscal policy shocks, eit, or, as stated in recent studies (e.g., Ilzetzki and Végh, 2008), as the reverse causality between output growth and fiscal policy.[29]

The second is the correlation between output growth and unobserved country-specific and time-invariant effects η: countries that are able to generate higher growth in their fiscal balances will, on average—as captured by higher values of the fixed effects η—tend to have a higher (or lower, depending on the sign of cyclicality) level of output growth; if this is not properly accounted for, the unobserved country fixed

[29] Rigobon (2004) and Jaimovic and Panizza (2007) question whether the fiscal policy shocks drive output and not the other way around. However, Ilzetzki and Vegh (2008) conduct a set of econometric tests to show that causality goes in both directions. But, once they take endogeneity into account, they find overwhelming evidence of procyclical fiscal policy in developing countries.

effects will exert an upward (or downward) bias on the estimated fiscal policy response to output growth.[30]

The third is serial correlation between the error term and the lagged dependent variable, which can cause endogeneity. Although the log differences of the variables are taken, endogeneity may still exist in the error term, if there was a persistent shock to the growth of the fiscal variable in the previous period.

In this linear panel framework, pooled OLS and dynamic fixed-effect estimations assume strict exogeneity of explanatory variables; however, this does not hold for this specification, and they produce biased and inconsistent estimators. Similarly, the IV estimates are also biased, and the precision of the IV estimates is lower than that of the OLS estimates. In the presence of weak instruments, the loss of precision will be severe, and the IV estimates may be no improvement over the OLS (Baum, 2007). However, all three sources of endogeneity bias can be addressed by using both difference (Diff-) and System (Sys-) GMM estimators (Arellano and Bond, 1991), as is commonly used in the literature. The Diff-GMM uses first-differenced equations with suitable lagged levels as instruments. The Sys-GMM augments the former by stacking the equation in first differences and the equation in levels together in a system of equations and employs both lagged levels and differences as instruments.

In general, if the explanatory variables are highly persistent, their lagged levels might only be very weak instruments for the first-differenced equations, due to serial correlation between the instruments and the error terms. As a result, the first-differenced GMM estimator potentially suffers from a downward bias (Blundell and Bond, 1998). An additional set of first-differenced instruments and equations in levels is used to make the system GMM estimator more efficient by overcoming the weak instrument problem inherent in the first-differenced GMM estimator. However, the

[30] Since the variables are differenced, the fixed effects may be eliminated. However, there may be fixed effects in the growth rates of the series.

Sys-GMM imposes more restrictions. As a result, equation (1) is estimated using both methods and the results are compared. Both methods take care of endogenity by instrumenting GDP growth and the lagged dependent variable. Widely used instruments are past values of the explanatory variables (Gali and Perotti, 2003; and Lane, 2003). In all GMM regressions, two lags of all endogenous variables (output growth and the lagged dependent variable) are used as instruments. In addition, the export-weighted GDP growth of a country's trading partners is used as an instrument for GDP growth, as in other studies (Jaimovic and Panizza, 2007).

The Diff-GMM and Sys-GMM estimation results with two statistics are reported in order to verify the appropriateness of the choice of instruments: p-values for the Hansen overidentification test of orthogonality restrictions, and the Arellano-Bond (1991) test for autocorrelation in first and second differences to verify the absence of serial correlation.

5.3.2 Data and Variable Descriptions

The key explanatory variable is the growth of real GDP, excluding the oil sector (non-oil GDP). Non-oil GDP is more relevant to assess the status of economic conditions and the use of the labor factor, as the oil sector is typically an enclave sector, highly capital intensive with limited spillovers to the rest of the economy. Similarly, Barnett and Ossowski (2002), among others, argue that non-oil measures are more reliable variables of fiscal policy in OPCs than the overall balance, since oil revenue originates from abroad and non-oil variables are largely under the control of the authorities. The fiscal measurements used as dependent variables are real total general government expenditure, real general government consumption, real government capital expenditure, real non-oil revenue, and real non-oil primary balance.[31,32]

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[31] Instead of central government data, general government data are used to capture the response of the total government to output changes. Nevertheless, the distinction is small for most of the countries.

[32] Another policy instrument that may be useful is government tax rates, but data limitations for the sample countries prevent us from using these rates as a dependent variable.

(continued)

After testing the basic specification, the following robustness checks are performed by introducing additional control variables:

- Two credit constraint variables are included to examine the origin of the possible credit constraint: domestic and external. As for domestic financing constraints, there are also two variables: credit to the private sector scaled in GDP as a proxy for the depth of the domestic credit market, and the real central bank interest rate to indicate the cost of domestic financing. As for the external financing constraint, the degree of access to international financing is measured by the ratio of net capital flows to GDP.

- As indicators of institutional quality and political structure, several variables from the *International Country Risk Guide* database are used: bureaucracy quality, corruption, and law and order. In addition, the composite index of institutional quality will be included, representing all of these. Furthermore, for political structure, variables such as political competition, democracy, constraints on the decision-making authority, and checks and balances from the Polity IV Project data set will be added[33].
- To control for the vulnerability of the country to oil price changes, as well as to serve as a proxy for dependence on oil income, oil revenue as a share of total revenue is used.

The macroeconomic data come from Villafuerte and Lopez-Murphy (2010), updated by the World Economic Outlook database of the IMF for the period 1991 – 2009. The frequency is annual. The availability of data varies by country. All variables

[33] The Polity IV Project has data on the political authority characteristics of states in 163 countries.

are converted to real values by deflating with each country's respective CPI's.[34] The data sources are listed in Table 5.A.1.

5.3.3 Estimation Results

Descriptive statistics in Table 5.A.2 in the Appendix describes the main variables. The data show that in general the growth of non-oil GDP and fiscal variables is more volatile in low income OPCs than in high-income OPCs. Average expenditure growth tends to be higher in low-income countries in part due to average higher growth in capital expenditure, while average consumption growth is higher in high-income countries. The non-oil primary balance shows more volatility than the other variables, as expected, since it is in growth form and obtained as a residual from the others.

Simple correlations between fiscal variables and some relevant macroeconomic, financial, political, and institutional variables are presented in Appendix Table 5.A.3, where correlations higher than 30 percent are highlighted. GDP per capita seems to be positively correlated with the fiscal variables, except for the non-oil primary balance, for both the full sample and the low-income group, which may indicate that countries in different income groups have consistently different fiscal behavior patterns. There is no clear correlation pattern in the full sample as there may be a large variation in series among countries. For the high-income group, gross international reserves and oil wealth show strong correlations; data reveal that the higher the income, the greater the accumulation in savings and oil wealth.

Various econometric techniques are applied to equation (1), and the same tests are repeated for the five different fiscal variables as dependent variables for the three income groups, as well as for the full sample. First, to provide a benchmark, a bivariate pooled OLS regression of fiscal variables and the output variable are carried out; then, the equation is tested with the fixed-effects method to control for country effects. Next

[34] CPI is used as a deflator since a non-oil GDP deflator was not available across the sample countries.

the IV estimation is run, together with the fixed effects, to introduce the instrument variables. Finally, the Diff-GMM and the Sys-GMM methods are used. Only the Diff-GMM estimation results are presented in the tables below; the other test results are presented in Appendix Tables 5.A.4 through 5.A.23.

The estimated coefficients for all fiscal variables for the full sample, except for the primary balance, are positive and statistically significant. It is worth noting that the OLS, fixed-effects, IV, and GMM results are qualitatively and quantitatively very similar. The results indicate that pooled OLS estimates had an upward bias and the fixed-effects model had a downward bias, confirming the appropriateness of using the GMM method for the model.

Estimates obtained from the Diff-GMM and Sys-GMM methods are consistent and in general are very close (Tables 5.2–5.6 and Appendix Tables 5.A.19–5.A.23). The estimation results show that most Diff-GMM estimations were overidentified with exogenous instruments.[35] Most p-values of AR(1) are low, and, as a result, the null of no autocorrelation is rejected.[36] However, the Sys-GMM estimations also point to an overidentified equation, with a high Hansen test p-value--in fact, the value is too high to cast doubt on the satisfaction of the moment conditions. As a result, Diff-GMM is chosen as the preferred method, and its results are reported in the text. The results of Sys-GMM are presented in Appendix Tables 5.A.19–5.A.23.

The results in Tables 5.2–5.6 below show that the cyclicality coefficient β in equation (1) is always significant and positive for expenditure and consumption variables for the full, low and middle-income countries. Only high-income countries show an indication of countercyclical policy on total expenditure-- perhaps because their greater accumulation of financial assets eases their financial constraints when

[35] The p-values for the **Hansen test** for over-identifying restrictions were high enough.

[36] Differenced errors are expected to follow an MA(1) process. But most of the p-values of AR(2) are high, so the null of no autocorrelation cannot be rejected, suggesting that the GMM estimator is consistent.

funds are needed. Non-oil revenue growth is strongly procyclical, especially in the middle-income sample, suggesting an increased tax collection as well as spillover effects of increased oil revenues. Capital expenditure growth also follows output growth positively and is significant for the full and low-income groups. Capital expenditure is countercyclical only for high-income countries. Again, as part of the countercyclical fiscal policies, high-income countries can afford to increase capital expenditure in recessions to stimulate the economy and to cut back during boom times to smooth output fluctuation. The non-oil primary balance is procyclical, and the sign of the coefficient is negative; as output grows, the non-oil primary balance declines, implying that spending exceed revenue, leading to a negative balance.

Table 5.2 Differenced GMM, Expenditure as Dependent Variable 1991–2009

Independent Variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**0.56***	**0.94***	**1.43***	**-0.57***
	(0.02)	(0.06)	(0.32)	(0.07)
Δ(log(Tot. Expend(t-1)))	0.10***	-0.15***	0.07	0.14***
	(0.01)	(0.02)	(0.21)	(0.02)
Δ(log(TOT))	0.22***	0.24***	-0.15*	0.25***
	(0.01)	(0.05)	(0.08)	(0.05)
Observations	416	209	80	127
No of countries	28	14	6	8
AR(1) test-p	0.0245	0.0843	0.0830	0.130
AR(2) test-p	0.155	0.0660	0.671	0.352
Hansen test-p	0.764	0.998	1	1

Table 5.3 Differenced GMM, Consumption as Dependent Variable

Independent Variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**0.72***	**1.16***	**0.57***	**0.17**
	(0.04)	(0.05)	(0.32)	(0.19)
Δ(log(Consump(t-1)))	-0.18***	-0.13***	-0.16	-0.41***
	(0.00)	(0.02)	(0.10)	(0.10)
Δ(log(TOT))	0.14***	0.21***	-0.22	0.11***
	(0.01)	(0.04)	(0.15)	(0.03)
Observations	408	204	78	126
No of countries	28	14	6	8
AR(1) test-p	0.000685	0.0122	0.0493	0.0443
AR(2) test-p	0.481	0.741	0.274	0.754
Hansen test-p	0.773	1.000	1	1

Table 5.4 Differenced GMM, Non-oil Revenue as Dependent Variable

Independent Variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**0.71*** **	**0.93*** **	**2.22** **	**0.11**
	(0.04)	(0.17)	(1.08)	(0.41)
Δ(log(Revenue(t-1)))	-0.28***	-0.28***	-0.21***	-0.39***
	(0.00)	(0.07)	(0.06)	(0.08)
Δ(log(TOT))	0.02	0.03	-0.04	-0.00
	(0.02)	(0.07)	(0.11)	(0.09)
Observations	404	203	79	122
No of countries	28	14	6	8
AR(1) test-p	0.00556	0.0942	0.0944	0.0839
AR(2) test-p	0.348	0.830	0.986	0.758
Hansen test-p	0.797	0.999	1	1.000

Table 5.5 Differenced GMM, Capital Expenditure as Dependent Variable

Independent Variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**1.34*** **	**1.43*** **	**1.30**	**-0.81***
	(0.06)	(0.21)	(1.05)	(0.48)
Δ(log(Capital Exp.(t-1)))	-0.12***	-0.24***	-0.22*	0.17
	(0.02)	(0.03)	(0.13)	(0.17)
Δ(log(TOT))	0.15***	0.42***	-0.20	-0.19***
	(0.04)	(0.11)	(0.17)	(0.03)
Observations	394	199	75	120
No of countries	28	14	6	8
AR(1) test-p	0.00109	0.0256	0.204	0.0293
AR(2) test-p	0.290	0.0853	0.442	0.383
Hansen test-p	0.552	0.994	1	1

Table 5.6 Differenced GMM, Non-oil Primary Balance as Dependent Variable

Independent Variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**-3.70*** **	**-1.45**	**-0.60**	**-10.02**
	(0.17)	(0.96)	(3.45)	(6.18)
Δ(log(Primary Bal.(t-1)))	-0.13***	-0.11***	-0.12**	-0.27***
	(0.00)	(0.00)	(0.05)	(0.02)
Δ(log(TOT))	1.52***	0.61***	0.15	7.43***
	(0.02)	(0.10)	(0.39)	(1.57)
Observations	416	209	80	127
No of countries	28	14	6	8
AR(1) test-p	0.684	0.161	0.111	0.537
AR(2) test-p	0.247	0.284	0.648	0.700
Hansen test-p	0.707	1.000	1	1

Before introducing the control variables related to financial constraints, as well as the political and institutional factors, into the regressions, the oil revenue share in total revenue is added to the estimation; this turns out to be significant. This variable indicates the country's degree of dependency on oil revenue. Then the financial constraint control variables are included in the regression. Tables 5.7 and 5.8 show the estimates of expenditure as a dependent variable with control variables for the full sample and subgroups, respectively.

The full sample results with financial constraints in Table 5.7 show that both the external and domestic credit markets matter for the full sample as they are significant. The results for the interest rate and the capital flows are weaker than those for the depth of financial markets (private credit to GDP). The sign of lagged net capital flows is negative, suggesting the countercyclical flow of external capitals, which is the opposite of what we had expected.

Only the significant results for the subgroups are presented in Table 5.8; the results are somewhat poor (the Hansen test p-values are very high). For the low-income group, the lagged central bank interest rate is significant but zero. For the middle- and high- income groups, the coefficients of lagged capital flows to GDP are significant and countercyclical, albeit very small.

Table 5.7 Financing Constraints, Impact on Procyclicality, 1991–2009

(Dependent variable: Expenditure, two-step, difference GMM estimates, full sample)

Δ(log(non-oil GDP))	**0.41*** **	**0.06** **	**0.33*** **	**0.43*** **	**0.21*** **	**0.45*** **
	(0.06)	(0.03)	(0.06)	(0.02)	(0.03)	(0.05)
Δ(log(Tot. Expend(t-1)))	0.18***	0.01	0.17***	0.15***	0.05***	0.17***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Δ(log(TOT))	0.22***	0.42***	0.20***	0.28***	0.37***	0.25***
	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
oilrevshare	0.38***	0.11*	0.38***			
	(0.03)	(0.06)	(0.05)			
lagged real central bank interest rate	0.01***			0.00***		
	(0.00)			(0.00)		
lagged net capital flows to GDP		-0.05***			-0.04***	
		(0.01)			(0.00)	
lagged pivate credit to GDP			0.16***			0.16***
			(0.02)			(0.02)
Observations	325	165	384	338	183	400
No of countries	27	24	28	27	24	28
AR(1) test-p	0.0211	0.167	0.0133	0.0196	0.132	0.00921
AR(2) test-p	0.168	0.269	0.120	0.127	0.282	0.129
Hansen test-p	0.824	0.977	0.744	0.754	0.894	0.644

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

All regressions include country fixed effects. GDP growth is instrumented using the growth of trading partners weighted by exports and past values of real GDP growth. For the lagged dependent variable, the past values are used as instrument.

Table 5.8 Financing Constraints, Impact on Procyclicality, 1991–2009

(Dependent variable: Expenditure, two-step, difference GMM estimates)

	Low to middle income	**Upper-middle income**	**High income**
Δ(log(non-oil GDP))	1.09***	0.00	-1.49***
	(0.30)	(0.00)	(0.38)
Δ(log(Tot. Expend(t-1)))	-0.25***	-6.88	-0.07
	(0.03)	(4.42)	(0.11)
Δ(log(TOT))	0.19***	4.59	0.46***
	(0.06)	(3.05)	(0.06)
oilrevshare	0.39***	-2.60*	0.66**
	(0.13)	(1.46)	(0.31)
lagged real central bank interest rate	-0.00***		
	(0.00)		
lagged net capital flows to GDP		-0.06*	-0.04*
		(0.04)	(0.02)
Observations	160	26	39
No of countries	13	4	7
AR(1) test-p	0.0982	-	0.233
AR(2) test-p	0.115	0.00708	0.415
Hansen test-p	1.000	1	1.000

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

All regressions include country fixed effects. GDP growth is instrumented using the growth of trading partners weighted by exports and past values of real GDP growth. For the lagged dependent variable, the past values are used as instrument.

Finally, the estimation results for the full sample, including the institutional and political control variables, are presented in Table 5.9. Among the political variables, bureaucracy quality, democracy, constraints on the decision-making authority (constraints on the executive), political competition, and checks and balances are significant. Except for democracy and checks and balances, the coefficients for the other variables are negative. From these results, it can be interpreted that fiscal behavior is more procyclical when the bureaucracy quality, the constraints on the executive and political competition are low. The coefficient for checks and balances is significant but very small. The coefficient for democracy is positive, indicating the higher the democracy variable, the higher is the expenditure, which partially supports the claim of Alesina and Tabellini (2005) that corrupt governments in democracies run procyclical fiscal policies.

Table 5.9 Political Factors, Impact on Procyclicality , 1991–2009

(Dependent variable: Expenditure, two-step, difference GMM estimates, full sample)

Δ(log(non-oil GDP))	**1.00*** **	**0.98*** **	**0.93*** **	**0.90*** **	**0.48*** **	**0.39*** **	**0.39*** **	**0.46*** **
	(0.05)	(0.05)	(0.04)	(0.05)	(0.02)	(0.04)	(0.04)	-0.03
Δ(log(Tot. Expend(t-1)))	-0.13***	-0.12***	-0.10***	-0.12***	0.10***	0.07***	0.07***	0.08***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.01)	(0.01)	-0.02
Δ(log(TOT))	0.09***	0.07***	0.07***	0.07***	0.15***	0.20***	0.19***	0.18***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)	(0.01)	-0.02
oilrevshare	0.36***	0.41***	0.44***	0.41***	0.43***	0.39***	0.39***	0.41***
	(0.04)	(0.08)	(0.07)	(0.03)	(0.04)	(0.04)	(0.04)	-0.05
bureaucracy quality	-0.62***							
	(0.09)							
composite index		-0.00						
		(0.01)						
law and order			0.02					
			(0.38)					
risk for international liquidity				-0.19***				
				(0.03)				
democracy					0.09***			
					(0.01)			
constraints on executives						-0.03***		
						(0.00)		
political competition							-0.03***	
							(0.00)	
checks and balances								0.00***
								(0.00)
Observations	377	377	377	377	382	382	382	387
No of countries	26	26	26	26	27	27	27	28
AR(1) test-p	0.00860	0.00760	0.00756	0.00914	0.0320	0.0345	0.0345	0.0277
AR(2) test-p	0.370	0.409	0.369	0.306	0.150	0.146	0.146	0.159
Hansen test-p	0.889	0.860	0.860	0.836	0.928	0.869	0.874	0.767

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

All regressions include country fixed effects. GDP growth is instrumented using the growth of trading partners weighted by exports and past values of real GDP growth. For the lagged dependent variable, the past values are used as instrument.

As for the groups, most of the variables are significant for the low-income group, whereas only the composite index and checks and balances are significant for middle-income countries (Table 5.10). None of the variables are significant for the high-income group. However, the validity of the estimation is poor, as the p-values for the Hansen statistics are too high. The full sample and low-income results seem to be similar, which suggests that the latter group constitutes a large share of the full sample.

Table 5.10 Political and Institutional Factors, Impact on Procyclicality, 1991–2009

(Dependent variable: Expenditure, two-step, difference GMM estimates)

	Low to middle income							**Upper-middle income**		
Δ(log(non-oil GDP))	**0.96*****	**0.94*****	**0.70*****	**0.82*****	**0.55****	**0.63****	**0.13*****	**1.71**	**3.41**	**9.27****
	(0.24)	(0.19)	(0.18)	(0.20)	(0.23)	(0.25)	-0.05	(2.77)	(2.64)	-4.35
Δ(log(Tot. Expend(t-1)))	-0.20***	-0.21***	-0.22***	-0.18***	-0.24***	-0.24***	0.85***	-0.37	0.36	-1.82*
	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	-0.18	(1.30)	(0.26)	-1.09
Δ(log(TOT))	0.15***	0.13***	0.13***	0.10**	0.14***	0.15***	-0.21***	-0.41*	-0.12	-1.41**
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	-0.04	(0.24)	(0.14)	-0.62
oilrevshare	0.56***	0.53***	0.54***	0.43***	0.39***	0.36***	0.43***	0.09	-0.62	3.84*
	(0.08)	(0.07)	(0.05)	(0.07)	(0.08)	(0.09)	-0.1	(2.18)	(1.46)	-2.03
bureaucracy quality	-0.93***									
	(0.18)									
composite index								0.08**		
								(0.04)		
law and order		0.37***								
		(0.11)								
risk for international liquidity			-0.13***						-0.58*	
			(0.05)						(0.34)	
democracy				0.08***						
				(0.02)						
					-0.02***					
					(0.00)					
						-0.02**				
						(0.01)				
checks and balances							0.00***			-0.10*
							(0.00)			-0.05
Observations	186	186	186	191	191	191	184	80	80	76
No of countries	13	13	13	14	14	14	14	6	6	6
AR(1) test-p	0.120	0.158	0.238	0.143	0.176	0.252	0.181	0.0545	0.291	0.035
AR(2) test-p	0.139	0.0551	1.48e-07	0.0410	0.0253	0.00352	0.0312	0.457	0.446	-
Hansen test-p	1	1	1	1	1	1	1	1	1	1

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

All regressions include country fixed effects. GDP growth is instrumented using the growth of trading partners weighted by exports and past values of real GDP growth. For the lagged dependent variable, the past values are used as instrument.

5.4 Conclusions and Policy Implications

This chapter analyzes the cyclicality of fiscal behavior thoroughly in 28 OPCs during 1991-2009. It examines five fiscal variables—non-oil revenue; the non-oil primary balance; and total expenditure and its components, consumption and capital expenditure— for the full sample and subgroups divided by their development levels and by correcting the endogeneity bias between the fiscal variables and the output variable. Since the OPCs are not a homogenous group, it is important to divide them into groups and observe whether their fiscal policies show different patterns by groups if so, this may help in designing effective fiscal policies. Indeed, the results are not uniform across income groups, and total expenditure is highly procyclical in the full sample, in the low and middle-income groups. The low-income group constitutes a large share of the full sample, therefore weighing heavily in the results of the full sample. But it is countercyclical in the high-income countries-- perhaps due to their greater accumulation of financial assets, which eases their financial constraints when funds are needed. It is also important to look at the aggregate fiscal variables, as well as at their subcomponents separately, since the subcomponents may move in offsetting ways. In fact, the estimation results show that, although expenditure is countercyclical for the high-income group, its components move in different directions: consumption is procyclical, while capital expenditure is countercyclical.

The results confirm that political and institutional factors, as well as financing constraints, play a role in the cyclicality of fiscal policies in the OPCs. Most of the variables on the quality of institutions and the political structure appear to be significant for the low- income group. Two of the variables are significant for the middle-income countries: the composite institution index and checks and balances. None of the institutional variables turns out to be significant for the high-income countries. Domestic financing constraints seem to matter for the low-income group. But fiscal policy is affected more by the external financing constraint in the middle- and high-income groups, as they may be more integrated into the global financial system than the low-income countries.

Despite their many differences, all the OPCs face volatile and unpredictable oil revenues, a situation that makes fiscal management challenging. For this reason, it is imperative for them to formulate effective countercyclical fiscal policies by which they can smooth government expenditure, decouple it from the volatile oil revenues, and prevent boom-and-bust cycles. Breaking away from a procyclical fiscal policy will enable them to sustain long-term growth and keep the safety net that the poor need. Sound fiscal policies and discipline require strong institutions, a higher-level bureaucracy, and more transparency. Strong institutions and transparency would also help reduce the “voracity effect,” which, in turn, would facilitate the accumulation of financial assets and build up confidence among investors to raise funds when needed.

5.A Appendix

Table 5.A.11 Definitions and Sources of Variables

Variable	Source	Description
Independent variable		
Real non-oil GDP growth	WEO	Growth in nominal GDP deflated using the CPI
Dependent variables	Villafuerte and Lopez-Murphy (2010) and WEO	
Real total government spending		Growth in nominal GDP deflated using the CPI
Real government consumption		
Real capital spending		
Real non-oil primary balance		
Real non-oil revenue		
Financial constraints variables		
Domestic		
Real central bank interest rate	WEO/IFS	
Private credit to GDP	WDI	
External		
Net foreign capital flows	WEO	
Debt-GDP ratio	WDI	
Inflation	WEO	
Political and Institutional Variables		
Bureaucracy Quality	ICRG	(Rating 0 to 4: low rating, low bureaucracy quality)
Composite Risk Rating	ICRG	(Rating 0 to 100; 0 is high risk, 100 is low risk)
Corruption	ICRG	(Rating 0 to 6; 0 is high, 6 is low corruption)
Law & Order	ICRG	(Rating 1 to 3; low rating, low law obedience)
Democracy	Polity4 database, polity2 variable	Difference between a democracy index (0 to 10) and an autocracy index (0 to 10)
Constraints on the executive	Polity4 database, xconst variable	Extent of institutionalized constraints on the decision making powers of chief
Political competition	Polity4 database, Polcom variable	Degree of institutionalization of political competition combined with the extent of government restriction on political competition, from 1 to 10
Other Control Variables		
Oil revenue as share of total revenue	WEO	

Table 5.A.12 Descriptive Statistics

		Low to middle income	Upper-middle income	High income	All countries
Real Non-oil GDP Growth	Mean	3.8	4.3	7.2	5.0
	Median	5.5	4.5	3.9	4.8
	St. Dev.	12.9	9.0	12.0	12.0
	Observation	241	89	155	485
Real Government Spending Growth	Mean	5.0	5.5	6.4	5.6
	Median	6.2	5.2	6.1	6.0
	St. Dev.	23.2	17.1	25.5	23.0
	Observation	244	98	173	515
Real Government Consumption Growth	Mean	4.0	5.9	5.6	4.9
	Median	7.2	5.9	5.1	6.2
	St. Dev.	23.3	16.4	13.6	19.3
	Observation	238	92	162	492
Real Government Investment Growth	Mean	9.3	9.3	8.9	9.2
	Median	7.1	9.3	4.1	7.1
	St. Dev.	42.2	33.5	29.5	36.8
	Observation	227	88	153	468
Real Non-oil Primary Balance Growth	Mean	-0.5	-18.3	45.2	10.9
	Median	5.6	0.1	6.7	5.8
	St. Dev.	216.7	194.0	637.9	402.2
	Observation	244	100	165	509
Real Non-oil Revenue Growth	Mean	4.5	4.1	4.7	4.5
	Median	6.2	5.5	4.3	5.6
	St. Dev.	24.1	22.4	34.8	27.7
	Observation	238	97	160	495
	Countries	14	6	9	29

Table 5.A.13 Correlation between Fiscal Variable and Other Relevant Variables

Low income	**Total expenditure**	**Consumption**	**Capital expenditure**	**Non-oil revenue**	**Non-oil primary balance**
Gross international reserve	0.414	0.414	0.351	0.356	-0.374
Share of oil revenue in total revenue	-0.330	-0.326	-0.274	-0.417	-0.018
Debt to GDP ratio	-0.301	-0.287	-0.331	-0.257	0.306
Inflation	-0.095	-0.094	-0.091	-0.100	0.048
Oil wealth	0.331	0.353	0.315	0.093	**-0.782**
GDP per capita	**0.955**	**0.943**	**0.903**	**0.902**	-0.684
The size of public sector	-0.368	-0.359	-0.347	-0.382	0.169
Capital flows	0.129	0.088	0.250	0.183	-0.015
Population	**0.746**	**0.729**	**0.655**	**0.785**	-0.310
Military expenditure (in % of GDP)	-0.291	-0.284	-0.260	-0.310	0.113
Domestic credit to private sector (% of GDP)	**0.625**	**0.602**	**0.689**	**0.560**	**-0.579**
Bureaucracy quality	**0.470**	**0.472**	**0.436**	**0.427**	-0.370
Corruption	0.002	-0.039	0.133	-0.011	-0.083
Composite index	0.152	0.126	0.245	0.113	-0.237
Law and order	0.113	0.092	0.215	0.053	-0.263
Risk for international liquidity	0.155	0.160	0.102	0.160	-0.066
Democracy	0.198	0.217	0.122	0.234	0.011
Constraints on executives	0.100	0.104	0.081	0.106	-0.037
Political competition	0.088	0.094	0.059	0.097	-0.017
Middle income					
Gross international reserve	-0.083	-0.058	-0.131	-0.048	0.095
Share of oil revenue in total revenue	0.025	0.030	0.014	-0.029	-0.094
Debt to GDP ratio	0.111	0.090	0.183	0.132	-0.035
Inflation	**0.443**	**0.392**	**0.574**	**0.548**	**-0.227**
Oil wealth	**0.555**	**0.593**	**0.430**	**0.551**	**-0.576**
GDP per capita	-0.200	-0.202	-0.194	-0.212	0.167
The size of public sector	0.365	0.342	0.424	0.356	-0.353
Capital flows	-0.242	-0.247	-0.225	-0.236	0.242
Population	-0.186	-0.157	-0.218	-0.152	0.198
Military expenditure (in % of GDP)	-0.087	-0.084	-0.083	-0.060	0.102
Domestic credit to private sector (% of GDP)	-0.187	-0.175	-0.216	-0.179	0.145
Bureaucracy quality	-0.282	-0.302	-0.241	-0.274	0.280
Corruption	-0.047	-0.082	0.010	-0.010	0.122
Composite index	**-0.343**	**-0.344**	**-0.431**	**-0.337**	**0.283**
Law and order	-0.320	-0.362	-0.237	-0.243	0.403
Risk for international liquidity	0.322	0.336	0.287	0.282	-0.357
Democracy	**0.460**	**0.464**	**0.441**	**0.490**	**-0.361**
Constraints on executives	0.399	0.395	0.395	0.435	-0.288
Political competition	0.362	0.367	0.349	0.405	-0.260

High income					
Gross international reserve	**0.827**	**0.788**	**0.932**	**0.832**	**-0.837**
Share of oil revenue in total revenue	0.045	0.024	0.067	0.004	-0.055
Debt to GDP ratio	0.160	0.182	0.039	0.123	-0.107
Inflation	-0.021	-0.048	0.224	0.012	-0.022
Oil wealth	**0.845**	**0.819**	**0.883**	**0.859**	**-0.839**
GDP per capita	0.293	0.306	0.298	0.302	-0.355
The size of public sector	-0.198	-0.199	-0.263	-0.199	0.206
Capital flows	0.090	0.076	0.215	0.029	-0.132
Population	**0.942**	**0.950**	**0.804**	**0.889**	**-0.913**
Military expenditure (in % of GDP)	-0.111	-0.113	-0.120	-0.121	0.127
Domestic credit to private sector (% of GDP)	0.366	0.376	0.279	0.364	-0.367
Bureaucracy quality	-0.122	-0.125	-0.128	-0.087	0.092
Corruption	-0.581	-0.596	-0.527	-0.552	0.608
Composite index	-0.038	-0.054	-0.071	0.009	0.032
Law and order	0.151	0.148	0.034	0.121	-0.107
Risk for international liquidity	-0.037	-0.032	-0.049	0.004	0.067
Democracy	-0.703	-0.713	-0.624	-0.638	0.684
Constraints on executives	**-0.661**	**-0.668**	**-0.582**	**-0.590**	**0.623**
Political competition	**-0.502**	**-0.514**	**-0.471**	**-0.473**	**0.524**

Estimation with OLS

Table 5.A.14 Pooled OLS, expenditure as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
		Base Regression		
Δ(log(non-oil GDP))	**0.78*****	**1.18*****	**1.24*****	**-0.06**
	(0.08)	(0.09)	(0.16)	(0.17)
Constant	0.02**	0.01	0.01	0.07***
	(0.01)	(0.01)	(0.02)	(0.02)
Observations	477	233	89	155
R-squared	0.17	0.43	0.41	0.00
		Regression with control variables		
Δ(log(non-oil GDP))	**0.62*****	**1.10*****	**1.25*****	**-0.16**
	(0.08)	(0.10)	(0.17)	(0.16)
Δlog(TOT)	0.30***	0.24***	-0.10	0.45***
	(0.05)	(0.06)	(0.10)	(0.09)
Δ(log(Tot. Expend(t-1)))	0.03	-0.10**	-0.00	0.14*
	(0.04)	(0.05)	(0.09)	(0.08)
Constant	0.02**	0.01	0.02	0.06***
	(0.01)	(0.01)	(0.02)	(0.02)
Observations	460	223	86	151
R-squared	0.19	0.41	0.40	0.19

Table 5.A.15 Pooled OLS, consumption as dependent variable

Independent Variables	Full sample	Low income	Middle income	High income
		Base Regression		
Δ(log(non-oil GDP))	**0.85*** **	**1.12*** **	**1.00*** **	**0.35*** **
	(0.06)	(0.09)	(0.17)	(0.09)
Constant	0.01	0.00	0.02	0.03**
	(0.01)	(0.01)	(0.02)	(0.01)
Observations	472	229	88	155
R-squared	0.29	0.40	0.29	0.10
		Regression with control variables		
Δ(log(non-oil GDP))	**0.73*** **	**1.00*** **	**1.03*** **	**0.29*** **
	(0.06)	(0.10)	(0.17)	(0.08)
Δlog(TOT)	0.15***	0.25***	-0.21**	0.12**
	(0.04)	(0.06)	(0.10)	(0.05)
Δ(log(Consump(t-1)))	-0.08**	-0.09*	-0.10	-0.19***
	(0.04)	(0.05)	(0.09)	(0.07)
Constant	0.02**	0.01	0.04*	0.05***
	(0.01)	(0.01)	(0.02)	(0.01)
Observations	452	218	84	150
R-squared	0.26	0.39	0.31	0.17

Table 5.16 Pooled OLS, non-oil revenue as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
		Base Regression		
Δ(log(non-oil GDP))	**0.82*** **	**0.97*** **	**0.99*** **	**0.51** **
	(0.09)	(0.10)	(0.21)	(0.22)
Constant	0.02	0.01	0.01	0.03
	(0.01)	(0.01)	(0.02)	(0.03)
Observations	466	227	89	150
R-squared	0.14	0.28	0.21	0.04
		Regression with control variables		
Δ(log(non-oil GDP))	**0.91*** **	**1.02*** **	**1.04*** **	**0.69*** **
	(0.10)	(0.11)	(0.22)	(0.23)
Δ(log(Revenue(t-1)))	-0.24***	-0.27***	-0.11	-0.26***
	(0.04)	(0.06)	(0.09)	(0.08)
Δlog(TOT)	0.07	0.08	-0.03	0.08
	(0.06)	(0.07)	(0.13)	(0.12)
Constant	0.03**	0.03**	0.02	0.03
	(0.01)	(0.01)	(0.02)	(0.03)
Observations	448	217	85	146
R-squared	0.20	0.31	0.22	0.12

Table 5.A17 Pooled OLS, capital expenditure as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
		Base Regression		
Δ(log(non-oil GDP))	**0.89*** **	**1.37*** **	**2.03*** **	**0.26**
	(0.13)	(0.21)	(0.35)	(0.20)
Constant	0.05***	0.04	0.01	0.07**
	(0.02)	(0.03)	(0.03)	(0.03)
Observations	465	213	86	153
R-squared	0.09	0.23	0.29	0.01
		Regression with control variables		
Δ(log(non-oil GDP))	1.12***	1.37***	2.06***	0.33
	(0.15)	(0.21)	(0.38)	(0.23)
Δ(log(Capital Exp.(t-1)))	-0.15***	-0.24***	-0.06	0.01
	(0.04)	(0.06)	(0.10)	(0.09)
Δlog(TOT)	0.14	0.40***	-0.01	-0.11
	(0.08)	(0.13)	(0.21)	(0.12)
Constant	0.04**	0.04	0.01	0.07**
	(0.02)	(0.03)	(0.04)	(0.03)
Observations	438	213	81	144
R-squared	0.13	0.23	0.29	0.02

Table 5.A.18 Pooled OLS, non-oil primary balance as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
		Base Regression		
Δ(log(non-oil GDP))	**-0.24**	**1.46**	**2.06**	**-4.80**
	(1.55)	(1.11)	(1.44)	(4.42)
Constant	0.16	-0.07	-0.12	0.84
	(0.20)	(0.15)	(0.14)	(0.62)
Observations	477	233	89	155
R-squared	0.00	0.01	0.02	0.01
		Regression with control variables		
Δ(log(non-oil GDP))	**-0.99**	**1.53**	**1.78**	**-5.90**
	(1.68)	(1.28)	(1.42)	(4.43)
Δ(log(Primary Bal.(t-1)))	-0.05	-0.09	0.07	-0.08
	(0.05)	(0.07)	(0.09)	(0.08)
Δlog(TOT)	2.97***	0.22	0.30	7.01***
	(1.01)	(0.81)	(0.81)	(2.54)
Constant	0.14	-0.09	-0.08	0.77
	(0.21)	(0.16)	(0.14)	(0.63)
Observations	460	223	86	151
R-squared	0.02	0.02	0.03	0.06

Estimation with Fixed effects

Table 5.A.19 Fixed Effects, expenditure as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**0.55*** **	**1.10*** **	**1.24*** **	**-0.31**
	(0.17)	(0.16)	(0.24)	(0.22)
Δlog(TOT)	0.31***	0.23***	-0.10	0.49**
	(0.10)	(0.08)	(0.14)	(0.23)
Δ(log(Tot. Expend(t-1)))	-0.00	-0.12	-0.04	0.09
	(0.13)	(0.10)	(0.13)	(0.26)
Constant	0.03	0.02	0.02	0.07*
	(0.02)	(0.01)	(0.02)	(0.04)
Observations	460	223	86	151
R-squared	0.16	0.38	0.38	0.21
No of countries	29	14	6	9

Table 5.A.20 Fixed Effects, consumption as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**0.67*** **	**0.98*** **	**1.02*** **	**0.16**
	(0.13)	(0.16)	(0.20)	(0.11)
Δ(log(Consump(t-1)))	-0.12*	-0.11	-0.12	-0.30***
	(0.07)	(0.09)	(0.08)	(0.08)
Δlog(TOT)	0.15***	0.25***	-0.21	0.14***
	(0.05)	(0.07)	(0.13)	(0.05)
Constant	0.02**	0.01	0.04**	0.06***
	(0.01)	(0.01)	(0.02)	(0.01)
Observations	452	218	84	150
R-squared	0.24	0.36	0.30	0.22
No of countries	29	14	6	9

Table 5.A21 Fixed Effects, non-oil revenue as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**0.88*** **	**0.98*** **	**1.09*** **	**0.64** **
	(0.13)	(0.10)	(0.35)	(0.28)
Δ(log(Revenue(t-1)))	-0.26***	-0.28**	-0.11	-0.27*
	(0.08)	(0.11)	(0.13)	(0.14)
Δlog(TOT)	0.06	0.08	-0.04	0.07
	(0.08)	(0.08)	(0.14)	(0.16)
Constant	0.03**	0.03*	0.02	0.04
	(0.01)	(0.02)	(0.02)	(0.03)
Observations	448	217	85	146
R-squared	0.18	0.28	0.22	0.12
No of countries	29	14	6	9

Table 5.A.22 Fixed Effects, capital expenditure as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**1.08*****	**1.39*****	**1.92*****	**0.20**
	(0.24)	(0.31)	(0.57)	(0.25)
Δ(log(Capital Exp.(t-1)))	-0.18***	-0.27***	-0.11	-0.02
	(0.07)	(0.09)	(0.12)	(0.12)
Δlog(TOT)	0.15	0.40**	0.01	-0.09
	(0.11)	(0.16)	(0.28)	(0.18)
Constant	0.05**	0.04	0.03	0.08**
	(0.02)	(0.03)	(0.04)	(0.03)
Observations	438	213	81	144
R-squared	0.13	0.23	0.26	0.01
No of countries	29	14	6	9

Table 5.A.23 Fixed Effects, non-oil primary balance as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**-3.24**	**2.16****	**1.67***	**-11.54**
	(3.91)	(0.91)	(0.92)	(9.59)
Δ(log(Primary Bal.(t-1)))	-0.12	-0.14	0.05	-0.17
	(0.11)	(0.10)	(0.07)	(0.16)
Δlog(TOT)	3.32	0.00	0.49	8.10
	(2.69)	(0.56)	(0.69)	(6.64)
Constant	0.26	-0.11	-0.08	1.20
	(0.33)	(0.16)	(0.13)	(1.06)
Observations	460	223	86	151
R-squared	0.04	0.03	0.03	0.11
No of countries	29	14	6	9

Estimation with 2SLS and Fixed effects

Table 5.A.24 2SLS with Fixed Effects, expenditure as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**0.55*****	**1.10*****	**1.24*****	**-0.31**
	(0.17)	(0.16)	(0.24)	(0.22)
Δlog(TOT)	0.31***	0.23***	-0.10	0.49**
	(0.10)	(0.08)	(0.14)	(0.23)
Δ(log(Tot. Expend(t-1)))	-0.00	-0.12	-0.04	0.09
	(0.13)	(0.10)	(0.13)	(0.26)
Constant	0.03	0.02	0.02	0.07*
	(0.02)	(0.01)	(0.02)	(0.04)
Observations	460	223	86	151
R-squared	0.16	0.38	0.38	0.21
No of countries	29	14	6	9

Table 5.A.25 2SLS with Fixed Effects, consumption as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**0.67*** **	**0.98*** **	**1.02*** **	**0.16**
	(0.13)	(0.16)	(0.20)	(0.11)
Δ(log(Consump(t-1)))	-0.12*	-0.11	-0.12	-0.30***
	(0.07)	(0.09)	(0.08)	(0.08)
Δlog(TOT)	0.15***	0.25***	-0.21	0.14***
	(0.05)	(0.07)	(0.13)	(0.05)
Constant	0.02**	0.01	0.04**	0.06***
	(0.01)	(0.01)	(0.02)	(0.01)
Observations	452	218	84	150
R-squared	0.24	0.36	0.30	0.22
No of countries	29	14	6	9

Table 5.A.26 2SLS with Fixed Effects, non-oil revenue as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(Revenue(t-1)))	-0.26***	-0.28**	-0.11	-0.27*
	(0.08)	(0.11)	(0.13)	(0.14)
Δlog(TOT)	0.06	0.08	-0.04	0.07
	(0.08)	(0.08)	(0.14)	(0.16)
Δ(log(non-oil GDP))	**0.88*** **	**0.98*** **	**1.09*** **	**0.64** **
	(0.13)	(0.10)	(0.35)	(0.28)
Constant	0.03**	0.03*	0.02	0.04
	(0.01)	(0.02)	(0.02)	(0.03)
Observations	448	217	85	146
R-squared	0.18	0.28	0.22	0.12
No of countries	29	14	6	9

Table 5.A.27 2SLS with Fixed Effects, capital expenditure as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(Capital Exp.(t-1)))	-0.18***	-0.27***	-0.11	-0.02
	(0.07)	(0.09)	(0.12)	(0.12)
Δlog(TOT)	0.15	0.40**	0.01	-0.09
	(0.11)	(0.16)	(0.28)	(0.18)
Δ(log(non-oil GDP))	**1.08*** **	**1.39*** **	**1.92*** **	**0.20**
	(0.24)	(0.31)	(0.57)	(0.25)
Constant	0.05**	0.04	0.03	0.08**
	(0.02)	(0.03)	(0.04)	(0.03)
Observations	438	213	81	144
R-squared	0.13	0.23	0.26	0.01
No of countries	29	14	6	9

Table 5.A28 2SLS with Fixed Effects, non-oil primary balance as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(Primary Bal.(t-1)))	-0.12	-0.14	0.05	-0.17
	(0.11)	(0.10)	(0.07)	(0.16)
Δlog(TOT)	3.32	0.00	0.49	8.10
	(2.69)	(0.56)	(0.69)	(6.64)
Δ(log(non-oil GDP))	**-3.24**	**2.16****	**1.67***	**-11.54**
	(3.91)	(0.91)	(0.92)	(9.59)
Constant	0.26	-0.11	-0.08	1.20
	(0.33)	(0.16)	(0.13)	(1.06)
Observations	460	223	86	151
R-squared	0.04	0.03	0.03	0.11
No of countries	29	14	6	9

Estimation with System GMM

Table 5.A.29 System GMM, expenditure as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**0.64*****	**1.16*****	**1.50*****	**-0.32****
	(0.05)	(0.05)	(0.50)	(0.16)
Δ(log(Tot. Expend(t-1)))	0.05***	-0.10***	-0.25	0.10
	(0.01)	(0.04)	(0.30)	(0.07)
Δ(log(TOT))	0.24***	0.19***	-0.26	0.29***
	(0.01)	(0.03)	(0.19)	(0.05)
Constant	0.02***	0.01***	0.02*	0.07***
	(0.00)	(0.00)	(0.01)	(0.01)
Observations	444	223	86	135
No of countries	28	14	6	8
AR1	0.0128	0.0464	0.135	0.196
AR2	0.151	0.0810	0.816	0.348
Hansen test-p	1.000	1	1	1

Table 5.A.30 System GMM, consumption as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**0.91*****	**1.04*****	**1.03**	**3.00****
	(0.05)	(0.16)	(0.87)	(1.42)
Δ(log(Consump(t-1)))	-0.11***	-0.13*	-0.13	-0.27
	(0.01)	(0.07)	(0.37)	(0.20)
Δ(log(TOT))	0.12***	0.21***	-0.13	-0.01
	(0.01)	(0.04)	(0.21)	(0.07)
Constant	0.01***	0.01	0.03	-0.16
	(0.00)	(0.01)	(0.02)	(0.11)
Observations	436	218	84	134
No of countries	28	14	6	8
AR1	0.000267	0.0109	0.250	0.167
AR2	0.822	0.879	0.844	0.182
Hansen test-p	1.000	1	1	1

Table 5.A.31 System GMM, non-oil revenue as dependent variable

Independent Variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**1.00*****	**0.87****	**1.92**	**5.26***
	(0.02)	(0.31)	(4.87)	(2.69)
Δ(log(Revenue(t-1)))	-0.20***	-0.18	-0.02	0.02
	(0.01)	(0.13)	(0.36)	(0.15)
Δ(log(TOT))	0.05***	0.05	-0.14	0.02
	(0.01)	(0.09)	(0.28)	(0.07)
Constant	0.02***	0.03	-0.03	-0.32
	(0.00)	(0.02)	(0.20)	(0.20)
Observations	432	217	85	130
No of countries	28	14	6	8
AR1	0.00495	0.0850	0.250	0.00356
AR2	0.0988	0.435	0.944	0.00998
Hansen test-p	1.000	1	1	1

Table 5.A.32 System GMM, capital expenditure as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**1.61*****	**1.95*****	**2.71**	**-0.16**
	(0.16)	(0.24)	(3.29)	(1.49)
Δ(log(Capital Exp.(t-1)))	-0.15***	-0.26***	-0.17	0.26
	(0.02)	(0.03)	(0.47)	(0.17)
Δ(log(TOT))	0.11***	0.39***	-0.18	-0.17***
	(0.02)	(0.10)	(0.20)	(0.03)
Constant	0.02**	0.02***	-0.01	0.08
	(0.01)	(0.01)	(0.08)	(0.11)
Observations	422	213	81	128
No of countries	28	14	6	8
AR1	0.000508	0.0177	0.0690	0.0329
AR2	0.347	0.0788	0.888	0.285
Hansen test-p	1.000	1	1	1

Table 5.A.33 System GMM, non-oil primary balance as dependent variable

Independent variables	Full sample	Low income	Middle income	High income
Δ(log(non-oil GDP))	**-1.17*****	**-0.34**	**-3.16**	**-5.59*****
	(0.11)	(1.25)	(10.85)	(1.46)
Δ(log(Primary Bal.(t-1)))	-0.04***	-0.10***	-0.18	-0.08***
	(0.00)	(0.00)	(0.22)	(0.00)
Δ(log(TOT))	1.76***	0.44***	0.23	6.18***
	(0.01)	(0.11)	(0.64)	(0.12)
Constant	0.22***	0.02	0.17	0.86***
	(0.00)	(0.04)	(0.39)	(0.14)
Observations	444	223	86	135
No of countries	28	14	6	8
AR1	0.237	0.163	0.174	0.0639
AR2	0.758	0.317	0.788	0.531
Hansen test-p	1.000	1	1	1

6 Causality between Commodity Prices and Currencies in Commodity Exporting Countries

6.1 Introduction

Volatile commodity prices are costly and have negative effects on the economies of commodity exporting countries. One channel through which the volatility of commodity prices is transmitted to the economy is through the volatility in their floating exchange rates[37]. Their currencies appreciate during a commodity price boom due to the increase in the relative demand for their home currencies as a result of large amount of export earnings which leads to a balance-of-payment surplus and accumulation of foreign reserves. Due to this strong link between commodity prices and currencies, earlier studies called the currency of these countries "commodity currencies". As an example, nearly 50% of Brazil's total exports were primary commodity exports in 2011. In the third quarter of 2011 when commodity prices were at record high level, the Brazilian Real appreciated against the USD by 12%. Usually the reverse occurs, e.g. currencies depreciate, when commodity prices declines and subsequently reduce the export revenues. For example, from the third quarter of 2008 to last quarter with the collapse of commodity prices, the Brazilian Real depreciated by 27%.

High price volatility during the past commodity boom which lasted over 10 years proved that forecasting commodity prices and understanding their effect on the exchange rates and economies of commodity producing countries is of key importance. Not only properly gauging commodity price movements is critical for inflation control, but it is also important for fiscal and production planning. That is why the interaction between commodity prices and exchange rates received a lot of attention in literature.

The majority of earlier research devoted to explaining the interaction between commodity prices and exchange rate is predominantly empirical and built on fundamental based exchange rate models. Commodity prices are used as part of

[37] Many countries adopted floating exchange rate regime after the demise of the Breton Woods system of fixed exchange rates in 1973.

determining the behavior of nominal or real exchange rates. These studies usually start with the observed correlation between the terms of trade (the value of a country's exports relative to that of its imports) and real exchange rates in commodity-exporting countries. Then they move on to show the long-run real effects of changes in commodity prices on the exchange rate as well as on the macroeconomic fundamentals; interest rate, money supply, trade balance, wages, employment, and output.[38] Some of the other studies investigate the impact of commodity prices or terms of trade shocks on growth and macroeconomic performance of the country under alternative exchange rate regimes.[39] Others examine the phenomenon called "Dutch disease" which is the negative effect of a booming commodity export sector on other sectors of the economy through a real appreciation of the county's exchange rate which hurts the other exporters and producers in the import-competing sector by increasing the cost and making them less competitive.[40]

The large body of research on this topic found some evidence of the link between fundamentals and exchange rates in the long run.[41] However, none of the result of these studies managed to overturn the findings of Meese and Rogoff (1983) who showed that economic fundamentals were insufficient in explaining and very ineffective in forecasting exchange rates over short time horizons. The many of these studies found that forecasts from economic fundamentals might work well for some currencies during certain sample periods but not for other currencies or sample periods. Main explanation for this is because the fundamental variables are themselves endogenous to exchange rates and jointly determined with exchange rates in equilibrium. For example exchange rates might Granger-cause money supplies because monetary policy makers react to the exchange rate in setting the monetary policy.

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[38] Edwards (1985), Cashin, Cespedes, and Sahay (2004), Chen and Rogoff (2003).

[39] Mendoza (1995), Broda (2004) and Edwards and Yeyati (2005).

[40] Corden (1984), Corden and Neary (1982), Neary and van Wijnbergen (1986).

[41] Engle, Mark and West (2007).

Recent studies pursue asset-pricing approach to the exchange rates and emphasize the endogeneity for the failure of fundamentals determining the exchange rates. They turn the argument around and argue that the exchange rates should be the predictor of fundamentals.[42] Chen, Rogoff and Rossi (2010) (CRR thereafter) follow this approach, take the exchange rates as prices of forward looking financial assets and argue that exchange rates would be better predictor of exogenous variables such as commodity prices than vice-versa, because the exchange rate is fundamentally forward looking; i.e. incorporates expectations about the values of its future fundamentals whereas commodity prices tend to be very sensitive to even small changes in current demand or supply balances. This would especially apply to currencies of commodity exporting small countries, because world commodity prices can reasonably be assumed to be independent of their exchange rates. CRR found a robust relationship between commodity price movements and exchange rate fluctuations for a group of commodity producing countries. They also showed that combined exchange rates of this set of countries can detect movements in the aggregate world commodity price index.

This chapter pursues the asset-pricing approach and explores the dynamic relationship between exchange rates and commodity prices for a group of advanced and developing commodity-exporting economies with a sufficiently long history of market-based floating exchange rates. The analysis includes testing Granger causality for both directions; from the exchange rates to commodity prices and *vice versa*, checking for parameter instability in Ganger-causality tests and finally testing out-of-sample forecasting ability of the exchange rates and commodity prices.

This study makes two contributions to the literature. First, it analyzes a broader range of emerging and advanced countries which have a significant portion of their production and exports in primary commodity products. In addition to the countries that were examined almost in all earlier studies such as Australia, New Zealand, Canada,

[42] Campbell and Shiller (1987) and Engel and West (2005).

Chile and South Africa, we expand our set of countries and include countries that have not been studied before such as Brazil, Mexico, Indonesia, Norway and Korea. Second, we focus on the type of commodities these countries produce to see if that creates different dynamics between commodity prices and currencies. For example, Korea heavily depends on semiconductor chip exports whereas countries such as Chile or Mexico predominantly produce one type of mineral source (copper and crude oil, respectively). However, other countries such as Brazil, Australia or Canada produce and export minerals as well as various crops (sugar cane, coffee, soybean and wheat) where the farmers have the ability and efficiency to switch from one crop to another depending on the return from the crops which may cause a sustained strength/appreciation in the currency. Although there are a number of research papers on this topic, there is not any study which differentiates the type of commodity the country heavily exports and its impact on the currency.

We find in-sample evidence of Granger causality from exchange rates to commodity prices for most of the countries in the sample. However, the out-of-sample forecasting results are not as robust as CRR found.

The structure of the chapter is as follows. In the next section, a brief review of the link between commodity prices and currencies and the theoretical basis are presented. In Section 3, the methodology and empirical specification are laid out. Then in Section 4, data, estimations and results are presented. Finally Section 5 has the conclusion remarks.

6.2 Literature Review

Sound theories in the earlier exchange rate literature rarely translated into sound empirical results mainly due to unaddressed endogeneity in the econometric testing. The standard exchange-rate fundamentals such as cross-country differences in money supply, interest rates, output, or inflation rate are fundamentally endogenous and jointly determined with exchange rates in equilibrium. Furthermore, they may directly react to exchange rate changes through policy responses. In this setting, a positive conclusion that exchange rate Granger-causes fundamentals could just be the outcome of endogenous response or reverse causality. For example, if one finds that exchange rates Granger-cause money supply or interest rate changes, this may be the direct result of monetary policy responses to exchange-rate fluctuations, as would be the case with a Taylor interest rate rule (Taylor (1993)) that targeted consumer price index (CPI) inflation. Exchange rate changes may also precede inflation movements if prices are sticky and pass-through is gradual. In this case, positive Granger-causality results for these standard fundamentals are difficult to interpret as the direction of interaction is not clear and cannot be taken as evidence for the present-value framework, unless the fundamental under consideration is exogenous to exchange-rate movements. [43]

Commodity prices are a unique exchange-rate fundamental for these countries because they can be taken as an exogenous measure of terms of trade and are not determined endogenously with the exchange rate in the model or in the individual countries. Commodities represent a large portion of exports of commodity currency countries, but their share of exports in the total world commodity trade is still small. Although to a degree they exert some market power, their influence over the individual commodity prices is not large. Substitution across various commodities would also diminish the market power these countries have; even within the specific markets they appear to be strong. Hence they can be treated as price takers as commodity prices are determined by the global demand supply conditions. Finally world commodity prices unlike other fundamentals are easy to observe from the global exchanges and they come in high frequency as exchange rate data.

The traded/nontraded goods model of Rogoff (1992) can explain why, for a major commodity producer, the real (and nominal) exchange rate should respond to changes in the expected future path of the price of its commodity exports. This model assumes fixed factors of production and a bonds-only market for intertemporal trade across

[43] Chen, Rogoff and Rossi (2010).

countries (i.e., incomplete markets). The real exchange rate depends at any point in time on the ratio of traded goods consumption to nontraded goods consumption; but traded goods consumption depends on the present value of the country's expected future income (and on nontraded goods shocks, except in the special case where utility is separable between traded and nontraded goods.) Thus the real exchange rate incorporates expectations of future commodity price earnings. If factors are completely mobile across sectors, the real exchange rate will depend only on the current price of commodities. But as long as there are costs of adjustment in moving factors, the real exchange rate will still contain a forward-looking component that incorporates future commodity prices. In general, therefore, the nominal exchange rate will also incorporate expectations of future commodity price increases. In addition to CRR (2010), Campbell and Shiller (1987) and Engel and West (2005) tested the present-value models of exchange rate determination and showed that since the nominal exchange rate reflects expectations of future changes in its economic fundamentals, it should help predict them.

Finally, financial markets for commodities also tend to be far less developed and much more regulated than those for the exchange rate. As a result, commodity prices tend to be a less accurate barometer of future conditions than are exchange rates.

6.3 Methodology

First we start with a general expression for the spot exchange which relates the nominal exchange rate s_t to its fundamentals f_t and its expected future value $E_t\, s_{t+1}$ as shown below.

$$s_t = \beta' f_t + E_t\, s_{t+1} , \qquad (1)$$

This approach brings forth to a present-value relation between the nominal exchange rate and the discounted sum of its expected future fundamentals as,

$$s_t = \gamma \sum_{j=0}^{\infty} \psi^{j} E_t(f_{t+j} | I_t) , \qquad (2)$$

where ψ and γ are parameters imposed by the specific structural model and E_t is the expectation operator given information I_t. This present-value equation shows that exchange rate *s* should Granger-cause its fundamentals *f*. We focus on the nominal exchange rate rather than the real exchange rate here, as it is measured more accurately and at very high frequency, as are commodity prices. But in principle the real exchange can also be used.[44]

To analyze the dynamic relationship between commodity prices and exchange rate, we put the equation (2) in an explicit form as exchange rate Granger Causes commodity prices:

$$E_t\Delta cp_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp_t \qquad (3)$$

where commodity prices and exchange rates are in first differences.[45] We also test the reverse where commodity prices determine exchange rates.

$$E_t\Delta s_{t+1} = \beta_0 + \beta_1 \Delta c_t + \beta_2 \Delta s_t \qquad (4)$$

Here we do not consider cointegration but use first differences in a simple OLS framework because our main interest is in short-term interaction not to measure the long-term behavior of a specific model. Chen and Rogoff (2003) showed that, in analyzing real exchange rates, dynamic OLS estimates of cointegrated models and estimates of models in differences produce very similar results.

We first test the null hypothesis of $\beta_0= \beta_1=0$ in equations (3) and (4) where we assume that the relationship is stable and coefficients are constant throughout the sample period. However, this assumption is hardly plausible since all of the commodity currency countries as well as commodity markets have gone through major structural

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[44] CRR (2010) argue that from a practical point of view, real and nominal exchange rates behave similarly.

[45] As standard unit root tests cannot reject the hypothesis that these series contain unit roots, we analyze the data in first differences, which we denote with a Δ.

and regulatory changes in the past several decades. One of the important changes was the adoption of inflation targeting by most of commodity producing countries in the 1990s where the focus was keeping the inflation under control by adjusting interest rates instead of concentrating on output growth. The countries and years that they adopted the inflation targeting are as follow: New Zealand (1990), Chile (1991), Canada (2001), Brazil (1999), Australia (1993), Mexico (1999) and South Africa (2000). The other important changes that took place in the commodity exchange markets in 2000. First, the Intercontinental Exchange was established which served as a global risk management platform for agricultural and energy commodities. The same year, in the United States, the Commodity Futures Modernization Act passed which allowed pension funds and other investors to enter into commodity futures index trading. Both events raised the liquidity considerably going into commodities in the following decade turning them into another class of assets. We therefore incorporate the possibility of structural breaks in our analyses by allowing parameter instability and test the joint null hypothesis that $\beta_0 = \beta_{0t} = 0$ and $\beta_1 = \beta_{1t} = 0$ in equations (3) and (4). After we conduct in-sample Granger causality tests, we move on to examine the out-of-sample forecasting ability of exchange rates and commodity prices using the same equations.

6.4 Data and Estimation Results

6.4.1 Data

We use quarterly data over the following time periods: Australia (1983:1-2012:4), Brazil (1995:1-2012:4), Canada (1974:1-2012:4), Chile (1989:1-2012:4), Indonesia (1998:1-2012:4), Korea (1998:1-2012:4), Mexico (1995:1-2012:4), New Zealand (1995:1-2012:4), Norway (1993:1-2012:4) and South Africa (1998:1-2012:4). Although the sample period spans until the end of 2012, we run two sets of estimations; one with which the data period ends before the financial crisis (2008Q1) and the other which the data end in 2012Q4, although this reduces the number of observations in estimation, it may provide a useful insight to observe the impact of the financial crisis and the collapse of commodity prices on the dynamics between commodity prices and currencies.[46]

For each country, we aggregate the relevant dollar spot prices in the world commodity markets to construct country-specific, export-earnings-weighted commodity price indices (labeled *cp* in equation 3 and 4. Individual commodity price data are collected from the World Bank, International Monetary Fund (IMF) and United Nations UNCTAD commodity databases. Some of the export weights are taken from CRR (2010) and others are calculated by export data from the United Nations UNCTAD database. Table 6.A.1 in appendix provides the country-specific weights used to aggregate individual world commodity prices into country-specific indices. For countries such as Chile, Mexico and Korea, only one commodity price is used as one major commodity dominates their export composition (copper for Chile, crude oil for Mexico and semiconductor for Korea). Except for these 3 countries, all other indices are based to 100 in the beginning of the sample.

For nominal exchange rates (labeled as *s* in equations 3 and 4), we use the end-of-period U.S. dollar rates from Bloomberg. We choose the sample period for each country during which exchange rate policy would be as close to free floating exchange rates. In addition, we use exchange rates denominated in non-USD currencies for two reasons. First, the strength of the U.S. dollar has an effect on commodity prices as most of them are priced in the U.S. dollar which can be a possible source of endogeneity. Second, the United States accounts for roughly 25% of total global demand in some major commodity groupings, and therefore its size might be an issue. As a result, testing the individual country currency relative to the US dollar and the commodity prices in the U.S dollar may induce endogeneity. In order to overcome this issue as well as to check for robustness, first we conduct the test with the individual country currencies relative to the US dollar, and then we repeat the same test with the

[46] Our data sample is not exactly the same as in CRR. In addition, some of their series start in earlier years. Some of the commodity index compositions may be also different.

currencies relative to the British pound and the Japanese Yen. Finally, we conduct the same tests using nominal effective exchange rates (from the International Finance Statistics, IFS).[47] We take the logarithms of the series. Summary statistics of the series are provided in the appendix, in Table 6.A.2. The skew and kurtosis values of the levels data indicate asymmetric series skewed towards to the right and more peaked than a Gaussian distribution. The differenced series however show more asymmetry toward to the left with accentuated peak compared to a Gaussian distribution.

In Figure 6.1, the charts with the raw data of USD exchange rate and commodity index for each country show that most of the commodity indices with the exception of Korea start to move up in 2004. Their rise accelerates and peaks in 2008 then is briefly stalled in 2009 before starts again later in 2009. The exchange rates of Australia, Brazil, Canada, Indonesia, Norway and New Zealand clearly follow the movement of commodity indices starting in the mid-2000's. The Brazilian Real was depreciated dramatically in the late 1990's with the start of economic crisis; however it stabilized first and then moved up along with the commodity prices with the onset of commodity boom. The exchange rates of Chile, Mexico and South Africa show somewhat similar trends with commodity indices. However, they are not as pronounced as previous ones mentioned which may suggest the possibility of not fully floating exchange rate regime and intermittent intervention. Korea, on the other hand, depicts a completely different picture. In contrast to other commodity prices, the semiconductor prices have been declining since 2000 due to increased competition and efficiency in production and rapid technological development which reduced the prices of existing products.[48] A quick glance at the charts in Figure 6.1 indicates no apparent similarities in the movement of the exchange rate and the semiconductor prices. The continuous decline in prices is not reflected in the currency except for the period from 2000 to 2001 when both currency and semiconductor prices went down.

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[47] Nominal effective exchange rate is not available for Indonesia, so the estimate with other currencies is conducted and with NEER is skipped.

[48] IMF, World Economic Outlook, October 2001.

In Figure 6.2, the charts with the transformed data in log of changes of the exchange rate and the commodity indices are shown. The sharp drop in commodity prices in 2009 is evident in most of the indices except for Chile and Korea. The high volatility in the Canadian commodity prices is worth noting which may be due to large share of metals and energy prices in the commodity index as their prices have become more volatile in the past decade compared to that of agricultural commodities. The sharp fluctuations in the Indonesian exchange rate in the late 1990's are as a result of financial crisis.

Figure 6.1 The USD exchange rate and Commodity price Indices

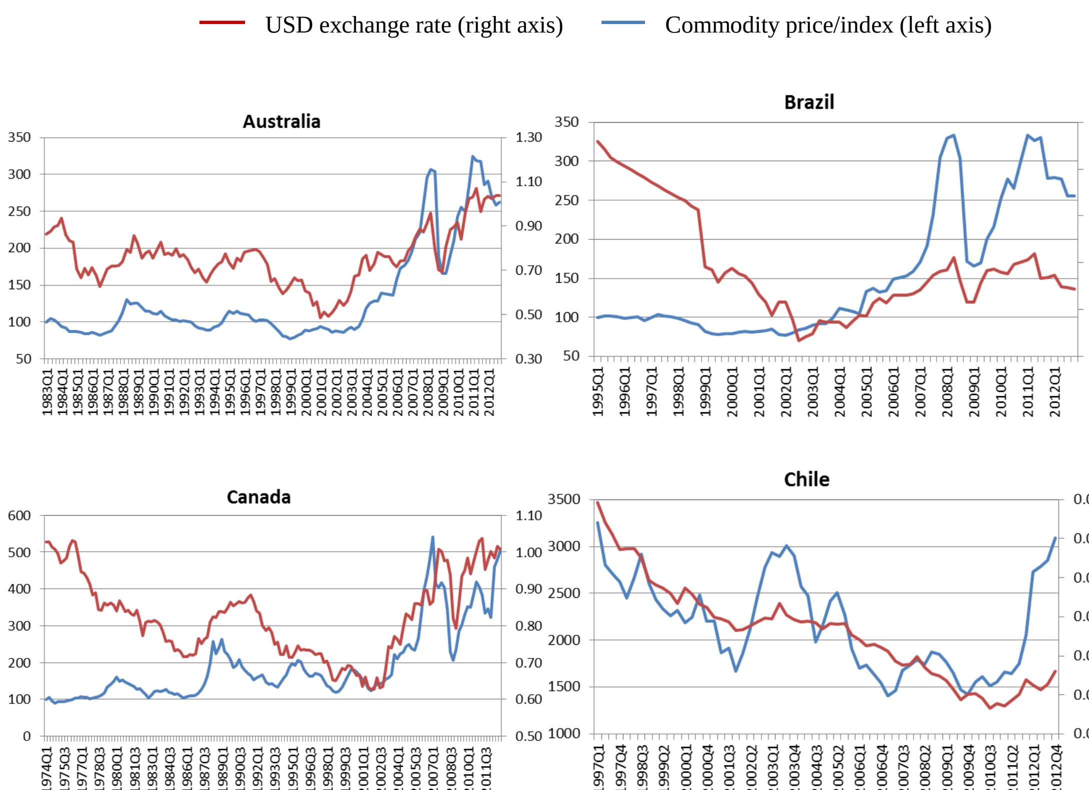


Figure 6.1- continued. The USD exchange rate and Commodity price Indices

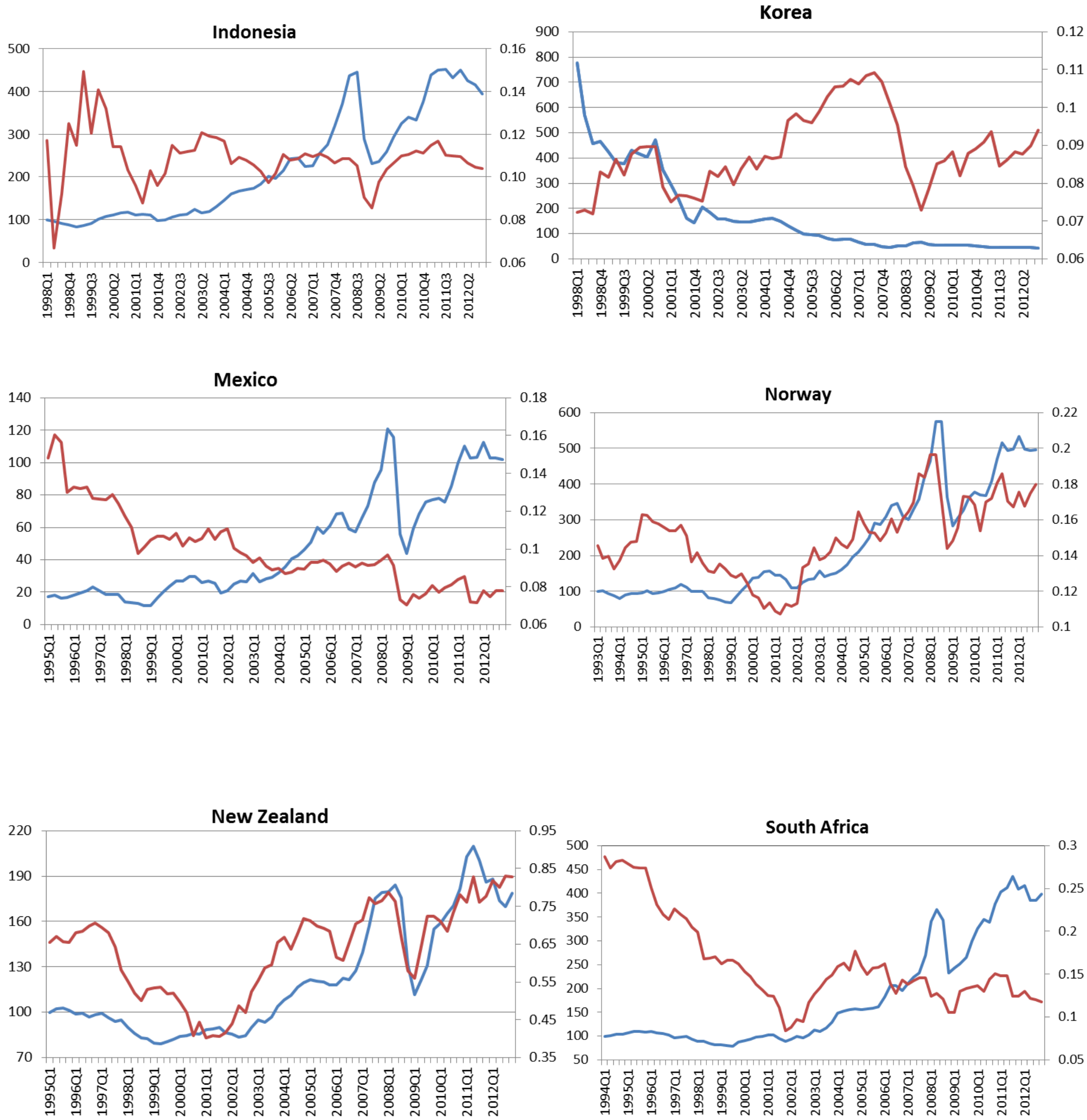
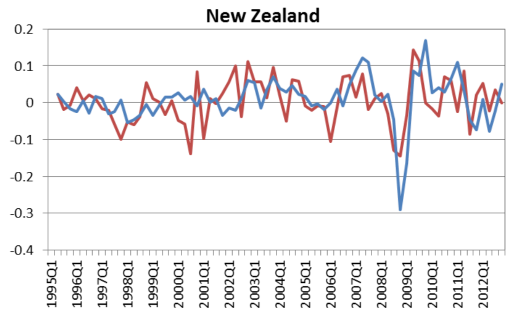
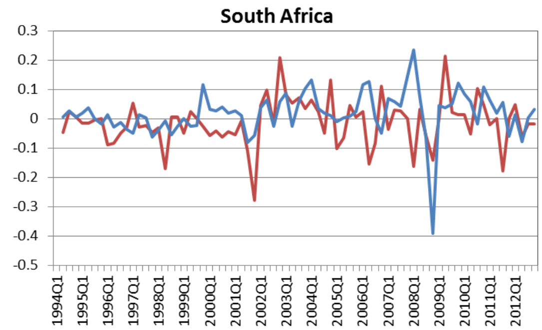


Figure 6.2 Changes of the log of the USD exchange rate and Commodity price Indices





6.4.2 Estimation and Results

6.4.2.1 In-Sample Granger Causality Tests

We start our analysis with the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests which are presented in Appendix Table 6.A.3. For most of the series in levels we cannot reject the hypothesis that these series contain unit roots. However, when the series are differenced we reject the existence of unit root, so we proceed to analyze the data in first differences. We continue with the levels with the series which do not have unit roots.[49] Then we move to investigate the empirical evidence on Grange causality (GC thereafter) between exchange rates and commodity indices, first ignoring the parameter instability. If there is GC we should reject the hypothesis that $\beta_0 = \beta_1 = 0$ in equations (3) and (4). We performed heteroscedasticity- and serial correlation–consistent Wald test and imposed restriction of β_0 and β_1 being zero for 2 set of samples one ending in 2008Q1 and the other ending in 2012Q4. Furthermore, we repeated the tests by including other lags into the regression but the result has not changed significantly so we present the result with one lag which are included in Table 6.1 and Table 6.2 with some evidence of causality especially for Korea. The results show that 4 different exchange rates for Korea consistently GC commodity prices in both samples, although the opposite is not true; commodity prices do not GC exchange rates. In addition to Korea, the results for Australia, New Zealand and S. Africa indicate causality from exchange rates to commodity prices in both sample periods. Exchange rates GC commodity prices in one sample but not in the

[49] Except for a few exchange rates; JPY for Australia, USD and GBP for Indonesia and GBP and NEER for Korea.

others; Canada, Brazil, Indonesia and Norway for example. For others such as Brazil. Chile, Indonesia, Norway and New Zealand, the direction of causality runs in both directions depending on the sample or the currency. In their study CRR found evidence of GC for Chile and South Africa.

Table 6.1 Bivariate Granger-Causality Tests, ending in 2008Q1*, null $\beta_0 = \beta_1 = 0$

Panel (a): $E_t\Delta cp_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp_t$

	USD	NEER	GBP	JPY
Australia	0.03**	0.44	0.44	0.41
Brazil	0.17	0.07*	0.24	0.11
Canada	0.05*	0.28	0.22	0.30
Chile	0.21	0.64	0.18	0.11
Indonesia	0.09*		0.08	0.08*
Korea	.00***	0.01**	0.00***	0.01**
Mexico	0.20	0.22	0.11	0.33
Norway	0.12	0.24	0.19	0.33
New Zealand	0.04**	0.48	0.20	0.20
S. Africa	0.06*	0.17	0.05**	0.15

Panel (a): $E_t\Delta s_{t+1} = \beta_0 + \beta_1 \Delta c_t + \beta_2 \Delta s_t$

	USD	NEER	GBP	JPY
Australia	0.65	0.95	0.92	0.50
Brazil	0.04**	0.71	0.02**	0.61
Canada	0.71	0.93	0.96	0.42
Chile	0.00***	0.95	0.48	0.16
Indonesia	0.24		0.07*	0.07**
Korea	0.56	0.18	0.81	0.82
Mexico	0.16	0.13	0.24	0.68
Norway	0.67	0.78	0.03**	0.69
New Zealand	0.16	0.53	0.12	0.55
S. Africa	0.52	0.30	0.20	0.50

Table 6.2 Bivariate Granger-Causality Tests, ending in 2012Q4*, null $\beta_0 = \beta_1 = 0$

Panel (a): $E_t\Delta cp_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp_t$

	USD	NEER	GBP	JPY
Australia	0.01**	0.44	0.18	0.12
Brazil	0.03**	0.72	0.19	0.06**
Canada	0.59	0.50	0.32	0.27
Chile	0.03**	0.96	0.04**	0.02**
Indonesia	0.35		0.27	0.41
Korea	0.00***	0.01**	0.01**	0.00***
Mexico	0.13	0.32	0.54	0.42
Norway	0.01**	0.30	0.05**	0.15
New Zealand	0.03**	0.48	0.09*	0.17
S. Africa	0.01**	0.21	0.16	0.27

Panel (b): $E_t\Delta s_{t+1} = \beta_0 + \beta_1 \Delta c_t + \beta_2 \Delta s_t$

	USD	NEER	GBP	JPY
Australia	0.96	0.66	0.98	0.22
Brazil	0.38	0.69	0.35	0.74
Canada	0.13	0.16	0.81	0.20
Chile	0.10	0.91	0.78	0.12
Indonesia	0.78		0.76	0.17
Korea	0.70	0.25	0.61	0.41
Mexico	0.19	0.14	0.22	0.31
Norway	0.11	0.87	0.16	0.16
New Zealand	0.95	0.68	0.03**	0.77
S. Africa	0.57	0.32	0.40	0.43

*Both tables report p-values for the GC test. Asterisks indicates rejection at the 1%(***), 5%(**), and 10%(*) significance levels, respectively indicating the evidence of Granger Causality.

After performing simple GC tests, we move to test for the parameter instability. As mentioned earlier commodity markets as well as commodity exporting countries went through significant policy as well structural changes in the past decades which should be taken into account in the tests. Table 6.3 and 6.4 report results from the parameter instability test for 2 sample periods, based on Andrews (1993), for the bivariate GC regressions. However, contrary to what we expect, we did not obtain strong evidence of time-varying parameters. Only country showed sign of structural change was Australia in the second quarter of 2008. CRR found structural breaks for Australia and South Africa in the early 2000's.

Table 6.3 Granger-Causality, Andrew's QLR test, ending in 2008Q1*

Panel (a): $E_t\Delta cp_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp_t$

	USD	NEER	GBP	JPY
Australia	0.84	0.69	0.76	0.68
Brazil	0.97	0.83	0.86	0.68
Canada	1.00	1.00	1.00	0.99
Chile	1.00	1.00	0.97	1.00
Indonesia	1.00		1.00	1.00
Korea	1.00	1.00	1.00	1.00
Mexico	1.00	1.00	1.00	1.00
Norway	1.00	0.81	1.00	0.99
New Zealand	1.00	0.94	1.00	0.99
S. Africa	0.52	0.71	0.50	0.88

Panel (b): $E_t\Delta s_{t+1} = \beta_0 + \beta_1 \Delta c_t + \beta_2 \Delta s_t$

	USD	NEER	GBP	JPY
Australia	1.00	1.00	1.00	0.97
Brazil	0.99	0.94	1.00	1.00
Canada	0.68	0.87	1.00	1.00
Chile	0.95	1.00	1.00	1.00
Indonesia	0.64		0.42	0.54
Korea	0.99	1.00	0.96	0.99
Mexico	0.95	0.99	1.00	1.00
Norway	0.99	0.98	1.00	1.00
New Zealand	0.90	1.00	1.00	1.00
S. Africa	0.78	0.96	0.84	0.57

Table 6.4 Granger-Causality, Andrew's QLR test, ending in 2012Q4*

Panel (a): $E_t\Delta cp_{t+1} = \beta_0 + \beta_1 \Delta s_t + \beta_2 \Delta cp_t$

	USD	NEER	GBP	JPY
Australia	**0.01*** (2008Q2)**	0.83	0.11	0.25
Brazil	0.41	0.99	0.76	0.86
Canada	1.00	1.00	1.00	1.00
Chile	1.00	0.97	0.92	1.00
Indonesia	0.99		1.00	1.00
Korea	1.00	1.00	1.00	1.00
Mexico	1.00	0.91	1.00	1.00
Norway	0.97	0.94	1.00	0.98
New Zealand	0.83	0.96	0.96	1.00
S. Africa	0.97	0.99	0.94	0.97

Panel (b): $E_t\Delta s_{t+1} = \beta_0 + \beta_1 \Delta c_t + \beta_2 \Delta s_t$

	USD	NEER	GBP	JPY
Australia	1.00	1.00	0.99	1.00
Brazil	1.00	0.94	0.99	1.00
Canada	0.68	0.87	1.00	1.00
Chile	0.81	0.99	0.96	1.00
Indonesia	0.20		0.13	0.75
Korea	1.00	1.00	0.99	1.00
Mexico	1.00	0.99	1.00	1.00
Norway	1.00	0.99	1.00	1.00
New Zealand	1.00	0.95	0.97	1.00
S. Africa	0.99	1.00	0.97	1.00

*The p-values are reported for Andrew's (1993) QLR test of parameter stability. Asterisks denote rejection at the 1%(***), 5%(**), and 10%(*) significance levels, respectively, indicating evidence of instability with the estimated break-dates in the parenthesis.

6.4.2.2 *Out of Sample Forecasts*

After in-sample testing, now we turn to check whether in-sample Granger causality translates into out-of-sample forecasting ability. We employ a rolling forecast scheme based on equation (3) and (4). We estimate parameters in these two equations using the size equal to half the total sample size, then roll the sample forward one quarter, use the parameter estimates to generate out-of-sample forecasts, and repeat the procedure until we exhaust all of the out-of-sample observations. Although structural breaks did not emerge in the Andrew's test, we choose the rolling forecast procedure rather than a recursive one, as it adapts more quickly to the presence of time-varying parameters, and requires no explicit assumption on the nature of the time variation in the data.

In order to gauge the performance of our forecasts we follow CRR's approach and use two benchmark models. First, we estimate equations (3) and (4) and produce forecasts as explained above, then we compare them against the forecasts obtained with the same method from an autoregressive (AR) model of order one (for commodity prices $E_t\Delta cp_{t+1} = \gamma_{0t} + \gamma_{1t}\Delta cp_t$ and for exchange rates $E_t\Delta s_{t+1} = \gamma_{0t} + \gamma_{1t}\Delta s_t$).[50] Second, we estimate a random walk without a drift model as it is the most common benchmark in the exchange-rate literature. For the random walk benchmark, we produce forecasts using the equations $E_t\Delta cp_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t$ and $E_t\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp_{t.}$ and compare the results relative to $E_t\Delta cp_{t+1} = 0$ and $E_t\Delta s_{t+1} = 0$, respectively, i.e no change.

Once we generate the forecasts from each model, we calculate mean squared prediction errors (MSPE) as the squared difference between the predicted and actual values. Then we make pairwise comparison between the models' MSPE's and calculate the statistics suggested by Diebold and Mariano (1995) and improved by Clark and West (2007). For example, suppose we calculate two MSPEs based on two models;

[50] The order of benchmark autoregressive model is selected by testing up to 4 lags. The results showed that the Bayesian information criteria (BIC) values didn't vary so much for some countries but one lag has the lowest BIC value for others.

$MSPE_1(t)$ and $MSPE_2(t)$. We then take the difference as $d(t) = MSPE_2(t) - MSPE_1(t)$. A significant negative value implies that model two has smaller squared errors than the model one so its predictive ability is better than the model one.

The null of equal predictive accuracy is: H_0: $E[d(t)]=0$

The Diebold-Mariano test statistics: $DM = \frac{\bar{d}}{\sqrt{\hat{\omega}/T}}$ where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d(t)$

$\hat{\omega}$ is a consistent estimate of the long-run variance of $T^{1/2}\bar{d}$ that takes into account of the serial correlation introduced by overlapping observations. The null hypothesis states that there is no difference in forecasting accuracy between the candidate model and the benchmark model. The DM statistics is asymptotically normally distributed; DM ~ N (0,1). According to DM statistics the null of equal predictive accuracy can be rejected at the 5% level if |DM|>1.96. However, Clark and West (2006, 2007) show that the asymptotic DM test statistics is undersized because of the limiting distribution of the DM under the null hypothesis that is not standard normal when nested models are compared. This means that it may not detect statistical significance (i.e., that the structural model outperforms the random walk model) even when it exists. Clark and West

(2006) propose a new asymptotic test for nested models, the CW, that builds on the asymptotic DM test. The CW test statistic takes into account the fact that the two models compared are nested by assuming that, under the null hypothesis, the exchange rate follows a random walk. Clark and West (2006) suggest one should reject the null hypothesis of equal forecasting power when the CW ≥1.282 at 10 percent and CW ≥ 1.645 at 5 percent.

After we produce the one-quarter forward forecasts and calculate the DM statistics as described above for each model pair, we end up with four sets of numbers for each country as show in Table 6.5. Panel A reports the performance of equations (3) and (4) with respective to AR model. Similarly, Panel B shows the forecast performance statistics between the random walk comparable version of our equations and random walk of no change in forecast. The negative values indicate that the model forecasts are better than the AR or random walk model. The first equation, exchange rate's forecasting commodity prices, yields more negative values then the second equation, commodity prices' forecasting exchange rates. Just looking at the signs of the results show the forecasting ability of first (equation (3)) is better than that of the second (equation (4)) relative to AR or random walk model.

A further review of the numbers reported in Table 6.5 reveals that the forecast performance statistics are quite small. Moreover, they are very close in magnitude especially in Panel A which may suggest that these two specifications are not too different. Finally, none of the statistics we obtain are higher than the critical values proposed by DM or CW; i.e. 1.96 or 1.65 at 5%. The calculated p-values are also too high for rejection of the null. Therefore, we fail to reject the null hypothesis that random walk is better over the proposed structural models. Contrary to our results CRR found significant evidence of out-of-sample ability for pretty much all countries in their sample especially with the AR benchmark model.

Table 6.5 DM-Statistics for Out-of-Sample Forecasting Ability, ending 20012Q4*

Panel A: Autoregressive Benchmark									
Australia	**Brazil**	**Canada**	**Chile**	**Indonesia**	**Korea**	**Mexico**	**Norway**	**New Zealand**	**S. Africa**
A. MSFE differences: model: $E_t\Delta cp_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp_t + \beta_{2t}\Delta s_t$ vs. AR(1): $E_t\Delta cp_{t+1} = \gamma_{0t} + \gamma_{1t}\Delta cp_t$									
-0.03	-0.02	0.01	0.02	-0.02	-0.02	0.03	-0.03	-0.03	-0.01
B. MSFE differences: model: $E_t\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t + \beta_{2t}\Delta cp_t$ vs. AR(1): $E_t\Delta s_{t+1} = \gamma_{0t} + \gamma_{1t}\Delta s_t$									
0.03	0.02	-0.02	0.02	0.05	0.00	0.03	-0.03	0.03	0.04
Panel B: Random Walk Benchmark									
Australia	**Brazil**	**Canada**	**Chile**	**Indonesia**	**Korea**	**Mexico**	**Norway**	**New Zealand**	**S. Africa**
A. MSFE differences: model: $E_t\Delta cp_{t+1} = \beta_{0t} + \beta_{1t}\Delta s_t$ vs. random walk: $E_t\Delta cp_{t+1} = 0$									
-0.10	-0.08	0.01	0.02	-0.05	-0.11	-0.01	-0.09	-0.07	-0.05
B. MSFE differences: model: $E_t\Delta s_{t+1} = \beta_{0t} + \beta_{1t}\Delta cp_t$ vs. random walk: $E_t\Delta s_{t+1} = 0$									
0.06	0.07	-0.04	0.03	0.13	0.05	-0.10	0.02	0.05	0.11

6.5 Conclusions

In this chapter we examined the dynamics between exchange rates and commodity prices for 10 commodity exporting countries with different commodity exporting profile, history of exchange rate policies and level of economic development. We applied some of the methodologies that CRR (2010) developed. Similar to their work, we focused on the structural link between exchange rates and commodity prices through the terms-of-trade and income effects and tested the resulting dynamic relationship between commodity price movements and exchange rate fluctuations. Our results could not show as robust relations as theirs did. We found stronger evidence of in-sample causality from exchange rates to commodity prices for most of the countries in our sample.

One interesting result was the consistent significant causality from exchange rates to commodities for Korea across all different denominated currencies, although the initial plot of Korean Won/USD currency and semiconductor prices did not seem to interact. Our findings did not uncover as many structural breaks as CRR did in the commodity price or exchange rate series. Furthermore, our out-of sample forecasts do not outperform the random walk forecasts.

Our results differed from that of the CRR. Perhaps, some of the underlying assumptions may not hold. For example, the link between the exchange rates and commodity prices are not as robust as claimed to be. Or maybe the relationship works well for some currencies during certain sample periods but not for other currencies or sample periods. Another possibility is that commodity prices may not be fully exogenous to the exchange rates and they are not independently determined. Additionally, commodity producing countries may have bigger market power than assumed. Especially in the recent commodity boom which is demand driven, along with tight balances, a supply disruption in any commodity producing country creates great pressure on the world commodity prices. Furthermore, during a commodity boom which lasted as long as the recent one, many farmers/exporters are well financed. So when domestic currencies appreciate farmers/exporters receive less for their commodity which discourages them from selling creating temporary shortages which in turn pushes the prices higher. Finally, some of the countries may not have adopted flexible exchange rate regime fully and may intervene to change the course of the currency time to time.

6.A Appendix

Table 6.A.6 Data Coverage and Trade Weights

Country	Commodity	Weight	Country	Commodity	Weight
Australia: 1983Q1-20122012Q4			**Indonesia: 1998Q1-2012Q4**		
	Aluminum	16%		Coal	18%
	Beef	8%		Copper	8%
	Coal	26%		Crude oil	23%
	Copper	3%		Nat gas	26%
	Cotton	3%		Palm oil	15%
	Gold	10%		Rubber	10%
	Iron ore	10%			
	LNG	5%	**Korea: 1998Q1-2012Q4**		
	Nickel	3%		Semi-conductor	100%
	Sugar	3%			
	Wheat	9%	**Mexico: 1995Q1-2012Q4**		
	Wool	4%		Crude oil	100%
Brazil: 1995Q1-2012Q4					
	Chicken meat	8%			
	Coffee Arabica	10%	**New Zealand: 1995Q1-2012Q4**		
	Iron ore	27%		Aluminum	10%
	Orange juice	5%		Beef	11%
	Soybean oil	15%		Butter	8%
	Soybeans	16%		Cheese	10%
	Sugar	13%		Fish	8%
	Wood Pulp	7%		Lamb	15%
Canada: 1974Q1-2012Q4				Timber+logs	10%
	Aluminum	5%		Whole MP	19%
	Beef	9%		Wool	9%
	Copper	2%			
	Crude oil	23%	**Norway: 1993Q1-2012Q4**		
	Gold	3%		Crude oil	67%
	Lumber	15%		Fish	7%
	Nat gas	12%		Nat gas	26%
	Nickel	3%			
	Wheat	4%	**South Africa: 1998Q1-2012Q4**		
	Wood Pulp	22%		Coal	22%
	Zinc	3%		Gold	48%
Chile: 1989Q1-2012Q2				Platinum	30%
	Copper	100%			

Table 6.A.7 Summary Statistics for the Full Sample

	Levels				First differenced logs			
	Mean	Standard deviation	Skewness	Kurtosis	Mean	Standard deviation	Skewness	Kurtosis
Australia								
USD exchange rate	0.76	0.13	0.35	3.13	0.00	0.06	-0.51	3.84
Commodity Index	133.65	66.91	1.58	4.20	0.01	0.07	-2.31	19.99
Nominal Effective Exchange Rate	92.70	12.70	0.48	3.05	0.00	0.04	-1.53	8.33
Brazil								
USD exchange rate	0.58	0.22	0.92	2.79	-0.01	0.09	-1.14	5.78
Commodity Index	152.77	84.02	1.01	2.53	0.01	0.10	-2.24	17.23
Nominal Effective Exchange Rate	134.12	41.90	0.82	2.53	-0.01	0.08	-1.43	9.00
Canada								
USD exchange rate	0.82	0.11	0.23	2.15	0.00	0.03	-0.07	5.35
Commodity Index	191.64	100.60	1.54	4.61	0.01	0.09	-0.07	6.81
Nominal Effective Exchange Rate	94.29	11.71	0.70	2.27	0.00	0.03	-0.30	5.27
Chile								
USD exchange rate	0.00	0.00	0.36	2.54	-0.01	0.04	0.63	3.29
Commodity Index	2150.34	489.72	0.22	1.75	0.00	0.09	0.14	3.15
Nominal Effective Exchange Rate	101.92	8.73	0.08	2.65	0.00	0.04	-0.29	3.29
Indonesia								
USD exchange rate	0.11	0.01	0.11	6.48	0.00	0.12	-0.98	10.59
Commodity Index	224.04	123.98	0.60	1.96	0.02	0.10	-2.02	10.50
Korea								
USD exchange rate	0.09	0.01	0.51	2.52	0.00	0.05	-0.21	3.63
Commodity Index	160.22	143.89	1.29	3.36	-0.05	0.12	0.12	5.28
Nominal Effective Exchange Rate	91.16	10.24	0.03	2.19	0.00	0.05	-1.06	9.38
Mexico								
USD exchange rate	0.10	0.02	1.00	3.94	-0.01	0.06	-1.64	6.82
Commodity Index	48.64	32.25	0.72	2.19	0.03	0.15	-1.91	10.80
Nominal Effective Exchange Rate	108.01	22.82	0.66	2.96	-0.01	0.04	-1.61	7.02
New Zealand								
USD exchange rate	0.64	0.12	-0.37	2.16	0.00	0.06	-0.21	3.00
Commodity Index	121.50	38.19	0.79	2.25	0.01	0.06	-1.52	10.52
Nominal Effective Exchange Rate	89.58	8.62	-0.63	2.29	0.00	0.04	-0.42	2.71
Norway								
USD exchange rate	0.15	0.02	-0.04	2.53	0.00	0.05	-0.17	4.43
Commodity Index	228.47	151.27	0.80	2.29	0.02	0.11	-1.38	7.32
Nominal Effective Exchange Rate	97.78	4.48	0.03	2.11	0.00	0.02	-1.64	10.37
South Africa								
USD exchange rate	0.16	0.05	1.14	3.48	-0.01	0.08	-0.17	4.91
Commodity Index	184.05	111.54	0.96	2.45	0.02	0.07	-1.73	13.79
Nominal Effective Exchange Rate	103.06	30.46	0.87	2.70	-0.01	0.06	-0.54	3.93

Table 6.A.8 Unit Root Tests, sample ends in 2012Q4

	Log levels						First differenced logs				
	ADF			PP			ADF			PP	
	t-statistics	p-value		t-statistics	p-value		t-statistics	p-value		t-statistics	p-value
Australia											
Index	-0.88	0.79		-0.52	0.88		-6.97	0.00		-6.55	0.00
usd	-1.46	0.55		-1.55	0.51		-10.26	0.00		-10.24	0.00
neer	-1.20	0.67		-1.41	0.58		-9.36	0.00		-9.30	0.00
gbp	-1.66	0.45		-1.61	0.48		-11.53	0.00		-11.53	0.00
jpy	-2.79	0.06	**	-2.80	0.06	**	-10.62	0.00		-10.62	0.00
Brazil											
Index	-0.92	0.77		-0.66	0.85		-5.96	0.00		-5.94	0.00
usd	-2.02	0.28		-2.02	0.28		-6.98	0.00		-6.90	0.00
neer	-2.09	0.25		-2.09	0.25		-7.03	0.00		-6.94	0.00
gbp	-1.96	0.31		-1.95	0.31		-7.33	0.00		-7.29	0.00
jpy	-1.49	0.53		-1.51	0.52		-6.92	0.00		-7.23	0.00
Canada											
Index	-1.14	0.70		-1.00	0.75		-9.74	0.00		-8.65	0.00
usd	-1.54	0.51		-1.63	0.46		-10.63	0.00		-10.65	0.00
neer	-1.72	0.42		-1.44	0.56		-8.64	0.00		-8.71	0.00
gbp	-2.60	0.10		-2.32	0.17		-10.67	0.00		-10.68	0.00
jpy	-1.90	0.33		-1.90	0.33		-11.25	0.00		-11.24	0.00
Chile											
Index	-1.95	0.31		-2.15	0.23		-5.81	0.00		-5.79	0.00
usd	-2.30	0.18		-2.26	0.19		-6.62	0.00		-6.60	0.00
neer	-2.12	0.24		-2.10	0.25		-6.99	0.00		-6.75	0.00
gbp	-1.59	0.48		-2.15	0.23		-5.96	0.00		-5.97	0.00
jpy	-1.87	0.34		-1.93	0.32		-7.35	0.00		-8.44	0.00
Indonesia											
Index	-0.79	0.81		-0.60	0.86		-5.67	0.00		-4.12	0.00
usd	-4.70	0.00	***	-4.81	0.00	***	-5.10	0.00		-11.56	0.00
gbp	-2.95	0.05	*	-3.54	0.01	**	-5.93	0.00		-11.86	0.00
jpy	-2.78	0.07		-2.70	0.08		-12.88	0.00		-12.51	0.00
Korea											
Index	-2.35	0.16		-2.24	0.19		-6.38	0.00		-6.38	0.00
usd	-2.24	0.20		-2.35	0.16		-7.29	0.00		-7.29	0.00
neer	-2.57	0.11		-2.62	0.09	*	-6.39	0.00		-6.40	0.00
gbp	-3.52	0.01	**	-3.44	0.01	**	-9.49	0.00		-9.61	0.00
jpy	-1.40	0.58		-1.57	0.49		-7.29	0.00		-7.32	0.00
Norway											
Index	-0.76	0.82		-0.20	0.93		-6.19	0.00		-5.52	0.00
usd	-1.40	0.58		-1.50	0.53		-8.15	0.00		-8.15	0.00
neer	-1.93	0.32		-2.11	0.24		-7.86	0.00		-7.83	0.00
gbp	-0.62	0.86		-0.79	0.82		-11.09	0.00		-10.97	0.00
jpy	-2.58	0.10		-2.63	0.09		-9.13	0.00		-9.13	0.00
Mexico											
Index	-0.77	0.82		-0.80	0.81		-6.85	0.00		-6.02	0.00
usd	-1.96	0.31		-1.92	0.32		-8.51	0.00		-8.66	0.00
neer	-2.25	0.19		-2.24	0.20		-7.79	0.00		-7.78	0.00
gbp	-1.82	0.37		-1.79	0.38		-8.69	0.00		-8.70	0.00
jpy	-0.98	0.76		-0.77	0.82		-8.72	0.00		-9.30	0.00
New Zealand											
Index	-1.08	0.72		-0.71	0.84		-4.80	0.00		-4.46	0.00
usd	-0.89	0.78		-1.16	0.69		-6.74	0.00		-6.74	0.00
neer	-1.94	0.31		-1.73	0.41		-6.19	0.00		-6.20	0.00
gbp	-0.66	0.85		-0.68	0.84		-8.71	0.00		-8.70	0.00
jpy	-2.15	0.23		-2.28	0.18		-7.80	0.00		-7.80	0.00
South Africa											
Index	-0.07	0.95		0.19	0.97		-6.28	0.00		-6.00	0.00
usd	-1.96	0.30		-2.00	0.29		-7.69	0.00		-7.71	0.00
neer	-1.73	0.41		-1.74	0.41		-7.19	0.00		-7.19	0.00
gbp	-2.28	0.18		-2.27	0.18		-7.89	0.00		-7.89	0.00
jpy	-1.50	0.53		-1.49	0.53		-7.89	0.00		-8.83	0.00

7 SUMMARY AND CONCLUSIONS

The recent commodity boom started in the early 2000's and lasted more than a decade during which the prices of all commodities rose, then crashed in 2008 after the onset of financial crisis and rebounded in 2009 before reaching to or above the pre-crisis levels in 2011. The large fluctuations in commodity prices have great impacts on the demand of individual consumers as well as on the economies of commodity producing and consuming countries. There have been a number of changes in the global market structure since the last commodity price boom during the 1970s which caused a structural shift in supply, demand and inventory dynamics of commodities markets. Hence, it is important to revisit and have a comprehensive analysis with the recent data to observe the impact of high and volatile commodity prices which is the focus of this thesis.

Chapter 2 examined the implications of commodity inventory levels on the futures price curves. This chapter adopted a comprehensive self-exciting threshold approach which included both inventories and interest rates along with spot and futures prices and found that there was a long-run cointegrating relationship between base metal spot prices, futures prices, inventories, and interest rates. When the system is away from equilibrium in response to a temporary shock, it adjusts back towards the steady state over time. The dynamics of this adjustment, however, vary across metals and depend on the initial state of the market.

Second, this study presented some evidence that a temporary scarcity shock, modeled as a spot price shock which changes the slope of the futures curve, does cause a reaction in commodity markets somewhat consistent with a theoretical model. In particular, inventories are drawn down and spot prices gradually fall back towards their initial level. However, the initial state of the market is an important conditioning factor for the subsequent adjustment. In a contangoed market with abundant inventories, spot price shocks produce a much more gradual inventory response, while the effect on price levels can be permanent. In contrast, in a backwardated market the inventory drawdown occurs much faster and the rise in both spot and futures prices are temporary.

Third, the results showed that the adjustment of prices and inventories back towards equilibrium was much more gradual in a contangoed market. But prices adjust much faster in a backwardated market where physical market is tight, even a small supply disruption can have large price effects, but these typically prove to be short-lived. These findings may have implications for consumers, producers and inventory holders of commodities. In particular, results suggest that market participants should prepare their response to market signals during periods of unusual conditions on the state of the inventory cycle, which is typically reflected in the slope of the futures curve.

Chapter 3 investigated whether the demand elasticity of gasoline price and income in the U.S. has changed in recent years compared to earlier periods which experienced similar high gasoline prices. The results are comparable to those of recent studies and confirmed the structural change in the U.S. market where consumers became insensitive to gasoline price changes. The estimated price elasticities in 1975-1980 are high however; they declined and became more inelastic in the following two subsamples. Similarly, the full sample results showed more inelastic values. The estimation of elasticities in a 61-month window by rolling one month from 1975 to 2013 also confirmed the varying and declining price elasticities over time. The VAR elasticity estimates of 1975-1980 period showed significant and higher elasticity than that of estimates of simpler models. The full sample estimation with VAR model revealed a lower price elasticity of demand. The income elasticity results were more consistent, although they too diminished over the last decade. The income elasticity too became inelastic in the recent decade and in the most recent sub-sample was estimated to be around -0.51 which may reflect the persistent high prices combined with fuel efficiency efforts and recovery in income level after a deep recession which produced a negative income elasticity implying gasoline demand declines as income rises.

There may be a number of potential explanations for the change in elasticities over time. First, the U.S. consumers have grown more dependent on automobiles for daily transportation than during the 1970's and 1980's and as a result, are less able to reduce vehicle miles traveled in response to higher prices. Second, with the record gasoline prices, drivers may change their driving behaviors in the short-run to save fuel and may switch to more fuel efficient vehicles in the medium to long term. Third, with the increasing income and wealth especially in the past decade, the share of gasoline consumption in total income has declined over the years, reducing the impact of an increase in gasoline prices on budget and making the consumers less sensitive to price increases. Finally, the overall improvement in vehicle fleet average fuel economy since the late 1970's and early 1980's may have also contributed to a decrease in the elasticity of price on gasoline demand. Given the lower price elasticity of demand compared to the elasticity in previous decades, smaller reductions in gasoline consumption will occur for any given gasoline tax increase. As a result, instead of imposing gasoline tax, investing in research and technologies to improve vehicle fuel economy, imposing higher fuel efficiency standards and improving public transportation system would be more viable solutions to reducing the gasoline consumption and subsequently reducing the carbon dioxide emissions produced by the transport sector.

Chapter 4 examined the dynamic effect of demand and supply shocks on gasoline prices in two very different markets: the U.S. and U.K. The results showed that all of the factors; supply, aggregate and gasoline demand played a role determining the price of gasoline in the US but the impact of a positive aggregate demand shock was larger than that of the others. For the U.K., the impact of aggregate and local gasoline demand were important to determine the gasoline price but supply did have a limited effect.

Chapter 5 examined the procyclicality of fiscal policies in 28 developing crude oil-producing countries. The results were not uniform across income groups, and total expenditure was highly procyclical in the full sample, in the low and middle-income groups. The low-income group constitutes a large share of the full sample, therefore weighing heavily in the results of the full sample. But it is countercyclical in the high-income countries-- perhaps due to their greater accumulation of financial assets, which eases their financial constraints when funds are needed. It was also important to look at the aggregate fiscal variables, as well as at their subcomponents separately, since the subcomponents may move in offsetting ways. In fact, the estimation results showed that, although expenditure is countercyclical for the high-income group, its components move in different directions: consumption is procyclical, while capital expenditure is countercyclical.

The results confirm that political and institutional factors, as well as financing constraints, play a role in the cyclicality of fiscal policies in the OPCs. Most of the variables on the quality of institutions and the political structure appear to be significant for the low- income group. Two of the variables are significant for the middle-income countries: the composite institution index and checks and balances. None of the institutional variables turns out to be significant for the high-income countries. Domestic financing constraints seem to matter for the low-income group. But fiscal policy is affected more by the external financing constraint in the middle- and high-income groups, as they may be more integrated into the global financial system than the low-income countries.

Chapter 6 examined the dynamic relationship between exchange rates and commodity prices to determine whether commodity prices Granger cause exchange rate or exchange rates Granger cause commodity prices for a group of advanced and developing commodity-exporting economies.

This study found stronger evidence of in-sample causality from exchange rates to commodity prices for most of the countries in the sample. One of the key findings was the consistent significant causality from exchange rates to commodities for Korea across all different denominated currencies. This study found a limited number of structural breaks compared to the earlier studies. Furthermore, the out-of sample forecasts do not outperform the random walk forecasts. These results may be related to the underlying assumption of the model tested. First, the link between the exchange rates and commodity prices may not be as robust as claimed to be. Another possibility is that commodity prices may not be fully exogenous to the exchange rates and they are not independently determined. Additionally, each country which produces the commodity has bigger market power than assumed. Especially in the recent commodity boom which was mainly demand driven, along with tight balances, a supply disruption in any commodity producing country resulted in pushing the prices higher indicating the power of the each producing country in the market.

There are some areas where further empirical research can be pursued. The structural VAR model for gasoline can be implemented for diesel fuel markets in the U.S. and the U.K. as the usage of diesel is higher in the U.K., consumer may be more responsive to price fluctuations of diesel. Furthermore, a joint VAR model of crude oil-gasoline and crude oil-diesel would be tested for the U.K. to measure the degree of linkage of the domestic fuel markets to the global energy markets.

None of the institutional variables turned out to be significant for high-income oil producing countries, yet they manage to run countercyclical fiscal policies. It would be interesting to examine whether institutional quality does not matter when countries are able to accumulate funds? Or they can accumulate funds because of different characteristics of their economy or political structure. In addition they can be jointly tested with the advanced oil producing countries such as Norway.

Another extension of research on the interaction between exchange rates and commodity prices would be to explore the determinants of exchange rates for countries that heavily dependent on the commodity imports. Similar to commodity exporting countries, they are also considerably vulnerable to fluctuations in commodity prices.

Finally, the present-value approach can be applied to another asset class and the linkage between equity, commodity and the exchange rate markets can be explored together. One can link the financial linkage across asset markets, where equity or bond markets in these countries may offer useful information for commodity market behavior.

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