OIL AND ELECTRICITY IN SMALL ISLAND DEVELOPING STATES

Unmasking the Risks and Opportunities

A thesis submitted for the degree
of Doctor of Philosophy of
The Australian National University.

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May 1, 2017

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like to a double cherry, seeming parted, but yet an union in partition, two lovely berries molded on one stem".

You have all made this journey a wholesome one; one I will never forget.

Abstract

In the first study of this thesis, I analyse the effects of oil price and global demand shocks on Small Island Developing States (SIDS). To do this, I employ a global vector autoregression (GVAR) framework for 26 SIDS using annual data over the period 1980 to 2015. A key innovation associated with this research is the use of remittance weights to capture the close financial linkages between SIDS and advanced economies such as the United States. I find negligible negative effects on economic growth in SIDS on average from a negative oil price shock, though each country reacts differently. In terms of a negative demand shock to US GDP, SIDS appear vulnerable with a marginal positive effect observed for the Pacific while small negative effects emerge for the Caribbean; Atlantic, Indian Ocean, Mediterranean and South China Sea (AIMS); and SIDS as a whole.

Since oil prices influence electricity prices, the second study looks at how electricity prices influence consumer behaviour in a particular country, using Jamaica as an example. To analyse how consumers respond to prices, I use the autoregressive distributive lag bounds testing approach to cointegration to obtain long-run elasticity estimates covering the period 1970 to 2014. The analysis focuses on aggregate electricity demand and three categories of consumers: residential, commercial, and industrial. The findings suggest that residential and industrial consumers are most responsive to price changes with long-run price elasticities of demand of -0.82 and -0.25, respectively. Price-based approaches are likely to be more successful in slowing electricity demand growth in these sectors.

We can use demand elasticities to analyse the behaviour of alternative electricity pricing schemes under different scenarios. Using Jamaica as a case study in the third study, my analysis confirms that in contrast to a price cap plan that uses Ramsey quantity weights, prices under a revenue cap increase as demand in a particular market becomes more elastic relative to the others. In this specific setting, a revenue cap does encourage energy conservation through reductions

in electricity use, but this is less likely when marginal cost is very large in the more elastic market relative to other markets. In contrast to a price cap plan, these overall results show that revenue cap schemes are welfare-reducing.

To analyse the efficiency of electricity sectors in SIDS, I apply a two-stage data envelopment analysis (DEA) method to a sample of 32 electricity distribution utilities operating in the Caribbean and Pacific regions. Using 2010 data for three inputs and one output, the overall results show that six utilities are on the efficiency frontier and utilities in the Caribbean are significantly more efficient than those in the Pacific region. I also do not find any statistically significant evidence that the efficiency of utilities is positively related to population density and inversely related to criminality. Notwithstanding the paucity of publicly available data, these results advance the idea that utility benchmarking is possible and can be used to set feasible efficiency targets for electricity networks in SIDS.

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List of acronyms

AIMS Atlantic, Indian Ocean, Mediterranean, and South China Sea

ARDL Autoregressive Distributive Lag

CARILEC Caribbean Electric Utility Services Corporation

CIF Cost, Insurance and Freight

DEA Data Envelopment Analysis

DMUs Decision Making Units

EBRD European Bank for Reconstruction and Development

ECM Error Correction Model

ESSJ Economic and Social Survey of Jamaica

EWI Energy World International

GCC Gulf Cooperation Council

GIRF Generalized Impulse Response Function

GVAR Global Vector Autoregressive

GWh Gigawatt hour

IMF International Monetary Fund

IPPs Independent Power Producers

ISIC International Standard Industrial Classification

ISO The International Organization for Standardization

JAMALCO Jamaica Aluminium Company

JPS Jamaica Public Service Company

kWh Kilowatt hour

LNG Liquefied natural gas

MW Megawatt

MENA Middle East and North Africa

OIRF Orthogonalised Impulse Response Function

OUR Office of Utilities Regulation

PICs Pacific Island Countries

PPAs Power Purchase Agreements

PPP Purchasing Power Parity

ROR Rate of Return Regulation

SFA Stochastic Frontier Analysis

SIDS Small Island Developing States

STATIN Statistical Institute of Jamaica

T&TEC Trinidad and Tobago Electricity Commission

UN United Nations

VAR Vector Autoregression

VARX Vector Autoregression models with exogenous variables

WASP Wien Automatic System Planning Package

WDI World Development Indicators

WEO World Economic Outlook

WWF Wigton Wind Farm

List of published works

Publication I

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Publication II

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Declaration

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Chapter 1

Main introduction

1.1 Background to study

Since the oil crisis of the 1970s, many researchers have sought to examine its effects on economic activity. As early as 1983, Hamilton (1983) showed that oil prices had a significant negative effect on economic growth. This finding was also supported by the empirical work of Mork et al. (1994) and Papapetrou (2001). Given the importance of this issue, much of the research was undertaken in developed and large developing economies. Presumably because of limited data availability and their smaller economies, many researchers have neglected this important relationship in the context of Small Island Developing States (SIDS). This is an issue worth investigating in SIDS since oil consumption accounts for up to 35% of GDP compared to only 3% in developed economies.

Further to this, oil remains by far the largest component of the electricity generation mix in many SIDS. For over 80% of the countries examined in this thesis, oil accounts for over 80% of the energy supply mix. Jamaica, for example, generates 95% of its electricity from oil-based fuels. This level of dependency on oil-based fuel imports is likely to have major impacts on domestic electricity prices which usually influence the price of all other goods and services in small states. Some countries may experience up to 100% pass-through of fuel cost to electricity prices. For example, the fuel adjustment clause for Jamaica's regulatory electricity pricing scheme allows for full cost pass-through of uncontrollable costs such as fuel after heat rate and distribution losses adjustment, irrespective of the price of fuel (see (Office of Utilities Regulation, 2004)). This creates a lot of volatility and uncertainty for consumers and producers in these economies. As a result, evaluating how consumers respond to electricity price changes is also an important issue that needs investigating.

The extent to which consumers are affected by electricity price changes can also depend on the nature of the regulatory structure in place. While many SIDS continue to operate state-owned monopoly electricity entities, some countries have undertaken major reforms of the sector. Large-scale reform measures in electricity sectors across developed countries date back to as early as the 1980s. However, the introduction of substantial reforms in the electricity sectors of SIDS has been a much more recent phenomenon. It was not until the early 1990s and 2000s that such reforms were initiated in countries such as Jamaica and Trinidad and Tobago. These reform measures were largely aimed at introducing private sector participation and promoting competition through economic regulation. As a result, economic regulation spurred the introduction of incentive regulation schemes such as price cap regulation and revenue cap regulation. However, these schemes can have varying effects on consumers and producers and is also examined in more detail in this thesis.

The initial motivation behind structural reform measures implemented in SIDS largely resulted from the need to improve financial performance and operational efficiency of government-owned enterprises. However, reforming the utility sector cannot by itself improve the efficiency of electricity sectors. To be able to improve the performance of electricity sectors, we need to know how they are performing relative to electricity companies operating in similar countries. There is a paucity of research on international benchmarking especially as it applies to SIDS and in this thesis I also aim to fill this gap by highlighting how reliable efficiency estimates can be obtained while considering differences in operating environments.

The map in Figure 1.1 shows the distribution of SIDS across the three regions: the Caribbean; Pacific; and Africa, Indian Ocean, Mediterranean and South China Sea (AIMS). The majority of countries are located in the Caribbean and the Pacific. No collective definition of SIDS exists, but they are a diversified group of countries that share common features and distinctive vulnerabilities. Vulnerability arises from their small size and inability to exploit economies of scale, remoteness leading to high transport costs, dependence on a narrow range of export products, and dependence on strategic imports such as fossil fuels (Briguglio, 1995).

Figure 1.1: **Small Island Developing States. Excluding Bahrain, the UN Department of Economic and Social Affairs (2015) identifies 51 states and territories as SIDS. Source: Osiris (2016).**

1.2 Statement of problem

A well-designed energy policy is essential in minimising the potential impact of oil price movements on SIDS and development electricity sectors that are efficient and can deliver low and stable prices. This is especially important in developing economies that are competitive and have a strong industrial base.

However, research on how oil prices affect SIDS and the impact of electricity prices on consumer behaviour remains an understudied area. Also, knowledge of how various pricing schemes affect society and the relative efficiency of electricity sectors for SIDS remains an area for which research remains absent.

If these important issues continue to be neglected by researchers, then we have no way of knowing how resilient these economies are to adverse price shocks. Furthermore, by continuing to neglect research in this area, policymakers cannot directly influence consumer behaviour which also creates uncertainty in capacity investment needs. Also, without adequate knowledge of how different electricity pricing schemes perform and the relative efficiency of utilities, consumers could be forced to pay higher prices under a particular scheme.

In light of these potential problems, I use a variety of methods to investigate several energy-related issues and broaden our understanding of electricity markets in SIDS. The specific questions that are addressed in this thesis are outlined below:

1. How do oil price and global demand shocks impact growth in Small Island Developing States (SIDS)?

2. Is consumer demand for electricity highly responsive to electricity price movements in the long run in SIDS?

3. What are the efficiency and welfare implications of a revenue cap regime versus a price cap scheme?

4. Can useful and comparable efficiency scores be derived for electricity distribution networks that are governed by incentive-based regulation plans?

1.3 Aim and research objectives

The aim in this thesis is to examine key issues related to electricity networks in SIDS, while the specific objectives are:

1. To determine if SIDS are negatively impacted by oil price movements over time.
2. To examine the degree to which consumers are responsive to electricity price changes.
3. To investigate the extent to which price cap schemes differ from revenue cap schemes in terms of price setting, energy conservation, and societal welfare.
4. To measure the efficiency of Caribbean and Pacific electric utilities and show how regulators can set X-factor efficiency targets for electricity distribution networks that operate under incentive-based regulation plans.

1.4 Rationale and significance

This thesis has a range of benefits towards policy formulation. For example, energy policies can be developed to examine practical ways to address a country's vulnerability to oil prices. Depending on a country's vulnerability status, the aim is to provide ideas as to whether that country should focus on energy conservation, diversification or exploration.

From a regulatory perspective, the thesis aims to improve our understanding of incentive regulation pricing schemes applied to electricity markets in small open economies and how they differ from developed countries. More specifically, it is expected to add to the field of regulatory economics through the examination of various issues that are less problematic in developed countries but are typically unique to small open economies.

Pragmatically, the results are likely to be useful to governments that are considering investments in electricity networks, liberalising their electricity sector, or considering implementing alternative forms of pricing schemes. Additionally, the outcomes of this thesis may have general applicability and might be suitable in reducing the regulatory challenges associated with other key infrastructure services such as telecommunication and water.

1.5 Thesis structure

This thesis comprises of six main Chapters. Chapter 1 covers the introduction, Chapters 2 to 5 describe the empirical work, and Chapter 6 contains the conclusions and directions for future research.

Specifically, Chapter 1 covers the general introduction and provides a background to the thesis along with the questions which I set out to address. The aims and objectives of the thesis are also outlined along with the rationale and significance of the research.

The empirical work begins in Chapter 2 which examines the role of oil price shocks in Small Island Developing States (SIDS). In this chapter, a global VAR model is used to capture the importance of financial linkages among countries.

In Chapter 3, I examine how electricity consumption in Jamaica for different consumer segments are affected by electricity price changes. In this chapter, I use the Bounds testing approach to cointegration to derive price elasticity of demand estimates.

Chapter 4 examines differences between two incentive regulation schemes: price cap and revenue cap. I use a constrained optimization problem to investigate differences in terms of prices, energy conservation, and welfare.

Chapter 5 explores issues related to measuring the efficiency of electricity utilities across the Caribbean and the Pacific. Using data envelopment analysis (DEA), I show how relative efficiency estimates derived from non-monetary variables can be used by regulators to set reliable X-factor efficiency targets for electricity distribution networks that operate under incentive-based regulation plans.

The final Chapter addresses the specific research questions posed in Chapter 1 of this thesis, highlights some limitations, and outlines a number of areas that can be examined in future research. Given the objectives of this thesis, some tentative conclusions are also drawn and the implications of the research findings discussed.

Chapter 2

Effects of oil price and global demand shocks on Small Island Developing States

2.1 Chapter overview

In the first chapter, I employ a global VAR framework for 25 Small Island Developing States (SIDS) using annual data over the period 1980 to 2015. A key innovation associated with this research is the use of remittance weights to capture the close financial linkages between SIDS and advanced economies such as the US. The global VAR analysis is carried out using a linear oil price specification. This approach assumes that oil prices have symmetric effects on the real economy. Therefore, an oil price rise or decline will have an impact on GDP growth that is opposite in effect, but similar in magnitude. I find that oil price shocks do not have a statistically significant negative effect on economic growth in most individual countries and in different regions. Economies that are oil-intensive perform better than their low-intensity counterparts, but economic growth is likely to be greater if economies transition towards a more diversified energy supply mix. In terms of a negative demand shock to US GDP, represented by a decline in US GDP, output in SIDS declines more for those regions that have close economic ties with the US and are within its geographical proximity. From a policy standpoint, these results highlight the importance of gearing policy towards energy diversification and designing outward-oriented economic policies to guard against future oil price shocks.

2.2 Introduction

Most Small Island Developing States (SIDS) rely solely on fossil fuel imports to meet their domestic energy needs. On average, the value of oil imports accounts for approximately 35% of US dollar-denominated GDP in SIDS, almost 12 times the share of GDP in other major economies such as the US, UK, China, and Japan. For this reason, an understanding of output response to oil price movements is necessary for the design of appropriate policies to absorb external shocks. Existing literature generally subscribes to the view that exogenous oil price shocks are likely to have a disproportionately greater impact on economic activity in smaller states than larger ones, as well as economies with limited energy diversification (see, for example, Finn (2000), Ghali and El-Sakka (2004), and Blanchard and Gali (2007)). This view builds on the initial argument of Briguglio (1995) who finds that in addition to their dependence on fossil fuel imports, SIDS tend to be more vulnerable to external shocks because of their small size and inability to exploit economies of scale, remoteness leading to high transport costs, and narrow export base.

SIDS have become more integrated into the world economy since the 1990s and it is therefore important to analyse external shocks to the domestic economy from a global perspective. Specifically, I investigate the impact of oil price shocks and negative demand shocks in the US on economic activity in SIDS and analyse whether differences in effects depend on the level of energy diversification and energy intensity. Considering the dominant role of the US in the world economy, shocks originating from the US can be considered as global demand shocks.

As the standard VAR is built around the closed-economy assumption, it would not be useful in capturing interlinkages of endogenous variables across countries. An additional limitation includes the inability to handle a large set of variables and countries. To overcome some of these limitations, I use the Global VAR (GVAR) framework proposed by Pesaran et al. (2004), which incorporates a large number of variables and countries as well as bilateral remittance linkages among countries, though dimensionality problems is still a concern for these models. The GVAR methodology has been used to analyse the transmission of shocks to various economies and regions throughout the world. For example, Mohaddes et al. (2012) used it to analyse growth spillovers from the Gulf Cooperation Council (GCC) region to Middle East and North Africa (MENA) countries; Dees et al. (2007) looked at how shocks to the US economy affect the Euro area while the impact of oil price shocks have been explored by Cashin et al. (2014), Feldkircher (2014), and Allegret et al. (2015).

I contribute to the body of work on the impact of oil price shocks by extending the emerging literature in a number of directions. First, unlike the majority of researchers who look at developed economies, I focus on SIDS spread over three regional blocs: the Caribbean; Pacific; and Africa, Indian Ocean, Mediterranean and South China Sea (AIMS). With the exception of the net oil-exporter Trinidad and Tobago, these countries have largely service-based economies that are often dependent on tourism. Secondly, in contrast to Jayaraman and Choong (2009) who use a time-series approach to analyse the causal relationship between GDP and the price of oil for four Pacific Island countries (PICS) over 1980–2007, I use a more integrated model that incorporates a larger set of countries, a longer time span, and accounts for bilateral financial linkages among countries. This is the first study to use remittance weights in a GVAR model to capture the close financial linkages between SIDS and the US economy.

The general findings from the GVAR, covering the period 1980 to 2015, reveal that global oil price shocks have very small and largely insignificant effects on individual SIDS and regions suggesting that these economies are more often than not resilient to external shocks of this nature. This is likely due to the offsetting effects of income recycling by oil exporters through tourism spending and remittance outflows from developed economies. Furthermore, oil-intensive SIDS perform better than their low-intensity counterparts, but economic growth is likely to be greater if economies transition towards a more diversified energy supply mix. Additional results reveal that a negative US GDP shock dampens output more in regions that have closer economic ties with the US and are within its geographical proximity.

The paper consists of five main sections. In Section 2.3, I delve briefly into the literature while the empirical methodology used is discussed in Section 2.4. This is followed by a review of the data set which I elaborate on in Section 2.5, with the results of the model reported and discussed in Section 2.6. Finally, I highlight the main conclusions drawn from the study in Section 2.7.

2.3 Oil, energy, and macroeconomic performance

2.3.1 Exogenous oil price shocks and economic fluctuations

The literature on the relationship between oil prices and GDP has evolved considerably since the 1970s. The linear negative relationship between oil prices and aggregate measures of output was first elaborated by Rasche and Tatom (1977). The focus later shifted to the study of asymmetric effects as it became apparent that the linear relationship has changed since the 1980s. This strand of the literature began with Mork (1989) and was later extended by Hamilton (2003). The essence of their arguments is that economic activity responded to oil price increases, but was largely insignificant when oil prices declined. The focus has shifted recently with oil price shocks being distinguished by virtue of their origin. The emerging consensus is that oil prices are not only determined by supply-side factors but also driven by demand conditions (see Lippi and Nobili (2008); Kilian (2009); Hamilton (2009); Peersman and Van Robays (2012)).

Another strand of literature such as that produced by Blanchard and Gali (2007) argues that the effects of oil prices have been declining over time owing to improvements in monetary policy, flexible labour markets, and a smaller share of oil in productive activity. According to Blanchard and Gali (2007), a 10 per cent oil price shock would have reduced GDP in the United States by 0.7 per cent prior to 1984 but this later declined to 0.25 per cent over a two- to three-year period.

A key similarity of the studies discussed above is that they are largely concentrated in developed countries, but despite SIDS being economies that are highly dependent on oil imports, this has not spawned a great deal of research in these countries. In one of the few studies for net oil-importing developing countries, Van Hoa (1992) argues that the effects of price shocks can be more detrimental in limited resource-endowed economies given that the cost of energy represents a much larger proportion of GDP relative to more advanced economies. In another study, Finn (2000) finds that an energy price shock causes GDP to decline much more than suggested by the energy expenditure share of GDP. Other arguments posit that there is likely to be very little effect on economic activity if the cost of energy represents a small proportion of GDP (Ghali & El-Sakka, 2004). The evidence presented by Anciaes (2012) shows that energy as a proportion of GDP ranges from 1.7 per cent to 2.3 per cent in the EU, US, China, and Japan, but this proportion is typically much larger in SIDS and therefore makes it very difficult to justify the presence of negligible impacts. For example, in 2010, the value of oil imports was approximately 6.7 per cent of GDP in Barbados and 12 per cent in Jamaica (International Monetary Fund, 2012). In light of these figures, higher oil intensity is likely to result in larger fluctuations in GDP growth in small open economies, and is an important issue that needs investigating.

However, building on an earlier argument by Krugman (1983), Helbling et al. (2011) and Rasmussen and Roitman (2011) seem to be challenging the view that oil price shocks are likely to have big effects on oil-dependent economies. These researchers highlight the importance of wealth effects and gain sharing in mitigating the negative effects of oil price shocks. For instance, Rasmussen and Roitman (2011) find that oil price shocks appear less costly for oil-importing countries due to the recycling of oil rents by oil exporters. The premise of their argument is that even though higher oil prices increase the import bill and transfer wealth from oil-importing countries to oil exporters, the negative effects on oil importers are partially offset by increases in external receipts. For most SIDS, external receipts are largely in the form of foreign aid, tourism, and remittances. Therefore, the overall impact on economic activity will depend on the degree of oil import dependence and the spending behaviour of oil exporters. Furthermore, a downturn in economic activity in the US can minimize the extent to which small states benefit from these foreign exchange inflows. In general, the above arguments imply that we should let the data reveal the exact response of domestic output in SIDS to an exogenous oil price shock since the over-reliance on theory can produce ambiguous answers.

2.3.2 Stylised facts and exploratory analysis

Before discussing the impact of oil price shocks in more detail, it would be instructive to first provide some evidence on the oil-GDP relationship from a series of preliminary analyses. To do this, I decompose oil prices and real output into their trend and cyclical components to capture short-term fluctuations in the time series and calculate the correlation coefficient in each country between the cyclical components over the period 1980–2013. The long-run trend component of oil prices and GDP is estimated using the Hodrick-Prescott filter with a smoothing parameter of 100 for annual data series. In 70 per cent of the countries[1] shown in Figure 2.1, positive values of the oil price cycle are associated with positive values of the real GDP cycle and vice-versa. It is not surprising that the countries that exhibit the highest levels of correlation are Trinidad and Tobago and Bahrain. Both economies are highly dependent on revenue from oil exports. For the Caribbean countries Haiti and Dominica, the correlation coefficients are negative, suggesting that these countries are likely to be less resilient to oil price shocks. Overall, these early results do indicate that oil price shocks may not necessarily have a negative effect on oil-intensive small open economies.

Next, I compare the trend in oil intensity for all SIDS combined with that of a few major economies over the period 1980 to 2013. This analysis is based

[1] The International Organization for Standardization(ISO) two-letter codes are used as official short names to represent each country: Antigua and Barbuda (AG), Bahamas (BS), Bahrain (BH), Barbados (BB), Belize (BZ), Cabo Verde (CV), Comoros (KM), Dominica (DM), Dominican Republic (DO), Fiji (FJ), Grenada (GD), Guinea-Bissau (GW), Guyana (GY), Haiti (HT), Jamaica (JM), Maldives (MV), Mauritius (MU), Papua New Guinea (PG), Samoa (WS), Sao Tome and Principe (ST), Seychelles (SC), Singapore (SG), Solomon Islands (SB), St. Kitts and Nevis (KN), St. Lucia (LC), St. Vincent and the Grenadines (VC), Suriname (SR), Tonga (TO), Trinidad and Tobago (TT), United States (US), and Vanuatu (VU).

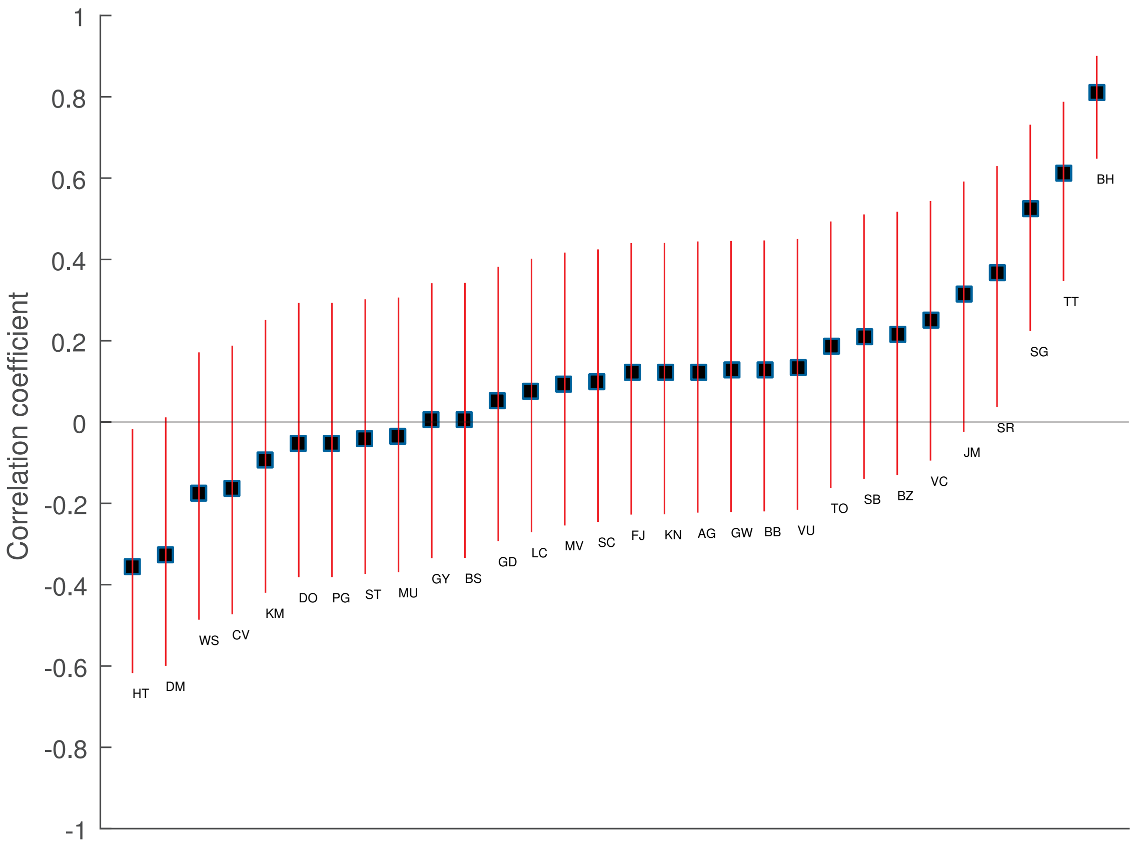

Figure 2.1: **Correlation between oil price and GDP cyclical components in 30 SIDS member countries with 95% confidence interval, 1980–2013. The cyclical components have been estimated using the Hodrick-Prescott filter with a smoothing parameter of 100 for annual data series.**

on the argument of Van Hoa (1992) who argues that oil price shocks have a greater impact on the economy when it is more dependent on oil. The evidence in Figure 2.2 shows that oil consumption represents only about 3% of GDP in the larger economies. However, for SIDS, oil-use intensity has risen sharply since the late 1990s and now accounts for up to 35% of GDP despite the impact of the 2007–2008 financial crisis. In contrast to the evidence in Figure 2.1, this implies that oil price changes should generate large fluctuations in the real output of SIDS.

Though many SIDS have largely service-based economies with tourism alone accounting for more than 20 per cent of GDP according to Denman et al. (2012), there has been no noticeable downward trend in oil intensity for most of the countries. The absence of reduced oil intensity could be due to the limited diversification of the energy mix and my analysis in Figure 2.3 illustrates this point. It plots the percentage change in the share of oil in the energy mix against the percentage change in energy intensity for 42 SIDS. Values above zero indicate an

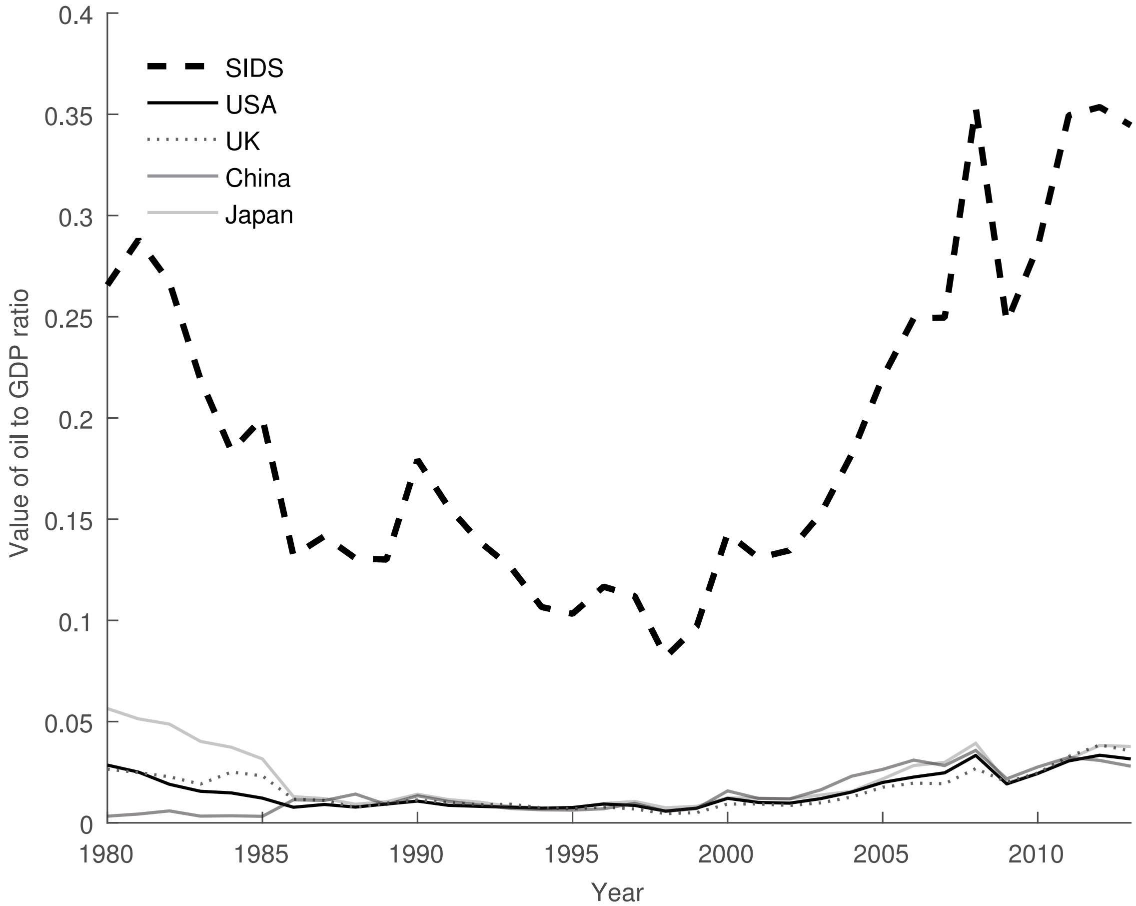

Figure 2.2: **Trend in oil intensity for sample of countries: 1980–2013. The ratios are based on the total value of crude oil consumption relative to total GDP in nominal US dollars for 27 SIDS for which data are available.**

increase in oil share or energy intensity. More than 50% of SIDS continue to use oil as their sole source of energy or have become more reliant on oil compared to 1980. Similarly, most SIDS are now using more energy to produce each unit of GDP compared to 1980.

Figure 2.3 is also divided into four quadrants to show changes in the share of oil in the energy mix and changes in energy intensity for each country. The top-left quadrant captures those countries with increased oil share and reduced energy intensity. Suriname is the only country in the sample that is located in this quadrant. The top-right quadrant shows that a few countries have become more oil- and energy-dependent. This contrasts with a larger group of countries in the bottom quadrants, which experienced some degree of substitution. Specifically, the net oil-exporting country of Trinidad and Tobago became less oil-intensive but more energy-intensive. Trinidad and Tobago possesses significant reserves

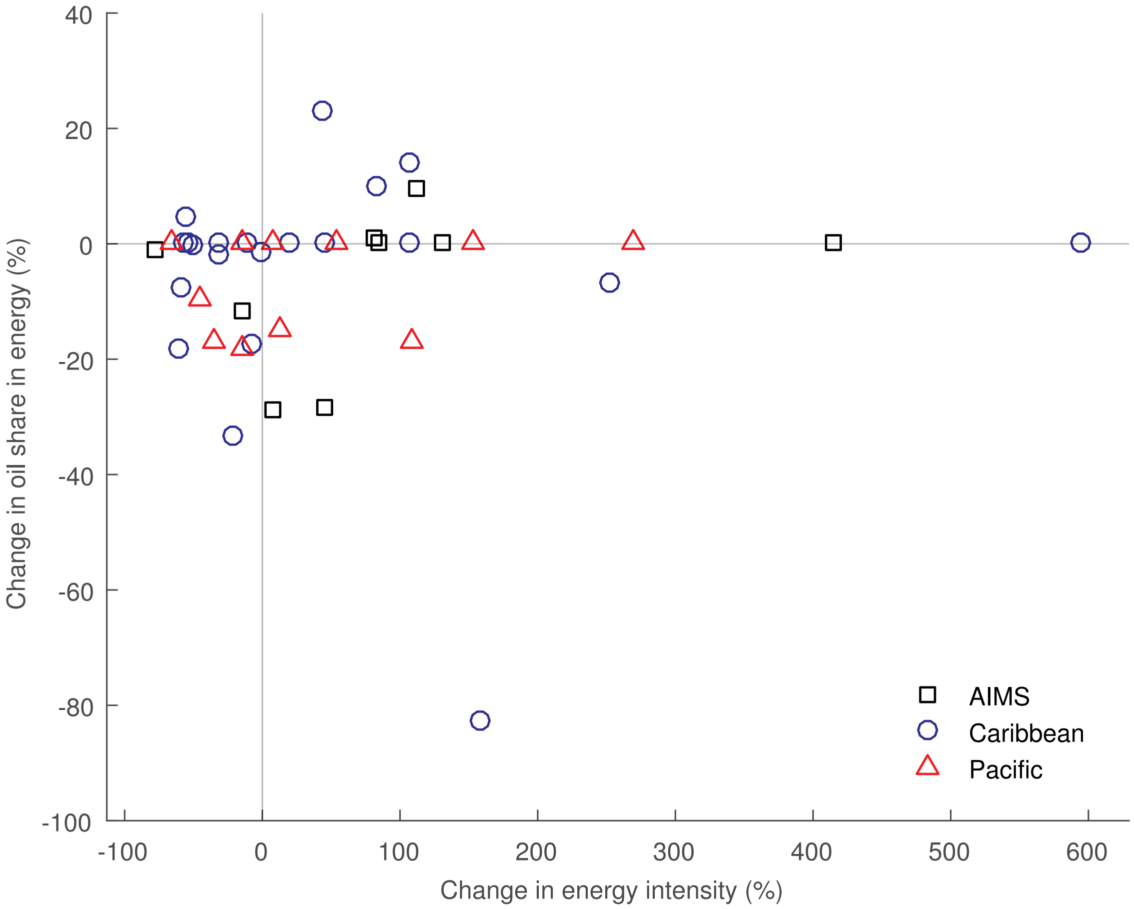

Figure 2.3: **Evolution of oil and energy importance between 1980 and 2011 for 42 SIDS.**

of natural gas and exports the majority of its refined crude oil. Countries such as Fiji and Jamaica, which are located in the bottom-left quadrant, have seen a considerable drop in oil share and energy intensity.

Even though the above results produce some insights on oil-use dependency, it is difficult to assess the vulnerability of SIDS to oil price shocks using such a simple cursory analysis. The next section discusses the econometric model that forms the basis of a detailed investigation of the effect of oil price shocks and their associated transmission channels on real output in SIDS.

2.4 Econometric model

Increasing economic linkages with the global economy and the openness of SIDS suggest that a common observed global shock such as changes in oil prices would have important spillover effects that necessitate an understanding of these links and the design of policy measures to mitigate their effects, where necessary. The GVAR modelling approach as developed by Dees et al. (2007) captures economic interdependencies in the global economy. The application in this paper is based on the Matlab GVAR Toolbox 2.0 provided by Smith and Galesi (2014). Each country is modelled separately using a VAR model. Each VAR model is then linked together using foreign-specific variables that are based on the remittance flows among the included countries. In addition, I include the United States (US) in the model to analyse how developments in a globally dominant economy transmit shocks to SIDS. Although the GVAR methodology can be applied to stationary and/or integrated variables, the method relies on the assumption that each model has some weakly exogenous $I(1)$ variables and that the variables in the system are dynamically stable over time.

The model consists of a set of $N+1$ countries $i = 0,1,2,..,N$, with country 0 being the US, which I use as a reference country primarily because of its dominance in the world economy and in order to analyse how developments in a globally dominant economy transmit shocks to SIDS. Each country model, excluding the US, has a $VARX^{*}(p_i,q_i)$ structure of the form

$$\begin{aligned} x_{i,t} &= \alpha_{i,0} + \alpha_{i,1}t + \sum_{j=1}^{p_i} \Phi_{i,j} \mathrm{x}_{i,t-j} + \\ & \sum_{j=0}^{q_i} \Lambda_{i,j} x^{*}_{itt-j} + \sum_{j=0}^{q_i} \Psi_{i,j} d_{t-j} + u_{i,t} \end{aligned} \tag{2.1}$$

where $x_{i,t} = (y_{i,t}, \pi_{i,t}, reer_{i,t})'$ is a $k_i \times 1$ vector of endogenous domestic variables, $x^{*}_{it} = \left(y^{*}_{it}, \pi^{*}_{it}, reer^{*}_{it}\right)'$ is a $k^{*}_i \times 1$ vector of weakly exogenous country-specific foreign variables, and a $m \times 1$ vector consisting of global variables $d_t = poil_t$. The vectors of fixed intercepts a_{i0} and of deterministic time trend coefficients a_{i1} are both $k_i \times 1$ while $\Phi_{i,j}$, $\Lambda_{i,j}$, and $\Psi_{i,j}$ are of dimension $k_i \times k_i$, $k_i \times k^{*}_i$, and $k_i \times m$, respectively and u_{it} is a $k_i \times 1$ vector of idiosyncratic country-specific shocks that are serially uncorrelated with mean zero and a non-singular covariance matrix such that $u_{it} \sim iid\,(0, \Sigma_{ii})$. Also, p_i, q_i, k_i, and k^{*}_i need not be the same for all countries.

The $reer_{it}$ variable is not included in the model for the US. Similar to Pesaran et al. (2004), I also treat $poil_t$ as endogenous in the US model and weakly exogenous in all SIDS models. The country-specific foreign variables are constructed using fixed weights w_{ij} based on bilateral remittance data. Computation method and reported weights are available in Appendix A.1.3. Hence, the vector of foreign-specific variables in $x^*_{i,t}$ are given by

$$y^*_{it} = \sum_{j=0}^{N} w^y_{ij} y_{it};\ \pi^*_{it} = \sum_{j=0}^{N} w^{\pi}_{ij} \pi_{it};\ reer^*_{it} = \sum_{j=0}^{N} w^{reer}_{ij} reer_{it} \tag{2.2}$$

With the exception of the US, all country models treat the foreign-specific variables π^*_{it} and y^*_{it} as weakly exogenous. Since most countries usually peg their currency to the US dollar, I follow Pesaran (2004) and exclude the foreign-specific variable $reer^*_{it}$ for all SIDS since it is generally strongly correlated with its endogenous counterpart. The US model is the only one that includes the foreign-specific variable $reer^*_{it}$ as weakly exogenous. The specific setup for the individual SIDS and the US economy can be seen in Appendix A.1.

Furthermore, to allow for the possibility that some or all of the variables have unit roots and there is cointegration, the individual country VARX models in Equation 2.1 are estimated in error-correction form given by

$$\Delta x_{i,t} = c_{i,0} + a_i \beta_i^{'} \varsigma_{i,t-1} + \Lambda_{i,0} \Delta x^*_{i,t} + \sum_{j=1}^{p_i-1} \Gamma_{i,j} \Delta z_{t-j} + \sum_{j=0}^{q_i-1} \Psi_{i,j} \Delta d_{t-j} + u_{i,t} \tag{2.3}$$

where $z_{i,t} = \left(x^{'}_{i,t}, x^{*'}_{i,t}\right)^{'}$, $\varsigma_{i,t} = \left(z^{'}_{i,t},\ d^{'}_t, t\right)^{'}$, a_i is a $k_i \times r_i$ matrix of rank r_i and β_i is a $\left(k_i + k^*_i + m_d\right) \times r_i$ matrix of rank r_i. By partitioning β_i as $\beta_i = \left(\beta^{'}_{i,x},\ \beta^{'}_{i,x^*}, \beta^{'}_{i,d}, \beta^{'}_{i,t}\right)^{'}$ conformable to $\varsigma_{i,t} = \left(z^{'}_{i,t},\ d^{'}_t, t\right)^{'}$, the r_i error-correction terms defined by Equation 2.3 are rewritten as $\beta^{'}_i \varsigma_{i,t-1} = \beta^{'}_{i,x} x_{i,t-1} + \beta^{'}_{i,x^*} x^*_{i,t-1} + \beta^{'}_{i,d} d_{t-1} + \beta^{'}_{i,t}(t-1)$, which shows that cointegration is possible both within $x_{i,t}$ and between $x_{i,t}$ and $x^*_{i,t}$, and consequently across $x_{i,t}$ and $x_{j,t}$ for $i \neq j$.

After estimating all the coefficients in Equation 2.3 for each country, I transform them to obtain all the coefficient estimates in the original VARX* models in

Equation 2.1. Written in lag operator form, the VARX model in Equation 2.1 is

$$\Phi_i(L, p_i)\, x_{i,t} = a_{i,0} + a_{i,1}t + \Lambda_i(L, q_i)\, x^*_{i,t} + \Psi_i(L, q_i)\, d_t + u_{i,t} \tag{2.4}$$

where $\Phi_i(L,p_i) = I - \sum_{j=1}^{p_i} \Phi_{i,j} L^j$, $\Lambda_i(L,q_i) = \sum_{j=0}^{q_i} \Lambda_{i,j} L^j$, and $\Psi_i(L,q_i) = \sum_{j=0}^{q_i} {}_{i,j} L^j$ are the matrix lag polynomial of the coefficients associated with the domestic, foreign, and global variables. Furthermore, since $z_{i,t} = \left(x'_{i,t}, x^{*'}_{i,t}\right)'$, Equation 2.4 becomes

$$\mathrm{A}_i(L, p_i, q_i)\, z_{i,t} = a_{i,0} + a_{i,1}t + \Psi_i(L, q_i)\, d_t + u_{i,t} \tag{2.5}$$

where $\mathrm{A}_i(L,p_i,q_i)$ is defined as $\mathrm{A}_i(L,p_i,q_i) = [\Phi_i(L,p_i), -\Lambda_i(L,q_i)]$ so that it is conformable to $z_{i,t} = \left(x'_{i,t}, x^{*'}_{i,t}\right)'$.

Following this, the GVAR model is solved simultaneously by linking the variables z_{it} with all the $k = \sum_{i=0}^{N} k_i$ endogenous variables of the global model, which are collected in the $k \times 1$ vector $x_t = \left(x'_{0t}, x'_{1t}, \ldots, x'_{Nt},\right)'$ using

$$z_{it} = W_i x_t \tag{2.6}$$

where W_i has a $k_i \times k$ dimension defined by the remittance weights matrix.

Even though p_i and q_i can vary between countries, $\mathrm{A}_i(L,p)$ is constructed from $\mathrm{A}_i(L,p_i,q_i)$ by setting $p = max(p_0, p_1, \ldots, p_N, q_0, q_1, \ldots, q_N)$ and augmenting the $p - p_i$ or the $p - q_i$ additional terms in the power of the lag operator by zeros. Given Equation 2.6, stacking the $N+1$ individual country models yields the $GVAR(p)$ model

$$G(L,p)x_t = \varphi_t \tag{2.7}$$

$$\text{where } G(L,p) = \begin{pmatrix} \mathrm{A}_0\,(L,p)\,W_0 \\ \mathrm{A}_1\,(L,p)\,W_1 \\ \vdots \\ \mathrm{A}_N\,(L,p)\,W_N \end{pmatrix}$$

$$\text{and } \varphi_{it} = \begin{pmatrix} a_{00} + a_{01}t + \Psi_0\,(L,p)\,d_t + u_{0t} \\ a_{10} + a_{11}t + \Psi_1\,(L,p)\,d_t + u_{1t} \\ \vdots \\ a_{N0} + a_{N1}t + \Psi_N\,(L,p)\,d_t + u_{Nt} \end{pmatrix}$$

The $GVAR(p)$ model has a recursive structure that can be conveniently used to carry out generalized impulse response function (GIRF) analysis to track the responses of variables in the system to global shocks. I focus on GIRFs since it is invariant to the ordering of variables in the model. Orthogonalization of the shocks may not be necessary if there is possible correlation of the various shocks among countries. However, Kim (2013) finds that GIRF analysis is an extreme case of identification and may produce misleading results. To lend support to the GIRF outcomes, I use orthogonalised impulse response function (OIRF) analysis to show that the results are similar for both methods. A more detailed exposition of both approaches with additional results is available in Appendix A.3.

The model proposed in this paper relies on a number of assumptions that need to be tested. These tests focus on the order of integration, appropriate lag structure, cointegration rank, weak exogeneity, and stability of the individual models over time. In general, most variables are integrated of order 1, with one or two possible long-run relations identified among them. Except for three cases, the null of weak exogeneity was not rejected. Furthermore, the stability tests showed that the estimated GVAR model is dynamically stable. All performed tests are described and discussed in more detail in Appendix A.2.

2.5 Data

To examine how oil price shocks affect SIDS, quarterly data of good quality would be ideal, but this is scarce. Therefore, I employ an annual panel data series spanning 26 countries (25 SIDS and the US) over the period 1980 to 2015. Despite the small number of observations for each country, this series represents the best and longest available dataset from which we can analyse how global developments affect macroeconomic performance in SIDS. Excluding the economy of the US, countries are divided into three distinct geographical regions: the Caribbean, the Pacific and the Atlantic, Indian Ocean, Mediterranean and South China Sea (AIMS). The list of countries in regional blocks is shown in Appendix A.1.1 and are defined according to the UN Department of Economic and Social Affairs (2015). These countries represent almost 80 per cent of the United Nations member states under the SIDS classification.

The main variables covered in my analysis are real GDP (y_{it}) in local currency values, real effective exchange rate ($reer_{it}$), inflation rate (π_{it}), and oil price ($poil_t$). Other variables include remittance flows measured in US dollars and GDP in current international dollars. In the preliminary exercise, I also included measures of oil intensity and energy mix diversification. Details related to the computation of variables and their data sources are available in Appendix A.1.

The y_{it} and $poil_t$ measures are included in the model since my main objective is to analyse how real output is affected by the oil price. The inclusion of the remaining variables π_{it} and $reer_{it}$ is motivated by arguments about the two main channels through which oil price movements indirectly influence economic activity. On the supply side, rising oil prices feed directly into higher input costs and create upward pressure on the price of energy-intensive goods causing inflation. This lowers real income and causes rational consumers to reduce their consumption spending, resulting in lower aggregate demand (Finn, 2000; Hamilton, 2009; Kilian, 2008). The demand-side channel emphasizes that oil price increases lead to income transfers from countries that are net importers of oil to oil-exporting countries, which then depresses demand for non-tradables. However, the negative impact on domestic GDP could be partly offset by a real depreciation of the domestic currency if the price of tradables relative to non-tradables rise by a bigger proportion than that of the oil-exporting country, and oil exporters spend their additional income in oil-importing countries (Ferderer, 1997; Rasmussen & Roitman, 2011).

A brief description of the main variables in this study is presented in Table 2.1. Average real GDP shows mild variation among the countries over time. The oil price variable has the highest degree of variability followed by the real exchange rate. The inflation variable has the least variability across countries and over time with the inflation rate being highest in Suriname in the 1990s.

Table 2.1: **Descriptive statistics for main variables included in the VAR analysis: 1981–2015.**

Variable	Mean	Maximum	Minimum	Standard Deviation
Real GDP (y)	4.23	4.84	2.86	0.12
Inflation rate (π)	0.08	0.89	−0.39	0.06
Real exchange rate ($reer$)	4.72	9.23	3.65	0.34
Oil price ($poil$)	3.45	4.72	2.54	0.67

Notes: Except for oil price, summary statistics are pooled across countries and over time. The inflation rate is in log differences and all other variables are in log levels.

2.6 Results and discussion

In this section I examine three scenarios to gauge the reaction of the real economy for SIDS to exogenous shocks. I first show output response to exogenous oil price shocks and then focus on the effects of a slowdown in the US economy. Finally, I explore differences in output response based on the proportion of oil in the energy mix and energy intensity use.

2.6.1 Shock to global oil prices

As oil price increases lead to income transfers from countries that are net importers of oil to oil-exporting countries, real output is expected to contract over time while increasing for oil exporters. Figure 2.4 presents the GIRFs of a positive one standard error shock to oil prices, which corresponds to an increase of about 21 per cent in the price of oil each year. It shows the results for individual countries and how they compare to the regional average. Overall, 8 out of 25 SIDS have negative average output effects, but this was less than 1 per cent in most cases.[2] In terms of average responses (see bottom-right panel of Figure 2.4) for SIDS as a group, the shock to oil prices showed that the average median response of GDP (1.2%) is small and positive but this is not statistically different from zero.

For Caribbean countries, oil price increases do not appear to have any significant negative impact on output except for in countries such as Belize, which experiences a decline over time, and St. Kitts and Nevis, which sees a fall in output within the first year. On the contrary, Trinidad and Tobago being the only oil exporter experiences a significant and positive long-run effect on GDP (3.4%) as expected. Output also increases for Jamaica but significant effects were observed only in the first year.

The Pacific Islands were the most affected by oil price shocks. The long-run effects stand out more clearly for Fiji and Papua New Guinea, which both had average output declines of 0.9% and 1.2%, respectively. The shocks do not appear to have much of an impact in Samoa, Solomon Islands, or Tonga. Unexpectedly, a significant and positive output response was observed for Vanuatu over the period.

As a group, the AIMS region had the smallest output response on average following an oil price shock (0.3%). However, the results were mixed for individual countries in this group. For example, significant positive average effects are observed for Cabo Verde (1.5%) and São Tomé and Príncipe (3.6%) respectively, while oil price shocks appear to have only a modest effect on real GDP for other oil importers in the region.

The above findings support recent evidence in the literature that focus on oil-importing countries and points to negligible oil price effects on output. For example, Rasmussen and Roitman (2011) reveal that with the exception of the

[2] These countries are Belize (-2.2%), Papua New Guinea (-1.2%), Fiji (-0.9%), St. Kitts and Nevis (-0.5%), St. Lucia (-0.3%), Dominica (-0.2%), Mauritius (-0.02%), and Grenada (-0.01%).

United States, oil price shocks do not result in a contemporaneous decline in output in many oil-importing countries. They argue that even though oil price increases transfer income from oil-importing countries to oil-exporting economies, the resulting reduction in domestic demand is partly offset by export demand or other international flows from the foreign recipients of the income transfer. A similar argument presented by Helbling et al. (2011) shows that a reduction in oil supply growth that causes an oil price hike does not lead to major output loss over the long run.

2.6.2 Negative shock to US real GDP

Since many SIDS are dependent on advanced economies such as the US for foreign exchange inflows, I also consider the impact of a negative GDP shock to US GDP – a global demand shock – and examine how it transmits to individual economies and the region as a whole. As the recent global financial crisis has shown, many economies are very sensitive to developments in the US economy. Therefore, dependence on external demand from the US should see SIDS economies reacting strongly to declines in US GDP.

The time profile of the impulse responses related to the negative one standard error shock to US GDP is displayed in Figure 2.5. In the US, this approximates to about a 1% decrease in GDP on an annual basis. Real output for the SIDS group falls by approximately 1% each year with statistically significant effects observed in some countries. In fact, with the exception of Belize, Papua New Guinea, Guinea-Bissau, and Guyana which experience positive but statistically insignificant effects, all countries have negative average median responses. If we look more closely at the regional averages in Figure 2.5 (bottom-right panel), GDP in the Caribbean fell the most compared to the other two regions (−1.2%) in light of the stronger economic ties with the US through tourism, remittances, foreign direct investment, and official development assistance. The economy with the largest negative and significant output drop – Trinidad and Tobago (−2.3%) – belongs to this group.

AIMS, which is the most heterogeneous of the SIDS groups, had a lower output response over the long run (−0.4%) than the Caribbean. I argue that the comparatively lower output losses for AIMS may be due to their stronger economic ties with European and African economies. Of all the countries in this group, Cabo Verde sees the biggest fall in output (−1.7%) following a negative US GDP shock. In general, even if AIMS economies do not have strong financial linkages with the US, they are likely to feel contagion effects if European economies are affected by global developments. Europe has strong economic ties with the US and those economies are more financially integrated. Therefore, adverse output shocks in the US could indirectly influence economic activity in AIMS through its effects on European economies.

Compared to the Caribbean and AIMS groups, the effect on Pacific SIDS is more muted and marginally positive at 0.04%, though the effect is not statistically significant. However, a larger deterioration in output (−0.7%) is observed for Samoa. The smaller output response for the Pacific group may be the result of fostering greater economic ties with China, which has been the main driver of global growth over the last decade. This region also benefits from remittance inflows from major source countries such as Australia and New Zealand, which have largely avoided the onslaught of recent global recessions.

In 2013, remittance inflows to several SIDS were close to 10% of GDP, accounting for as much as 15% in countries such as Jamaica. This foreign exchange flow has been used for human capital formation through spending on schooling for children (Amuedo-Dorantes et al., 2010) as well as the financing of business investments (Woodruff & Zenteno, 2007).

As a group, SIDS experience declines in output, though the effect is not statistically significant. The overall evidence suggests that the effect of a negative shock to US output is strongest for those regions that have close economic ties with the US and are within its geographical proximity. This does not mean that Pacific Island states are insulated from these negative demand shocks since advanced economies such as Australia and New Zealand are strongly integrated with the

US and can influence economic activity in Pacific countries. Therefore, depressed demand in the US could also see reduced foreign exchange outflows from Australia and New Zealand to Pacific Island economies.

2.6.3 Energy diversification and energy intensity

I examine whether dissimilarities in output response for individual countries or groups could arise from differences in the proportion of oil in the energy mix and energy intensity despite the muted response of GDP to oil price shocks. This is in line with arguments advanced by Blanchard and Gali (2007), Cologni and Manera (2009), Peersman and Van Robays (2012), and Anciaes (2012) who suggest that countries with a higher energy intensity of production or higher oil share in their energy mix are likely to have stronger output responses following a negative oil price shock. To explore these differences, I separate the countries into a 'high' and 'low' category by using the mean energy intensity and oil share as a cut-off point (see Appendix A.1 for classification of countries). These results are presented in Figure 2.6 and do not appear to show any distinct differences among country groupings.

I begin by looking at differences in terms of energy intensity, that is, energy consumed per unit of economic output. Contrary to expectations, these results show that output increases irrespective of whether economies are more or less energy intensive, but low energy-intensive economies do experience a smaller output increase in the long run (0.9%) compared to more energy-intensive economies (1.9%).

In terms of the share of oil in the energy mix, this was generally high with over 80 per cent of the countries in the sample relying on oil for at least 80 per cent of their domestic consumption needs. The impulse responses show that countries with a lower share of oil in the energy mix performed noticeably better than those countries with a less diversified energy mix, that is, 1.5% compared to 0.5%. These general results suggest that positive growth outcomes are more likely for SIDS that combine increased energy intensity with transition towards a more diversified energy supply mix.

Despite the differences in terms of energy intensity and oil share, the generally positive output effects observed seem to be a reflection of the sectoral composition of these economies. The sectoral structure of small states have allowed many of them to harness their natural resource base by orienting economic activity towards labour-intensive and service-based activities in addition to their specialization in niche markets (Briguglio et al., 2006). While tourism is the key component of the services industry in many states, countries such as Trinidad and Tobago have strengthened the importance of the financial services sector in an attempt to reduce its dependence on the energy sector. Financial services account for approximately 11.5 per cent of domestic activity in that country (Tsikata et al., 2009).

The sectoral structure of SIDS is also related to the subsistence nature of the economy and the ability to access land, and is seen as a contributory factor in alleviating the adverse effects of potentially limited economic growth performance. In the presence of external shocks, individuals gravitate towards subsistence agriculture to minimize the impact on their livelihood. Bayliss-Smith and Feachem's study (as cited in Yari (2003)) refers to this phenomenon as 'subsistence affluence'. The United Nations Economic and Social Commission for Asia and the Pacific (2003) argues that policies should be geared towards complementing the cash-based economy with improvements in the productivity of the subsistence sector. For these reasons and others, SIDS do not appear to be susceptible to the devastating impact of oil price shocks that is often touted in the literature.

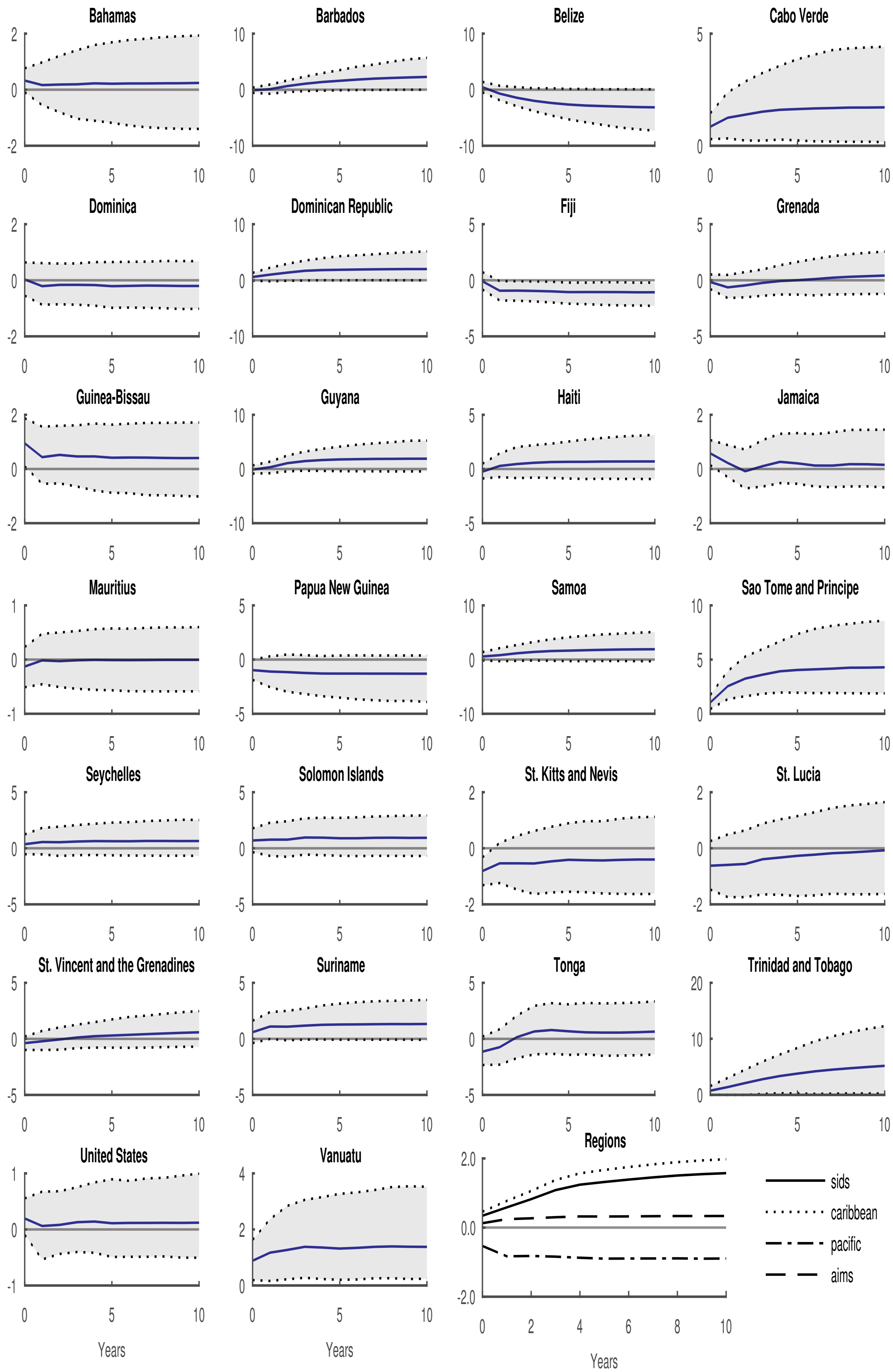

Figure 2.4: **Median impulse response of GDP to a positive one standard error shock to oil prices. Solid lines represent the annual change (%) in output for a given country and associated 95% confidence interval bands (thick dashed line). Median impulse response of GDP for regional aggregates is displayed in the bottom-right panel. PPP-based GDP weights are used to calculate regional aggregates.**

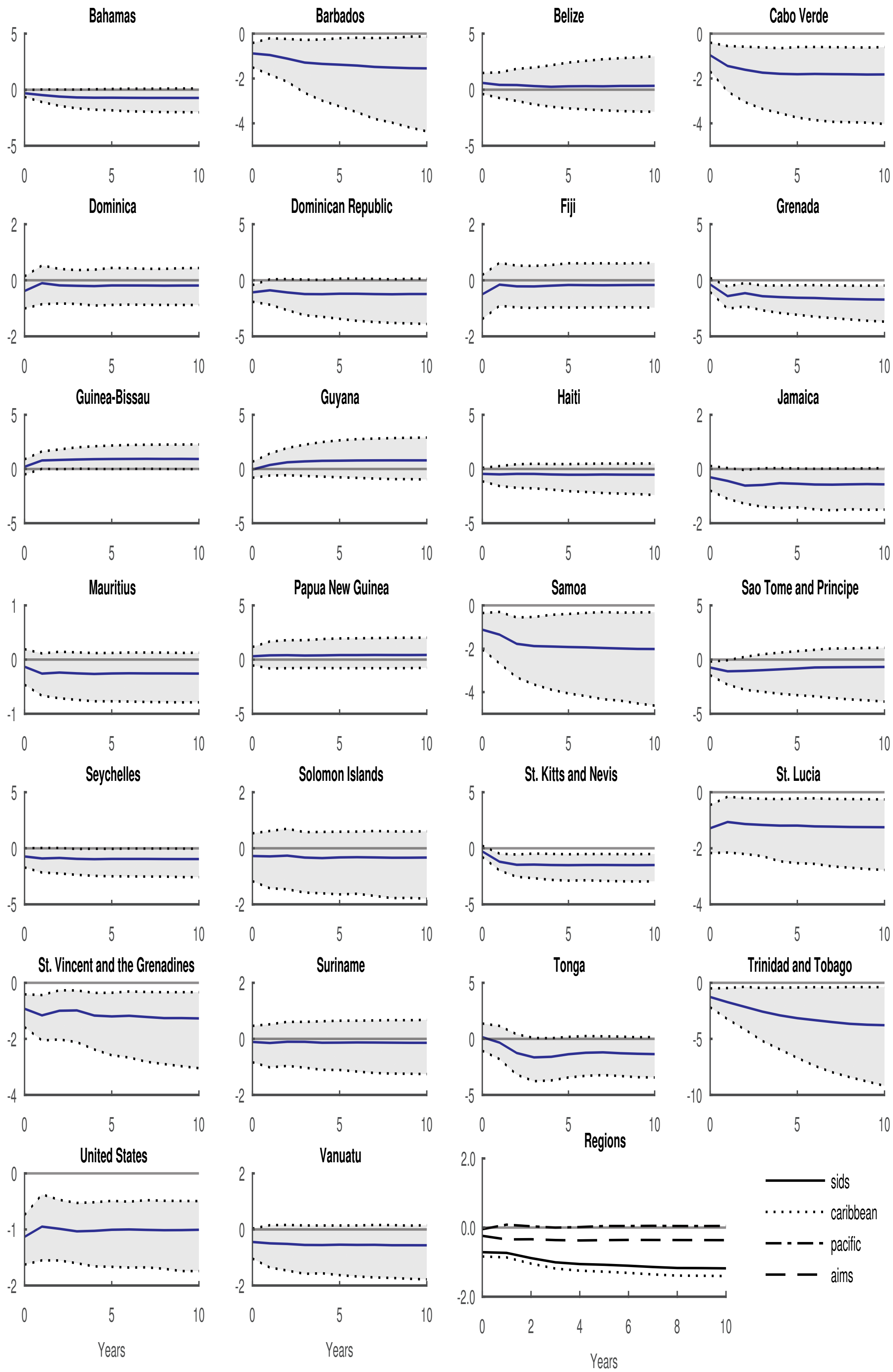

Figure 2.5: **Median impulse response of GDP to a negative one standard error shock to US GDP. Solid lines represent the annual change (%) in output for a given country and associated 95% confidence interval bands (thick dashed line). Median impulse response of GDP for regional aggregates is displayed in the bottom-right panel. PPP-based GDP weights are used to calculate regional aggregates.**

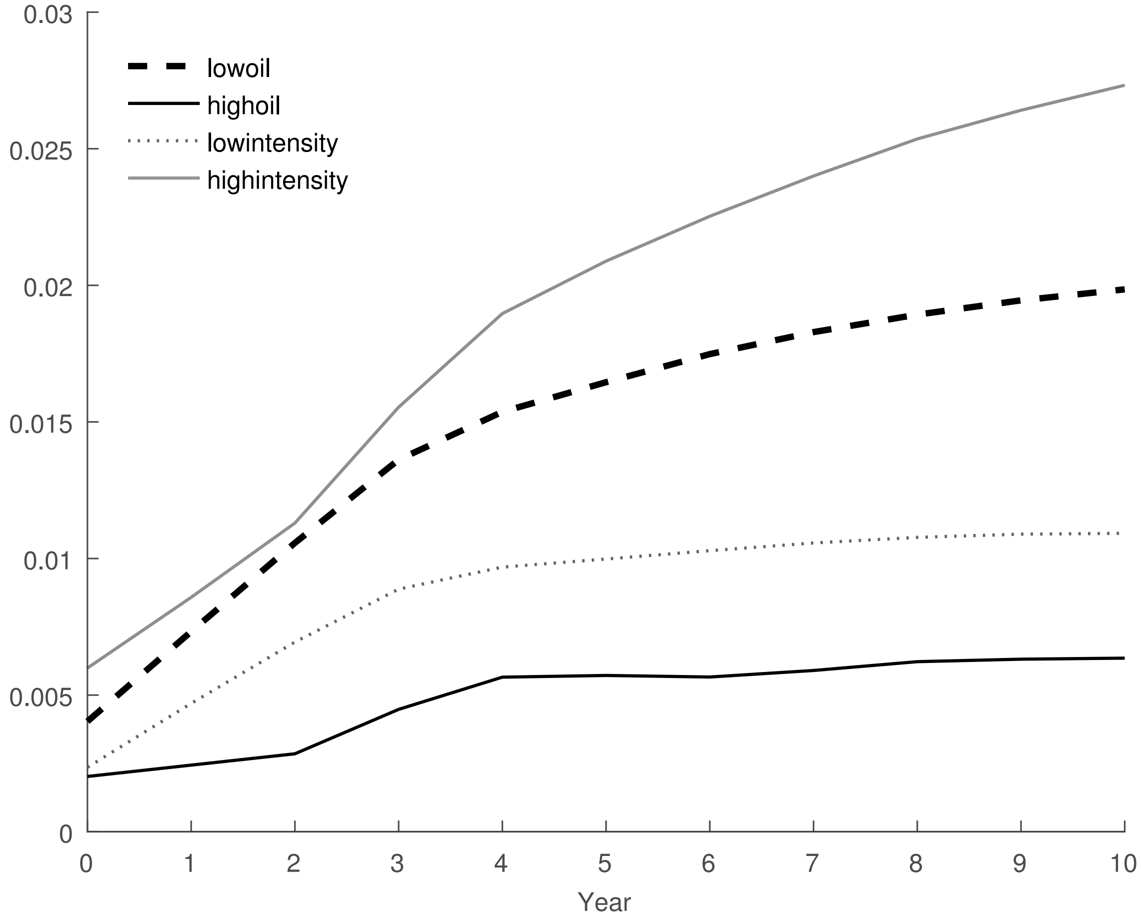

Figure 2.6: **Median impulse response of GDP to a positive one standard error shock to oil price under different energy mix and energy intensity scenarios. PPP-based GDP weights are used to calculate group aggregates.**

2.7 Concluding remarks

Several studies show how oil price shocks affect developed and large developing countries, but work in this area is generally lacking for SIDS and this study has tried to fill this gap. As oil consumption accounts for a significant proportion of GDP in most SIDS compared to many advanced economies, it is expected to result in significant adverse output effects in SIDS. Moreover, the impact on these economies is expected to be greater the less diversified they are in terms of energy use. However, the findings in this study contravene these long-established views.

To determine if SIDS are susceptible to oil price shocks, I used a Global Vector Autoregressive (GVAR) model, estimated with annual data from 1980 to 2015 and using remittance weights. I did this for a set of 25 SIDS grouped into three regions: AIMS, Caribbean, and the Pacific. Though individual economies such as those in Belize, Fiji, and St. Kitts and Nevis do show significant negative output responses, oil price shocks do not have a statistically significant negative effect on economic growth in most SIDS and different regions. This null finding of low output response is similar to that described by Rasmussen and Roitman (2011), who find no contemporaneous decline in output for many oil-importing countries following an oil price increase. Additional results in this study also reveal that oil-intensive SIDS perform better than their low-intensity counterparts, but economic growth is likely to be greater if economies transition towards a more diversified energy supply mix.

As oil price shocks can affect SIDS economies indirectly, I have also analysed the impact of a negative demand shock in the US on output in SIDS. An oil price shock that depresses economic activity in the US is likely to reduce foreign exchange inflows to SIDS. The overall evidence reveals that the effect of a negative shock to US output is strongest for those regions that have close economic ties with the US and are within its geographical proximity.

While I do not discount future oil price increases having a larger adverse economic impact on SIDS as global conditions continue to change, these results dispel the notion that SIDS would experience large output fluctuations because they are more energy-intensive and less-diversified than advanced economies. From a policy perspective, this evidence underscores the need for SIDS to continue exploring energy diversification opportunities, and highlights the importance of designing outward-oriented economic policies to enhance foreign exchange inflows and encourage resiliency to oil price shocks.

A Appendix

This appendix contains details of data and sources, model specification and diagnostics, and some additional results.

A.1 Data sources and construction of variables

I use data for 26 countries including the US. The list of countries and the respective groups are displayed in Table A.1.1. Data on real GDP is based on the annual series in national currency extracted from the United Nations National Accounts Main Aggregates database. It is indexed so that real GDP in 2010 equals 100 and then transformed into logarithms.

The real effective exchange rate is from the Bruegel Database and is based on the proposed approach by Darvas (2012). This time series was normalized such that 2010 is 100 and then log-transformed.

The IMF's IFS database is the main source of the consumer price index data. However, Cabo Verde, Guinea-Bissau, Guyana, and Sao Tome and Principe all had missing data which resulted in the entire series for these countries being replaced with data from the World Economic Outlook (WEO) database. This series was subsequently normalized so that 2010=100 and log-transformed. The final dataset was used to construct the inflation rate $\pi_{i,t} = ln(CPI_{it}) - ln(CPI_{i,t-1})$ where CPI_{it} is the consumer price index for the i^{th} country at time t.

The series for oil prices is the price of Brent crude oil measured in US dollars per barrel and are taken from the IMF's IFS database. The time series is annual and expressed in logarithms.

For the preliminary exercise conducted in Section 2.3, I define oil intensity as the value of crude oil consumption relative to GDP in nominal US dollars. I use the value of crude oil imports from the World Economic Outlook (WEO) database as a proxy for oil consumption. This GDP series is also from the same database. Oil share in energy is calculated as oil consumption divided by the total energy (renewable and non-renewable sources). Both are expressed in British Thermal Units and are taken from the US Energy Information Administration (EIA) database. The specific calculation for each relevant variable is shown in Equation A.1.1.

$$\begin{aligned}
y_{it} &= \ln(100.GDP_{it}/GDP_{i,2010}) \\
reer_{it} &= \ln(100.REER_{it}/REER_{i,2010}) \\
\pi_{it} &= ln(CPI_{it}) - ln(CPI_{i,t-1}) \\
poil_t &= \ln(100.nop_t/nop_t) \\
\Delta\text{oil intensity}_{it} &= ln(oil/GDP)_{i,2013} - ln(oil/GDP)_{i,1980} \\
\Delta\text{oil share}_{it} &= ln(oil/energy)_{i,2013} - ln(oil/energy)_{i,1980} \qquad \text{(A.1.1)}
\end{aligned}$$

where CPI_{it} is the consumer price index for the i^{th} country at time t and nop is the nominal oil price in US dollars. The classification of countries based on oil intensity and oil share is shown in Table A.1.2.

I use bilateral remittance flows data to compute remittance weights for the foreign variables in the model. Bilateral remittance data for all included SIDS are only available for 2015 and is obtained from the World Bank's Migration and Remittances database.[3] While I only use data for one year, remittance weights w_{ij} covering data for multiple years are generally computed as an average over period T to reduce the impact of individual yearly changes using

[3]This is based on bilateral remittance estimates for 2015 using Migrant Stocks, Host Country Incomes, and Origin Country Incomes (millions of US$) (April 2016 version).

$$w_{ij} = \frac{\sum_{t=1}^{T} REM_{ij,t}}{\sum_{t=1}^{T} \sum_{j=0}^{N} REM_{ij,t}} \tag{A.1.2}$$

where $REM_{ij,t}$ is the remittance of country i with country j during a particular year t for $t = 1, 2, .., T$. Using weights based on remittances allow us to analyse the importance of the remittance channel in propagating the adverse effects of oil price shocks in SIDS. These estimates are presented in Table A.1.3.

To construct regional impulse responses, I use purchasing power parity (PPP) converted GDP in current international dollars obtained from the World Bank Development Indicators (WDI) database. In this particular case, I use an average covering 1981 to 2015.

Table A.1.1: **Countries and regions in the GVAR model.**

Systemic Economy – U.S.A (US)		
Caribbean	**Pacific**	**AIMS**
The Bahamas (BS)	Fiji (FJ)	Cabo Verde (CV)
Barbados (BB)	Papua New Guinea (PG)	Guinea-Bissau (GW)
Belize (BZ)	Samoa (WS)	Mauritius (MU)
Dominica (DM)	Solomon Islands (SB)	São Tomé and Príncipe (ST)
Dominican Republic (DO)	Tonga (TO)	Seychelles (SC)
Grenada (GD)	Vanuatu (VU)	
Guyana (GY)		
Haiti (HT)		
Jamaica (JM)		
St. Kitts and Nevis (KN)		
St. Lucia (LC)		
St. Vincent and the Grenadines (VC)		
Suriname (SR)		
Trinidad and Tobago (TT)		

Notes: The International Organization for Standardization(ISO) two-letter country codes are used as official short names.

Table A.1.2: **Country groupings based on oil share and energy intensity.**

Low energy intensity	**High oil share**
Bahamas	Bahamas
Barbados	Barbados
Belize	Cabo Verde
Cabo Verde	Grenada
Dominica	Guinea-Bissau
Dominican Republic	Guyana
Fiji	Haiti
Grenada	Jamaica
Guinea-Bissau	St. Kitts and Nevis
Haiti	St. Lucia
Mauritius	St. Vincent and the Grenadines
Papua New Guinea	Sao Tome and Principe
St. Kitts and Nevis	Seychelles
St. Lucia	Solomon Islands
St. Vincent and the Grenadines	Tonga
Samoa	Vanuatu
Sao Tome and Principe	**Low oil share**
Solomon Islands	Belize
Tonga	Dominica
Vanuatu	Dominican Republic
High energy intensity	Fiji
Guyana	Mauritius
Jamaica	Papua New Guinea
Seychelles	Samoa
Suriname	Suriname
Trinidad and Tobago	Trinidad and Tobago

Notes: The classification is based on 2011 – the most recent year for which data are available for all countries. The International Organization for Standardization(ISO) two-letter country codes are used as official short names.

Table A.1.3: **Bilateral remittance weights in 2015.**

	BS	BB	BZ	CV	DM	DO	FJ	GD	GW	GY	HT	JM	MU	PG	WS	ST	SC	SB	KN	LC	VC	SR	TO	TT	US	VU
BS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
BB	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.03	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.14	0.11	0.00	0.00	0.01	0.01	0.00
BZ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
CV	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.87	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00
DM	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00
DO	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.06	0.02	0.00	0.00	0.00	0.00	0.51	0.00
FJ	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.01	0.09
GD	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.03	0.00	0.00
GW	0.00	0.00	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
GY	0.01	0.03	0.00	0.00	0.01	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.05	0.03	0.76	0.00	0.03	0.03	0.00
HT	0.71	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.18	0.00
JM	0.14	0.03	0.01	0.00	0.02	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.03	0.02	0.00	0.00	0.01	0.22	0.00
MU	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
PG	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.29	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.02
ST	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
SB	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.48
KN	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
LC	0.00	0.04	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
VC	0.00	0.04	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.04	0.00	0.00
SR	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
TO	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.02
TT	0.00	0.02	0.00	0.00	0.01	0.00	0.00	0.18	0.00	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.15	0.00	0.00	0.00	0.01	0.00
US	0.13	0.83	0.98	0.93	0.91	0.88	0.98	0.74	0.20	0.93	0.71	0.99	0.83	0.80	0.97	0.12	0.70	0.33	0.88	0.70	0.66	0.13	0.98	0.86	0.00	0.39
VU	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.36	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Remittance weights are computed as percentage shares displayed by column such that each column sums to 100 per cent.

A.2 Model specification and diagnostics

The specific form of individual country models and the US economy are shown in Table A.2.1.

Table A.2.1: **Variable specification of the country-specific VARX* models.**

SIDS Individual Models		US Model	
Domestic	Foreign	Domestic	Foreign
y_{it}	y^*_{it}	y_{it}	y^*_{it}
π_{it}	π^*_{it}	π_{it}	π^*_{it}
$reer_{it}$	–	–	$reer^*_{it}$
–	$poil_t$	$poil_t$	–

I also outline test results related to the integration properties of the variables, lag structure and cointegration rank statistics, weak exogeneity assumption, and stability of the individual models over time.

To test the integration properties of the variables in the system, I utilize the weighted symmetric estimation of ADF type regressions proposed by Park and Fuller (1995) (ADF-WS) since it is believed to have higher statistical power than the standard ADF test (see Leybourne et al. (2005)). According to the evidence presented in Table A.2.2, inflation appears to be an $I(1)$ variable. Real output is also stationary in most countries. The ADF-WS test also shows that the real effective exchange rate was stationary in all countries. The results indicate that in addition to the country-specific variables, most variables are generally $I(1)$ thus supporting their inclusion in the $VARX^*$ structure.

Tests for the optimal order p_i of the domestic variables x_i are conducted using the Schwarz Bayesian criterion (SBC), which may be more appropriate for small sample size problems as it typically chooses a lower lag length than the Akaike Information criterion (AIC). Many researchers have shown that AIC often shows a tendency to overfit models in small samples (see, for example, Hurvich and Tsai (1989)). Under the constraints imposed by data limitations, I follow Dees et al. (2007) and others, and set $p_i = 2$. For the same reason I set the number of lags of the foreign-specific variables x^*_i to one (see Table A.2.3).

Having tested the integration properties of the variables, it is now possible to determine the number of long-run relations for each country (Johansen, 1991, 1995). I use the case where unrestricted constants and restricted trend coefficients (Case IV) are included in cointegrating VAR models with exogenous $I(1)$ variables. The rank selections are conducted at the 95 per cent critical value level and are based on the trace statistic which is known to have a better small sample power compared to the maximal eigenvalue statistic (Lutkepohl et al., 2001). A cointegration rank of one was found in most countries and two for most of the others (see Table A.2.3). Samoa was the only country in which full rank was observed though the domestic variables appear to have a unit root. This apparent contradiction may be due to the low power of the cointegration test stemming from the small sample size.

To ensure that there is no long-run feedback from individual country models to the weighted sum of other counterparts, I test the weak exogeneity assumption of the foreign-specific and common global variables as described in Dees et al. (2007). To be specific, I run the following regression and test the joint significance of the estimated error-correction terms under the null of weak exogeneity for each l^{th} element of x^*_{it}

$$\Delta x^*_{it,l} = \mu_{il} + \sum_{j=1}^{r_i} \gamma_{ij,l} ECM^j_{i,t-1} + \sum_{k=1}^{p_i} \varphi_{ik,l} \Delta x_{i,t-k} + \sum_{m=1}^{q_i} \vartheta_{im,l} \Delta \tilde{x}^*_{i,t-m} + \varepsilon_{it,l} \quad \text{(A.2.1)}$$

where $ECM^j_{i,t-1}$ is the estimated error-correction term with $j = 1, 2, \ldots, r_i$ and r_i is the cointegrating rank found for the i^{th} country model. The set of foreign-specific and global variables in first differences is given by $\Delta\tilde{x}^*_{it} = \left(\Delta x^{'*}_{it}, \Delta reer^*_{it}, \Delta poil_t\right)'$ for country $i = 1, 2, .., N$. The $\Delta reer^*_{it}$ term is implicit in Δx^*_{it} for the US model. The F-test overwhelmingly supports non-rejection of the null for all variables except for foreign inflation in Cabo Verde. These results are presented in Table A.2.4.

Prior to analysis of the impulse responses, I examine the GVAR's eigenvalues to ensure that the model displays dynamic stability. According to Pesaran (2004), this requires that the eigenvalues be either on or inside the unit circle. As evidenced in Table A.2.5, all 156 eigenvalues of the GVAR fall on or within the unit circle suggesting that the estimated model is dynamically stable. The model has 42 eigenvalues equal to unity, which corresponds to the number of unit roots in the model, with the remaining 114 eigenvalues having moduli all less than unity.

Table A.2.2: **Unit root tests.**

	y	Δy	$\Delta\Delta y$	π	$\Delta\pi$	$\Delta\Delta\pi$	$reer$	$\Delta reer$	$\Delta\Delta reer$	y^*	Δy^*	$\Delta\Delta y^*$	π^*	$\Delta\pi^*$	$\Delta\Delta\pi^*$	$reer^*$	$\Delta reer^*$	$\Delta\Delta reer^*$	$poil$	$\Delta poil$	$\Delta\Delta poil$
BS	-2.36	-2.74	-4.52	-2.42	-4.09	-4.75	-2.77	-3.45	-5.75	-2.26	-4.24	-6.09	-2.46	-4.44	-6.61	-2.94	-4.33	-6.28			
BB	-3.14	-3.05	-4.13	-2.19	-5.14	-6.44	-2.20	-3.71	-6.39	-1.88	-3.08	-4.23	-3.05	-4.52	-7.42	-1.85	-3.20	-6.25			
BZ	-1.73	-1.72	-6.71	-2.47	-5.49	-6.69	-2.52	-2.30	-5.72	-1.93	-3.59	-4.37	-3.25	-5.05	-8.33	-2.06	-2.88	-7.93			
CV	-1.85	-2.62	-5.86	-2.58	-4.48	-6.67	-3.15	-4.44	-5.80	-1.94	-3.89	-4.92	-4.43	-6.62	-7.28	-1.13	-3.15	-6.34			
DM	-0.85	-3.21	-6.60	-2.24	-3.91	-7.52	-3.43	-3.79	-5.47	-1.98	-3.52	-4.28	-3.12	-4.83	-8.08	-1.63	-2.27	-7.00			
DO	-1.71	-4.31	-6.12	-3.74	-6.55	-8.76	-2.16	-4.86	-4.33	-2.48	-3.87	-4.48	-3.12	-4.95	-6.23	-3.12	-4.55	-6.32			
FJ	-2.45	-5.20	-6.63	-3.19	-5.97	-8.94	-2.53	-4.12	-5.83	-1.94	-3.16	-4.37	-3.03	-4.73	-8.28	-1.06	-4.08	-5.79			
GD	-2.64	-3.10	-6.33	-1.52	-3.82	-7.00	-3.45	-3.99	-6.08	-1.62	-2.74	-4.63	-2.33	-4.50	-7.86	-1.51	-3.09	-5.50			
GW	-2.35	-5.78	-6.95	-3.05	-6.96	-9.98	-1.37	-3.35	-6.59	-1.71	-2.76	-5.85	-2.54	-4.28	-6.50	-3.15	-4.44	-5.80			
GY	-1.23	-1.77	-4.40	-3.41	-3.77	-5.89	-2.07	-3.21	-7.02	-2.04	-3.59	-4.36	-3.78	-5.47	-8.96	-2.07	-4.54	-6.84			
HT	-1.53	-4.01	-6.08	-2.53	-4.74	-6.85	-3.13	-4.55	-6.32	-2.49	-4.08	-5.52	-4.07	-6.76	-6.66	-2.19	-4.85	-4.33			
JM	-0.76	-2.28	-10.27	-2.79	-4.43	-6.36	-2.29	-3.08	-7.52	-1.95	-3.60	-4.34	-3.14	-4.87	-8.33	-3.05	-3.74	-6.12			
MU	-1.04	-3.48	-6.73	-2.87	-4.20	-6.77	-1.26	-3.72	-7.34	-2.10	-4.20	-5.16	-3.36	-6.05	-8.81	-2.04	-3.13	-6.80			
PG	-1.88	-3.08	-5.29	-3.33	-7.05	-9.32	-0.19	-2.45	-8.04	-2.24	-4.36	-5.29	-3.37	-5.10	-8.86	-1.18	-3.78	-7.27			
WS	-2.19	-4.19	-7.29	-4.42	-6.82	-6.97	-1.07	-3.44	-5.13	-1.93	-3.15	-4.43	-3.02	-4.75	-8.25	-1.56	-4.48	-5.46			
ST	-0.23	-0.93	-7.42	-2.23	-4.96	-8.86	-0.71	-2.90	-7.40	-1.77	-2.71	-5.87	-2.58	-4.37	-6.52	-3.13	-4.40	-5.76			
SC	-2.85	-4.94	-5.61	-5.13	-7.50	-6.28	-2.03	-3.09	-6.74	-1.48	-2.56	-4.73	-2.74	-3.75	-5.73	-1.23	-3.67	-7.28			
SB	-2.75	-3.39	-6.04	-3.85	-7.13	-9.94	-1.31	-3.92	-7.44	-2.78	-3.66	-4.35	-3.52	-4.57	-7.96	-0.14	-4.30	-6.33			
KN	-1.57	-3.11	-5.23	-2.67	-4.89	-8.29	-2.11	-3.37	-5.62	-2.03	-3.69	-4.67	-3.86	-5.92	-6.38	-1.85	-4.39	-4.96			
LC	-1.79	-2.31	-4.79	-3.90	-4.93	-8.00	-2.55	-3.02	-5.15	-2.29	-3.48	-4.38	-2.99	-4.44	-7.09	-1.68	-3.54	-6.19			
VC	-0.68	-2.93	-6.50	-2.82	-2.98	-12.11	-2.78	-3.49	-5.74	-1.77	-2.83	-4.53	-2.28	-4.07	-7.21	-1.66	-3.19	-5.61			
SR	-0.55	-3.27	-6.78	-4.07	-5.87	-7.12	-2.17	-4.55	-6.90	-1.14	-1.78	-4.30	-3.38	-3.88	-5.89	-2.17	-3.08	-6.82			
TO	-1.90	-2.23	-4.47	-3.09	-6.05	-8.46	-2.19	-4.50	-5.23	-1.94	-3.16	-4.38	-2.99	-4.72	-8.49	-0.84	-2.85	-3.52			
TT	-2.00	-1.94	-5.20	-1.65	-8.28	-8.18	-1.34	-3.53	-6.14	-2.02	-3.50	-4.33	-3.09	-4.45	-7.44	-2.18	-3.34	-6.25			
US	-1.94	-3.61	-4.34	-3.16	-4.88	-8.35				-1.98	-4.40	-6.56	-3.64	-6.46	-8.35	-1.89	-4.60	-4.56	-1.36	-4.04	-7.34
VU	-3.23	-4.19	-6.25	-3.21	-3.46	-5.99	-0.81	-5.42	-4.48	-2.88	-3.84	-6.30	-3.63	-6.08	-9.44	-1.09	-3.69	-7.26			

Notes: The WS-ADF statistics for all the level variables are based on regressions including a linear trend. The 95% critical value for the regression with trend is –3.24, and for regressions in differences –2.55.

Table A.2.3: **VARX order and number of cointegration relations in individual models.**

Country	**p**	**q**	**# Cointegrating Relations**
Bahamas	1	1	1
Barbados	1	1	2
Belize	1	1	2
Cabo Verde	1	1	2
Dominica	1	1	1
Dominican Republic	1	1	2
Fiji	1	1	2
Grenada	1	1	1
Guinea-Bissau	1	1	2
Guyana	1	1	2
Haiti	1	1	1
Jamaica	2	1	1
Mauritius	1	1	1
Papua New Guinea	2	1	1
Samoa	1	1	3
Sao Tome and Principe	1	1	1
Seychelles	1	1	1
Solomon Islands	1	1	1
St. Kitts and Nevis	1	1	2
St. Lucia	1	1	1
St. Vincent and the Grenadines	2	1	1
Suriname	1	1	1
Tonga	2	1	1
Trinidad and Tobago	1	1	1
United States	1	1	1
Vanuatu	2	1	1

Table A.2.4: **Test for weak exogeneity of country-specific foreign variables and global variable at the 5% significance level using F-statistics.**

Country	F – test	$Fcrit_{0.05}$	y^*	π^*	$reer^*$	poil
Bahamas	F(1,23)	4.28	0.05	0.24		0.08
Barbados	F(2,22)	3.44	0.23	0.07		1.51
Belize	F(2,22)	3.44	0.89	0.66		0.63
Cabo Verde	F(2,22)	3.44	1.89	3.62		3.16
Dominica	F(1,23)	4.28	0.45	0.18		0.35
Dominican Republic	F(2,22)	3.44	0.25	0.02		0.12
Fiji	F(2,22)	3.44	0.16	0.35		0.44
Grenada	F(1,23)	4.28	0.12	0.20		0.68
Guinea-Bissau	F(2,22)	3.44	0.12	0.09		0.18
Guyana	F(2,22)	3.44	1.24	2.29		2.04
Haiti	F(1,23)	4.28	0.03	1.52		0.11
Jamaica	F(1,23)	4.28	0.96	1.49		2.75
Mauritius	F(1,23)	4.28	0.12	2.07		2.83
Papua New Guinea	F(1,23)	4.28	0.56	2.89		0.26
Samoa	F(3,21)	3.07	1.13	1.10		1.17
Sao Tome and Principe	F(1,23)	4.28	1.02	2.86		0.09
Seychelles	F(1,23)	4.28	0.14	0.25		1.49
Solomon Islands	F(1,23)	4.28	0.16	0.05		0.18
St. Kitts and Nevis	F(2,22)	3.44	2.68	0.19		2.99
St. Lucia	F(1,23)	4.28	0.16	0.15		0.01
St. Vincent and the Grenadines	F(1,23)	4.28	1.64	4.02		0.21
Suriname	F(1,23)	4.28	0.08	0.24		0.07
Tonga	F(1,23)	4.28	0.56	0.72		0.04
Trinidad and Tobago	F(1,23)	4.28	1.12	0.04		0.01
United States	F(1,23)	4.28	0.02	0.00	0.03	
Vanuatu	F(1,23)	4.28	2.77	3.07		0.27

Table A.2.5: **Eigenvalues and moduli of the GVAR model in descending order.**

Eigenvalues	Moduli	Eigenvalues	Moduli	Eigenvalues	Moduli
1	1	−0.12	0.50	0	0
1	1	0.36	0.49	0	0
1	1	−0.10	0.47	0	0
1	1	0.63	0.47	0	0
1	1	−0.37	0.36	0	0
1	1	0.43	0.33	0	0
1	1	−0.17	0.33	0	0
1	1	0.25	0.30	0	0
1	1	−0.01	0.30	0	0
1	1	0.14	0.28	0	0
1	1	0.10	0.28	0	0
1	1	0.76	0.27	0	0
1	1	−0.56	0.26	0	0
1	1	0.05	0.26	0	0
1	1	0	0.23	0	0
1	1	0	0.20	0.52	0
1	1	0	0.20	−0.54	0
1	1	0	0.20	−0.05	0
1	1	0	0.20	0.12	0
1	1	0	0.18	−0.26	0
1	1	0	0.17	−0.07	0
1	1	0	0.17	−0.09	0
1	1	0	0.16	0.56	0
1	1	0	0.16	−0.76	0
1	1	0	0.15	−0.14	0
1	1	0	0.12	−0.18	0

Continued on Next Page…

Table A.2.5 – Continued

Eigenvalues	Moduli	Eigenvalues	Moduli	Eigenvalues	Moduli
1	1	0	0.12	−0.18	0
1	1	0	0.09	−0.27	0
1	1	0	0.07	−0.36	0
1	1	0	0.05	−0.28	0
1	1	0	0.05	−0.60	0
1	1	0	0	−0.50	0
1	1	0	0		
1	1	0	0		
1	1	0	0		
1	1	0	0		
1	1	0	0		
1	1	0	0		
1	1	0	0		
1	1	0	0		
1	1	0	0		
1	1	0	0		
0.82	0.82	0	0		
0.80	0.80	0	0		
0.73	0.73	0	0		
0.72	0.72	0	0		
0.63	0.67	0	0		
0.60	0.67	0	0		
0.57	0.67	0	0		
0.56	0.67	0	0		
0.49	0.67	0	0		
0.94	0.67	0	0		

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Table A.2.5 – Continued

Eigenvalues	Moduli	Eigenvalues	Moduli	Eigenvalues	Moduli
−0.06	0.66	0	0		
0.35	0.66	0	0		
0.25	0.63	0	0		
0.23	0.60	0	0		
0.82	0.57	0	0		
−0.48	0.56	0	0		
0.15	0.53	0	0		
0.27	0.53	0	0		
−0.01	0.52	0	0		
0.38	0.52	0	0		

A.3 Impulse response functions

Standard GIRFs

In using GIRFs, no attempt is made to identify shocks to a particular variable or establish a causal relationship among variables. To consider the effects of a global or exogenous variable in the model, Pesaran et al. (2004) suggest that this can be done using a weighted average of variable-specific shocks across all the countries in the model. This involves a shock to the l^{th} variable in the i^{th} model and integrating the effects of other shocks using a historically observed distribution of the errors. To see this more clearly, I use the errors obtained from Equation 2.7 and define the GIRF as

$$\text{GIRF}\left(x_t; u_{ilt}, h\right) = E\left(x_{t+h} \,\middle|\, u_{ilt} = \sqrt{\sigma_{ii,ll}}, I_{t-1}\right) - E\left(x_{t+h} \mid I_{t-1}\right) \tag{A.3.1}$$

where I_{t-1} is the information set at time $t-1$, $\sigma_{ii,ll}$ is the diagonal element of the variance-covariance matrix Σ_u corresponding to l^{th} equation in the i^{th} country model, and h is the time horizon.

Under the assumption of normality of u_t, the effect of a one standard error global shock at time t to the l^{th} variable on the j^{th} variable at time $t+h$ is given by the j^{th} element of

$$\text{GIRF}(x_t; u_{lt}, h) = \frac{e_j^{'} A_h G_0^{-1} \sum_u e_l}{\sqrt{e_j^{'} \sum_u e_l}} \text{ for } h = 0, 1, 2, \ldots; l, j = 1, 2, \ldots, k \tag{A.3.2}$$

where $e_l = (0,\ 0, \ldots,\ 0,\ 1,\ 0, \ldots, 0)'$ is a selection vector with the l^{th} element being unity.

Considering the price of oil as the global variable and the l^{th} variable in all $N+1$ countries, its effects can be simulated by simultaneously aggregating to a single shock using weights based on GDP in purchasing power parity dollars and current prices. These weights reflect the relative importance of individual countries in the global model. This data were extracted from the World Development Indicators database and cover the period 1981 to 2015.

Despite some criticism by Kim (2013), for example, GIRFs avoid the use of the identifying assumptions of standard orthogonalized impulse response analysis (Sims, 1980). According to Pesaran et al. (2004), the short-run restrictions method by Sims (1986) and Bernanke (1986) and the long-run restrictions approach proposed by Blanchard and Quah (1988) are feasible when only a few variables are included in the VAR. However, when a large number of countries are involved, the structural identification of shocks in the global economy depends on the suitable ordering of the variables within each country as well as of the countries in the GVAR model (Dees et al., 2007).

With $N+1$ countries and k_i endogenous variables, a total of $\sum_{i=0}^{N} k_i(k_i - 1)$ identifying restrictions would be required for the GVAR model. Imposing 156 identifying restrictions would have been an arduous task to accomplish in this study. Hence, without strong prior beliefs and economic theory to guide the ordering of the variables and countries in the GVAR model, Pesaran et al. (2004) recommend the use of GIRFs to describe what happens to changes in a variable following a particular shock without identifying the specific source of those changes.

Orthogonalised IRFs (OIRFs) using remittance weights

Apart from being guided by the results of diagnostic tests, a number of assumptions are made in relation to the identification of structural shocks to different variables in the models for each country. In this case we need to select the appropriate order for all countries and variables in the GVAR. The identification approach used follows from the Cholesky decomposition which assumes a recursive ordering with zero-restrictions imposed on the system of linear equations. The recursive structure assumes that some variables do not respond to shocks contemporaneously. The causal ordering is defined in the following way: $x_{i,t} = (poil_t, \pi_{i,t}, y_{i,t})$. Therefore, the orthogonalised impulse response functions originating from Equation 2.7 are given by:

$$\text{OIRF}\left(x_t; u^*_{lt}, h\right) = e_j^{'} A_h G_0^{-1} Q e_l \text{ for } h = 0, 1, 2, \ldots; l, j = 1, 2, \ldots, k \tag{A.3.3}$$

where $e_l = (0,\ 0, \ldots,\ 0,\ 1,\ 0, \ldots, 0)'$ is a selection vector with the l^{th} element being unity.

Starting with the US model which is placed as the first country-specific model in the GVAR, I assume that the price of oil is contemporaneously exogenous such that innovations in inflation and GDP do not affect oil prices within the same year. An inflation shock hits inflation and GDP immediately but does not change oil price until the next period while a GDP shock affects GDP in the current period but does not affect the other variables until the next period.

For all SIDS economies, we have $x_{i,t} = (reer_{i,t}, \pi_{i,t}, y_{i,t})$ where oil price is treated as globally exogenous to see how the system reacts to shocks to this variable. Golub (1983) and Krugman (1983) argue that higher oil prices will transfer wealth from the oil importers to the oil exporters. Hence, the distortion in the balance of trade is likely to influence the exchange rate. Therefore, I first assume that exchange rate changes feed directly into inflation and GDP. In the second equation, inflation changes influence GDP changes contemporaneously. In the final equation, I assume that changes in GDP are dependent on the inflation rate and exchange rate movements. While the US is included as the first economy in the GVAR due to its comparatively larger economic size, no attempt is made to order the other countries which I assume to be too small for innovations in those economies to affect each other.

In general, the OIRFs results in Figures A.3.1 and A.3.2 are similar to the results in Figures 2.4 and 2.5, respectively.

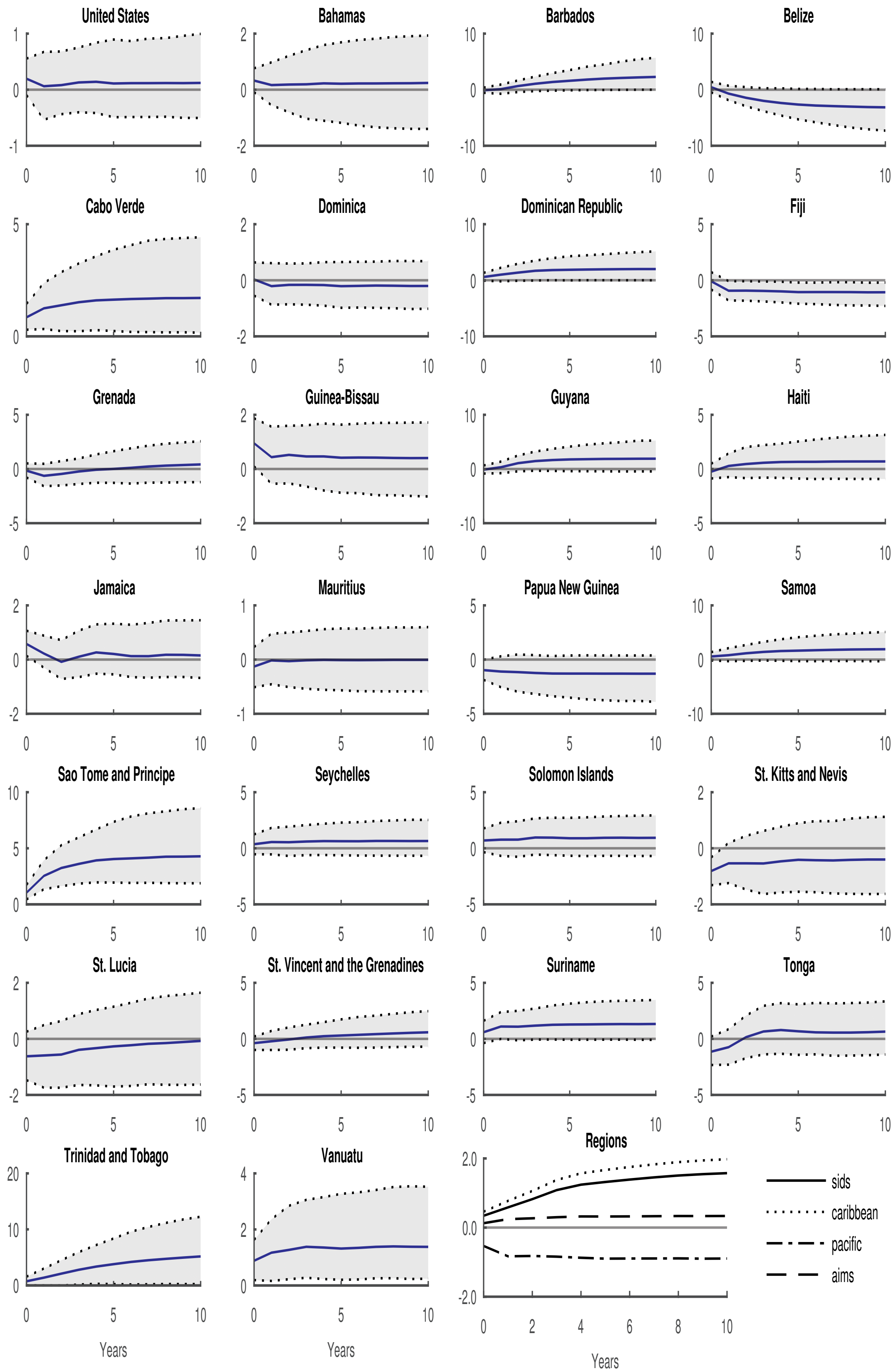

Figure A.3.1: **GDP response in individual SIDS to a positive oil price shock. Results are based on the orthogonalised impulse response function (OIRF). Solid lines represent the annual change (%) in output for a given country and associated 95% confidence interval bands (thick dashed line). Median impulse response of GDP for regional aggregates is displayed in the bottom-right panel. PPP-based GDP weights are used to calculate regional aggregates.**

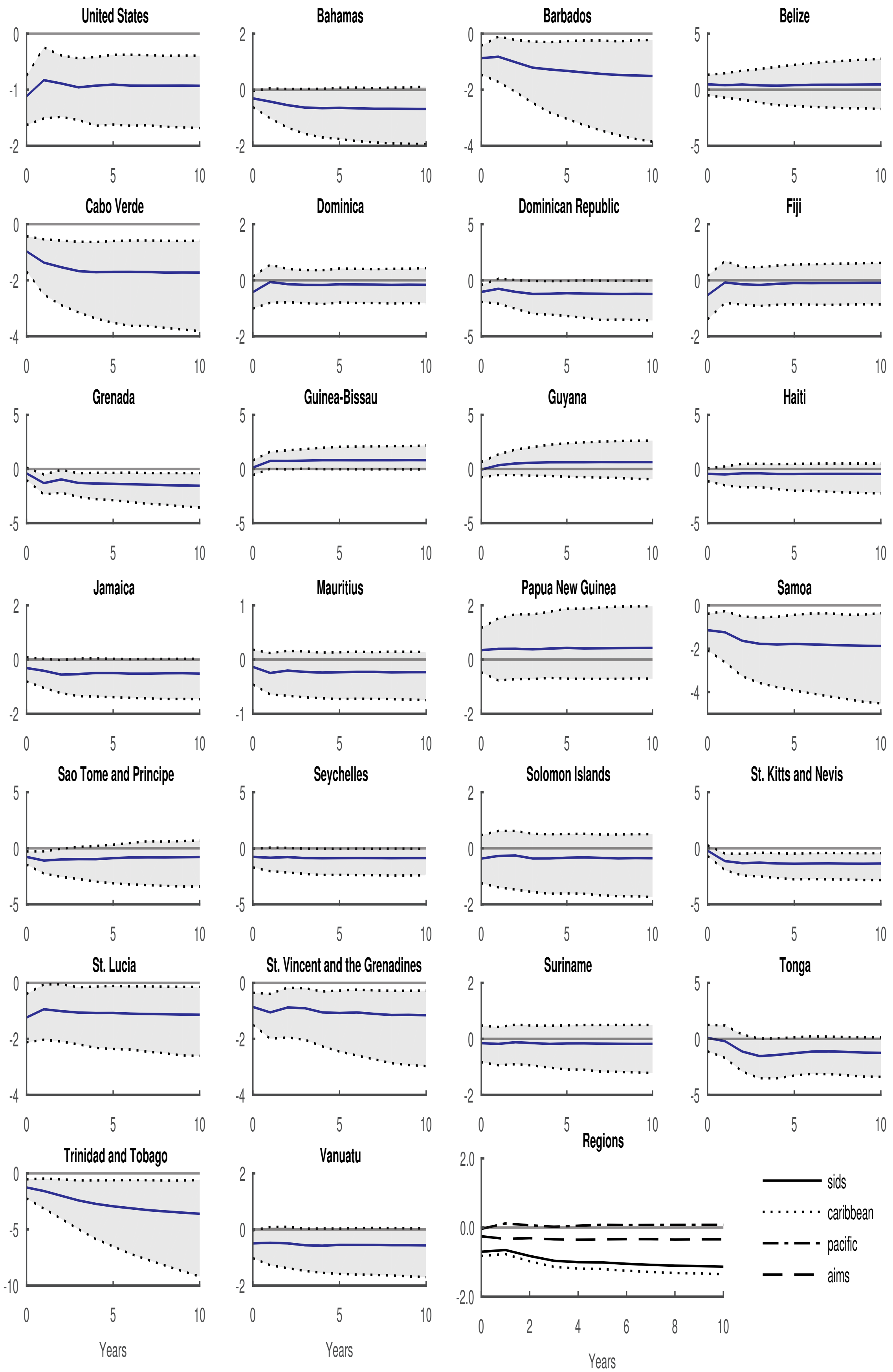

Figure A.3.2: **GDP response in individual SIDS to negative demand shock to US GDP. Results are based on the orthogonalised impulse response function (OIRF). Solid lines represent the annual change (%) in output for a given country and associated 95% confidence interval bands (thick dashed line). Median impulse response of GDP for regional aggregates is displayed in the bottom-right panel. PPP-based GDP weights are used to calculate regional aggregates.**

Chapter 3

Price and income elasticities of electricity demand: Evidence from Jamaica

3.1 Chapter overview

In Chapter 2 I showed that oil prices do not seem to reduce economic activity in many oil-importing Small Island Developing States (SIDS). As SIDS are largely oil-intensive economies, the expectation is that movements in global oil prices will also influence strong changes in domestic electricity prices and electricity use. In this chapter, I set out to determine if consumers of electricity are responsive to electricity price movements and income changes, among other factors.

Jamaica serves as a useful case study as the electricity sector grapples with supply-side challenges. Demand-side policies have the potential to improve electricity use efficiency and reduce the likelihood of electricity disruptions. Here, I use the bounds testing approach to cointegration to obtain long-run price elasticity of demand estimates for the period 1970–2014. The analysis focuses on aggregate electricity demand and three categories of consumers: residential, commercial, and industrial. The findings suggest that residential and industrial consumers are most responsive to price changes, with long-run price elasticities of demand of –0.82 and –0.25, respectively. Therefore, price-based approaches are likely to be more successful in slowing electricity demand growth in these sectors. In terms of income changes, commercial and industrial consumers were found to be very responsive with income elasticities of demand of 0.77 and 1.22, respectively.

3.2 Introduction

Total electricity consumption in Jamaica has grown steadily at an annual average rate of 3.4% over the last 45 years, moving from 735.1 GWh in 1970 to 2,997.8 GWh in 2014. Over the same period, residential electricity demand increased its share of total electricity consumption from 28% to 32%, while the industrial sector share moved from 16% to 20%. The commercial sector accounts for a significant portion of electricity demand (45%), but its share has not changed much since the 1970s.

Projections by the regulatory body – Office of Utilities Regulation (OUR) – suggest that electricity demand growth is expected to exceed supply in the next few years if there are no major investments in additional capacity. To meet the forecasted demand, approximately 1,400 MW of new generating capacity will need to be constructed by 2030, more than doubling existing capacity (Office of Utilities Regulation, 2010b). According to the Jamaica Public Service (2014), a 381 MW LNG-fired power plant should have been completed by mid-2016 but the licence was withdrawn by the Ministry of Energy due to breaches in the power purchase agreement by Energy World International (EWI), the company tasked with building the new generation facility (Nationwide Newsnet, 2014). Though competition exists in generation, the Jamaica Public Service (JPS), which is vertically integrated and has the sole licence to distribute electricity island-wide, continues to grapple with high electricity losses. System losses – mainly due to theft – consistently hover above 20% and act as a further constraint on the firm's ability to expand capacity due to lost revenue.

With the sector potentially experiencing supply-side challenges and the quantity of electricity consumed growing, the utility may be forced to use load shedding to manage the excess demand. This has implications that extend beyond the electricity sector. In a 2010 survey conducted by the World Bank, Jamaican firms reported that they lost about 0.2 per cent of annual sales due to electrical power outages (World Bank, 2016a). With an annual growth rate in real GDP of 0.9%

between 1970 and 2014, load shedding is likely to stymie economic activity in the already fragile economy.

To elaborate on why load shedding could be a problem for Jamaica, Figure 3.1 displays trends in generation capacity, peak demand, and reserve capacity from 1986 to 2013. In recent years, capacity has been growing faster than peak demand, but this is mostly due to plant upgrades. The JPS reports that delays in the acquisition of new generating capacity has forced the firm to engage in rehabilitation of its existing generating units to maintain system reliability with substantially higher maintenance costs incurred in the process (Jamaica Public Service, 2014).

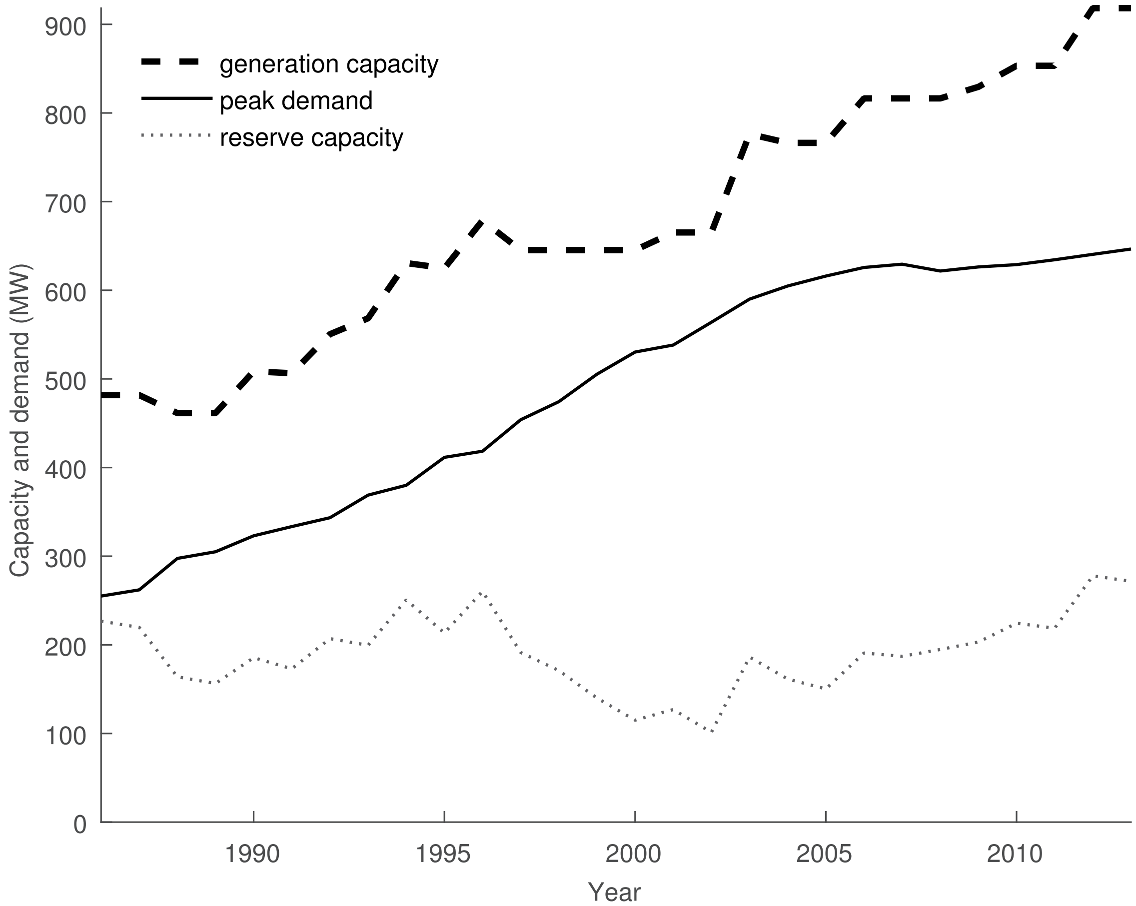

Figure 3.1: **Trends in generation capacity and peak demand, 1986–2013. Source: Compiled using data from Jamaica Public Service (2004, 2014).**

However, continuous system upgrades are unsustainable and new generating capacity is expensive and takes time to build. Until the institutional problems associated with attracting new investors and the high level of system losses are addressed, the short-term response may necessitate electricity price increases to fund new investment in capacity or limit demand growth so as to prevent outages. For these reasons, I estimate price elasticities of demand for electricity at the aggregate and disaggregate level to determine how responsive consumers are to price changes. The use of prices divert consumption away from low value uses of electricity such as unnecessary lighting. Consumers will use electricity until their marginal benefit is equal to the price they have to pay. Using prices to control demand is economically efficient as both the consumer and the utility benefits.[1] It creates incentives for consumers to engage in energy conservation and efficiency and increases the options available to the utility provider to maintain security of the supply network.

Price elasticity of demand estimates are also important in understanding the social welfare implications associated with different incentive pricing schemes. The decision by the regulator to apply revenue cap pricing to the electricity sector in 2016 instead of price cap regulation serves as a notable example in this regard.[2] In general, a rigorous understanding of how electricity prices affect electricity demand is critical and can serve as a useful energy policy guide to government, regulators, and electricity providers.

Ramcharran (1990) is the only known researcher to have estimated demand elasticities for end-users in Jamaica. This was done over two decades ago using annual data covering the period 1970 to 1986. Therefore, I make two main contributions in this paper. First, I use more recent advances in econometric modelling along with a longer time span (1970–2014) to improve the reliability of price elasticity estimates for three categories of end-users: residential, commercial, and industrial. Second, I contribute to the paucity of research on electricity demand behaviour that exists for Small Island Developing States (SIDS)[3] and

[1]As electricity prices in Jamaica are already high by global standards, cash transfer schemes or concession limits could be used to target vulnerable groups such as low-income households who are affected by high prices.

[2]Under a price cap, constraints are placed on a weighted average of prices rather than revenues as is the case with revenue cap regulation.

[3]SIDS are a diversified group of countries whose vulnerability arises from their small size and inability to exploit economies of scale, remoteness leading to high transport costs, narrow export base, and in most cases, dependence on fossil fuel imports (Briguglio, 1995). The UN Department of Economic and Social Affairs (2015) classifies them into three distinct geographical regions: Caribbean, Pacific, and the Atlantic, Indian Ocean, Mediterranean and South China Sea (AIMS).

developing countries as a whole.

This paper is organized as follows: The research topic is introduced in Section 3.2. This is followed by Section 3.3 in which I provide an overview of the electricity sector in Jamaica. I then discuss the literature for Jamaica and various developing and developed countries in Section 3.4. In Section 3.5 I elaborate on the employed model, data sources, and the econometric technique – autoregressive distributive lag (ARDL) bounds testing approach to cointegration. In Section 3.6, the results and analysis of the bounds testing approach are presented. Finally, I highlight the conclusions and policy implications emanating from the results in Section 3.7.

3.3 Overview of Jamaica's electricity sector

In 2001 the government of Jamaica sold 80% of its stake in the Jamaica Public Service (JPS) – the sole electricity supplier in Jamaica – and opened up the generation segment to full competition in 2004. A number of private entities now operate alongside the formerly state-owned generator to supply electricity to the national grid, owned and operated by the monopoly distributor. Up to 80% of current capacity available is operated by the JPS with the rest provided by four independent power producers (IPPs): Jamaica Energy Partners (JEP), Jamaica Private Power Company (JPPC), Jamaica Aluminium Company (JAMALCO), and Wigton Wind Farm (WWF) (Jamaica Public Service, 2013b).

In terms of regulation, oversight of the electricity sector falls under the purview of the Office of Utilities Regulation (OUR) Act of 1995, which was established in 1997 by an Act of Parliament. In addition to the issuance and review of licenses, investigation of breaches by the electricity provider, and issuing and reviewing Requests for Proposals (RFPs) for capacity addition to the electricity grid, a key responsibility of the OUR is the regulation of tariff applications and annual rate increases (Office of Utilities Regulation, 2004). Initially, rate-of-return regulation prevailed so that prices were set to equate revenues with costs. In 2001 price cap regulation was introduced but in 2014 the JPS requested that the Office of Utilities Regulation change to a revenue cap scheme (Jamaica Public Service, 2014).

In 2010, 92% of the population had access to electricity and the sector performed well above the world average in terms of service quality and reliability. World Bank data shows that power cuts average 6.4 outages per month globally and last about 2.4 hours. However, Jamaica fares much better with only 2.5 outages in 2010 with an average duration of up to 1.3 hours. Jamaica's quality of supply also outperforms the Latin America and Caribbean average of 2.8 outages and 1.4 hours of interrupted service (World Bank, 2016a).[4]

However, service quality is likely to deteriorate if major investments in additional capacity are not forthcoming within the next few years. Demand projections by the OUR show that the country's demand for electricity is likely to double by 2030, outpacing the capacity of the grid (Office of Utilities Regulation, 2010b). Recognising this, the government through the Ministry of Science, Technology, Energy and Mining has been pursuing a variety of measures to address Jamaica's growing energy needs such as investments in additional capacity, increasing the amount of renewables to 20 per cent by 2030, and the introduction of natural gas into the energy mix (Ministry of Energy and Mining, 2009). In 2010, the OUR invited bids for the delivery of additional base load generating capacity of 480 megawatts to be commissioned in two tranches, April 2014 and January 2016. The main purpose was to replace about 292 MW of the country's existing generating units which are outdated, inefficient, and some of which have been in operation since the 1960s (Office of Utilities Regulation, 2010c).

Figure 3.2 provides a comparison among five Caribbean economies between 1970 and 2014, including Jamaica. It shows that Jamaica's per capita electricity use has been rising steadily since the 1980s, albeit slower than other economies. Over the entire period, electricity use in Jamaica rose by an annual average of 2.8% but had remained relatively flat in the 1970s and mid-1980s at around 513 kilowatt hours (kWh) per person. By the 1990s, per capita consumption use was close to 700 kWh before peaking at 1,195 kWh in 2009. Major structural and economic reforms in the late 1980s and early 1990s including the removal of exchange rate

[4]Frequency of power outages is measured by the system average interruption frequency index (SAIFI) and the system average interruption duration index (SAIDI) measures the duration of power outages in the largest business city of each country.

controls and the abolishment of the Jamaica Commodity Trading Board – the sole importer of energy and other basic necessities – as well as financial liberalization may have had a role to play in the steady growth in electricity use until early 2000. At the sectoral level (Figure 3.3), the pattern in electricity consumption over the period was similar to the aggregate level except that electricity use grew the fastest between 1970 and 2014 for the industrial sector (3.63%) followed by residential consumers (3.58%) and commercial consumers (3.15%). Some of this growth was fuelled by changes in population demographics. The proportion of people living in urban areas grew quickly during the economic crises of the 1970s and 1980s resulting in the spread and intensity of slums (Harris & Fabricius, 2005).

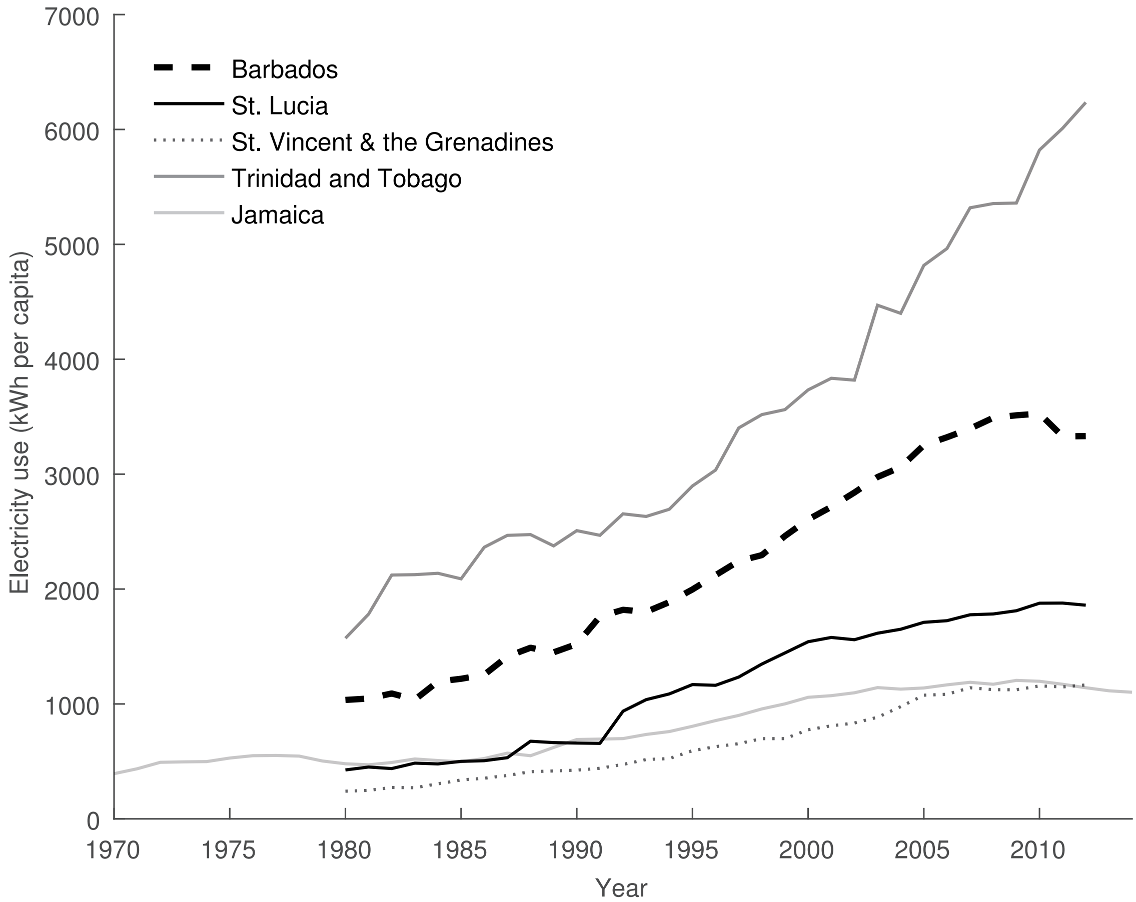

Figure 3.2: **Trends in electricity consumption per capita, select Caribbean countries: 1970–2014. Source: Compiled using data from US Energy Information Administration (2016), United Nations Statistics Division (2016b), United Nations Statistics Division (2016a), and various issues of the Economic and Social Survey of Jamaica (ESSJ). Excluding Jamaica, data was only available between 1980–2012.**

A cross-country comparison of electricity prices is displayed in Table 3.1. Due to its dependence on oil-based fuel imports such as heavy fuel oil (HFO) and

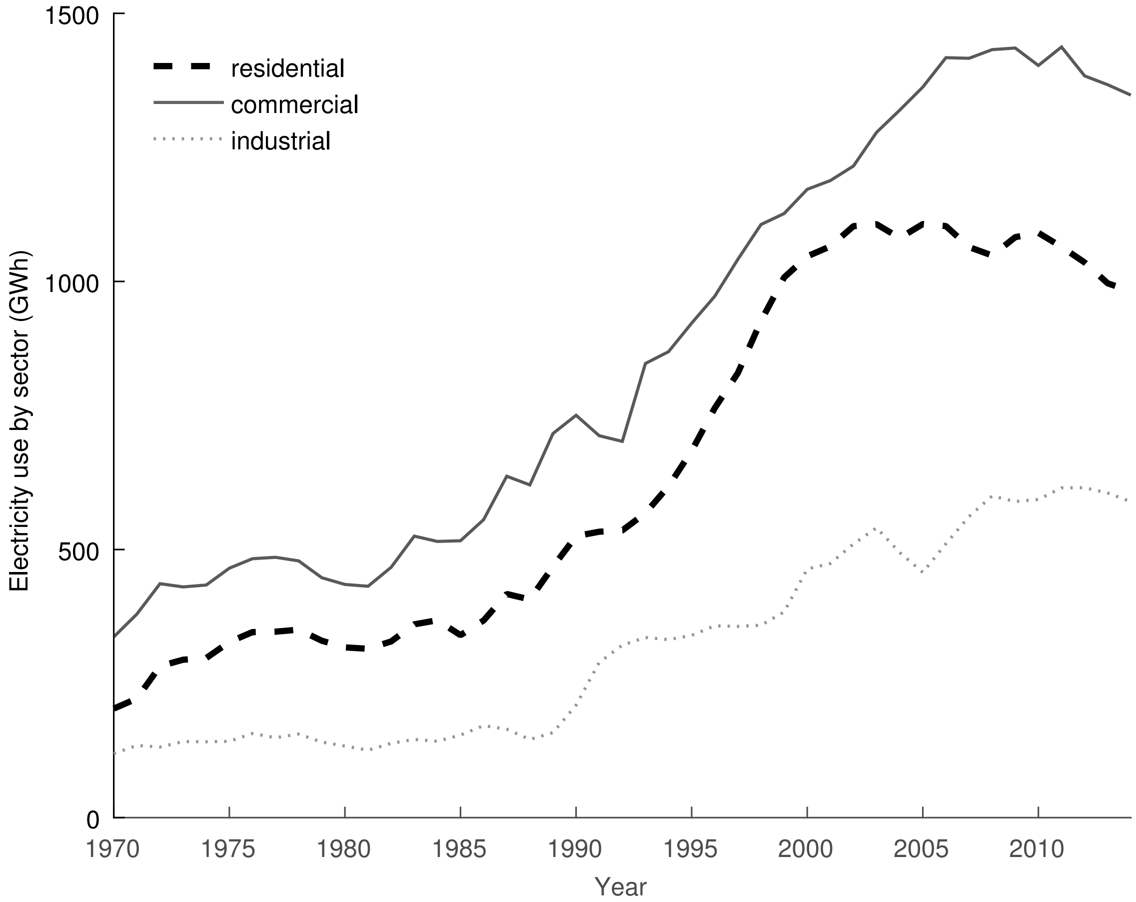

Figure 3.3: **Trends in sectoral electricity consumption in Jamaica, 1970–2014. Source: Compiled using data from various issues of ESSJ.**

diesel to meet 95% of the country's electricity needs, Jamaica's electricity prices are high by international standards given the lower prices observed in the USA and UK. The country fares better when compared to the Caribbean average of US$0.40 per kWh, even though prices are much lower in Trinidad and Tobago – an oil-producing country – and Belize.

The reform measures introduced in Jamaica in the early 1990s also resulted in persistent exchange rate depreciation against the US dollar[5] and sharp increases in nominal electricity prices, but this was not enough to slow electricity consumption, since real prices had not changed much prior to 2001. Figure 3.4 traces the evolution in nominal prices for the different sectors in Jamaica along with the GDP deflator. As expected, nominal electricity prices in all sectors rose faster than the GDP deflator which indicates that the price of electricity in the various sectors rose substantially in real terms, especially since 2001.

A comparison of Figures 3.3 and 3.4 suggests that electricity use might have slowed since 2001 as a result of tariffs becoming more cost-reflective, especially in the residential consumer segment. This follows the period of privatisation of the electric company and implementation of market-based regulatory approaches. Prior to 2001 real prices rose by 2% annually with consumption growth of 5% per year. However, since 2001 real prices have increased by 5% each year at the same time that electricity consumption grew by 0.7 per cent annually.

[5]Between 1991 to 2000, the nominal exchange rate had depreciated by over 8% annually.

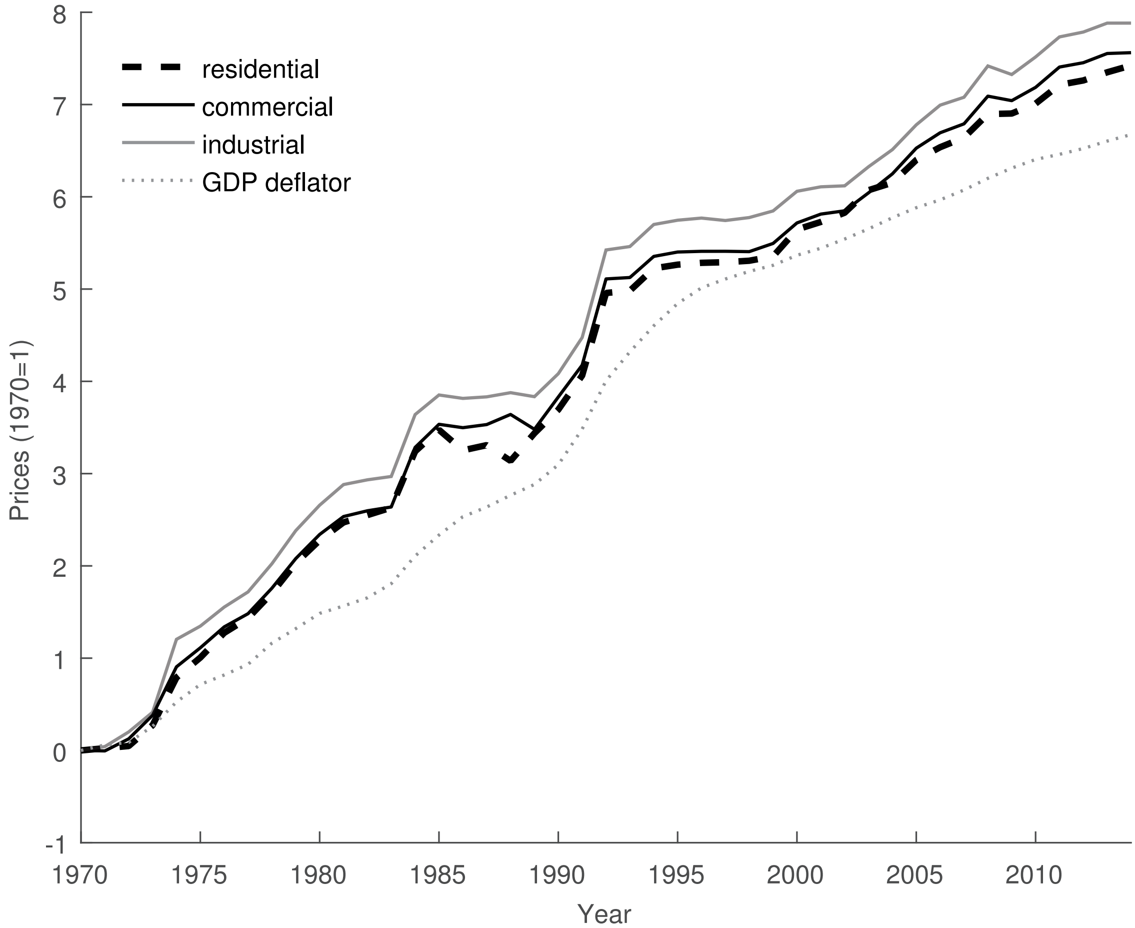

Figure 3.4: **Trends in sectoral electricity prices and GDP deflator in Jamaica: 1970–2014 (log scale). Source: Compiled using data from United Nations Statistics Division (2016b) and various issues of ESSJ.**

Table 3.1: **Average retail tariffs by country in 2012.**

Country	US$/kWh
Trinidad and Tobago	0.05
USA	0.07
Belize	0.20
UK	0.22
Barbados	0.34
St. Lucia	0.35
Bahamas	0.37
St. Kitts and Nevis	0.37
Jamaica	**0.37**
Curacao	0.38
St. Maarten	0.38
St. Vincent and the Grenadines	0.39
Antigua	0.40
Anguilla	0.41
Cayman	0.41
Grenada	0.42
Bahamas	0.45
Dominica	0.45
Bermuda	0.50
Montserrat	0.51

Source: Compiled using data from Bailey et al. (2013) and the US Energy Information Administration (2016).

3.4 Literature survey

Several aggregate demand studies have examined how consumption of electricity is influenced by price, income, and other determinants of electricity demand. For instance, De Vita et al. (2006) used quarterly data for Namibia between 1980 and 2002 and found long-run price and income elasticities of –0.3 and 0.6, respectively. In contrast, Amusa et al. (2009) did not find any significant influence of price but found that the effect of income on demand was elastic with a 1% increase in income resulting in aggregate demand rising by 1.7% in South Africa over the period 1960–2007. The short-run demand elasticities were also shown to be insignificant.

Many previous studies have adopted a disaggregated approach to estimating electricity demand with a primary focus on residential consumption. For example, Holtedahl and Joutz (2004) find a low long-run price elasticity (–0.15) but a high long-run income elasticity of 1.04 in Taiwan. In the South African case, Ziramba (2008) estimates long-run price and income elasticities of –0.01 and 0.33, respectively. A more recent study by Blázquez et al. (2013) find low short-run price and income elasticities (–0.07 and 0.23) in Spain with respective long-run elasticities of –0.19 and 0.61. In looking at the commercial sector, Bose and Shukla (1999) find that electricity consumption is price-inleastic (–0.26) and income-elastic (1.27) in the short run. For the industrial sector, Kamerschen and Porter (2004) find long-run price elasticity estimates in the range of –0.34 and –0.55 in the United States.

Ramcharran (1990) is the only known study to have examined electricity demand at the disaggregate level for Jamaica. Using a sectoral decomposition of electricity demand over the period 1970 to 1986, Ramcharran (1990) showed that for residential consumers, income was the only significant variable with respective short- and long-run elasticities of 1.21 and 4.17. For small industrial and large industrial consumers[6], income did not have any significant influence in the short or long run. However, the respective short- and long-run price elasticities were –0.26 and –0.43 for small industrial consumers and –0.19 and –0.52 for the large industrial sector.

The types of econometric techniques used to analyse the demand for electricity vary widely (Khanna & Rao, 2009). Ramcharran (1990) and Holtedahl and Joutz (2004), for example, apply Ordinary Least Squares (OLS) to estimate short-run and long-run elasticity coefficients. In testing for long-run cointegrated relationships, Asafu-Adjaye (2000) and Athukorala and Wilson (2010) used Johansen's cointegration technique. Glasure and Lee (1998) utilised Engle and Granger's cointegration and error-correction models. However, in recent times, the Pesaran et al. (2001) bounds testing approach to cointegration has become popular among econometricians because of its small-sample properties and the ability to mix the integration order of the independent variables. Rather than using single-country models, panel data methods also feature prominently in other studies such as Chen et al. (2007).

[6]These sectors correspond to the respective commercial and industrial categories used in this paper.

This paper combines a number of the above approaches to capture the effects of price and income on electricity demand in Jamaica. Specifically, it utilizes the bounds testing approach to cointegration to derive long-run price elasticities at the aggregate and sectoral level.

3.5 Methods and data

3.5.1 Econometric method and identification

To estimate price and income elasticities of electricity demand at the aggregate and disaggregate consumption levels, I begin with a simple logarithmic demand function relation without lagged effects given by

$$ec_{s,t} = \alpha_{s,0} + \alpha_{s,1} D88_{s,t} + \alpha_{s,2} p_{s,t} + \alpha_{s,3} y_{s,t} + \alpha_{s,4} u_{s,t} + \epsilon_{s,t} \tag{3.1}$$

where in year t, $ec_{s,t}$ is per capita electricity consumption at the aggregate level when $s = 1$ and per capita residential consumption when $s = 2$, while it represents total electricity consumption in the commercial and industrial sectors when $s = 3$ and $s = 4$, respectively. Electricity prices for the corresponding sectors are represented by $p_{s,t}$. The variable $y_{s,t}$ denotes per capita GDP at the aggregate level and per capita disposable income for residential consumers while total sectoral GDP is used to measure income for the respective commercial and industrial sectors. The urban share of the population $u_{s,t}$ is the same for all sectors and represents the proportion of people living in major cities in Jamaica. As cities become more densely populated over time, greater access and the diffusion of electricity-using devices can lead to sharp increases in electricity use, independent of electricity prices and income. Due to extensive damage to the electricity infrastructure caused by Hurricane Gilbert in 1988, I use a pulse dummy variable to account for a possible break in the electricity consumption series for each sector. This is defined as $D88_{s,t} = 1$ for the period 1988 and zero otherwise. The random-error term is given by $\epsilon_{s,t}$. All variables are in logs except the urban share of the population, which is expressed as a percentage. The use of a per capita specification for the aggregate level and the residential sector follows from standard practice while use of non-averaged values for the commercial and industrial sectors provide for a more rational interpretation of the models.

Excluding price p_t, all variables are expected to increase electricity consumption. However, the inclusion of price warrants further discussion as it is well-established that electricity consumption may be endogenous to price (see discussion by Anderson (1973), Taylor (1975), and Reiss and White (2005)). This implies that there may be a causal link going from consumption to price resulting in the price elasticity of demand being potentially biased upwards and appearing more elastic than expected. The relative magnitude of the bias is unlikely to be severe for a number of reasons. Firstly, most of the period under study is characterised by public ownership and rate-of-return regulation, as the electric utility was not privatised until 2001. Under this system, prices were set based on cost and demand projections using data from previous years. Therefore, prices at a particular point in time were not directly influenced by the contemporaneous use of electricity. Secondly, the World Bank (1996) reports that tariff increases were generally delayed or not approved while most of the annual variation in electricity prices is dictated by a complete pass-through of fuel cost[7] that is based on prices determined in global markets. This means that factors exogenous to the system had a major role in price determination. A similar line of argument was provided by Paul et al. (2009) in a study of electricity demand in the United States and Bernstein and Griffin (2006) who looked at regional differences in price elasticities of demand for energy.

Even if a reasonable solution to the potential endogeneity problem exists, good instruments for electricity prices are often difficult to find (Reiss & White, 2005). Instead, I identify the demand curve under the assumption that price is exogenous as previously argued and that all demand-related variables that affect electricity use are included in the model. While the latter assumption is necessary to allow shifts in the supply curve to trace out movements along the demand curve when the demand curve is fixed, the omission of some important demand or supply-side

[7]This can range between 70–75% of the total bill (Jamaica Public Service, 2014).

factor that influences price would result in omitted-variable bias (OVB). But in this case, the direction of the bias is less obvious.

In light of concerns related to biased coefficients in the static formulation, Autoregressive Distributed Lag (ARDL) models have evolved to correct parameters for endogeneity and spurious relations among variables that are driven by time effects (see Pesaran and Shin (1998)). In my final specification, I extend Equation 3.1 by employing the following ARDL bounds testing model which is estimated using OLS

$$\begin{aligned}\Delta ec_{s,t} &= \alpha_{s,0} + \alpha_{s,1} D88_t + \pi_{s,1} ec_{s,t-1} + \pi_{s,2} p_{s,t-1} + \pi_{s,3} y_{s,t-1} + \pi_{s,4} u_{s,t-1} \\ &\quad + \lambda_{s,i} \sum_{i=1}^{q-1} \Delta ec_{s,t-i} + \varphi_{s,i} \sum_{i=0}^{q-1} \Delta p_{s,t-i} + \psi_{s,i} \sum_{i=0}^{q-1} \Delta y_{s,t-i} + \delta_{s,i} \sum_{i=0}^{q-1} \Delta u_{s,t-i} + \epsilon_{s,t} \qquad (3.2)\end{aligned}$$

where $ec_{s,t}$, $p_{s,t}$, $y_{s,t}$, $u_{s,t}$, and $\epsilon_{s,t}$ are as previously defined, and i is the number of lags up to the optimal lag length q.

Aside from being suitable for small or finite sample sizes, an added benefit of this approach is the use of a single equation when the focus is only on those factors that influence electricity demand. This specification is also applicable when the underlying regressors are purely I(0), I(1), or mutually cointegrated (Pesaran et al., 2001). In contrast to the traditional cointegration techniques of Engle and Granger (1987), Johansen (1988), and Johansen (1991), testing of the variables under consideration for non-stationarity or unit root prior to determining the existence of level or long-run relationships is usually not required. According to Pesaran et al. (2001), pre-testing introduces additional uncertainty when modelling relationships among variables.

The bounds test model is based on the assumption that all regressors are weakly exogenous, but in the case of the commercial and industrial sectors, income may also be a source of reverse causality. In other words, electricity consumption in these sectors may increase income resulting in biased and inconsistent estimates. However, the size of this effect is likely to be smaller than the income elasticity of demand. Furthermore, if the model contains all the relevant demand shifters and cointegration is present, OLS estimates of such cointegrated variables are superconsistent than in models with stationary series. In such situations, there should be little concern about simultaneity bias.

The long-run relationship between ec_t, p_t, y_t, and u_t for each sector s is defined by $\gamma_2 = -(\pi_2/\pi_1)$, $\gamma_3 = -(\pi_3/\pi_1)$, and $\gamma_4 = -(\pi_4/\pi_1)$, respectively while the difference terms represent the short-run dynamics of the model which are not the focus of this paper. Instead of using non-linear functions to derive the long-run parameters, it is often more convenient to use an alternative specification of the model in Equation 3.2 so that the long-run parameters and their standard errors can be directly estimated. Two techniques are suggested by Pesaran and Shin (1998): the delta method and the instrumental variable (IV) approach of Bewley (1979). This study uses the Delta method to compute the long-run estimates and is discussed in more detail in Appendix A.3.

As Ouattara (2004) points out, even though most time series variables are either I(0) or I(1), the bounds test may be invalid when I(2) variables exist. To test for possible existence of I(2) variables, unit root testing is performed using Dickey and Fuller (1979) and Kwiatkowski et al. (1992) tests in the first stage. In the second stage, the null hypothesis of no cointegration among the variables is tested by restricting the coefficients of the lagged level variables in Equation 3.2 by setting them equal to zero and then testing their joint significance using the F-test. I use the Akaike information criterion (AIC) and Schwarz Bayesian Criterion (SBC) to select an appropriate lag length as proposed by Pesaran et al. (2001).

In the presence of a constant term and taking into account the number of regressors, the computed F-statistic should be compared with the critical value bounds available in Table CI Case III of Pesaran et al. (2001). Critical values are established at all three conventional levels of significance for both I(0) and I(1) variables. The lower bound represents I(0) variables and the upper bound represents I(1) variables. If the calculated F-statistic exceeds the upper bound, the null hypothesis of no cointegration is rejected. If the calculated value lies below the lower bound, the null hypothesis cannot be rejected. The test is, however, inconclusive if the F-statistic falls between the lower and upper bound as this would imply that the order of integration is not known.

The final step requires testing the stability of the ECM regression coefficients. Pesaran and Timmermann (2002) suggested using the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMQ) plots of Brown et al. (1975) to test the structural stability of the model. If the test statistic crosses the probability bands, then the hypothesis of parameter constancy is rejected. Additionally, a range of diagnostic tests are performed including Ljung and Box (1978) test for serial correlation, Jarque and Bera (1987) test for normality, Ramsey and Schmidt (1976) Reset test for functional form, and Engle (1982) test for heteroscedasticity. The absence of serial correlation is a crucial requirement for the validity of bounds testing. Pesaran et al. (2001) suggested that choice of an appropriate lag order is necessary to produce serially uncorrelated errors. In this case, the absence of serial correlation justifies the lag order selection for the ECM model. Confirmation of homoscedastic residuals indicates that errors have constant variance through time, a crucial requirement that also supports the validity of the bounds test. Normal distribution of the errors implies that valid inferences can be drawn from the results of the model.

3.5.2 Data

The time series data used in this study are annual and cover the period 1970 to 2014. The JPS currently serves twelve categories of customers, but I focus on three main customer segments: residential (Rate 10), commercial (Rate 20 and Rate 40), and industrial (Rate 50). At the aggregate level and for the residential sector, estimation is done in per capita terms. To proxy income of residences, I use real disposable income per capita denominated in 2007 local currency prices. The measure for income in the commercial and industrial sectors is based on the International Standard Industrial Classification (ISIC) of GDP. For the commercial sector, I use the wholesale, retail trade, restaurants, and hotels (ISIC G – H) and transport, storage, and communication (ISIC I) categories to measure the sector's annual income while the mining, manufacturing, utilities, and construction (ISIC C – F) GDP categories serve as a measure of income for the industrial sector. The nominal disposable income series were sourced from the Edward Seaga Research Institute (2016). Data on real GDP in local currency prices was provided by the staff of the Jamaica Productivity Centre (JPC) and the total population series were obtained from United Nations Statistics Division (2016a). Electricity tariff (J$/kWh) and consumption (GWh) data were gathered from various issues of the Economic and Social Survey of Jamaica. The electricity consumption series excludes electricity generated by captive plants for their own use but includes excess power sold to the grid. Nominal values are deflated using the implicit price GDP deflator obtained from United Nations Statistics Division (2016b).

I use the GDP deflator to capture broader changes in the price of all domestically produced goods and services rather than a subset of goods that are typically captured by other inflation measures. Choosing an appropriate deflator is important, especially in developing countries, since energy costs represent a key input cost component to other sectors of the economy. This means that changes in energy costs will directly influence the consumer price index. After food, services provided by the utility sector represents the second largest component of a consumer's typical budget in Jamaica (STATIN, 2016). Therefore any movement in the price of electricity would have a larger effect on the consumer price index relative to the GDP deflator. For comparison purposes, I also examine cases where deflating is carried out using the consumer price index or no deflator is used.[8] The descriptive statistics associated with the main variables are presented in Table 3.2 and shows some variability in the data from year to year for the different sectors especially as it relates to electricity consumption.

[8]Similar price elasticity estimates are derived when the consumer price index is used though the estimate for the residential sector is closer to unity and insignificant for the commercial sector. A nominal price measure was also used but the price elasticities were generally insignificant and had the wrong sign.

Table 3.2: **Descriptive statistics for main variables: 1970–2014.**

Variables	Mean	Maximum	Minimum	Standard Deviation
Aggregate				
Electricity consumption (kWh)	787.13	1205.16	393.31	285.22
Real electricity price (J$/kWh)	16.57	28.56	8.06	5.00
Real income (J$,$10^3$)	267.59	334.79	213.32	25.80
Residential				
Electricity consumption (kWh)	264.55	421.13	108.72	112.80
Real electricity price (J$/kWh)	18.66	33.29	10.23	5.49
Real income (J$,$10^3$)	261.11	341.09	175.30	49.71
Commercial				
Electricity consumption (GWh)	867.08	1437.28	337.00	392.39
Real electricity price (J$/kWh)	16.63	27.98	7.89	4.99
Real income (J$,$10^9$)	194.53	268.27	122.02	48.65
Industrial				
Electricity consumption (GWh)	320.04	615.31	119.50	182.59
Real electricity price (J$/kWh)	13.53	23.54	4.99	4.51
Real income (J$,$10^9$)	1668.65	2031.84	1259.03	198.36
Urban population share (%)	49.39	54.56	41.32	3.71

Source: Author's calculations. Real values are based on 2007 prices. For the aggregate level and residential sector, electricity consumption is measured in per capita terms. I also use real GDP per capita and real disposable income per capita to proxy income for those respective segments while total sectoral GDP is used for the commercial and industrial sectors, respectively.

Price measurement debate

In addition to concerns surrounding the endogeneity of price, there is some debate as to whether consumers respond to average or marginal prices. Traditionally, electricity prices in Jamaica have been based on a combination of a two-part tariff scheme and decreasing block rate design especially in the case of residential and commercial consumers. The two-part tariff consists of a fixed customer charge and variable component. The variable component follows the block rate structure where a higher energy charge per kWh is incurred for the first few units of electricity consumed within a certain range and a lower price for subsequent consumption blocks. As early as 2001 when the utility was privatised, an increasing block schedule was in place where large residential and commercial consumers pay higher prices. Also, a cross-subsidy in the form of a concessional rate currently exists with residential consumers of up to 100 kWh per month paying a much lower price than those who consume above that limit.[9] These issues highlight distinct differences in the average and marginal price among different users and across time, and the potential for biased coefficient estimates with block rate pricing structures.

In theory, consumer decisions are made at the margin and the correct price to use in the electricity demand equation is marginal price and not average price. Furthermore, consumption decisions are usually influenced by expected prices rather than the average price which is *ex-post* observed. However, the computation of marginal prices is infeasible for a number of reasons. Firstly, estimating a marginal price for each year requires detailed knowledge of the individual consumer total electricity bill and units of electricity consumed which is unavailable. Secondly, consumers face different price schedules throughout the year and not a constant marginal price. Despite these issues, some studies (for example, Halvorsen (1975)) have estimated marginal prices. However, Reiss and White (2005) point out that mis-measurement of the marginal price introduces measurement bias, which results in the price elasticity coefficient being biased towards zero and more inelastic

[9]The provision of a concessional rate for residential consumers is explicitly outlined in the 2001 and 2016 Jamaica Public Service Electricity Licence.

than it actually is. Furthermore, Halvorsen (1975) shows that price elasticities of demand are similar in log-linear models when marginal or average price is used, while Ito (2014) finds that consumers respond to average prices. For these reasons, I use the average unit price, which is calculated as total revenue attributable to each customer class divided by their respective sales volume.

3.6 Empirical results and discussion

Table 3.3 displays the OLS estimates for Equation 3.1. Panel A shows that naive estimation of the baseline model with only price and income as explanatory variables produces price coefficients that generally have incorrect signs and low explanatory power.[10] Additionally, the income coefficients are large and highly statistically significant except at the aggregate level where price was marginally significantly different from zero. The suspicion is that estimation of Equation 3.1 results in substantially biased electricity demand elasticities because important variables such as urban population share, population, and measures of infrastructure quality are omitted from the specification.

Panel B shows that controlling for an omitted variable such as urban population share produces estimates that differ considerably from the baseline model. The extended model has an exceptionally good fit, as measured by the adjusted R^2, between 0.93 and 0.99.[11] Furthermore, all coefficients have proper signs with the dummy variable being the only statistically insignificant variable in the case of the commercial sector. The test for cointegration on the static regression using the residuals-based approach shows that the spurious regression problem does not apply and there exists a long-run relationship among the variables for each sector. The coefficient for urban population share is highly significant in all sectors, but is unusually large and may be picking up the effects of time-related factors such as the diffusion of electricity-using devices. The estimates show that a one percentage point increase in urban population share leads to an approximate 10% increase

[10] In Appendix A.1.1, first-differencing the logarithms of the variables improve the results.
[11] Similar results are obtained with the dummy variable excluded.

in electricity use annually at the aggregate level and for commercial consumers, and by 11% and 17% for residential and industrial customers respectively, all else being the same. Assuming, *ceteris paribus*, the dummy variable shows that electricity consumption fell in 1988. These results suggest that the absence of the urban population share from the basic model results in biased coefficients.[12]

Table 3.3: **OLS estimates of the effect of price and income on electricity demand – static model.**

	Aggregate	Residential	Commercial	Industrial
Dependent variable: Log of electricity consumption				
Panel A				
Price	0.32	0.30**	0.49***	0.85***
	(0.24)	(0.13)	(0.08)	(0.28)
Income	1.47*	1.99***	1.78***	2.83***
	(0.80)	(0.20)	(0.10)	(0.84)
1988 Dummy	−0.18	0.06	0.01	−0.56
	(0.38)	(0.26)	(0.17)	(0.55)
Intercept	−12.60	−20.21***	−27.14***	−53.75**
	(10.46)	(2.67)	(2.63)	(22.17)
Adjusted R^2	0.02	0.69	0.20	0.09
Panel B				
Price	−0.22***	−0.42***	−0.15***	−0.34***
	(0.04)	(0.06)	(0.04)	(0.10)
Income	0.91***	0.42***	0.63***	0.88***
	(0.13)	(0.11)	(0.07)	(0.26)
Urbanisation	0.10***	0.11***	0.10***	0.17***
	(0.00)	(0.01)	(0.01)	(0.01)
1988 Dummy	−0.15**	−0.28**	−0.03	−0.42**
	(0.06)	(0.09)	(0.05)	(0.16)
Intercept	−9.18***	−3.70***	−0.11	−10.53
	(1.72)	(1.30)	(1.62)	(6.73)
Adjusted R^2	0.97	0.96	0.99	0.93
DF statistic	−2.12**	−2.90***	−2.88***	−3.39***
Observations	45	45	45	45

Notes: Asterisks '***', '**', and '*' denote significance at the 1%, 5%, and 10% critical levels, respectively with standard errors given in brackets. Electricity consumption and income are in per capita terms for the aggregate level and residential consumers. I use Dickey and Fuller (1979) (DF) regression to test the residuals from the estimated regression under the null of a unit root with a constant term included. If the null is rejected, cointegration exists among the unit root variables. The critical value for the test is –1.95.

Following the arguments outlined in Section 3.5, I report the results of the dynamic log-linear model from Equation 3.2 in Table 3.4. This model includes the

[12]If a time variable is used instead of urban population share, the price coefficients remain almost identical.

urban population share variable and captures lagged effects that were previously ignored. The urban population share was trend stationary while all other variables were first-difference stationary (see Appendix A.2 for more details). Each model passes the tests for serial correlation, heteroscedasticity, and normality at the 5 per cent level of significance using an optimal lag length of one. A lag length of three was used for the residential sector to address serial correlation and heteroscedasticity problems. The models for the commercial and industrial sector failed the functional form specification test based on Ramsey and Schmidt (1976) using the square of the fitted values. Therefore, the equations for these sectors may be mis-specified on the basis that there may be non-linearities in some of the independent variables which have not been accounted for. Compared to the results of Panel B in Table 3.3, the adjusted R^2 for the commercial and industrial sectors are similar, but slightly larger for the residential and aggregate level.

I then test the joint significance of the lagged level variables and the computed F-statistic confirms that the null hypothesis of no long-run cointegrated relationship is rejected for all sectors. The F-statistic value exceeds the values of the critical bounds at the 5 per cent level of significance for the optimal lag length, except for the commercial sector where cointegration is confirmed at the 10% level (see Appendix A.2 for more details on F-tests and optimal lag length selection). Given the presence of cointegration, the long-run coefficients are derived by normalizing on the lag level of *ec* in Equation 3.2 and are presented in Table 3.5.

The long-run results from Table 3.5 show some similarity to the estimates in Panel B of Table 3.3. For instance, the urban population share coefficient is within the same range (0.07–0.17) and highly significant. At the aggregate level, the income elasticities of demand are about the same (0.90) while the preferred bounds testing estimates suggest that the absolute value of the price elasticity is twice as large though still inelastic. For the most part, the price elasticities are larger except for the commercial sector where they were similar (–0.15). Electricity consumption was most inelastic in this sector with a 10% increase in price causing consumption to fall by 1.5%. In terms of magnitude,

Table 3.4: **OLS estimates of the ARDL model.**

	Aggregate	Residential	Commercial	Industrial
Dependent variable: Log difference of electricity consumption				
Panel A: Coefficients				
Intercept	−1.94	0.34	−0.89	−7.70*
	(1.20)	(0.68)	(1.38)	(4.06)
Electricity consumption$_{t-1}$	−0.27***	−0.35**	−0.41**	−0.39**
	(0.09)	(0.13)	(0.16)	(0.08)
Price$_{t-1}$	−0.11***	−0.29**	−0.06	−0.10
	(0.03)	(0.10)	(0.04)	(0.06)
Income$_{t-1}$	0.24**	0.09	0.31***	0.47***
	(0.10)	(0.07)	(0.11)	(0.17)
Urbanisation$_{t-1}$	0.03**	0.03*	0.03	0.07***
	(0.01)	(0.02)	(0.02)	(0.02)
1988 Dummy	−0.10***	−0.14***	−0.05	−0.17**
	(0.03)	(0.04)	(0.04)	(0.07)
ΔPrice$_t$	−0.19***	−0.19***	−0.17***	−0.08
	(0.03)	(0.04)	(0.04)	(0.07)
ΔIncome$_t$	0.46***	−0.01	0.35***	0.13
	(0.13)	(0.12)	(0.10)	(0.25)
ΔUrbanisation$_t$	−0.14	−0.24**	−0.22	0.15
	(0.10)	(0.11)	(0.15)	(0.27)
ΔElectricity consumption$_{t-1}$	0.04	0.12	0.03	0.35**
	(0.14)	(0.12)	(0.18)	(0.14)
ΔPrice$_{t-1}$	0.01	0.01	0.00	0.06
	(0.04)	(0.08)	(0.05)	(0.08)
ΔIncome$_{t-1}$	−0.18	0.01	−0.15	−0.16
	(0.16)	(0.11)	(0.13)	(0.28)
ΔUrbanisation$_{t-1}$	0.03	0.01	0.07	−0.07
	(0.08)	(0.16)	(0.13)	(0.23)
ΔElectricity consumption$_{t-2}$		−0.27**		
		(0.10)		
ΔPrice$_{t-2}$		0.01		
		(0.06)		
ΔIncome$_{t-2}$		−0.12		
		(0.11)		
ΔUrbanisation$_{t-2}$		0.13		
		(0.14)		
ΔElectricity consumption$_{t-3}$		0.09		
		(0.12)		
ΔPrice$_{t-3}$		0.02		
		(0.04)		
ΔIncome$_{t-3}$		0.03		
		(0.10)		
ΔUrbanisation$_{t-3}$		−0.11		
		(0.13)		
Panel B: Diagnostics				
$\bar{R}^2$	0.68	0.82	0.57	0.43
N	43	41	43	43
SC: χ_{lbq}	0.65[0.42]	0.00[0.99]	0.00[0.97]	0.60[0.44]
FF: χ_{rr}	5.12[0.16]	1.94[0.59]	23.18[0.00]	9.48[0.02]
Het:χ_{ea}	0.03[0.86]	1.40[0.24]	1.16[0.28]	0.11[0.74]
Norm: χ_{jb}	2.23[0.17]	1.76[0.25]	1.22[0.41]	1.63[0.29]

Notes: Asterisks '***', '**', and '*' denote significance at the 1%, 5%, and 10% critical levels, respectively with standard errors in brackets. $\bar{R}^2$ is the adjusted squared Pearson correlation and N is the number of observations. Standard errors are derived used the Delta method. Values in brackets for diagnostics represent p-values. Subscripts lbq, rr, ea, and jb are Ljung-Box Q-Test for serial correlation, Ramsey and Schmidt (1976) Reset test for functional form, Engle (1982) **A**RCH test for heteroscedasticity, and Jarque and Bera (1987) test for normality, respectively.

Table 3.5: **Long-run elasticity of demand estimates – ARDL model.**

Variables	Aggregate	Residential	Commercial	Industrial
Price	-0.40^{***}	-0.82^{***}	-0.15^{*}	-0.25^{*}
	(0.10)	(0.12)	(0.11)	(0.15)
Income	0.90^{***}	0.26^{*}	0.77^{***}	1.22^{***}
	(0.26)	(0.28)	(0.15)	(0.16)
Urbanisation	0.08^{***}	0.08^{***}	0.07^{***}	0.17^{***}
	(0.02)	(0.01)	(0.02)	(0.02)

Notes: Asterisks '***', '**', and '*' denote significance at the 1%, 5%, and 10% critical levels, respectively with standard errors given in brackets. Standard errors are derived using the Delta method.

these elasticity of demand estimates are within the bounds of previous studies in other countries. For example, Khanna and Rao (2009) show that in a survey of approximately 53 studies, the average value of the price elasticity of demand was between –0.11 and –1.01 in the long run with an average value of –0.6. In contrast to Ramcharran (1990) who did not find any significant effect, residential consumers appear to be most sensitive to price changes (–0.82) in Jamaica. The absolute value of the long-run price elasticity estimates in Ramcharran (1990) were also larger for the commercial and industrial sectors suggesting that there is an upward bias in the estimated coefficients due to the omission of the urban population share variable.

Excluding the industrial sector, electricity consumption appears to be income-inelastic in Jamaica. These results also differ from Ramcharran (1990) who found that residential consumption was highly income-elastic (4.17) compared to 0.26 in this study. In fact, residential consumption was the least responsive to income changes. Also, statistically significant income effects do emerge for the commercial and industrial sectors, but Ramcharran (1990) did not find any significant influence from these sectoral real income variables.

The results of the CUSUM and CUSUMQ tests are presented in Figures 3.5 and 3.6, respectively. The plots indicate that neither test rejects the null hypothesis that coefficients are stable. This is evidenced by the plot of both curves being confined within the 5 per cent critical region. The stability of all models over the period 1983 to 2014 at the aggregate level and for the commercial and industrial sectors and 1993 to 2014 for the residential sector is further evidence that the price elasticities are reliable and can be used to estimate the effects on future demand growth.

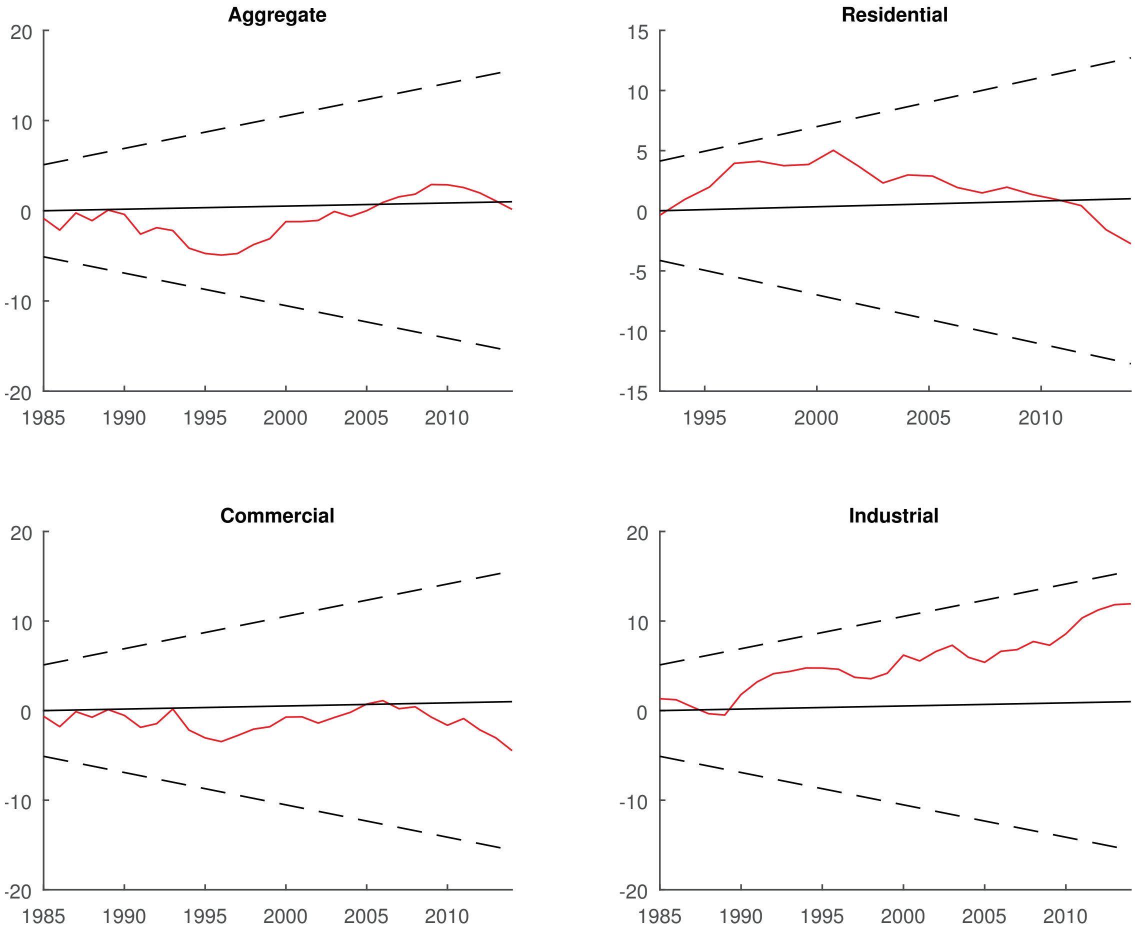

Figure 3.5: **Plot of cumulative sum (CUSUM) residuals. Dashed lines represent critical bounds at the 5 per cent level of significance.**

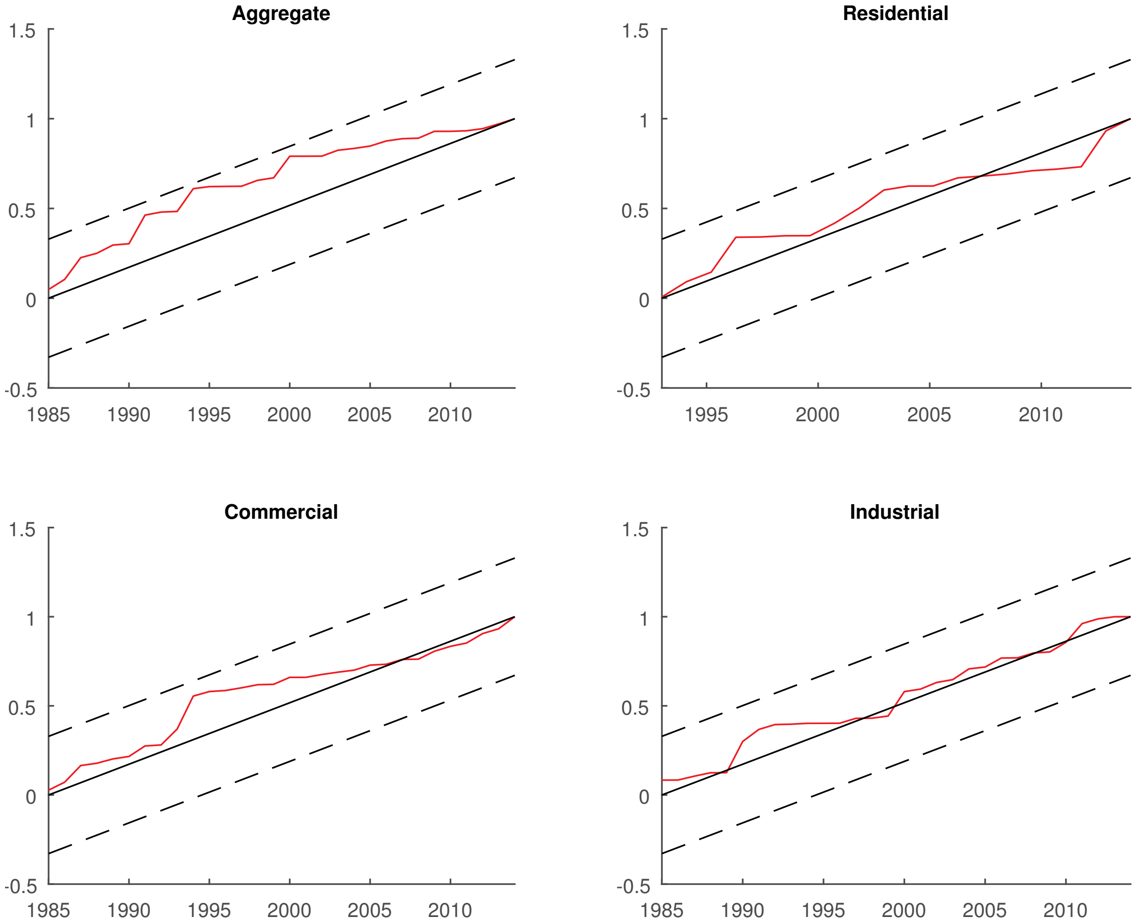

Figure 3.6: **Plot of cumulative sum of squares (CUSUMQ) residuals. Dashed lines represent critical bounds at the 5 per cent level of significance.**

3.7 Conclusions and policy implications

In this paper I have estimated the impact of the price of electricity, income, and urban population share on electricity consumption in Jamaica at the aggregate level and for three sectors: residential, commercial, and industrial. I used time series data covering the period 1970 to 2014 with the bounds testing approach to cointegration as my primary regression technique. My main empirical results suggest that price is a significant determinant of electricity at the aggregate level with a own-price elasticity of –0.40. The estimated price elasticities are –0.82, –0.15, and –0.25 in the residential, commercial, and industrial sectors, respectively. Commercial and industrial consumers are very responsive to changes in income as the respective income elasticities of 0.77 and 1.22 suggests.

By 2030, electricity consumption in Jamaica is expected to outstrip the available generating capacity. To meet the projected demand for electricity, the Office of Utilities Regulation estimates that approximately 1,400 MW of new generating capacity will need to be constructed, more than doubling existing capacity. Plans were put in place to have 360 MW added by 2016, but due to issues related to securing bids and financing, construction is yet to begin. In regards to these developments, demand management policies will become much more critical. It is natural to question the logic of slowing down the growth of electricity use. However, aside from obtaining environmental objectives, which is not such a major policy focus in Jamaica, probably the strongest argument is related to keeping demand in balance with existing generating capacity in light of the difficulties in attracting investments to expand the supply network. From a public policy perspective, use of the price instrument to ration electricity supply would be the least distortionary and more cost-effective especially in the case of residential consumption. Since raising prices will disproportionately affect vulnerable groups such as low-income households and the elderly, this should be done in a context that considers equity implications and distributional concerns.

It is not possible to say with certainty that these estimated long-run elasticities are more reliable than those in previous studies such as that conducted by Ramcharran (1990). However, the longer time span examined, the newly advanced econometric technique applied, and the tests for parameter constancy that confirm stability of the coefficients over time – an *a priori* assumption in many of the earlier studies – give credibility to these results. Nevertheless, one should be cautious and take these findings as being informative rather than definitive, since other factors such as the availability of alternative energy substitutes and technology could alter consumer responsiveness to price changes over time.

A Appendix

This appendix contains details of robustness tests performed, unit root tests, lag length selection, and a brief discussion of the Delta method.

A.1 Robustness analysis

As noted in Section 3.6, I estimated the static model without the urban population share in log-first-differences as a check against the level estimates. These estimates are reported in Table A.1.1. An important first observation is that all coefficient estimates have the correct signs, though price and income are insignificant for the industrial sector model.

A.2 Unit root tests and lag length selection

I test the integrational properties of each transformed variable in the dataset using the Augmented Dickey and Fuller (1979) test (ADF) and the Kwiatkowski et al. (1992) test (KPSS), with a null hypothesis of unit root and stationarity, respectively. The ADF test is based on estimating the following equation

$$x_t = \gamma^{'} D_t + \alpha x_{t-1} + \sum_{i=1}^{p} \beta_i \Delta x_{t-i} + \varepsilon_t \tag{A.2.1}$$

where D_t is a vector of deterministic terms: constant, trend or a combination of both. The coefficient vectors are represented by γ, α, and β while p is the number

Table A.1.1: **Log difference estimates of the effect of price and income on electricity demand – static model.**

Variables	Aggregate	Residential	Commercial	Industrial
Dependent variable: Log difference of electricity consumption				
ΔPrice	−0.12**	−0.15**	−0.16***	−0.05
	(0.04)	(0.06)	(0.04)	(0.08)
ΔIncome	0.61***	0.34*	0.37***	0.27
	(0.14)	(0.18)	(0.11)	(0.25)
1988 Dummy	−0.11**	−0.15**	−0.07	−0.19**
	(0.04)	(0.07)	(0.04)	(0.09)
Intercept	0.03**	0.03***	0.03***	0.04**
	(0.01)	(0.01)	(0.01)	(0.01)
Adjusted R^2	0.43	0.15	0.42	0.05
Observations	44	44	44	44

Notes: Asterisks '***', '**', and '*' denote significance at the 1%, 5%, and 10% critical levels, respectively with standard errors given in brackets. Electricity consumption and income are in per capita terms for the aggregate level and residential consumers.

of lagged difference terms of the variable x_t. The value of p is set so that the error term ε_t is serially uncorrelated.

The KPSS test on the other hand is used to assess whether the series are unit root non-stationary. It assumes the following model

$$x_t = c_t + \delta t + u_t \tag{A.2.2}$$

$$c_t = c_{t-1} + \epsilon_t \tag{A.2.3}$$

where u_t is a stationary process and ϵ_t is an independent and identically distributed process, $i.i.d \sim (0, \sigma_\epsilon^2)$. The initial value c_0 is assumed to be fixed and is regarded as an intercept term. The test is $H_0 : \sigma_\epsilon^2 = 0$ (the series is trend stationary), against $H_1 : \sigma_\epsilon^2 > 0$ (not trend stationary) where the time series x_t is characterized by a deterministic trend. If $\delta = 0$, under the null hypothesis, x_t is stationary around a constant c_0 rather than a trend. Thus, the KPSS test serves as a useful complement to the commonly employed ADF test since it can be used to verify its results.

As graphical evidence highlights the presence of a trend especially in the electricity consumption series and income series, I only consider the case where both the constant and trend terms are included in the ADF test. The results of the ADF and KPSS procedures are presented in Table A.2.2. The ADF test could not reject the null hypothesis of unit root for all variables in log levels at the 5% level of significance except in the case of income for the commercial sector which seems to be trend stationary. The differenced series showed support for stationarity for all variables at the 5 per cent level of significance except the urban population share variable for the commercial sector. In some cases the KPSS test supports the results of the ADF test, but there are contradictions as well. For example, the urban population share variable is trend stationary and first-difference stationary based on the KPSS test but non-stationary when the ADF test is applied. In instances like these I use the results of the KPSS test since it is believed to be more robust to structural breaks in the series. Therefore, I assume that urban population share is I(0) since it is also stationary at the 10% level of significance when the ADF test is used.

The confirmation of $I(0)$ or $I(1)$ variables based on the applied unit root testing procedures allow us to apply the bounds F-test to Equation 3.2 , but choice of an appropriate lag length is important since the specification assumes serially uncorrelated errors. To determine the optimal lag length, Equation 3.2 is estimated by OLS for $q = 1, 2, 3$. The maximum lag length is restricted to three based on the common rule of thumb $\sqrt[3]{T}$, and the small sample size available. As the results of Table A.2.3 show, both AIC and SBC confirm a lag order of one as being appropriate in both models to avoid residual serial correlation and sufficiently capture the dynamics in the model.

A.3 Deriving long-run parameters using Delta method

The Delta method is more common and simpler than the Bewley (1979) regression approach. In terms of the Delta method, if G is a transformation function and the random variable X has mean μ, then $G(X)$ can be approximated by $G(X) = G(\mu) + (X - \mu)G^{'}(\mu)$ where $G^{'}$ is a vector of partial derivatives of $G(X)$. Therefore, the variance of $G(X)$ is given by $Var(G(X)) = G^{'}(\mu)Var(X)[G^{'}(\mu)]^{'}$ where $Cov(X)$ is

Table A.2.2: **Results of ADF and KPSS unit root tests.**

Variable	ADF		KPSS		Conclusion
	Log Levels	Log-first-differences	Log Levels	Log-first-differences	
Aggregate					
Electricity consumption	−1.47	−4.67***	0.25***	0.15**	I(1)
Price	−2.23	−3.65**	0.27***	0.17**	I(1)
Income	−3.36*	−5.03***	0.31***	0.10	I(1)
Urbanisation	−3.31*	−1.55	0.17*	0.14*	I(0)
Residential					
Electricity consumption	−2.18	−4.94***	0.24***	0.15**	I(1)
Price	−2.16	−3.87**	0.25***	0.13*	I(1)
Income	−2.92	−4.37***	0.32***	0.09	I(1)
Urbanisation	−3.31*	−1.55	0.17*	0.14*	I(0)
Commercial					
Electricity consumption	−1.21	−5.33***	0.23***	0.11	I(1)
Price	−2.24	−3.71**	0.27***	0.15**	I(1)
Income	−4.72***	−1.96	0.30***	0.12*	I(1)
Urbanisation	−3.31*	−1.55	0.17*	0.14*	I(0)
Industrial					
Electricity consumption	−2.65	−4.53***	0.24***	0.09	I(1)
Price	−2.53	−3.39*	0.29***	0.18*	I(1)
Income	−2.50	−4.19***	0.21**	0.10	I(1)
Urbanisation	−3.31*	−1.55	0.17*	0.14*	I(0)

Notes: The critical values for the ADF model in levels and first differences with only a constant and trend term included at 1%, 5%, and 10% are –4.19, –3.52, and –3.19, respectively. These values are 0.216, 0.146, and 0.119, respectively, for the KPSS test for both levels and first differences. Asterisks '***', '**', and '*' denote rejection of the null at the 1%, 5%, and 10% critical levels, respectively. Maximum lag length for the ADF and KPSS test is based on Schwert Criterion. The optimal lag length is selected using the SBC criterion for the ADF test while the KPSS test uses the maximum lag. All variables are in logs except urban population share which is in percentages.

Table A.2.3: **Lag order selection.**

Sector	Lag lengths	AIC	SBC	SC statistics	F-statistics
Aggregate	1	16.69	39.58	0.65	8.86
Residential	3	32.58	68.56	0.00	5.10
Commercial	1	17.01	39.91	0.00	3.96
Industrial	1	17.71	40.61	0.60	6.08

Notes: Optimal lag length is based on $\sqrt[3]{T}$ and SC is the serial correlation statistic. The pairs of critical values for the F-statistic at 1%, 5%, and 10% are 4.29–5.61, 3.23–4.35, and 2.72–3.77 respectively, with $k = 3$ independent variables. Critical values are from Pesaran et al. (2001), Case III.

the variance-covariance matrix of X.

Chapter 4

Cap prices or cap revenues? The dilemma of electric utility networks

4.1 Chapter overview

Having estimated the price elasticity of electricity demand at the aggregate level and for different markets, one can use these estimates to analyse the behaviour of alternative electricity pricing schemes under different scenarios. Similar to the previous study, I use Jamaica as a case study and set out to determine if price cap regulation leads to greater efficiency and lower welfare losses than a revenue cap pricing scheme.

In this chapter, I set out to specifically analyse the behaviour of a monopoly electricity provider that serves three distinct markets under a price cap or revenue cap plan. I make comparisons in terms of their effects on price setting, energy conservation, and total welfare.

In addition to contravening the Ramsey pricing rule, I find that under conditions of information asymmetry, when demand becomes more elastic or marginal cost increases, revenue cap price increases are larger relative to price cap regulation. In this specific setting, revenue cap price increases encourage energy conservation but are less likely to do so when marginal cost is large in a market that is more elastic relative to others. In contrast to a price cap plan, these overall results show that revenue cap schemes are welfare-reducing.

For public decision-making purposes, price cap regulation is more desirable especially in developing economies that often experience substantial inflationary pressures from global oil market developments but is less suitable than revenue cap regulation when electricity supply constraints and climate change are major policy concerns.

4.2 Introduction

Public network industries such as electricity markets were traditionally governed by rate-of-return (ROR) regulation. However, this regulatory approach was often criticised for its lack of incentives in minimising costs and tendency to encourage too much investment in capital (Averch & Johnson, 1962; Laffont & Tirole, 1993; Sappington, 1994). As electricity sectors underwent major market reforms, ROR was eventually replaced with incentive regulation schemes to constrain the market power of privatized utilities and encourage efficiency.

In light of the many incentive schemes that exist, advocates such as the Australian Energy Regulator (2013) and the Jamaica Public Service (2014) claim that replacing price cap with revenue cap regulation will provide greater incentives for cost recovery and investment in energy efficiency and promote energy conservation in electricity markets. The ineffectiveness of price cap regulation in encouraging energy conservation from a demand-side perspective is widely discussed in the literature (see, for example, Wirl (1995) and Sappington and Weisman (2010)). However, proponents of price cap regulation argue that in contrast to price cap regimes, revenue cap regulation incentivises price increases that depart from the Ramsey pricing rule, creates output restrictions, and may lead to major reductions in societal welfare (Comnes et al., 1995; Crew & Kleindorfer, 1996b; Decker, 2009). Others such as Dutra et al. (2015) find that price cap regulation induces incentives for supply-side energy efficiency by reducing network losses while both schemes can be implemented to achieve the same level of welfare.

The arguments in support of a particular incentive pricing plan have evolved from a theoretical framework without knowledge of behavioural differences in practice. Therefore, I aim to reconcile the arguments by using actual industry parameters to quantitatively assess differences in revenue and price cap schemes in terms of prices, energy conservation, and welfare. This represents the first known attempt at performing a comparative analysis of both schemes using parameters calibrated with industry data. I take a demand-side management focus and use a firm operating under a vertically integrated electricity market structure. To capture the regulator's problem of information asymmetries recognised by Laffont and Tirole (1993), I also address cost and demand uncertainties.

Understanding differences between either scheme has important policy implications. For example, developing countries that generate a substantial portion of their electricity from imported fuels are more prone to price instability and may show a preference for price cap regulation to ease inflationary pressures on the local economy. This is of particular significance when there is substantial pass-through to domestic inflation. However, if the argument for energy conservation holds for a revenue cap, heightened security of supply and climate change concerns may necessitate the use of revenue cap regulation which favours price increases. This is important since climate-induced changes in the quantity of electricity demand can give rise to higher emissions during peak demand hours (Chen et al., 2015) and end-use efficiency has the potential to create substantial reductions in greenhouse gas emissions in developing countries (Kroeze et al., 2004). In this particular case, caution should be exercised since increased prices could result in the substitution of oil and gas-fired generating units for cheaper and more carbon-intensive technologies such as coal (Xie et al., 2014). In general, choice of a specific scheme will involve trade-offs and is dependent on the goals of government and regulators.

To reconcile the theoretical arguments linked to both schemes, I use a constrained optimization problem similar to Brennan (1989) and De Villemeur et al. (2003) and apply it to the electricity network in Jamaica. The remainder of the paper is organized as follows: Section 4.3 provides a brief overview of market reforms and various incentive regulation schemes. Section 4.4 presents the main electricity pricing models used. In sections 4.5 and 4.6, I calibrate each pricing model with parameter values that approximate the key characteristics of the regulated entity, perform analyses, and report their results. Section 4.7 highlights the main conclusions and policy implications of the study.

4.3 Market reforms and incentive regulation

Policymakers in both developed and developing countries have long believed that it is most efficient for electricity to be supplied by a single firm. It is this thinking that gave rise to the creation of a natural monopoly characterized by common ownership and sole responsibility for electricity generation, transmission, and distribution services. Joskow (1997) postulates that utilities have maintained this vertically integrated structure because of significant operating and investment complementarities that allowed them to benefit from economies of scale and scope. However, this traditional belief is increasingly being challenged. Indeed, many developed and developing countries have implemented major structural and regulatory reforms to promote competition within the electricity sector.

Large-scale reform measures in electricity sectors across developed countries date back to as early as the 1980s. These reform measures were largely aimed at introducing private sector participation and the promotion of competition through economic regulation. In contrast, the introduction of substantial reforms in the electricity sectors of developing countries has been a much more recent phenomenon. It was not until the early 1990s and 2000s that such reforms were initiated.

To clarify the way in which a country's power sector reform measures have transitioned, a classification system was subsequently developed by the European Bank for Reconstruction and Development (EBRD). The EBRD classifies countries into five categories with Level 1 involving extensive government control and Level 4+ consisting of large-scale private involvement. Based on the EBRD's definition of sector transition, many developing countries have transitioned according to Level 4. Under this transition process, "Law[s] for industry restructuring [are] passed and implemented providing for: separation of the industry into generation, transmission and distribution; setting up of a regulator, with rules for setting cost-reflective tariffs formulated and implemented. Arrangements for network access (negotiated access, single buyer model) [are] developed. [There is also] substantial private sector involvement in distribution and/or generation" (European Bank for Reconstruction and Development, 1998).

Bacon and Besant-Jones (2001) argue that, comparatively, introducing electricity reform measures in developing countries is more challenging than in developed countries and every effort should be made to ensure that such measures are both desirable and politically feasible before implementation.

4.3.1 Incentive regulation plans

Tariff setting in electricity markets consist of either rate of return regulation or incentive regulation schemes. Traditionally, rate of return regulation has been the primary means of regulating utilities, where the utility is allowed to recover its costs and a guaranteed rate of return. This pricing methodology has been criticized on a number of grounds, most notable of which is the incentive it gives to firms to over-invest in capital as was first pointed out by Averch and Johnson (1962). As Laffont and Tirole (1993) argued, optimal incentive schemes should be designed to address the principal-agent problem associated with asymmetric information. The principal (regulator) has far less information about the utility's (agent) operations. For instance, regulated firms are better informed about the cost of providing electricity and consumer demand behaviour.

A myriad of incentive regulation schemes exist in practice but in this work I only discuss common types such as price cap regulation, revenue cap regulation, sliding-scale regulation, and yardstick competition (see discussion in Vogelsang (2002)). Relative to ROR where consumers bear all the risks and since operating and investment costs are reflected in price increases, differences among incentive schemes are largely explained by risk allocation and incentives.

I begin the discussion with price cap regulation which is the preferred form of regulation used to incentivise cost reductions and constrain the market power of privatized utilities in the United Kingdom and many Latin American countries. Under a price cap, constraints are placed on the path of prices for services provided by a regulated firm during a fixed period of time. With prices constrained, firms increase profits by reducing cost or increasing sales. Therefore, unexpected cost changes and volumetric risk are borne mostly by the firm. This reduces the moral hazard problem present in managerial effort, but if regulators have limited knowledge of the firm's ability to reduce costs this can potentially allow the firm to extract significant rent from consumers or it can lead to the firm's detriment (Joskow, 2007). Another drawback of price caps is the potential to deter investment and reduce service quality (Sappington, 2002) as effort is expended at minimising cost though Banerjee (2003) does not find any evidence that price cap causes deterioration in service quality. Despite its shortcomings, Armstrong and Vickers (2012) show that total welfare can increase when regulated firms operate under a price cap by limiting cross-subsidizing pricing behaviour.

In order to overcome volumetric risk, European countries such as Norway and Sweden show a preference for revenue cap regulation (Jarvis, 2011). In its simplest form, constraints are placed on the regulated firm's revenues rather than prices. Hirst et al. (1994) advocated for the use of revenue caps based on the idea that they provide greater incentives for demand-side management compared to price cap regulation. Though both schemes encourage cost reduction, price cap encourages higher sales while a revenue cap promotes energy savings through flexible price adjustments. Under a binding revenue cap, the only lever for the firm to increase profit is to reduce costs by reducing output or increasing price. Revenue caps are more suitable in situations where the positive covariance between costs and sales is low. If tariffs are reflective of the utility's costs and demand is inelastic, a price rise will reduce the quantity of electricity demanded and total costs, while increasing revenue. With the revenues of the utility capped, the reduction in costs will translate directly into profits. This incentivises price increases for the least inelastic market segments served by utilities. This idea was advanced by Jamison (2007) and was similarly supported by Lantz (2008) who emphasized that use of revenue caps is a 'bad idea' when detailed information on the firm's cost function is not available. A revenue cap may also lead to substantial reductions in social welfare since the regulated firm is likely to deviate from Ramsey pricing by charging higher prices to consumers as demand becomes more elastic (Comnes et al., 1995; Crew & Kleindorfer, 1996b). Crew and Kleindorfer (1996b) also claim that revenue caps provide incentives for price increases that could exceed the unregulated monopoly level resulting in substantial reductions in total welfare.

Price caps are bad at extracting information about the firm's ability to reduce costs and can lead to supernormal profits, but provide good incentives for managers to minimise production costs – a limitation of ROR schemes. As a result, sliding-scale regulation serves as a compromise between price cap and ROR schemes (Lyon, 1996). Many incentive regulation schemes are hybrid in nature, but the general rule is that sliding-scale regulation allows for provisions that redistribute extra rents to customers if the company earns profits in excess of the allowed rate of return. They can also be symmetric – allowing for price increases when the firm is exposed to losses beyond a certain limit (Parker & Kirkpatrick, 2005). In either case, downside and upside risks are shared by consumers and the firm. However, information requirements can be substantial relative to other schemes (Parker & Kirkpatrick, 2005) and the utility may not be motivated to pursue efficiency as strongly when excess profits are shared (Crew & Kleindorfer, 1996a).

In terms of yardstick competition, this entails comparing firms engaged in the same line of business with each other. To infer the efficient cost level, the regulator uses the costs of comparable firms as a benchmark (Shleifer, 1985). As the firm's price and own cost drivers are delinked, this regulatory mechanism provides the regulated firm with robust incentives to employ optimal effort in reducing costs below the industry average since it is the sole beneficiary of these cost reductions. The heterogeneous environment that regulated entities operate in may not be suitable for this kind of regulatory mechanism (Jarvis, 2011). For instance, it would be misleading or impractical to compare firms that differ in terms of geographical location and customer base and the integrated and monopolistic nature of electricity markets in developing countries makes it an infeasible policy approach. Furthermore, the possibility of collusive behaviour among firms cannot be ruled out (Potters et al., 2004). This regulatory approach is typically used alongside other schemes and is generally applicable in developed countries that often have unbundled market structures. Norway's incentive regulation scheme also has elements of yardstick regulation (see Appendix A.1).

Despite the many incentive regulation schemes that exist, I focus only on differences between price and revenue cap regulation in light of the regulator's plan to switch from a price cap to revenue cap in Jamaica. Before exploring this issue, however, I discuss Jamaica's electricity market in more detail in the next section. Examples of other countries that use price and revenue cap regulation schemes are provided in Appendix A.1.

4.3.2 Price cap regulation in Jamaica

The initial motivation behind structural reform measures implemented in Jamaica largely resulted from the need to improve financial performance and operational efficiency of government-owned enterprises. This was primarily seen as an opportunity to relieve taxpayer burden and to improve the operational efficiency of the utility rather than a genuine means to introduce competition. The process of reform measures undertaken can be broadly divided into three categories: (1) private sector participation; (2) structural reforms to address the vertical separation of electricity supply functions such as generation, transmission and distribution; and (3) regulatory reforms that codify behaviour and provide incentives for utilities to operate efficiently.

In 2001, the Government of Jamaica sold 80% of its stake in the Jamaica Public Service – the sole electricity supplier in Jamaica. Majority share ownership is held jointly between Marubeni Caribbean and Korea East-West Power Company Limited (Jamaica Public Service, 2013b). The government of Jamaica retained 19% while the final 1% is owned by minority shareholders. That same year, price cap regulation in the small developing country was applied to a vertically integrated electricity network with approximately 820 MW of installed generating capacity. Under the Office of Utilities Regulation (OUR) Act of 1995, regulation and oversight of the sector remains the responsibility of the OUR which was established in 1997 by an Act of Parliament. Its responsibilities include the issuance and review of licenses, review of five-year tariff applications and requests for annual increases, and the investigation of breaches by the electricity provider. In addition to this, the OUR issues and reviews Requests for Proposals (RFPs) for capacity addition to the electricity grid (Office of Utilities Regulation, 2004).

Jamaica's electricity generation sector was fully liberalized in 2004 but most of the approximately 820 MW of electricity needed to meet demand in the country is still generated by the JPS. The majority of JPS' electricity is generated from imported fossil fuel, but it also owns eight hydro-electric plants with capacity of approximately 25 MW. Of the total required capacity of the country, 215 MW of capacity is available to the distributor under long-term (20 years) power purchase agreements (PPAs) with the four independent power producers (IPPs).

Even though competition has been introduced into the generation segment and regulatory entry barriers have been eliminated, the JPS retained its vertical structure and continues to perform the functions of generation, transmission, and distribution. On the generation side, a number of private entities operate alongside the state-owned generator to supply electricity to the national grid owned and operated by the monopoly distributor (Jamaica Public Service, 2013b).

Price cap regulation was introduced alongside privatisation in 2001. The specific form of the cap is

$$p_t = p_{t-1}(1 + dI + X + Q + Z) \tag{4.1}$$

where p_{t-1} is the non-fuel tariff at the beginning of the price cap period, dI accounts for inflation and exchange rate devaluation, X is an efficiency target, Q is the allowed price adjustment to reflect changes in the quality of service provided to the customers, and Z is the allowed rate of price adjustment for special reasons not captured by the other elements of the formula (Office of Utilities Regulation, 2004).

Under this regime, all costs except fuel are passed on fully to customers –

irrespective of the price of fuel – subject to heat rate and electricity distribution loss adjustments. It was originally implemented for three years with X and Q set to zero. The idea was to allow the utility some time to improve efficiency and give the regulator time to develop appropriate measures of X and Q before the regime was fully implemented in June 2004 and the price cap period extended to five years.

In 2014, the JPS requested that the Office of Utilities Regulation change the existing price cap plan to a revenue cap (Jamaica Public Service, 2014). Without any empirical justification, the electricity provider argued that a revenue cap would ensure that sufficient revenues are earned to cover all prudent costs in addition to the return on investment. Additionally, it advocated for a revenue cap on the basis that it encourages energy conservation and efficiency. After nine months of deliberations, the regulator rejected the proposal in January 2015 using theoretical arguments similar to those presented by Comnes et al. (1995) and Crew and Kleindorfer (1996b). In January 2016, however, the proposal was approved by the regulator. In light of this situation, the regulated electric utility in Jamaica serves as a natural case study since it has an established price cap regulatory regime that has been in operation since 2001, but now operates under a revenue cap scheme.

4.4 Optimisation models

To examine how price regulation compares with revenue cap regulation, I first present a basic model of a regulated, multi-product distribution firm with a monopoly in each market segment. This is followed by the specific setup of the Ramsey (1927) pricing, price cap, and revenue cap constrained optimisation problems.

If $i = 1 \ldots n$ represent each market segment, c_i is marginal cost for market i, q_i is the electricity sold in each market, p_i is the retail price of electricity in market i, and F is common fixed cost, the firm seeks to maximize the profit function at time

t such that

$$\pi_t = \sum_{i=1}^{n} [p_{i,t} - c_{i,t}]\, q_{i,t}(p_{i,t}) - F_t \tag{4.2}$$

To simplify the model, I assume that demand in each market segment is independent so that the cross-price elasticities are zero. Residential consumers, for instance, do not use more electricity in response to an increase in the price of commercial or industrial electricity tariffs.

I also assume a constant-elasticity demand function for each market segment of the form

$$q_{i,t}(p_{i,t}) = \alpha_i {p_{i,t}}^{-\epsilon_i}, \quad 0 \leq \epsilon_i < 1 \tag{4.3}$$

where $\epsilon_i = -\frac{\partial q_{i,t}}{\partial p_{i,t}}.\frac{p_{i,t}}{q_{i,t}}$ is the elasticity of demand for electricity with respect to electricity tariffs. This functional form assumes that there will be some demand for electricity irrespective of the price if $\alpha_i > 0$.

Using the inverse demand function $p_{i,t}(q_{i,t})$, total value V to consumers of consumption quantity $q_{i,t}$ is the area under the demand curve given as

$$V(q_{1,t},..,q_{n,t}) = \sum_{i=1}^{n} \int_0^{q_{i,t}} p_{i,t}(q_{i,t})\, dq_{i,t}. \tag{4.4}$$

We can then determine consumer surplus CS by evaluating Equation 4.4 over the range (0, $q_{i,t}$) and substituting Equation 4.3 into its solution such that

$$CS(p_{1,t},..,p_{n,t}) = V(q_{1,t}(p_{1,t}),\ldots,q_{n,t}(p_{n,t})) - \sum_{i=1}^{n} p_{i,t} q_{i,t}(p_{i,t}) \tag{4.5}$$

On the other hand, the value of producer surplus PS is calculated as

$$PS(p_{1,t},..,p_{n,t}) = \sum_{i=1}^{n} [p_{i,t} - c_{i,t}]\, q_{i,t}(p_{i,t}) \tag{4.6}$$

4.4.1 Ramsey pricing

The first-best solution for pricing electricity is marginal cost pricing because it maximizes social welfare. However, marginal cost pricing will result in the regulated firm making a loss, thus requiring the regulator to opt for the second-best Ramsey (1927) pricing rule, which maximizes social welfare subject to the constraint that the firm break even. Under this pricing rule, the firm will increase prices, above marginal cost, for goods with inelastic demand. In contrast, goods with higher elasticities of demand will have lower prices. Ramsey pricing therefore serves as a natural benchmark for analysing the differences between price and revenue cap schemes and is discussed first.

Formally, a regulator that is well-informed about the firm's cost and demand structure will aim to maximize total welfare defined as the sum of consumer surplus CS and producer surplus PS, subject to the break-even constraint. Thus, Ramsey prices maximize the following Lagrangian

$$\max_{p_{i,t},\lambda} \mathcal{L} = CS + PS - \lambda \left(\sum_{i=1}^{n} [p_{i,t} - c_{i,t}]\, q_{i,t}(p_{i,t}) - F_t \right) \tag{4.7}$$

The first order condition with respect to price is

$$\frac{\partial \mathcal{L}}{\partial p_{i,t}} = p_{i,t}\frac{\partial q_{i,t}}{\partial p_{i,t}} - c_{i,t}\frac{\partial q_{i,t}}{\partial p_{i,t}} - \lambda \left[q_{i,t} + p_{i,t}\frac{\partial q_{i,t}}{\partial p_{i,t}} - c_{i,t}\frac{\partial q_{i,t}}{\partial p_{i,t}} \right] = 0 \tag{4.8}$$

Solving Equation 4.8 results in

$$\mu_i = -\left(\frac{\lambda}{1-\lambda} \right) \frac{1}{\epsilon_i} \qquad i = 1, \ldots, n \tag{4.9}$$

where $\mu_i = \frac{p_{i,t} - c_{i,t}}{p_{i,t}}$ and λ is the shadow price indicating how much total welfare will increase when profits are reduced by one dollar.

With Ramsey prices, the mark-up of price over cost is inversely proportional to the price elasticity of demand in each market. This implies that prices and mark-ups are higher in market segments with lower price elasticity of demand (Baumol & Bradford, 1970). Under the assumption that price is greater than marginal cost, we have that $\lambda < 0$. However, if $\lambda = 0$, the break-even constraint is not binding and Equation 4.9 reduces to first-best pricing where price equals marginal cost, that is $p_{i,t} = c_{i,t}$.

4.4.2 Price cap

In light of information asymmetries that usually exist between the regulator and the regulated entity, Laffont et al. (1996) and De Villemeur et al. (2003) argue that the regulator can decentralize Ramsey prices using a global price cap formula that allows the utility to choose its prices when there is uncertainty about the firm's demand and cost structure. To move directly to Ramsey prices, quantity weights under the price cap must be proportional to actual quantities generated from the Ramsey pricing equation in Section 4.4.1.

To illustrate the mechanics of this process, I follow Neu (1993) and assume that the regulated firm maximizes profit subject to a global price cap constraint where the weighted average of price changes of the n regulated market segments between $t-1$ and t must not exceed zero shown by

$$\sum_{i=1}^{n} (p_{i,t} - p_{i,t-1})\, w_i \leq 0 \tag{4.10}$$

where w_i is the weight of service i in the consumption basket. Note that the Jamaican case in Equation 4.1 is similar to Equation 4.10 except that dI, X, Q, and Z are set to zero to allow for ease of comparison with the revenue cap.

Combining Equations 4.2 and 4.10 give the firm's objective function as

$$\mathcal{L} = \sum_{i=1}^{n} [p_{i,t} - c_{i,t}]\, q_{i,t}(p_{i,t}) - F_t - \lambda\left(\sum_{i=1}^{n} (p_{i,t} - p_{i,t-1})\, w_i\right) \tag{4.11}$$

where λ is the Lagrange multiplier so that differentiating with respect to $p_{i,t}$ gives the first order conditions

$$\frac{\partial \mathcal{L}}{\partial p_{i,t}} = q_{i,t} + p_{i,t}\frac{\partial q_{i,t}}{\partial p_{i,t}} - c_{i,t}\frac{\partial q_{i,t}}{\partial p_{i,t}} - \lambda w_i = 0 \tag{4.12}$$

By setting $w_i = q_{i,t}$, it is easy to see why the global price cap satisfies the inverse elasticity rule where

$$\mu_i = (1-\lambda)\frac{1}{\epsilon_i} \qquad\qquad i = 1, \ldots, n. \tag{4.13}$$

In general, Equation 4.13 is different from Equation 4.9 because the firm is allowed to earn a profit under a price cap, but if the exogenous weights are proportional to each market's electricity consumption level realized under Ramsey pricing such that $w_i = q^*_{i,t}$, one readily verifies that the Lagrange multiplier of the price cap constraint and Ramsey equation are related as follows

$$\lambda = \frac{1}{(1-\lambda^*)} \qquad i = 1, \ldots, n. \tag{4.14}$$

where λ^* is the Lagrange multiplier given by the solution to Equation 4.7 and $q^*_{i,t}$ is Ramsey quantity weight. Thus, the prices induced by the global price cap are optimal and are the same as those given by the Ramsey solution to Equation 4.7.

With $0 < \lambda < 1$, the global price cap moves towards Ramsey prices as λ increases and the constraint becomes more binding. Thus, the prices and quantities derived maximize welfare subject to prices not exceeding the cap. This encourages cost-minimizing behaviour since inefficient production practices will only reduce profits without generating any additional welfare (Brennan, 1989).

4.4.3 Revenue cap

If the firm maximizes profit in accordance with Equation 4.2, the Lagrangian for a regulated firm that is subject to a revenue cap is

$$\mathcal{L} = \sum_{i=1}^{n} [p_{i,t} - c_{i,t}]\, q_{i,t}(p_{i,t}) - F_t - \lambda \left(\sum_{i=1}^{n} p_{i,t} q_{i,t}(p_{i,t}) - \sum_{i=1}^{n} p_{i,t-1} q_{i,t-1}(p_{i,t-1}) \right) \tag{4.15}$$

Differentiating with respect to $p_{i,t}$ gives the first order conditions

$$\frac{\partial \mathcal{L}}{\partial p_{i,t}} = q_{i,t} + p_{i,t}\frac{\partial q_{i,t}}{\partial p_{i,t}} - c_{i,t}\frac{\partial q_{i,t}}{\partial p_{i,t}} - \lambda \left(q_{i,t} + p_{i,t}\frac{\partial q_{i,t}}{\partial p_{i,t}} \right) = 0 \tag{4.16}$$

which can be rewritten as

$$\mu_i = (1-\lambda)\frac{1}{\epsilon_i} + \lambda \qquad i = 1, \ldots, n \tag{4.17}$$

where $\mu_i = \frac{p_{i,t} - c_{i,t}}{p_{i,t}}$.

As long as $\epsilon_i < 1$, which is usually the case for the utility industry, λ will be greater than one and the revenue cap delivers prices that satisfy an interior solution, but deviate from the Ramsey pricing rule. This can be easily seen by rearranging Equation 4.16 so that

$$p_{i,t} = \frac{c_{i,t}\epsilon_i}{(1-\lambda)(\epsilon_i - 1)} \qquad i = 1, \ldots, n \tag{4.18}$$

This means that prices are higher in markets with more elastic demand and lower in inelastic markets as the revenue cap becomes more binding.

4.5 Calibration of model parameters

To estimate the parameters in the constrained optimization models, we need basic data on prices, quantities, marginal costs, and price elasticities of demand for the regulated firm for each market segment as well as total fixed costs. The JPS currently serves twelve blocks of customers which I have reclassified into three main customer segments: residential (Rate 10), commercial (Rate 20/40), and industrial (Rate 50). Each rate class is divided into different customer blocks. For example, Rate 10 may include customers that consume below 100 kWh per month and those that consume above that limit.

I use data for 2013 with initial parameters for electricity prices and quantities obtained from the Jamaica Public Service (2013a). The average unit price of electricity is denominated in US$ and calculated as total revenue attributable to each customer class divided by their respective sales volume. The Office of Utilities Regulation (2010a) is the source of the price elasticity estimates employed in this paper. Up-to-date marginal cost data are not publicly available, but the Jamaica Public Service (2014) has published 2013 data on total variable cost, exclusive of the fuel component. Since the original data does not give any information about the variable cost attributable to each customer class, marginal cost is approximated using the formula discussed in Section 4.5.2.

4.5.1 Estimating the demand function

For each of the three market segments served by the regulated utility, I assume a constant-elasticity demand function of the form similar to Equation 4.3 where $q_{i,t}(p_{i,t}) = \alpha_i {p_{i,t}}^{-\epsilon_i}$. An estimate of α_i is obtained after calibrating the demand function with the known parameters $q_{i,t}$, $p_{i,t}$, and ϵ_i. While it is common practice to assume a constant elasticity of demand for ease of estimation in parametric equations, one can expect rising elasticities of demand in some market segments as substitutes become increasingly attractive. This could result in substantial differences in relative prices for various customer segments. For simplification, zero transmission and distribution losses are assumed so that output $q_{i,t}$ of electricity generated is also extracted by consumers. This assumption is important for two reasons. First, it is difficult to attribute the proportion of losses to a particular customer segment. Second, it removes the effect that losses have on price since utilities often try to recover lost revenue – especially due to theft – by charging existing customers higher prices. In 2013, residential customers consumed approximately 996 GWh of electricity at an average price of US\$0.3891 per kWh. Commercial customers were billed for 1,366 GWh at US\$0.3640 per kWh while the smallest customer class, industrial customers, was billed 605 GWh at US\$0.3030 per kWh. The absolute value of the price elasticity of demand for each customer class is 0.2532, 0.0657, and 0.0632, respectively. These values are notably different from those of Ramcharran (1990) who showed that the elasticity estimates were larger in magnitude for the commercial segment and industrial segments, even though residential demand had the wrong sign and was insignificant.

4.5.2 Cost parameters

Assuming constant marginal cost, the cost per unit of electricity generated and sold at time t can be derived as

$$c_{i,t} = \frac{\sum_{i=1}^{n} VNF_{i,t} \times \varphi_{i,t}}{qs_{i,t}} + \frac{FC_t}{Q_t} \tag{4.19}$$

where $VNF_{i,t}$ is the variable non-fuel cost, FC_t is the total fuel cost, Q_t is the aggregate electricity sold, $qs_{i,t}$ is the amount of electricity sold to customer block i, and $\varphi_{i,t}$ is the allocation factor for each block. If marginal cost is allowed to rise with output, unless the firm can increase price for a particular customer segment, it may refuse to provide electricity to some customers. The assumption of constant marginal cost removes this volumetric effect as regulatory schemes generally include policies against discriminatory practices.

Following a similar approach by the Jamaica Public Service (2014), a uniform fuel charge FC_t/Q_t is ascribed to each customer block. To calculate the allocation factor for each block, I assume that the variable non-fuel cost can be allocated based on the share of total energy and demand charge for each block. Since data on energy and demand charge for each customer block and total variable non-fuel costs are published in Jamaica Public Service (2014), marginal costs for 2013 can be approximated using Equation 4.19. Marginal costs are computed across the twelve blocks of consumers and simple averages taken for the main customer segments. In US$ per kWh, these estimated values are 0.2710, 0.2735, and 0.2413 for the residential, commercial, and industrial segments, respectively. The fixed cost estimate for JPS is US$413 million and is also obtained from Jamaica Public Service (2014). It represents approximately 89% of the company's total non-fuel costs. This cost mainly includes depreciation, cost of capital, and purchased power from independent power producers.

4.6 Analysis and discussion

Using the solution and functions provided in the previous sections, prices and quantities are calculated for the price cap and revenue cap schemes for the three markets served by the utility provider. Recall that in the case of the price cap, the weights applied to Equation 4.10 are based on the quantities obtained from maximizing Equation 4.7. I also calculate the welfare changes associated with each scheme using 2013 tariffs as the benchmark case.

4.6.1 Prices, output, and welfare changes

By using the estimates from the constrained optimization problems, I explore differences in prices for the respective customer segments under both schemes. To allow for comparisons, I also report the marginal cost estimates and actual tariffs for 2013 in Table 4.1.

Table 4.1: **Elasticities, marginal cost, and tariff changes under the optimal price cap and revenue cap schemes.**

Markets	Demand Elasticities	Marginal Costs	2013 Tariffs	Optimal Price Cap Tariffs	Revenue Cap Tariffs	Optimal Price Cap (%Δ)	Revenue Cap (%Δ)
Residential	0.2532	25.83	38.91	29.05	91.04	−25	134
Commercial	0.0657	26.05	36.40	45.47	19.04	23	−45
Industrial	0.0632	24.82	30.30	44.64	17.41	37	−33

Notes: Marginal costs, 2013 tariffs, optimal price cap tariffs using Ramsey weights, and revenue cap tariffs are in US cents per kWh and percentage tariff changes are based on comparison with 2013 tariffs.

Three key findings emerge from Table 4.1. Firstly, if demand elasticities are correct, 2013 tariffs in Jamaica contravene the inverse elasticity rule which requires the mark-up of price over marginal cost to be inversely proportional to the elasticities of demand. Secondly, optimal price setting – a price cap based on Ramsey weights – would require an increase in price for the commercial and industrial customers of 23% and 37%, respectively and a drop in price for residential customers (25%). In this situation the inverse elasticity rule is satisfied since the price mark-up is lowest in the least inelastic market. As a result, this suggests that existing consumers in the commercial and industrial markets are being cross-subsidized by residential consumers. Finally, prices under a revenue cap contravene the inverse elasticity rule. Specifically, residential prices would be 134% larger than existing tariffs with a 45% and 33% decline observed in the commercial and industrial markets, respectively. In the latter cases, prices also fall below marginal cost. This evidence shows why Crew and Kleindorfer (1996b) support price caps and believe that demand-side management policies based on revenue caps are inefficient.

Under a revenue cap, large increases in price will lead to a reduction in electricity sold to the more price sensitive residential customers. As electricity use falls, total costs fall more than the decline in revenues. This leads to an overall increase in the utility's profits. In fact, the utility may be more inclined to move towards peak-load pricing to induce residential consumers to shift their consumption to the off-peak period where marginal cost is lower. In this case, it is able to generate the majority of the revenue from commercial and industrial customers that continue to consume in the peak period. In general, the utility has an incentive to minimize its fixed charges, so it is not hard to understand why such a scheme is likely to undermine new investment in capacity. Without additional investments, this could also reduce the incentive for the utility to move to 100% electricity coverage (Ministry of Energy and Mining, 2009), thus conflicting with Jamaica's 2030 National Development Plan.

The price changes associated with the various schemes have significant implications for energy conservation and social welfare. Relative to a scenario based on 2013 prices and quantities, total electricity consumption rises by 1.4% under the price cap scheme, but falls by about 4% under a revenue cap. This supports the energy conservation view of a revenue cap. However, consumers are exposed to a possible price shock if actual demand is less than forecasted and the utility loses revenue. Under a price cap, the utility would be forced to make the necessary investment to reduce losses and increase sales, but there is no guarantee under a revenue cap since new investments send signals of higher X-factor efficiency requirements in the future. Under a revenue cap, the utility would simply recover the losses in the next price review by charging higher prices. In developing countries, transmission and distribution losses are a major source of inefficiency making demand targets more difficult to achieve. For example, data by the US Energy Information Administration (2016) showed that transmission and distribution losses in 2013 were 26% for Jamaica compared to 2%, 8%, and 8% in Trinidad and Tobago, Norway, and the UK, respectively.

The change in total welfare as depicted in Table 4.2 is calculated as the sum of the changes in consumer and producer surpluses. With 0.6 million customer accounts in 2013, the decline in total welfare under a revenue cap would approximate to US$110 per customer per year while US$2 would be gained under a price cap. These results suggest that the revenue cap scheme is welfare-reducing and presents the price cap scheme as a better option for regulators.

Table 4.2: **Output, consumer surplus, producer surplus, and total welfare changes under the optimal price cap and revenue cap schemes.**

Variables	Optimal Price Cap	Revenue Cap
Total Output Sold (%Δ)	1.42	−3.77
ΔCS (US$/customer)	−176.38	−229.52
ΔPS (US$/customer)	178.53	119.60
ΔW (US$/customer)	2.16	−109.92

Notes: Changes are based on comparison with total output sold and tariffs in 2013.

4.6.2 Behavioural differences under asymmetric information

Laffont and Tirole (1993) argued that the presence of information asymmetries means that regulators generally have limited knowledge about a regulated firm's operations. In this section, I verify the sensitivity of the price cap and revenue cap models to changes in demand elasticity and marginal cost parameters and examine the effect of demand uncertainty on the price cap.

Impact of demand elasticity changes

As firms tend to be more knowledgeable than regulators about how responsive electricity consumers are to price changes, the size of demand elasticities can have very large effects on relative prices, quantities, and welfare under each scheme. To demonstrate, I increase elasticity for the residential customer segment by 25% while holding all other variables constant. Specifically, I increase demand elasticities to 0.3165 and 0.3956. The results in Table 4.3 show a strong preference for price cap regulation given the increase in welfare per customer. As demand becomes more elastic for residential customers, price falls slowly for that customer segment under a price cap but rises sharply under a revenue cap. Since the utility has an incentive to encourage consumption under a price cap, total electricity sold also increases but this is in sharp contrast to a revenue cap where output of electricity sold falls because of the price increase to residential customers. This shows that although a revenue cap transfers volume risk away from the utility to consumers, this comes at the expense of major price shocks and large reductions in societal welfare.

Table 4.3: **Impact of demand elasticity changes on tariffs.**

	Optimal Price Cap	Revenue Cap
BASE CASE		
Residential Tariff (%Δ) – [0.2532]	−25	134
Commercial Tariff (%Δ) – [0.0657]	23	−45
Industrial Tariff (%Δ) – [0.0632]	37	−33
Total Output Sold (%Δ)	1.42	−3.77
ΔTotal Welfare/customer (US$)	2.16	−109.92
INCREASE TO 0.3165		
Residential Tariff (%Δ) – [0.3165]	−27	177
Commercial Tariff (%Δ) – [0.0657]	24	−51
Industrial Tariff (%Δ) – [0.0632]	38	−39
Total Output Sold (%Δ)	2.34	−5.90
ΔTotal Welfare/customer (US$)	4.80	−183.93
INCREASE TO 0.3956		
Residential Tariff (%Δ) – [0.3956]	−29	244
Commercial Tariff (%Δ) – [0.0657]	25	−56
Industrial Tariff (%Δ) – [0.0632]	39	−44
Total Output Sold (%Δ)	3.53	−9.00
ΔTotal Welfare/customer (US$)	8.25	−305.52

Notes: Values in brackets are demand elasticities and changes in each variable are based on comparison with actual output sold and tariffs in 2013.

Impact of cost changes

The generation and distribution of electricity requires large investments in infrastructure such as poles, transformers, distribution lines, and system upgrades to minimise losses. As a result, the marginal cost of supplying electricity to residential communities with low population density could be quite high relative to other sectors, but regulators do not have precise information about cost. In this case, the utility could exploit the limited knowledge of the regulator. Given the comparatively larger demand elasticity of the residential market, it is useful to demonstrate the behavioural differences of the price and revenue cap schemes when it becomes more expensive to supply electricity to that particular market.

To undertake the numerical analysis, I isolate the effect of marginal cost changes by increasing this parameter by 10 US¢ for the residential customer segment only, while holding all other parameters fixed. Specifically, I assume that marginal cost increases for residential customers from its current level to 37.10 US¢ and then to 47.10 US¢. The results are presented in Table 4.4.

Table 4.4: **Impact of residential marginal cost changes on tariffs.**

	Optimal Price Cap	Revenue Cap
BASE CASE		
Residential Tariff (%Δ) – [25.83]	−25	134
Commercial Tariff (%Δ) – [26.05]	23	−45
Industrial Tariff (%Δ) – [24.82]	37	−33
Total Output Sold (%Δ)	1.42	−3.77
ΔTotal Welfare/customer (US$)	2.16	−109.92
INCREASE TO 35.83 US¢		
Residential Tariff (%Δ) – [35.83]	3	163
Commercial Tariff (%Δ) – [26.05]	22	−54
Industrial Tariff (%Δ) – [24.82]	36	−42
Total Output Sold (%Δ)	−1.40	−3.62
ΔTotal Welfare/customer (US$)	−7.84	−106.00
INCREASE TO 45.83 US¢		
Residential Tariff (%Δ) – [45.83]	32	184
Commercial Tariff (%Δ) – [26.05]	21	−60
Industrial Tariff (%Δ) – [24.82]	35	−47
Total Output Sold (%Δ)	−3.36	−3.34
ΔTotal Welfare/customer (US$)	−5.78	−89.52

Notes: Values in brackets are marginal costs in US cents per kWh and changes in each variable are based on comparison with actual output sold and tariffs in 2013.

The requirement that price remains above marginal cost results in residential prices rising with marginal cost under the price cap, but because residential demand is more elastic, price increases get larger under a revenue cap. Under these parameter settings, when marginal cost is lower, a revenue cap is the better regulatory option in terms of energy conservation. But at higher relative marginal cost, the argument for energy conservation becomes less convincing as the decline in total output is lower under a revenue cap than a price cap. If higher marginal costs are reflective of additional investments that target improvements in the energy efficiency of generating units, this is consistent with the view of Dutra et al. (2015) who find that price caps incentivise supply-side energy efficiency by minimising network losses. However, in my particular setting, it is the cost pass-through to higher end-user prices that force consumers to conserve energy. Irrespective of the level of marginal cost, total welfare under a price cap is always greater.

Demand uncertainty

Laffont et al. (1996) demonstrate that to move directly to Ramsey prices, quantity weights under the price cap must be proportional to actual quantities generated under Ramsey pricing, given conditions of information symmetry. However, if the regulator cannot accurately predict the Ramsey quantity weights, it may opt to wait and set $w_i = q_{i,t-1}$ in Equation 4.10 so that the weights are based on the consumption basket in the previous period. The results of this simulation are detailed in Table 4.5.

Table 4.5: **Demand uncertainty.**

Variables	Price Cap	Optimal Price Cap
Residential Tariff (%Δ)	−17.00	−25.00
Commercial Tariff (%Δ)	11.00	23.00
Industrial Tariff (%Δ)	12.00	37.00
Total Output Sold (%Δ)	1.10	1.42
ΔWelfare/customer (US$)	4.91	2.16

Notes: Price cap uses quantity weights from the previous period instead of Ramsey quantity weights under the optimal price cap. Changes in each variable are based on comparison with actual output sold and tariffs in 2013.

These results suggest that if the given elasticity estimates represent precise demand information which the utility is likely to have, total welfare per customer will increase. Though small, compared to the results in Table 4.2, this scenario represents a bigger improvement in total welfare over 2013. This also implies that it would be more beneficial to the utility and society if the utility maintains the existing price cap regime and use the demand elasticities to discriminate among the different customer segments.

Two-part tariffs can be easily incorporated into this scheme by allowing the electric utility to discriminate within customer classes by using a fixed access fee and a usage charge, instead of using uniform prices. The inclusion of the access fee allows the usage charge to be set equal to the firm's marginal cost. Therefore, the access fee for each customer class should be set to reflect the difference between price and marginal cost. This approach is justified as long as high access fees do not prevent some customers from participating in the market (Sappington & Sibley, 1992). However, the inelastic nature of electricity demand is such that all customers are likely to participate.

4.7 Conclusion and policy implications

In this paper I have used actual data for a vertically integrated monopoly provider of electricity in Jamaica to simulate performance under price cap and revenue cap regulation and make comparisons in terms of their effects on price setting, energy conservation, and total welfare. Under certain circumstances, the results reveal a preference for price cap regulation.

I found that in contrast to a price cap plan, a revenue cap scheme generates prices that depart from the Ramsey pricing rule and the magnitude of the differences is striking. For example, a revenue cap produces prices that are almost three times their 2013 levels for the least inelastic residential customer segment compared to a 25% decline under a price cap scheme. Prices also fall below marginal cost for the more inelastic commercial and industrial customer segments. Furthermore, as demand becomes more elastic or marginal cost increases for the residential customer segment, price increases are larger under a revenue cap relative to a price cap. Therefore, information asymmetries can have more devastating effects under a revenue cap scheme.

The comparative analysis also shows that a revenue cap is more desirable when it comes to energy conservation since higher prices result in a lower quantity of electricity consumed. However, at high relative marginal cost for residential consumers, the argument for energy conservation becomes less convincing as the decline in total electricity consumption is lower under revenue cap relative to a price cap. This means that a price cap encourages energy conservation at relatively high marginal cost because of additional utility investments that are reflected in higher end-user prices. Furthermore, I also find that in contrast to the price cap, the inefficient price setting encouraged under a revenue cap scheme reduces social welfare. In light of demand uncertainty which poses a problem for regulators, further gains in welfare are achievable under a price cap if quantity weights from the previous year are used in the regulatory process.

From a policy perspective there are certain situations that arguably favour the use of a particular scheme, especially in developing countries. For instance, if there are climate change concerns, the higher price elasticity of residential electricity demand implies that there is the potential to use the price instrument under a revenue cap to reduce electricity consumption, though this may be less effective when marginal cost is high. Furthermore, if the electricity network is supply-constrained then a revenue cap is more conducive to using prices to balance supply with demand and avoiding power outages. As developing countries generally suffer from higher rates of inflation than developed countries, an electricity provider that incurs fuel costs that are sensitive to oil prices determined in world markets will pass these costs on to customers. The price cap is not immune to this problem, but as both schemes reflect changes in input costs, nominal prices will rise faster under a revenue cap scheme. Therefore, a revenue cap can have more damaging effects on the overall economy since higher electricity prices feed through to further inflation. Although the ultimate performance of any scheme depends on the quality of information and the potential for welfare gains, the decision to implement should also consider the potential trade-offs among the goals of policymakers.

Despite the intuitive nature of these results, there are a few shortcomings. I assumed an environment of zero transmission and distribution losses, but losses can be substantial, especially in developing countries. Likewise, the static setting examined assumes that the firm's technology requirements are fixed and there is no dynamic interplay between the regulator and the firm. However, one of the benefits of incentive regulation schemes is that over time regulators learn more about the firm's ability to reduce costs. It is also difficult to determine if these results can be generalised to unbundled markets especially where competition exists in wholesale and retail market segments. By integrating these issues into the analysis, additional research can reveal more about the desirability of a particular scheme.

A Appendix

In the following section, I provide three case study examples of other countries that have applied cap regulation to their electricity networks. I focus on issues related to privatization, structure of the industry, and the specific part of the industry to which incentive schemes are applied.

A.1 Case studies of price and revenue cap schemes

Trinidad and Tobago

The Trinidad and Tobago Electricity Commission (T&TEC) is the sole retailer of electricity in Trinidad and Tobago and has full responsibility for the design, construction, operation, and maintenance of the country's electrical transmission and distribution network, but the ownership structure differs in the sense that T&TEC is wholly owned by the government of Trinidad and Tobago (McGuire, 2007).

Even though Trinidad and Tobago's electricity sector was opened up to competition in 1993 to attract foreign investment, the network is still vertically integrated. Various legislations were amended which allowed T&TEC to form companies, hold shares, and operate its generation and transmission and distribution segments independently (Ministry of Energy and Energy Affairs, 2013). The state-owned T&TEC retains majority ownership in PowerGen – the largest generator, while Trinity Power and Trinidad Generation Unlimited (TGU) are privately owned. Together, all three IPPs have an installed capacity of approximately 2,289 MW. Of this total, PowerGen produces 1,344 MW and the rest is produced by Trinity Power and TGU.

The Regulated Industries Commission (RIC) was established in 2001 to supervise the operations of the two generators (Trinity Power and PowerGen) and T&TEC. Incentive regulation in Trinidad and Tobago is in the form of a revenue cap

$$R_t = R_{t-1}[1 + (CGA \times CUST) + (RPI - X)] + Z \tag{A.1.1}$$

where R_{t-1} is the authorized revenue for time $t-1$, RPI is the annual change in prices, X is the reduction in prices imposed by the regulator, Z is a cost pass-through variable, $CUST$ is the annual change in the number of customers (or the annual change in output), and CGA is a customer growth factor which can be expressed in percentage terms. In Trinidad and Tobago, this fixed revenue cap regime took effect in June 2006 and covered a five-year regulatory period (Regulated Industries Commission, 2006).

United Kingdom

Prior to 2010, the United Kingdom pioneered the use of price cap regulation and applied it for over 20 years after wide-scale privatization and decoupling of state-owned network utilities in the late 1980s and early 1990s. In 1999, the Office of Gas and Electricity Markets (Ofgem) was established as the key oversight body for the industry after a merger between the Office of Energy Regulation (Offer) and the Office of Gas Regulation (Ofgas). The industry consists of over 436 generating facilities and over 70 electricity retailers with established competition in both segments (Mandel, 2014). Installed capacity was estimated at approximately 93,784 MW in 2012 (US Energy Information Administration, 2016). The transmission system operator (National Grid Company (NGC)) and the distribution segment are regulated as natural monopolies and both are subject to price cap regulation under Ofgem oversight. The price cap sets the maximum base revenue the regulated businesses can earn for each year of the regulatory period. The price cap takes the form

$$p_t = p_{t-1}(1 + RPI - X) \tag{A.1.2}$$

where p_{t-1} is the price of electricity at the beginning of the price cap period, CPI is the annual rate of inflation and X is the offset to inflation (annual real price increase or decrease) resulting from productivity changes in the electricity industry. This '$RPI - X$' formula was applied to electric utilities in five-year regulatory periods in which Ofgem specified the maximum rates a utility could charge for its services. The UK currently uses the RIIO (Revenue = Incentives + Innovation + Outputs) model which is seen as an extension of price cap regulation.

Norway

Like the UK, competition in Norway's electricity sector has been encouraged through vertical separation. In 2012, installed capacity was approximately 32,283 MW with approximately 92% coming from hydro power (US Energy Information Administration, 2016). Statnett (Norway's transmission system operator) and its over 155 electricity distribution companies operate under a revenue cap introduced by the Norwegian Water Resources and Energy Directorate (NVE) in 1997 (Norwegian Water Resources and Energy Directorate, 2014). It sets an upper limit for revenues intended to cover the network's costs such as operation and maintenance of the grid and earn a reasonable return on capital invested. The annual cap is based on 40% cost recovery and a 60% cost norm. A simplified version of the revenue cap formula is

$$R_t = 0.4C_{t-2} + 0.6C^*_{t-2} \tag{A.1.3}$$

where R_t is the revenue cap in year t and C_{t-2} is the two-year lag on the cost base for each network operator. C^*_{t-2} is the cost norm for each network company derived through benchmarking with local and regional utilities and other international transmission operators in the case of Statnett. Statnett's cost norm is derived from the 2012 e3GRID study which analysed the cost efficiency of 22 transmission system operators in Europe.

Chapter 5

Electricity benchmarking in Small Island Developing States

5.1 Chapter overview

In the previous chapter, the X-factor, which is a measure of efficiency, was assumed to be zero and did not form part of the analysis, but this is an important measure that is of interest to regulators. Measuring the efficiency of electricity systems in Small Island Developing States (SIDS) poses a significant challenge due to the unavailability of data and/or poor data quality.

Electricity prices are high in SIDS relative to developed economies (see Table 3.1 of Chapter 3). While inefficiency may be one factor that explains this situation, very little is known about relative efficiency performance. In this study I apply a two-stage data envelopment analysis (DEA) method to a sample of 32 electricity utilities in SIDS for 2010. I estimate the efficiency scores in the first stage with three inputs and one output and apply a truncated regression model with bootstrap in the second stage. To explain the variation in efficiency scores, I divide utilities into the Caribbean and the Pacific region and include criminality and population density to account for differences in environmental operating conditions.

The overall results suggest that there are major differences in efficiency performance with only six utilities on the frontier. The results of the second-stage regression analysis reveal that, on average, utilities in the Caribbean were significantly more efficient than those in the Pacific region. The regression estimates also reveal that there is no statistically significant relationship between efficiency and environment variables such as population density and criminality.

Notwithstanding the null findings in the second-stage regression, these preliminary results advance the idea that by using a combination of non-monetary variables, bias correction techniques, and weighted aggregate indices, useful and comparable efficiency scores can be derived for electricity distribution networks that are governed by incentive-based regulation plans.

5.2 Introduction

It is no secret that island economies are understudied, especially as it relates to electricity sectors in the Caribbean and Pacific regions. Electricity sectors in these regions are characterized by isolated grids, a single utility responsible for production, transmission, and distribution of electricity, and electricity prices that are among the highest in the world. This is compounded by the high cost of undersea transmission, minimal cost differences in power generation among islands, dependence on fossil fuel imports, and the lack of dialogue among states on issues related to energy integration and security (National Renewable Energy Laboratory, 2012).

High electricity prices in SIDS may be a feature of their dependence on fuel imports, but could also be reflective of the limited incentives firms have to control costs due to lack of competition. This is borne out of the idea by Leibenstein (1966), who argued that the average cost of production may be higher than necessary when firms fail to use their internal resources optimally to produce a given level of output. To constrain this behaviour and encourage efficient practices, utility regulators resort to the setting of an efficiency target called the X-factor to force firms to engage in cost reduction. The X-factor target is crucial to the regulated firm because it acts as both a reward and a punishment mechanism. If it is set too high, it threatens the financial viability of the regulated firm and if set too low it provides the firm with a significant opportunity to extract rents at the expense of consumers. Since many SIDS have a single utility that provides electricity, relative efficiency is best determined from benchmarking performance with other countries. In this context, the setting of the X-factor has been a major challenge for SIDS and other developing countries.

Estache et al. (2004) argued that it is difficult to apply international benchmarking to electricity distribution systems to estimate efficiency because of differences in environmental operating conditions. Therefore, the reliability of efficiency estimates requires appropriate choices of environmental variables to capture differences across operating environments. In addressing the heterogeneity in operating environments, Estache et al. (2004) argued that basing environmental variables on physical measures would provide for more consistent international benchmarking. However, choosing a unique set of environmental variables presents an additional challenge.

In this study, I set out to analyse differences in efficiency across island utilities using data envelopment analysis (DEA) by relying on the use of non-monetary variables, and theorize that criminality and population density are factors that explain differences among countries. I also test whether or not there are efficiency differences between Caribbean and Pacific utilities. The overall purpose of this study is to obtain preliminary estimates of relative efficiency across island utilities that can be used by regulators to set X-factor targets that are geared towards the overall efficiency of electricity distribution networks that operate under incentive-based regulation plans.

This paper is organized as follows: In Section 5.2, I provide a brief introduction to the research topic. I examine the literature among various developing and developed countries in Section 5.3. This is followed by Section 5.4 in which I discuss the data used and the employed model. In Section 5.5, the results and analysis of the model are presented while the final section, Section 5.6, details the conclusions and outlines the policy implications emanating from the results.

5.3 Literature survey

There is a large and growing body of literature on frontier methods (data envelopment analysis (DEA) and stochastic frontier analysis (SFA)) applied to the energy sector in developed countries (see, for example, Coelli et al. (2008), Giannakis et al. (2005), and Kuosmanen et al. (2013)). However, fewer studies for developing countries exist. Notable exceptions include those conducted by Meibodi (1998) and Domah (2002). Domah (2002) provides the only known study to have applied frontier methods that involved a few island states. Using DEA and SFA, Domah (2002) investigated differences in the production structure between islands and non-islands electric utilities, but found no apparent difference in technical efficiency between the two groups.

DEA modelling uses a mathematical programming technique to estimate the efficient frontier. DEA is a non-parametric method that was first proposed by Charnes et al. (1978). It defines the relative efficiency of a utility as the ratio of its total weighted outputs to its total weighted inputs. It differs from other common methods such as the total factor productivity (TFP) index number approach that uses index numbers to measure total factor productivity and SFA, which is a parametric method that uses a maximum likelihood estimation framework to calculate parameter estimates for regressors in a model.

The SFA approach was developed independently by Aigner et al. (1977) and Meeusen and van Den Broeck (1977). The basic model uses a maximum likelihood estimation framework to calculate parameter estimates for regressors in a model. The model is accompanied by a composite term which consists of a technical inefficiency measure with a half-normal distribution and random error term which accounts for noise in the data, and is normally distributed. The idea of measuring the efficiency of a decision-making unit relative to a best practice frontier originated with Koopmans (1951). This was later extended by the work of Farrell (1957) who proposed that technical inefficiency could be measured as the deviation from the isoquant boundary. As Seiford and Thrall (1990) points out, SFA has a number of weaknesses. In order to estimate the coefficients of the production function, it requires the functional form to be pre-specified. The functional form will not in general be known, however, and adoption of an arbitrary functional form will produce misspecification errors. SFA does not readily yield a summary judgement on efficiency as only residuals are produced.

The ability of the econometric model to identify sources of inefficiency is weak and is influenced by outliers. Finally, by estimating a function on the basis of average response, it ignores the important distinction between firms that optimize their selection of inputs and those that do not. Despite its limitations, the ability of the SFA model to distinguish random statistical noise from management induced inefficiencies is one of its key advantages. Additionally, unlike DEA, model specification and the statistical significance of included variables can also be tested using standard econometric tests.

In contrast to SFA, DEA is an extremal process that analyses each firm separately and measures its relative efficiency with respect to the entire set of decision-making units (DMUs) being evaluated. The major advantage of the DEA technique is that it does not require *a priori* assumptions on the analytic form of the production function. A DEA-based production model can also accommodate a variable that is neither an economic resource nor a product, such as attributes of the environment or the production process (Charnes et al., 1978). DEA also generates solutions using standard techniques of linear programming and thus provides the benefits of computational efficiency, dual variables, and clear interpretations. Despite these advantages, the literature recognizes a number of disadvantages. Notable amongst these is the sensitivity of the DEA technique to the presence of outliers or errors in data measurement (Australian Competition and Consumer Commission, 2012).

While efficiency measurement analysis can be distinctly categorized into non-parametric and parametric approaches, recent efforts have been geared towards combining key features of SFA and DEA. For example, Land et al. (1993) and Olesen and Petersen (1995) introduced the idea of stochastic DEA (SDEA). In this case, the production function incorporates both inefficiency and stochastic error to minimize the effects of extreme outliers which can lead to substantial differences in results obtained from standard DEA models. To account for firm heterogeneities, others such as Tsionas (2002) and Greene (2005) combine a random parameters SFA model with firm-specific coefficients, which is generally a feature of DEA.

In an additional extension, Henderson and Simar (2005) and Kumbhakar et al. (2007) estimated non-parametric SFA models using kernel regression and local maximum likelihood techniques.

In addition to the methods discussed previously, in many cases, non-frontier methods that allow for direct comparisons have been used to assess the performance of utilities in developing countries. Tallapragada et al. (2009) used Key Performance Indices (KPIs) to compare utilities using technical, operational, and financial elements related to the utility's day-to-day operations. In a similar vein, attempts have been made to benchmark the performance of utilities in the Pacific and compare them with those in the Caribbean (Pacific Power Association, 2011).

Instead of relying on the direct comparison of industry measures, many regulators have opted for regulatory benchmarking that relies on the estimation of efficiency frontiers. This is particularly important for small open economies that are usually dominated by a single distributor of electricity. If the industry consists of a single distributor, international benchmarking can be the only feasible option. In an extensive review of electricity systems around the world, Jamasb and Pollitt (2001) show that many countries have been gravitating towards some form of incentive regulation plan that involves measuring a utility's efficiency against a reference performance target. Jamasb and Pollitt (2001) found that regulators showed a preference for non-parametric methods such as DEA in measuring efficiency.

Given the preference for DEA in the literature, I use recent DEA methods proposed by Simar and Wilson (2007), Simar and Zelenyuk (2006), and Simar and Zelenyuk (2007). Also, getting accurate price information on inputs such as capital is often difficult in developing countries, while it is easier to obtain data on input and output volumes; therefore, DEA is a more appropriate benchmarking tool for efficiency analysis.

In an attempt to address the paucity of data and shed some light on the performance of electric utilities in the Caribbean and Pacific region, I extend this research in various dimensions. First, I put together a database of consisting of key variables for utilities in the Caribbean and Pacific. Second, I apply a two-stage DEA to assess the differences between the two groups. Finally, I show how the DEA scores can used to set X-factor targets for island utilities.

5.4 Data and methods

5.4.1 Description of variables

The cross-country analysis in this study comprises of data gathered for a sample of 32 electric utilities in the Pacific and the Caribbean for 2010. While it would have been useful to have time series observations for each utility to have a better understanding of dynamic behaviour, the study was limited to the use of cross-sectional data rather than a panel due to difficulties in compiling a consistent data set for each utility over time. These difficulties were largely related to the limited coverage of utilities in each region in other years and inconsistencies in measurement of various input and output measures. While no attempt is made at establishing homogeneity, these utilities are typically vertically integrated and operate in countries with similar environmental conditions.

To carry out the analysis, I rely on the use of non-monetary input and output variables. The estimated model adopts the input-oriented approach and includes one output and three inputs. An input-oriented model is used to determine how much inputs used by a network operator could contract if used efficiently while keeping output at its current level. The output is electricity sales while the inputs are installed capacity, labour, and fuel. The outputs produced by electricity networks are not easily influenced by network operators and therefore justifies the use of the input-oriented approach in DEA models (Ajodhia & Petrov, 2004). Also, non-monetary measures are used to avoid exchange rate impacts and inconsistencies in accounting rules and allows for comparability of utilities. The data is compiled from several sources, comprising the Pacific Power Association (2011), Reegle (2012), Carilec reports, statistical yearbooks, and annual reports of various utilities.

As is the convention in the literature, electricity sales (GWh) is an output variable that describes demand characteristics within each country. Production and distribution of electricity requires the three major inputs: fuel, labour, and capital. Fuel is measured in terajoules (TJ) while installed capacity in megawatts (MW) is used as a measure of capital on the grounds that in developing countries it is likely to constitute an effective constraint on output. While the ideal situation is to have labour data for different functions within the utility, such a breakdown is not publicly available and the annual average number of employees is used instead. Other variables used for the regression analysis are population density and the homicide rate.

The inclusion of homicide rate in the regression analysis is in need of further explanation. It is the only indicator that is available for each country that could reasonably be used to proxy electricity theft or the prevalence of crimes due to theft. This is the case because of the difficulties in gathering data on electricity theft by country in addition to the limited availability of crime statistics by type of crime committed. Electricity theft remains a major threat to the viability of electric utilities in many developing countries. Without adequate revenue recovery, this can lead to lower network maintenance, load shedding and impede capital investments, which contributes to the operational inefficiency of utilities. According to released statistics by Northeast Group (2015), non-technical electricity losses due mainly to theft cost the world US$58.7 billion per year, and is mostly a problem for developing economies. World Bank (2016b) estimates that total transmission and distribution losses for small states were 6.6% in 2014 on average, but some countries such as Haiti and Jamaica lose up to 60% and 26% of their electricity produced, respectively. In Jamaica, about 8% of these losses are generally technical in nature with the rest attributable to theft (Office of Utilities Regulation, 2004). As the majority of electricity losses due to theft originates in developing countries, it is reasonable to assume that this could be an effective constraint on utility efficiency.

Table 5.1 presents a summary of all the variables considered in this exercise.

The summary statistics show a lot of variability in the variables with the largest utilities located mainly in the Caribbean. Trinidad and Tobago has the largest utility network based on installed capacity and the smallest is in Tuvalu.

Table 5.1: **Descriptive statistics for main variables in 2010.**

Variables	Mean	Maximum	Minimum	Standard Deviation
Labour	464	2649	54	556
Installed capacity (MW)	177	1600	2	307
Fuel (TJ)	9732	118 061	46	21 715
Sales (GWh)	749	8415	5	1541
Homicide rate (%)	13	52	1	12
Population density	239	1264	3	261

Notes: Labour refers to the average number of employees, homicide rate is expressed per 100,000 population, and population density is measured as population per km^2.

It is important to maintain a good balance between the number of variables and the number of decision making units (DMUs). Problems related to discrimination may arise if the number of variables relative to the number of DMUs is large, resulting in a large number of inefficient units being incorrectly classified as efficient. The literature is silent on an appropriate discriminatory power; however, the rule of thumb is that the number of variables should be less than one third of the number of the DMUs (Friedman & Sinuany-Stern, 1998).

5.4.2 Efficiency measurement

Much of the literature on efficiency measurement has examined the ability of managers to allocate and manage resources in such a way that allows them to attain a certain level of output. In practice, however, productive capacity is also influenced by external factors beyond the scope of management's control. Recent studies have sought to explore the effects of environmental variables on efficiency and interest is growing in the area; see for example, Barros and Assaf (2009), Demchuk and Zelenyuk (2009), and Barnum et al. (2012). In this paper I adopt a two-stage data envelopment analysis (DEA) bootstrap method. In the first stage, I estimate the DEA, while the second stage involves a bootstrapped truncated regression to explain differences in utility efficiency performance. In the first stage, my main model is based on the constant returns to scale (CRS) assumption, but I also consider variable returns to scale (VRS) and non-increasing returns to scale (NIRS) for comparison purposes.

Estimating efficiency scores

The standard approach to DEA requires a definition of feasible combinations of inputs and outputs. This can be done using either an input-oriented approach (I-O) or output-oriented approach (O-O). The input-oriented approach captures the extent to which input combinations could be reduced to produce the same output level while the output-oriented approach examines how much more output could be produced without changing the current level of inputs. In the I-O case inefficient units have a score between zero and one (outside the arc), while scores above one would be considered inefficient (inside the arc) using the O-O method. Both cases are shown in Figure 5.1. All firms operating along the curve are considered efficient.

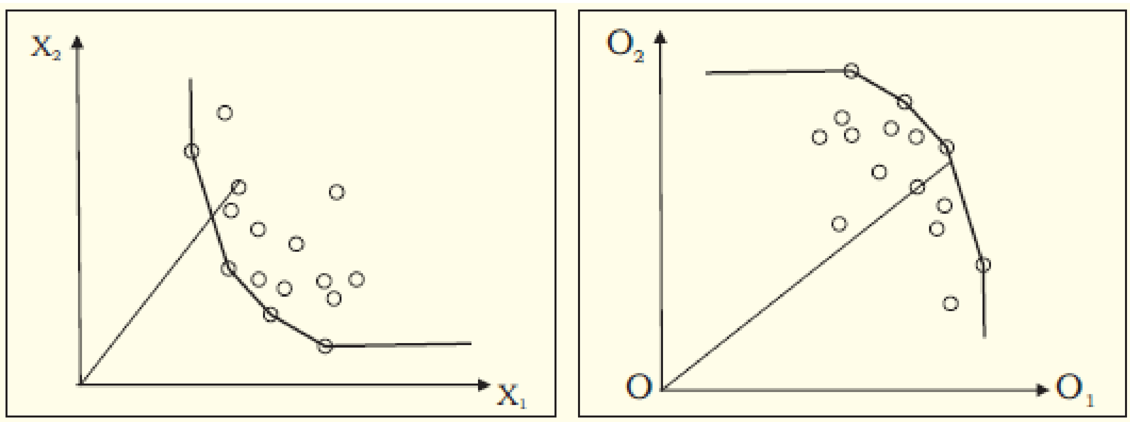

Figure 5.1: **Efficient frontier representation in DEA. The diagram on the left represents the input-orientation (2 inputs and 1 output) approach while the right diagram is the output-orientation (2 outputs and 1 input) case. Source: Coelli et al. (2005).**

To analyse the production frontier of the utility in this study, I employ an input-oriented distance function that follows in the spirit of Färe et al. (2013). The utility is assumed to use an input vector $x = (x_1, x_2, \ldots, x_n) \in \Re^n_+$ to produce an output vector $y = (y_1, y_2, \ldots, y_m) \in \Re^m_+$. The input correspondence $y \to V(y) \subseteq \Re^n_+$ is such that for any $y \in \Re^m_+$, $V(y)$ denotes the subset of all input vectors $x \in \Re^n_+$, which produce at least y. Each utility or DMU minimises current input levels conditional on outputs

$$D_I(y,x) = sup\{\theta > 0 : x/\theta \in V(y)\} \tag{5.1}$$

where θ is a scalar that represents the radial distance estimate.

This is the Shephard (1953) input-oriented distance function, which is the reciprocal of the Farrell input-oriented technical efficiency measure.[1] Specifically, the input distance function is the reciprocal of the minimum equi-proportional contraction of the input vector x given outputs y and is formulated as $TE_I(y,x) = 1/D_I(y,x)$. It is a scalar between zero and one represented by the absence of efficiency and full efficiency, respectively. The efficiency for utility $j, j = 1, \ldots, J$ is determined by solving the following optimization problem in the first stage

$$\begin{aligned}
\underset{\theta,\lambda_1,\ldots,\lambda_n}{min} \quad \widehat{TE}_I(y_j,x_j) = \frac{1}{D_I(x_j,y_j)} &= \theta \\
\text{s.t. } \theta x_{ij} \geq \sum_{k=1}^{n} \lambda_k x_{ik}, &\qquad i = 1,2,\ldots,N \\
y_{jm} \leq \sum_{k=1}^{n} \lambda_k y_{km}, &\qquad m = 1,2,\ldots,M \\
\lambda_k \geq 0 \quad \forall_k &
\end{aligned} \tag{5.2}$$

where θ is the efficiency measure to be calculated and λ_k is a measure of intensity variable for observation $k = 1,\ldots,n$. This model is based on the CRS technology assumption that is common in the literature. If VRS is assumed to account for scale effects, then $\sum_{k=1}^{n} \lambda_k = 1$ would be an additional constraint in Equation 5.2 while non-increasing returns to scale is imposed when $\sum_{k=1}^{n} \lambda_k \leq 1$ is added.

Figure 5.2 provides a graphical depiction of input-oriented technical efficiency under different technologies: constant returns to scale (CRS), non-increasing returns to scale (NIRS), and variable returns to scale (VRS). The firm uses input x to produce y. Here we can see that firms P_c, R, and P_v are operating on the frontier for CRS, NIRS, and VRS, respectively. Firms P and Q are operating below the

[1] For a detailed exposition of the properties underlying the input-oriented distance function, see Shephard (1953).

frontiers and could reduce their inputs without changing the current output level. In terms of scale, firm P is too small because $TE_{VRS} > TE_{NIRS}$, while firm Q is too big because $TE_{VRS} = TE_{NIRS}$, and R is at optimal size because $TE_{VRS} = TE_{CRS}$.

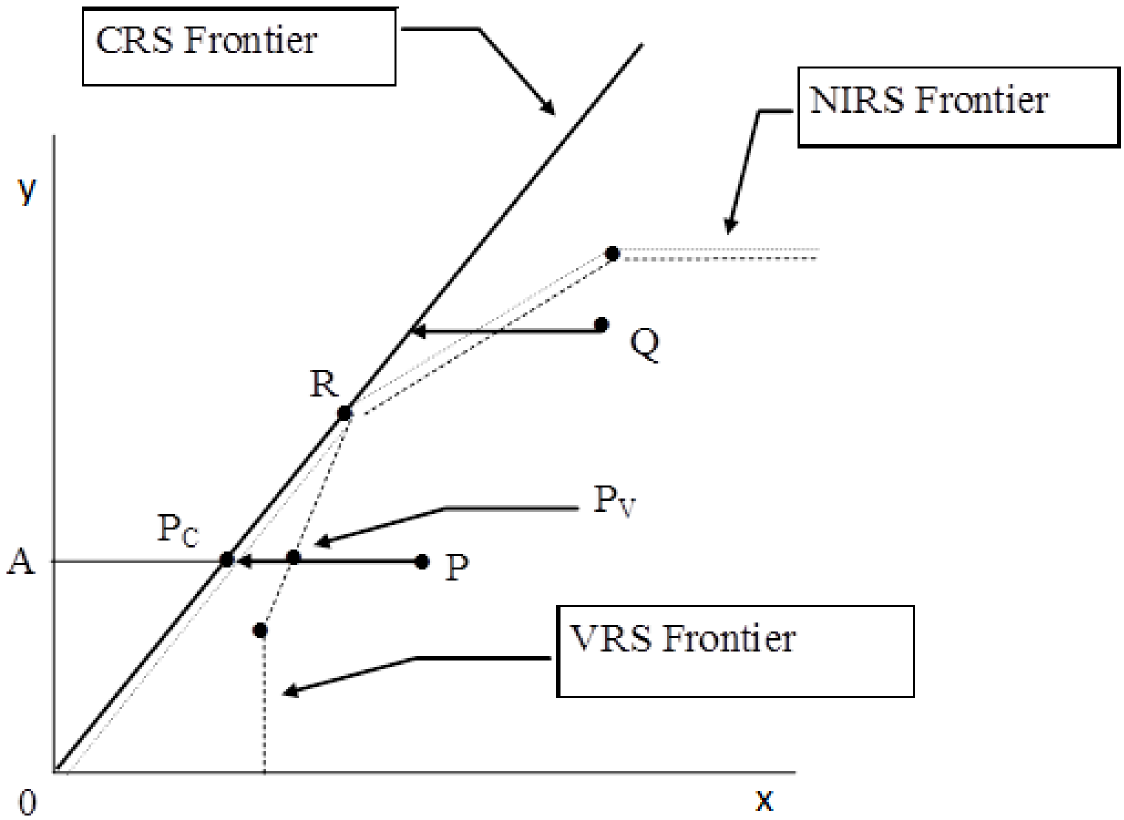

Figure 5.2: **Input-oriented technical efficiency with different technologies. Source: Adapted from Coelli et al. (2005).**

Truncated regression

In the second stage, I analyse the relationship between individual efficiency scores and factors specific to each DMU using regression analysis. Here, we assume and test the following specification

$$\widehat{\theta_j} = z_j\beta + \varepsilon_j, \quad j = 1, 2, ..n \tag{5.3}$$

where the dependent variable $\widehat{\theta_j}$ is the first-stage efficiency score, the row vector of exogenous variables z_j are explanatory factors that are thought to have an influence on the efficiency score through the vector of parameters β to be estimated, and an error term given by $\varepsilon_j \sim N\left(0, \sigma_\varepsilon^2\right)$ with left truncation at $0 - z_j\beta$ and right truncation at $1 - z_j\beta$.

Previous studies such as that carried out by Domah (2002) relied on the Tobit estimator to explain inefficiency, but Simar and Wilson (2007) showed that efficiency scores estimated in the first stage are likely to be biased and conventional inference methods invalid since the error term ε_j is, by construction, serially correlated.

To overcome this problem, Simar and Wilson (2007) propose the use of truncated regression with bootstrap to produce bias-corrected estimates of $\widehat{\theta}_j$. The approach by Simar and Wilson (2007) is predicated on several assumptions to obtain consistency of the second stage estimated results. Two of these are of relevance and are assumed to hold. First, the two-stage method requires the separability condition, which holds if second-stage environmental variables affect the efficiency scores of DMUs but not the frontier. Second, I assume that true efficiency scores follow a truncated normal distribution with a mean of zero and unknown variance. To perform the analysis, Simar and Wilson (2007) proposed the use of two algorithms. Algorithm I is based on a single bootstrap procedure while Algorithm II uses double bootstrap. As Olson and Vu (2009) confirms, both procedures yield equivalent results. The procedure outlined in this paper follows from Algorithm II in order to produce both bias-adjusted efficiency scores and conduct consistent inference. Algorithm II was originally developed for output orientation and needs to be modified to suit the needs of the input orientation method. The modification of Algorithm II is detailed in the following steps:

1. Calculate the input-oriented efficiency score $\widehat{\theta}_j$ for each utility using the optimisation problem in Equation 5.1

2. Use the maximum likelihood method to estimate the truncated regression of $\widehat{\theta}_j$ on z_j to provide and estimate $\widehat{\beta}$ of β and an estimate $\widehat{\sigma_\varepsilon}$ of σ_ε

3. For each utility, $j = 1, 2, ..J$, repeat the next four steps B times to yield a set of bootstrap estimates $\left\{\widehat{\theta}^*_{j,b}, b = 1, 2, ..B\right\}$

   (a) Draw ε_j from $N\left(0, \widehat{\sigma}^2_\varepsilon\right)$ with left truncation at $0 - z_j\widehat{\beta}$ and right truncation at $1 - z_j\widehat{\beta}$

i. Compute $\theta_j^* = z_j\widehat{\beta} + \varepsilon_j$

ii. Construct a pseudo data set $\left(x_j^*, y_j^*\right)$, where $x_j = x_j \times \frac{\theta_j}{\theta_j}$ and $y_j^* = y_j$

iii. Compute a new efficiency estimate θ_j^* on the set of pseudo data $\left(x_j^*, y_j^*\right)$

4. For each firm, compute the bias-corrected estimate $\widehat{\widehat{\theta}}_j = \widehat{\theta}_j - \widehat{bias}_j$, where $\widehat{bias}_j$ is the bootstrap estimator of the bias obtained as $\widehat{bias}_j = 1/B\sum_{b=1}^{B}\widehat{\theta}_{j,b}^* - \widehat{\theta}_j$

5. Use the maximum likelihood method to estimate the truncated regression of $\widehat{\widehat{\theta}}_j$ on z_j, providing estimates $\left(\widehat{\widehat{\beta}}, \widehat{\widehat{\sigma}}\right)$ of $(\beta, \sigma_\varepsilon)$

6. Repeat the next three steps $(1-3)$ B_2 times to obtain a set of bootstrap estimates $\left\{\left(\widehat{\widehat{\beta}}_b^*, \widehat{\widehat{\sigma}}_b^*, b = 1, 2, ..B_2\right)\right\}$

   (a) For $j = 1, 2, ..J$, ε_j is drawn from $N\left(0, \widehat{\widehat{\sigma}}\right)$ with left truncation at $0 - z_j\widehat{\widehat{\beta}}$ and right truncation at $1 - z_j\widehat{\widehat{\beta}}$

   (b) For $j = 1, 2, ..J$, compute $\theta_j^{**} = z_j\widehat{\widehat{\beta}} + \varepsilon_j$

   (c) The maximum likelihood method is again used to estimate the truncated regression of θ_j^{**} on z_j , providing estimates $\left(\widehat{\widehat{\beta}}^*, \widehat{\widehat{\sigma}}^*\right)$

7. Use the bootstrap results to construct confidence intervals for the efficiency scores.

Setting the X-factor

The use of weighted aggregate indices is important to understand differences among groups and could provide useful information to regulators especially in incentive regulation schemes that rely on X-factor targets. Weighted aggregate indices reflect average conditions/characteristics specific to a particular region/group of countries rather than relying on the assumption that environmental conditions for utilities in a particular country are similar to those of countries on the frontier. The X-factor is seen as an efficiency target that encourages firms to engage in cost-cutting. In this section I estimate a regional and overall efficiency aggregate and propose an approach that could be used to integrate the X-factor into utility industry settings. The proposed approach follows from the aggregation procedure introduced in Färe and Zelenyuk (2003) and Simar and Zelenyuk (2007).

First, I define the share-weighted input-oriented group or aggregate technical efficiency $\overline{\theta}$ as

$$\overline{\theta} = \sum_{j=1}^{J} \theta_j . w_j \tag{5.4}$$

where $w_j = \frac{1}{m} \sum_{m=1}^{M} \left[\frac{x_j^m}{\sum_{j=1}^{J} x_j^m} \right]$ is the share of total inputs for utility j, M is the number of input variables, and x is the input variable. In the input orientation case, w_j is known as price-independent weights and were first derived by Mayer, Zelenyuk et al. (2014). They sum to one and are non-negative. A key assumption is that the share of industry cost from each input is a known constant across DMUs, but can vary across time. This assumption is analogous to the one made by Färe and Zelenyuk (2003) and Färe and Zelenyuk (2007) to derive the weights for the output orientation method.

In the second step, the regulator could set the X-factor target as the distance from the group aggregate or overall aggregate as

$$XT = \begin{cases} \left(\frac{\theta_j}{\overline{\theta}} \right)^{1/t} - 1 - \omega_j, & \text{if } \theta_j < \overline{\theta} \\ -\omega_j, & \text{otherwise} \end{cases} \tag{5.5}$$

where $\overline{\theta}$ is the aggregate efficiency score, ω is the stretch factor, and t is the length of the regulatory period in years.

In the top part of Equation 5.5, since efficiency estimates for DEA are constrained on a zero to one scale, X-factor targets for firms are set so that the efficiency score declines cumulatively over the regulatory period, which is usually set at five-year intervals, minus the firm-specific stretch factor. The stretch factor is also called a customer productivity dividend (CPD), and is generally applied to utilities that are new to regulatory incentive pricing mechanisms. It is used to reflect the enhanced incentives that the new regulatory scheme provides since newly regulated firms that are less efficient have a greater scope for productivity improvements compared to their more efficient counterparts. Firms that were more efficient prior to the introduction of regulatory pricing are generally assigned a lower value of the stretch factor relative to more efficient firms (see Bernstein and Sappington (1999) and Australian Competition and Consumer Commission (2012) for further discussion.). Utilities with efficiency scores on the frontier or greater than the average would have an X-factor of $-\omega$ as the bottom part of Equation 5.5 shows. All the other utilities will need to remove unnecessary slack equivalent to the distance from the aggregate score.

If one was to compare all utilities in the Caribbean and Pacific region with all of those in the US, it is quite possible that all utilities in the SIDS region would fall below the frontier given environmental differences. Therefore, the frontier established should reflect average conditions that are common to a group of utilities. This weighted average approach has the added advantage of being more conservative and does not produce unreasonable efficiency targets that are unlikely to be achieved because of how far the utility is from the frontier. This is also more plausible in an environment where mismeasurement and data quality is of major concern.

Despite the advantages of this method, deriving X-factors in this way has an important shortcoming. Since the DEA efficiency estimates are generated from volume measures and the X-factor focuses on cost reductions, the assumption is that this would translate directly into cost reductions when the firm uses its physical inputs more efficiently. However, there is unlikely to be a high positive correlation between input use and costs. This does not mean that using monetary values alone would have been better as there is the additional problem of choosing an appropriate deflator. A mix of non-monetary and monetary variables may introduce double counting so this approach was also avoided.

5.5 Empirical results and discussion

5.5.1 Cross-country efficiency results

First, I estimate the model in Equation 5.3 and present the results in Table 5.2. The evidence under CRS assumption shows a wide disparity in the technical efficiency of electricity utilities in the different countries, ranging from approximately 49% to 100%. All utilities on the frontier (Antigua, Aruba, Bermuda, Cayman, and Trinidad and Tobago) are from the Caribbean region, except Fiji. The performance of Pacific utilities shows substantial levels of inefficiency with the majority operating at less than 80% of their potential level. If a utility in the Pacific (such as a utility in Nauru) was to become more efficient, it would need to reduce current slack in its operations by as much as 28%. Putting the reliability of the sample aside, the impetus to improve efficiency would require that it emulate the operational conditions of utilities on the frontier.

Apart from almost all countries forming the reference frontier coming from the Caribbean, economies of scale may have a role to play as the utilities with the largest electricity output, Jamaica and Trinidad and Tobago, are on or close to the frontier. To check for scale effects, Equation 5.1 is re-estimated under variable returns to scale (VRS) and non-increasing returns to scale (NIRS) assumptions. The results under CRS and NIRS are the same, but three utilities in the Pacific grouping appear efficient under VRS. As all 5 Caribbean islands remain efficient under VRS, size probably does not matter. Also, a plot of efficiency scores against electricity sales did not reveal size importance but the largest utility (Trinidad and Tobago) was on the frontier (see Figure 5.3). This may be expected since Trinidad and Tobago is the only net-oil exporter in the sample. Utilities in Micronesia and Tuvalu may have been inefficient under CRS because they are archipelagos and have much smaller electricity systems.

Table 5.2: **Efficiency scores of SIDS under CRS, NIRS, and VRS assumptions in 2010.**

Country	CRS	NIRS	VRS
Anguilla	0.77	0.77	0.97
Antigua	1	1	1
Aruba	1	1	1
Bahamas	0.88	1	1
Barbados	0.88	0.90	0.90
Belize	0.92	0.92	0.98
Bermuda	1	1	1
Cayman	1	1	1
Curacao	0.72	0.74	0.74
Dominica	0.76	0.76	0.79
Grenada	0.84	0.84	0.85
Guyana	0.58	0.62	0.62
Jamaica	0.87	0.89	0.89
Montserrat	0.86	0.86	1
St. Lucia	1.00	1.00	1
St. Maarten	0.87	0.87	0.89
St. Vincent	0.72	0.72	0.73
Suriname	0.69	0.69	0.69
Trinidad	1	1	1
American Samoa	0.71	0.71	0.73
Cook Islands	0.79	0.79	1
Fiji	1	1	1
Guam	0.94	1	1
Kiribati	0.75	0.75	0.98
Micronesia	0.66	0.66	1
Nauru	0.72	0.72	0.90
Papua New Guinea	0.58	0.64	0.64
Samoa	0.65	0.65	0.68
Solomon Islands	0.49	0.49	0.51
Tonga	0.75	0.75	0.82
Tuvalu	0.54	0.54	1
Vanuatu	0.57	0.57	0.86

Notes: These estimates are based on a slightly modified version of the Matlab programming codes used in Simar and Zelenyuk (2007).

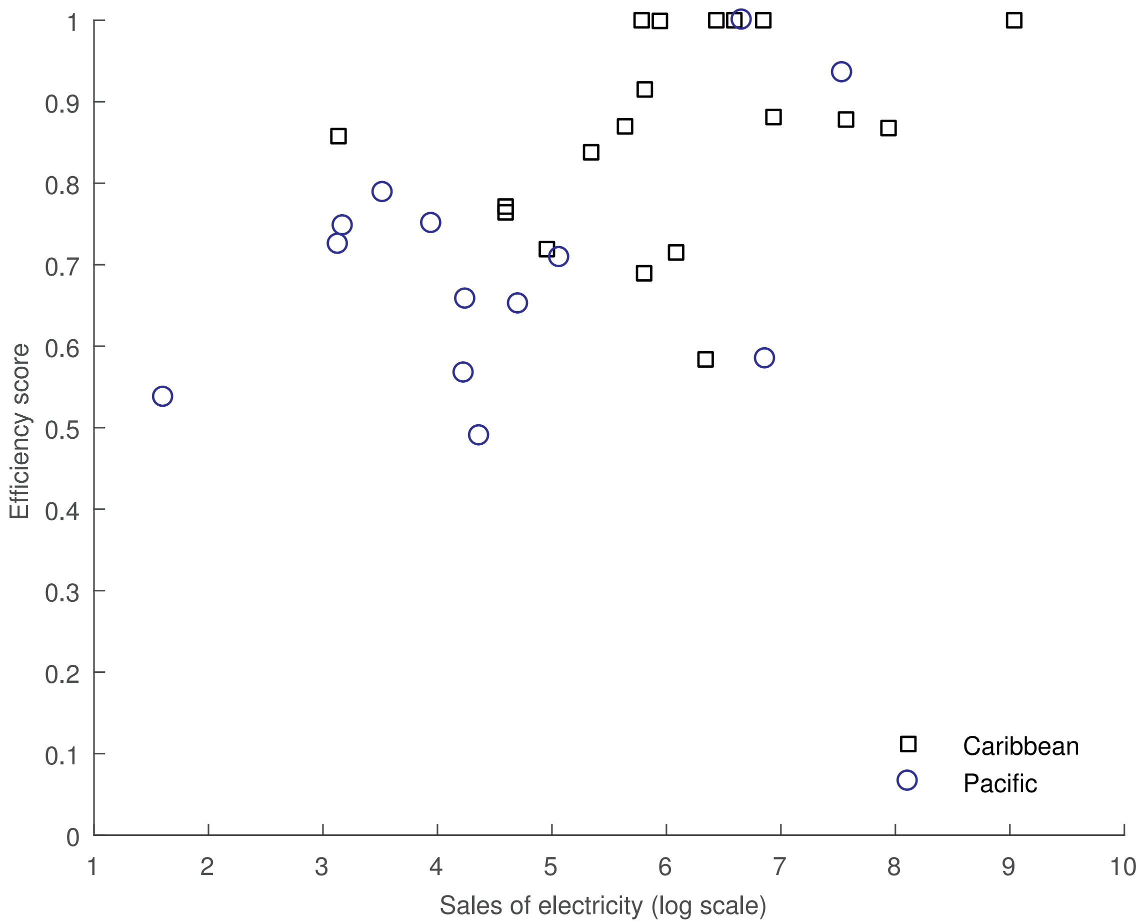

Figure 5.3: **Efficiency scores versus electricity sales.**

5.5.2 Group-wise results

In Table 5.3, the group efficiency scores for the Caribbean and the Pacific are reported along with the aggregate efficiency scores, bias-corrected scores, and confidence intervals. The group efficiency score for the Caribbean (0.86) is higher than for the Pacific (0.66) and both are significant at the 5% confidence level. The aggregate average score (0.82) is relatively high and is also significant at the 5% level. This is also higher than the mean overall efficiency of 69% for developing countries estimated by Hawdon (1998). This suggests that the estimated technical efficiency for island economies of 0.23 posited by Domah (2002) may be too low.

The higher bias-corrected technical efficiency scores show that utilities in the Caribbean are twice as efficient as those in the Pacific. Specifically, Caribbean utilities could reduce inputs by 14% and still maintain the existing output level while Pacific utilities could reduce inputs by as much as 34%. I also use the Simar and Zelenyuk (2007) test for differences in the quotient of the group efficiency

Table 5.3: **Subgroup estimated and bias-corrected weighted aggregate efficiency scores.**

Groups	Mean score (non-weighted)	DEA Score (weighted)	Bias-corrected Score	95% upper CI	95% lower CI
Caribbean	0.86	0.90	0.86	0.99	0.80
Pacific	0.70	0.75	0.66	0.87	0.52
Aggregate	0.80	0.87	0.82	0.96	0.75
Caribbean/Pacific	1.23	1.20	1.27	1.52	0.92

Notes: These estimates are based on a slightly modified version of the Matlab programming codes used in Simar and Zelenyuk (2007).

scores. Specifically, I test the null hypothesis $H_0 : RD_{C,P} = 1$ versus the alternative $H_1 : RD_{C,P} \neq 1$, where $RD_{C,P} = TE_C/TE_P$. TE_C and TE_P are the respective technical efficiency scores for the Caribbean and Pacific.The null hypothesis of equality in efficiency ($H_0 = 1$) between the two groups is not rejected since the confidence interval (0.92 – 1.52) includes unity. Therefore one can reasonably expect both groups to achieve similar levels of efficiency using the same level of inputs.

5.5.3 X-factor target setting

Using the above results combined with Equation 5.5, I provide estimates of X-factor targets for the sample of countries in Table 5.4. For expository purposes, I assume a regulatory period that is fixed for five years and an annual stretch factor of 0.2% for the industry. This stretch factor estimate is in line with the 0.2% and 0.6% range established in a study by the Australian Competition and Consumer Commission (2012). If regulators decide to implement incentive pricing schemes such as price cap or revenue cap in SIDS, X-factor targets tell us that utilities (many of which are currently state-run) could reduce their operating and capital costs annually by a certain percentage over a 5-year period with no loss in output. For example, since the aggregate score is 0.82, the Solomon Islands will need to reduce its inputs by 10% annually to achieve the average performance of all utilities. This is a greater requirement than compared to say the Bahamas, which is operating above the average of all countries. It only needs to reduce its inputs by the equivalent of the stretch factor estimated at 0.2% annually.

Table 5.4: **Estimated X-factor targets for each country.**

Country	Efficiency score	X-factor target
Anguilla	0.77	−0.014
Antigua	1	−0.002
Aruba	1	−0.002
Bahamas	0.88	−0.002
Barbados	0.88	−0.002
Belize	0.92	−0.002
Bermuda	1	−0.002
Cayman	1	−0.002
Curacao	0.72	−0.029
Dominica	0.76	−0.016
Grenada	0.84	−0.002
Guyana	0.58	−0.068
Jamaica	0.87	−0.002
Montserrat	0.86	−0.002
St. Lucia	1.00	−0.002
St. Maarten	0.87	−0.002
St. Vincent	0.72	−0.028
Suriname	0.69	−0.036
Trinidad	1	−0.002
American Samoa	0.71	−0.031
Cook Islands	0.79	−0.010
Fiji	1	−0.002
Guam	0.94	−0.002
Kiribati	0.75	−0.020
Micronesia	0.66	−0.045
Nauru	0.72	−0.026
Papua New Guinea	0.58	−0.068
Samoa	0.65	−0.047
Solomon Islands	0.49	−0.100
Tonga	0.75	−0.020
Tuvalu	0.54	−0.083
Vanuatu	0.57	−0.073

Notes: These estimates are based on a slightly modified version of the Matlab programming codes used in Simar and Zelenyuk (2007).

5.5.4 Regression estimates

The estimated coefficients and standard errors for the model in Equation 5.4 are reported in Table 5.5. The specification includes three regressors: a measure of criminality, population density, and a dummy variable for capturing region-specific differences in efficiency. The regressors would not have any significant effect on efficiency if the 95% confidence interval bands contain zero. I use the algorithm outlined in the previous section, 1,000 bootstrap replications for the bias correction and 1,000 bootstrap replications for the confidence intervals, to estimate the model parameters.

Table 5.5: **Second-stage regression estimates.**

Variable	Estimates	95% lower CI	95% upper CI
Constant	0.30	−0.00	0.62
Region Dummy	0.31	0.11	0.53
Population Density	0.04	−0.02	0.10
Criminality	−0.04	−0.12	0.04
Standard error	0.04	0.03	0.06

Notes: These estimates are based on a slightly modified version of the Matlab programming codes used in Simar and Zelenyuk (2007).

The results in this model appear to support the hypothesis that utilities in densely-populated countries are more efficient, but the effect was not significant. The estimate for criminality also has the correct sign, but the effect on utility efficiency appears to be insignificant. Finally, the estimated coefficient of the regional dummy is positive and statistically significant, indicating therefore that utilities in the Caribbean region are more efficient than those in the Pacific, ceteris paribus. This is consistent with the observation in the previous section.

However, the conclusions drawn about the coefficients of population density and criminality should be interpreted with caution. Studies with small sample sizes tend to have low statistical power and a reduced chance of detecting a true effect. Therefore, the possibility exists that a Type II error may have been committed as implied by the failure to reject the null hypothesis of the coefficients being zero (McQuitty, 2004).

5.6 Conclusions and policy implications

In this study, I examined the efficiency of 32 SIDS electric utilities in 2010 using the DEA technique. The results showed that under CRS assumption, five utilities were on the frontier, all located in the Caribbean region. Adopting the reference frontier could see Caribbean and Pacific utilities reduce inputs by 14 and 34 per cent, respectively, without affecting the existing output level. The weighted group efficiency scores suggest Caribbean utilities are more efficient than their Pacific counterparts.

In the second stage, which involves truncated regression analysis, I hypothesise that utility efficiency differs systematically according to population density, level of criminality, and a dummy variable for firm location. The criminality and population density estimates had the correct signs, but this was not found to have a significant influence on firm efficiency. However, the region-specific dummy supported the earlier observation of higher efficiency in the Caribbean and was shown to be significant. Judging from the technical efficiency estimates, appropriate measures of X-factor targets can be derived to give managers incentives to reduce costs. Contrary to arguments in the literature that exaggerate the need to benchmark similar utilities, the results suggest that reasonable estimates can be obtained when environmental conditions are taken into account.

While there is the tendency to believe that efficiency is low in island states because of size constraints, I did not find any clear evidence of this in this study. However, I did find that many utilities are inefficient, which requires the development of policy approaches to remove unnecessary slack in the operations of utilities.

When assessing these results, the quality of the data must be taken into account. However, this is one of the first studies to examine utility efficiency in the Caribbean and the Pacific and represents the best use of the limited data available, which can prove invaluable to the utility industry and regulatory bodies. With improved mechanisms for data dissemination and collection, electricity sectors in SIDS are likely to benefit from further research and more reliable efficiency estimates.

Chapter 6

Main conclusions

6.1 Summary of findings

This study was undertaken to investigate four different issues outlined in the Introduction. First, I set out to investigate whether oil price shocks adversely affect domestic activity in Small Island Developing States (SIDS). This was seen as an important issue worth investigating since the cost of oil represents a larger proportion of GDP and energy sources are less diverse in SIDS. Under these conditions, the common belief in the literature is that adverse oil price shocks are likely to have a much larger impact on SIDS. However, in this study I found that oil price movement does not have any significant adverse effects on domestic activity in SIDS. This speaks to a greater need for research that tries to uncover the factors that contribute to their perceived resiliency. The only factor that seems to make SIDS vulnerable is negative demand shocks to developed economies such as the US. I found that the Caribbean region which has closer economic ties with the US through, for example, remittances is more affected by adverse output shocks than countries in the Pacific region. In drawing these conclusions I looked at a sample of 26 countries over the period 1980 to 2015 and divided them into three regions. The analysis was conducted within a global VAR framework to capture interdependencies among the countries.

Since oil represents a substantial portion of the fuel needed to generate electricity in many states, it is only natural to examine issues related to the electricity sector. The aim here was to investigate the degree of responsiveness of electricity demand to electricity price changes. I restricted my analysis to a time series study instead of panel data estimation due to data constraints. Jamaica was used as a case study in this regard and was worth looking at since the last study on electricity demand was done more than two-and-a-half decades ago. This study was designed under the assumption that Jamaica faces potential electricity supply constraints and may need to raise prices to slow demand since there is difficulty in attracting investors to build new capacity. In looking at three categories of consumers and using a bounds testing approach to cointegration covering the period 1970 to 2014, I found that consumers were generally responsive to price changes. Specifically, prices would be more successful in reducing consumption of electricity in the long run for the residential and industrial consumers given their elasticity values of -0.80 and -0.33, respectively.

Price elasticities of electricity demand can be used to investigate differences associated with incentive regulation schemes such as price and revenue caps. This investigation was also restricted to Jamaica since I was able to extract parameters needed for the analysis from various publicly available documents. Data for 2012 was used to build a constrained optimization model for the utility under both schemes. The results revealed a preference for price cap regulation in terms of price setting and welfare but was less suitable than revenue cap for energy conservation purposes. In terms of specific results, I found that prices under a revenue cap scheme were inefficiently set because they contravene the Ramsey pricing rule. This means that prices under a revenue cap were higher for customers such as residential consumers who had more price-elastic demand. Despite the energy conservation argument for revenue caps that is often cited in the literature, price caps seem to be a better option at encouraging energy conservation when marginal cost increases for more elastic consumers relative to other market segments. This is important given information asymmetry problems that usually exist between regulators and the regulated firm.

In the final stage of my investigation in this thesis, I explore the possibility of using non-monetary electricity inputs and outputs to conduct a comparative efficiency benchmarking exercise. This was thought to be important given that incentive regulation schemes are gaining prominence in many developing countries, including SIDS. An underlying assumption is that it would be best to use utilities that have similar operational constraints to benchmark against each other. Efficiency estimates obtained can then be used to inform the efficiency target of individual utilities that operate under different electricity incentive regulation schemes. Using a two-stage data envelopment analysis (DEA) method applied to 32 electricity distribution utilities in SIDS, I estimate the efficiency scores in the first stage with three inputs and one output, and apply a truncated regression with bootstrap in the second stage. Using data for 2010, I restricted my analysis to utilities operating in the Caribbean and the Pacific. I found that Caribbean utilities were significantly more efficient than those in the Pacific. However, the second stage results did not reveal any evidence to suggest that the variation in efficiency across the different utilities was due to factors such as crime and the density of populations within each country.

In light of the results emanating from each study, there are various policy implications which I highlight in the next section.

6.2 Policy implications

The findings in this thesis provide some insights into policy direction for SIDS. Firstly, the negligible negative effects of oil price shocks on output growth for SIDS point to the need for countries to not become complacent, but rather to take advantage of the situation to consolidate and align domestic policies with economic growth strategies.

This could involve the development of outward-oriented economic policies. This encompasses leveraging the negative effects of brain drain by encouraging remitting behaviour by migrant workers from small states. This foreign exchange inflow has been used for human capital formation through spending on schooling for children (Amuedo-Dorantes et al. (2010)) as well as the financing of business investments (Woodruff & Zenteno, 2007). To further encourage foreign exchange flow into small states, governments should endeavour to negotiate worker mobility programs with partner countries. This should aim to target programs that require seasonal workers including the agriculture and hospitality industry. In light of the benefits derived from remittance inflows, a 'training for export' model involving skilled professionals such as nurses and teachers similar to that proposed by Lewis (2011) can be pursued as a viable external shock mitigation and development strategy for small states.

Through the targeted programmes mentioned previously, SIDS could forge important relationships with more stable economies such as the US in the case of Caribbean economies and Australia and New Zealand in the case of Pacific SIDS. It also provides an opportunity for SIDS to seek out capital investment and capacity building to improve efficiency of their energy sectors. In cases where governments are considering liberalising their electricity sector or considering implementing alternative forms of pricing schemes, results in this study provide some guidance on issues to consider when choosing between alternative forms of incentive pricing regulation schemes. It shows that liberalising electricity sectors should not be seen as an isolated exercise, but should also be considered as part of a broader strategic framework that considers other aspects such as efficiency benchmarking.

The macroeconomic consequences of oil price fluctuations could increase in the future with increased threats of unrest in the Middle East. Therefore, this points to the importance of having a diverse energy mix to relieve the dependence on oil imports and minimise future energy supply and price risks. This is supported by evidence in this study that shows that SIDS that were less dependent on oil as the sole source of energy were likely to experience stronger output growth. Moving towards natural gas use and renewables such as wind and solar are likely to be avenues for disentangling the dependency on oil imports. However, in the context of the limited fiscal space in many countries, supporting energy diversification may prove challenging.

If the focus is on addressing consumer demand, this study points to the implementation of peak-load pricing policy in countries where the electricity network is supply-constrained. This pricing policy would involve charging higher prices during peak-load hours to force consumers to use more electricity during off-peak hours where there is generally a lower demand on the network. A further policy implication emanating from this is the evidence it provides that could assist policymakers in forecasting capacity expansion. Currently, capacity expansion plans in Jamaica are based on the Wien Automatic System Planning Package (WASP) which uses a linear programming approach. However, use of this package could produce misleading results since it focuses more on the technical constraints of the system and is not flexible enough to adequately determine how responsive consumers are to price and income changes.

The policy suggestions emanating from this thesis could also benefit from having better quality data. For example, all of the analyses are done using annual data, but data at a higher frequency such as quarterly are likely to produce better results. For this reason, this exercise highlights the need for regional bodies such as the CARILEC and Pacific Electricity Corporation to work together so that more consistent and reliable measures of utilities performance in the region can be obtained.

6.3 Limitations of research

Although this thesis has been carefully thought out, it still bears a number of limitations and shortcomings. First, accessing the data needed to do particular kinds of analyses have been especially challenging. For instance, I wanted to include the majority of the 52 SIDS when looking at oil price shocks but I had to restrict my sample size to approximately half of that due to the absence of a longer time span for many of the variables needed for the different countries. In terms of looking at oil price shocks, it would have been good to make the distinction between net oil-importing and oil-exporting SIDS, but due to data being available for only one oil exporter – Trinidad and Tobago – this did not seem like a rational comparison to make.

Second, the lack of data was also the main reason for limiting the study of consumer demand behaviour to only Jamaica since I could not identify a suitable series that would allow me to examine other countries or conduct panel data analysis. Since the JPS is the only utility considered for model testing, generalizing the results would also require a larger sample of small open economies. Absence of data was also a similar concern for the study of incentive regulation schemes and the benchmarking exercise. Conducting the benchmarking exercise was especially problematic due to data quality issues and the inconsistency of measurements across space and time. For example, it was not immediately clear whether key variables such as labour included only full-time equivalent staff or whether other variables such as installed capacity were measured in gross or net terms.

Third, no distinction was made between types of exchange rate regimes in place when analysing the impact of oil price shocks. However, Friedman (1953) and Hoffmann (2007) found that developing countries with flexible exchange rate policies are better able to absorb adverse external economic shocks compared to those that have fixed exchange rate regimes. Generally, most SIDS have adopted or have their currencies pegged to a single foreign currency or to a basket of foreign currencies. In the Pacific, Fiji and Kiribati operate fixed (pegged) exchange rate regimes. The basket currencies for the Fiji dollar are those of Fiji's major trading partners, Australia, New Zealand, the United States, the United Kingdom, Germany, and Japan. Kiribati has adopted the Australian dollar as the currency of legal tender. The Caribbean countries of Jamaica and Trinidad and Tobago along with Mauritius have a managed float with no pre-announced path of the exchange rate.

While the models used to assess the performance of price and revenue caps fare well under linear pricing and the stationary environment analysed, another shortcoming of this exercise is that conclusions drawn may be different with other pricing methods and under different assumptions. For example, non-linear pricing schemes such as two-part tariffs were not considered in great detail and the analysis may have other drawbacks in a non-stationary environment. Additionally, I assume zero distribution losses in my analysis of price cap and revenue cap, but while this simplifies the model, results will certainly differ if these assumptions are relaxed. Furthermore, the setting examined does not consider the influence of competitive behaviour within electricity markets.

In addition, as electricity prices change often throughout the year, the electricity demand study would benefit more from having data of a higher resolution such as quarterly. This would allow for detailed analysis of the relationship between electricity demand and various factors and is likely to lead to more precise elasticity estimates.

Finally, the benchmarking study was only limited to the use of data envelopment analysis (DEA). While this method is commonly used, extending the analysis to include other approaches such as the total factor productivity (TFP) index number approach, data envelopment analysis (DEA), and stochastic frontier analysis (SFA) could enhance the reliability of efficiency estimates.

6.4 Future work

In light of the shortcomings identified previously, this points to a number of interesting avenues for future research. First, it is hoped that the current version of the GVAR model adopted in this thesis presents a logical framework for understanding global interdependencies, but shocks do not transmit only through financial variables. Transmission could occur through the trade channel and a combination of both trade and financial factors. This serves as a useful complement to the analysis in addition to other weighting schemes such as geophysical distance.

Second, the expansion of the analysis to see how SIDS compare to other developing countries would be of interest since those developing economies are also likely to have high oil shares and intensity and also typically depend on remittances from developed economies. Another promising extension could also involve modifications to the GVAR model to account for time-varying effects. This is useful since many studies have shown that the impact of oil price shocks have become smaller over time. It is also possible to use the GVAR model to forecast the effects of global factors on economies while accounting for global interactions. This is certainly an area that should be given consideration in future work.

The reliability of the efficiency measurement estimates could also be improved if utilities from other countries are included in the comparative exercise. If we can improve the measurement quality of monetary values across countries, it would also be good to complement this exercise with results from stochastic frontier analysis. As previously discussed, I have left aside competitive behaviour issues but peak load pricing and investment issues were also not discussed in great detail. I do hope that future research will address these questions.

Since electricity sectors throughout SIDS and many other developing countries have been the target of many policy interventions, important insights could be obtained by examining how economic regulation reforms have impacted electricity prices in these countries. We could use a variety of approaches to investigative this issue such as difference-in-difference method (DAD) or propensity score matching.

Finally, as the thesis has general applicability, it would be useful to examine these same issues in other key infrastructure services such as telecommunications and water.

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