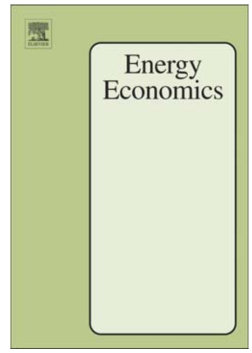

Price and Income Elasticities of Electricity Demand: Evidence from Jamaica

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Price and Income Elasticities of Electricity Demand: Evidence from Jamaica

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Abstract

Jamaica's electricity sector faces supply-side challenges. Demand-side policies have the potential to improve electricity use efficiency and reduce the likelihood of electricity disruptions. In this paper, 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. Price-based approaches are likely to be more successful in slowing electricity demand growth in these sectors.

JEL classifications: C22; Q41; Q43

Keywords: Bounds testing; Elasticity; Electricity demand

1 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, 2010a). 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Public Service (2014), a 381 MW LNG-fired power plant should have been completed by mid-2016 but the licence was withdrawn by the Ministry of Energy due to breaches in the power purchase agreement by Energy World International (EWI), the company tasked with building the new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, 2016). 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 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).

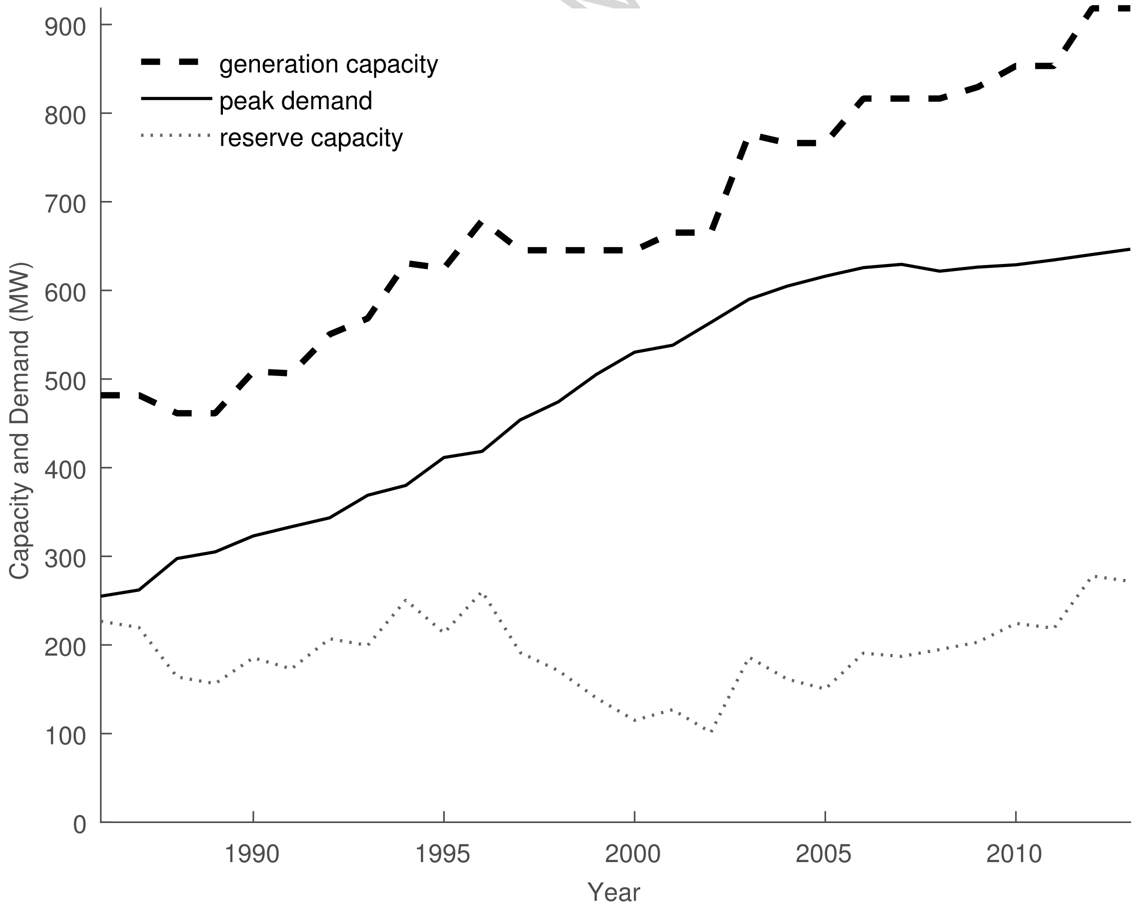

Figure 1: Trends in generation capacity and peak demand, 1986–2013. Source: Compiled using data from Jamaica Public Service (2004, 2014).

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.[2] 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.[3] 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)[4] and developing countries as a whole.

This paper is organized as follows: The research topic is introduced in Section 1. This is followed by Section 2 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. In Section 4 I elaborate on the employed model, data sources, and the econometric technique – autoregressive distributive lag (ARDL) bounds testing approach to cointegration. In Section 5, the results

[2] 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.

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

[4] 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).

and analysis of the bounds testing approach are presented. Finally, I highlight the conclusions and policy implications emanating from the results in Section 6.

2 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, 2013).

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, 2016).[5]

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, 2010a). 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

[5]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.

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, 2010b).

Figure 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 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), 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).

A cross-country comparison of electricity prices is displayed in Table 1. Due to its dependence on oil-based fuel imports such as heavy fuel oil (HFO) and 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[6] 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 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

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

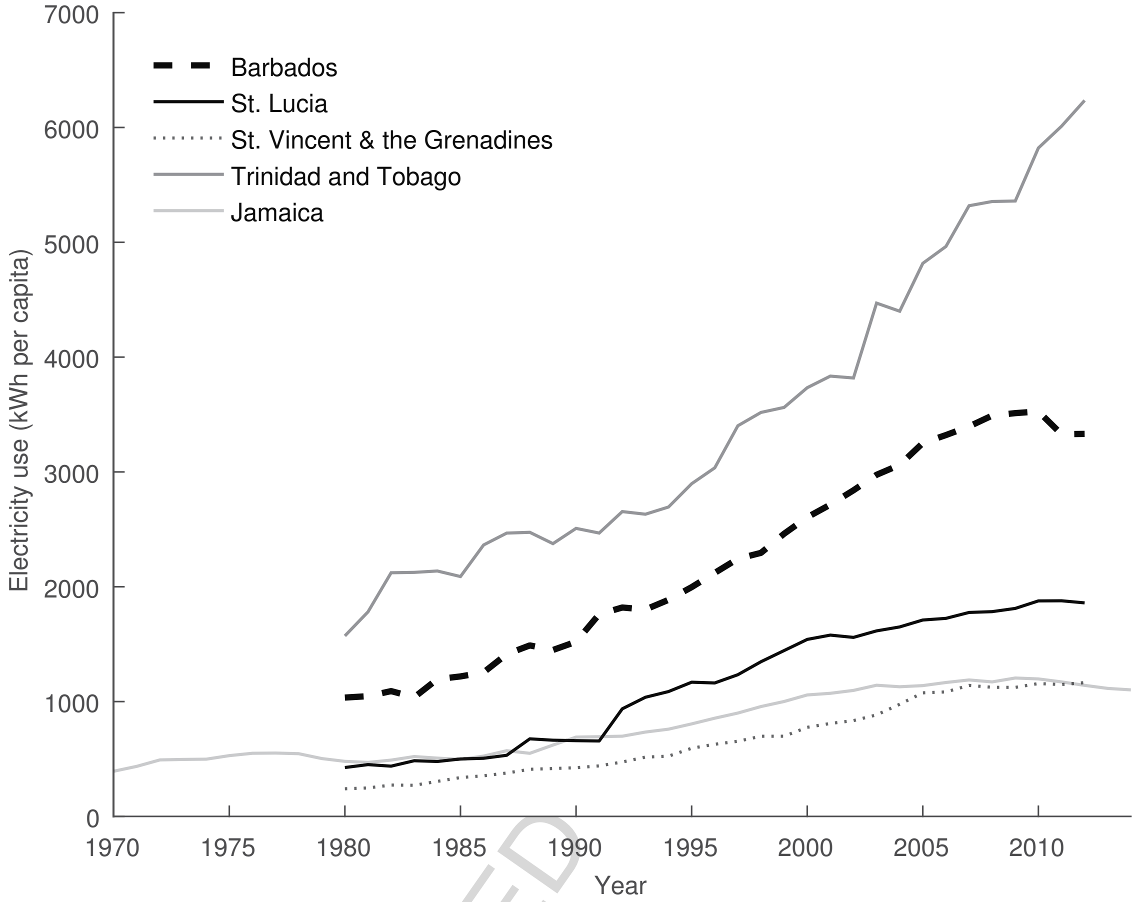

Figure 2: Trends in electricity consumption per capita, select Caribbean countries: 1970–2014. Source: Compiled using data from US Energy Information Administration (2016), United Nations Statistics Division (2016b), United Nations Statistics Division (2016a), and various issues of the Economic and Social Survey of Jamaica (ESSJ). Excluding Jamaica, data was only available between 1980–2012.

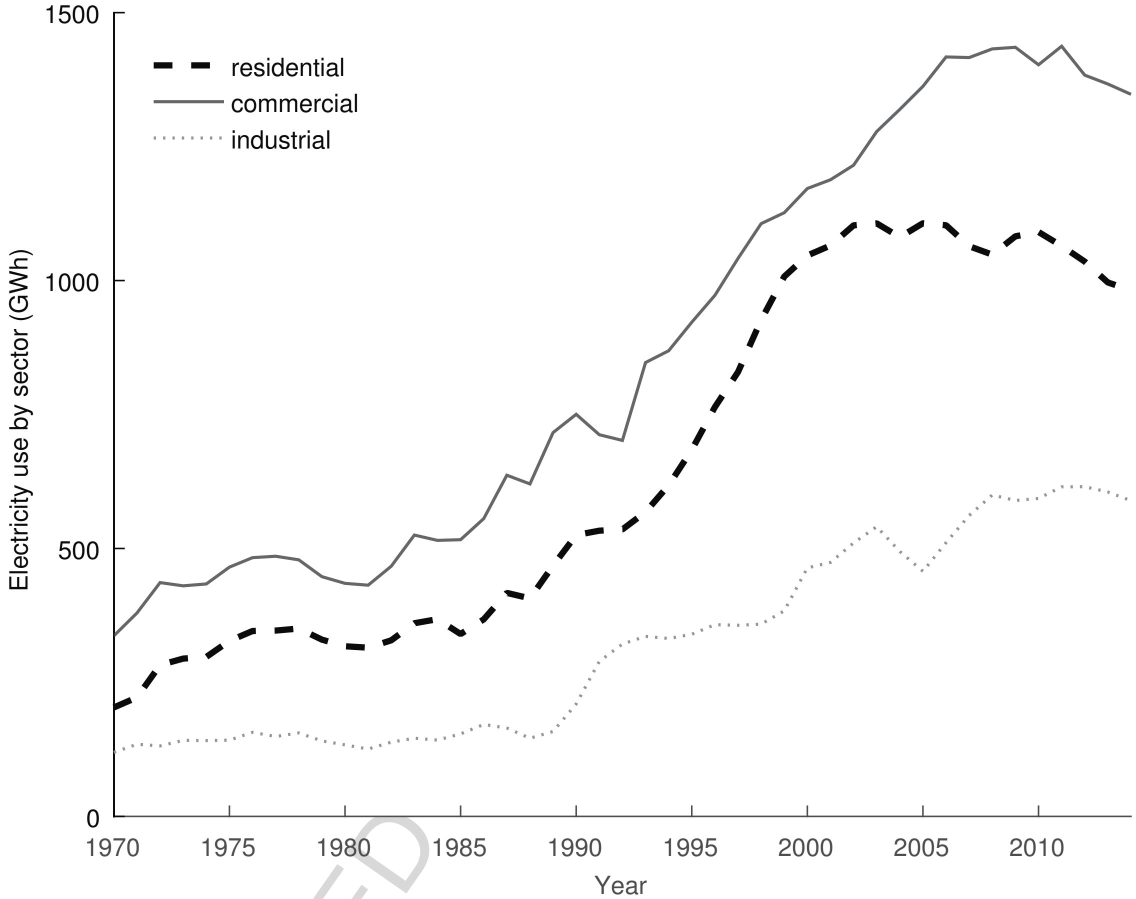

Figure 3: Trends in sectoral electricity consumption in Jamaica, 1970–2014. Source: Compiled using data from various issues of ESSJ.

substantially in real terms, especially since 2001.

A comparison of Figures 3 and 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.

Table 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).

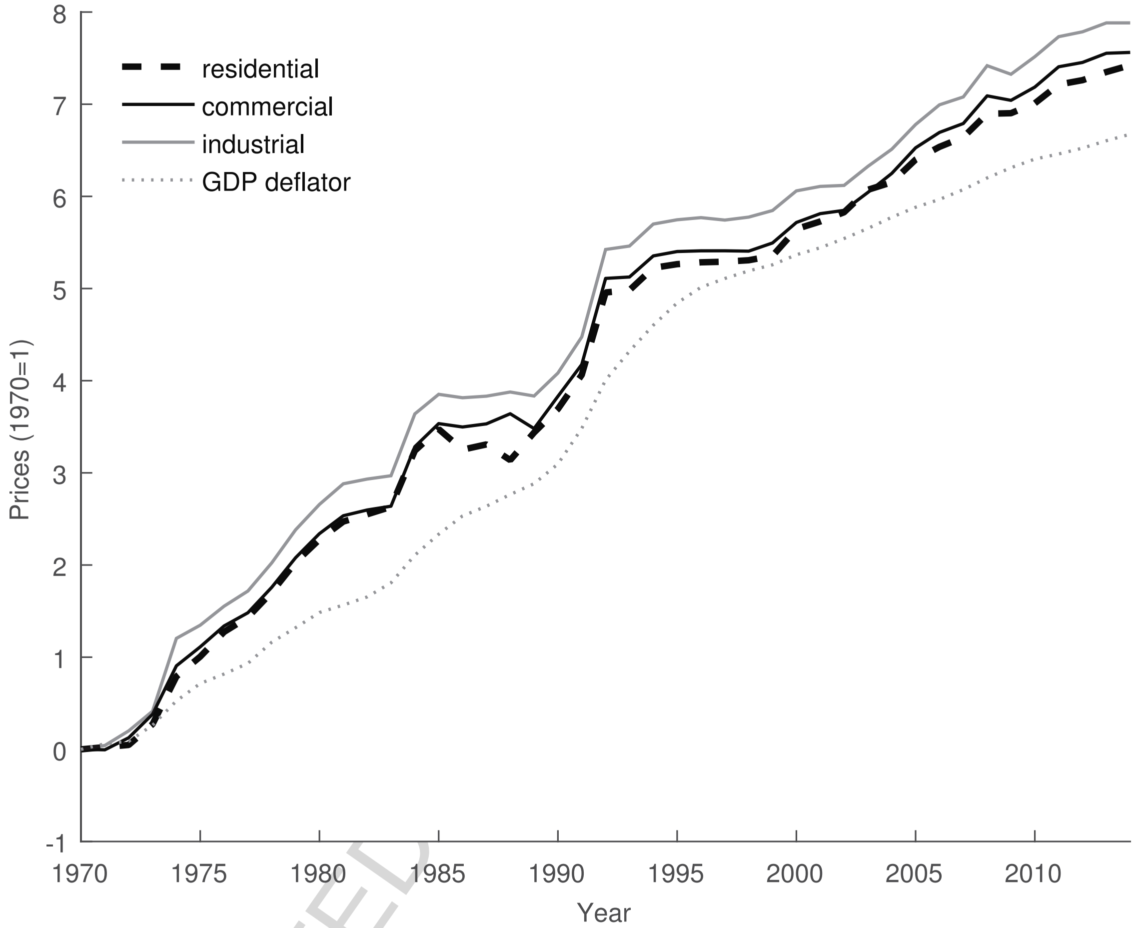

Figure 4: Trends in sectoral electricity prices and GDP deflator in Jamaica: 1970–2014 (log scale). Source: Compiled using data from United Nations Statistics Division (2016b) and various issues of ESSJ.

3 Survey of Literature

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[7], 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

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

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).

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.

4 Methods and Data

4.1 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

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

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[8] 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 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 1 by employing the following ARDL bounds testing model which is estimated using OLS

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

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

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 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 C.

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 and Perron (1989) exogenous break test in the first stage. Despite its limitations, the augmented Dickey and Fuller (1979) test is used as a starting point as it is the most widely used approach in the literature. I use the Kwiatkowski et al. (1992) test to complement the results of the Dickey and Fuller (1979) test since it tests the null of stationarity and is more useful when we have trend-stationary processes. Given that I assume a single breakpoint in the data that is known *a priori*, Perron (1989) argues that the standard Dickey and Fuller (1979) test results could be biased towards non-rejection of the null in the presence of a structural break. In light of this, I follow De Vita et al. (2006) and apply the Perron (1989) exogenous unit root test as an additional check instead of the more recent class of endogenously determined or unknown breakpoint unit root tests (see for example, Lee and Strazicich (2003) and Narayan and Popp (2010)).

In the second stage, one of three approaches can be used to test the null hypothesis of no cointegration among the variables. The first two approaches, according to Pesaran et al. (2001), involves using the F-statistic (F_{PSS}) or the Wald statistic (W_{PSS}) which are calculated from restricting the coefficients of the lagged level variables in Equation 2 by setting them equal to zero and testing their joint significance. Pesaran et al. (2001) also suggest a third approach which involves using the t-statistic (t_{BDM}) of Banerjee et al. (1998) to test the hypothesis that there are no long-run relation among the variables. 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).

The next step in the process involves comparing the computed F_{PSS}, W_{PSS}, or t_{BDM} statistics with the relevant critical value bounds taken from Pesaran et al. (2001) or Narayan (2005) in the case of smaller sample sizes (30–80). 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_{PSS}, W_{PSS}, or t_{BDM} 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 tests are, however, inconclusive if the calculated value 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.

4.2 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.[9]

[9] 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.

The descriptive statistics associated with the main variables are presented in Table 2 and shows some variability in the data from year to year for the different sectors especially as it relates to electricity consumption.

Table 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.

4.2.1 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.[10] Following from the argument of Woodland (1993), the two-part tariff structure used in Jamaica also implies that the average electricity price is a function of consumption. 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 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. Despite the many studies arguing for and against the marginal or average price, I use the less ideal measure of average price as it is the only price measure available in the Jamaican context. Therefore, the average unit price of electricity is calculated as total revenue attributable to each customer class divided by their respective sales volume.

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

5 Empirical Results and Discussion

Table 3 displays the OLS estimates for Equation 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.[11] 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 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.[12]

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.[13] 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 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.[14]

Following the arguments outlined in Section 4, I report the results of the dynamic log-linear model from Equation 2 in Table 4. This model includes the 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 B 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

[11] In Appendix A.1, first-differencing the logarithms of the variables improve the results.

[12] As re-emphasized by De Vita and Trachanas (2016), this functions as a powerful reminder of the common problem and substantial adverse effects of the omitted variable bias (OVB) when the regression equation is mis-specified.

[13] Similar results are obtained with the dummy variable excluded.

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

Table 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.

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, 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 ARDL bounds 'constant only' model for evidence in support of cointegration. Conflicting results are observed across all three tests except for the industrial sector for which a cointegrating relationship is confirmed for at least the 5% level of significance. For the aggregate level and the commercial sector, I find evidence of cointegration when the F_{PSS} and W_{PSS} statistics are used, but not for the t_{BDM} statistic. The values of the F_{PSS} and W_{PSS} statistic fall within the critical bounds at the 10 per cent level for the residential sector so evidence of a long-run relationship is inconclusive[15] (see Appendix B for more details on F_{PSS}, W_{PSS}, t_{BDM}, 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 2 and are presented in Table 5.

The long-run results from Table 5 show some similarity to the estimates in Panel B of Table 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, 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.

The heterogeneity in the own-price elasticity of demand estimates warrants further discussion. The price elasticity of demand being larger for the residential

[15] In the search of a long-run relationship, cointegration is confirmed when higher lag orders of 4 and 5 are used.

Table 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 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.

sector relative to other sectors can be largely explained by the prevalence of electricity theft via illegal connections to the grid for this consumer segment. The US Energy Information Administration (2016) showed that total electricity losses in 2013 were 26% for Jamaica compared to 8% in more developed economies like the UK. Of this total for Jamaica, 18.04% arises from theft with the rest attributable to technical constraints in the power network (Jamaica Public Service, 2014). Most of this theft is attributed to vulnerable groups such as low-income residential households that are confined to inner city communities and rural areas. Illegal connections within these communities are not easily removed without the assistance of the police due to the volatile nature of some of these communities (Jamaica Public Service, 2014). This implies that if electricity costs represent a large share of the consumer's budget, an increase in price is likely to incentivise theft if the benefits of stealing outweigh the costs of being caught. As electricity demand is based on actual sales of electricity, a larger reduction in electricity observed for the residential consumer segment in comparison to other sectors may be reflective of increasing theft when prices are rising rather than increased usage of substitute sources of energy. Industrial and commercial customers have more inelastic demands due to greater reliance on the power network which stems from their heavier demand loads, lower tariffs, and the need to have access to standby electricity demand service in case on-site generating units fail.

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 5 and 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.

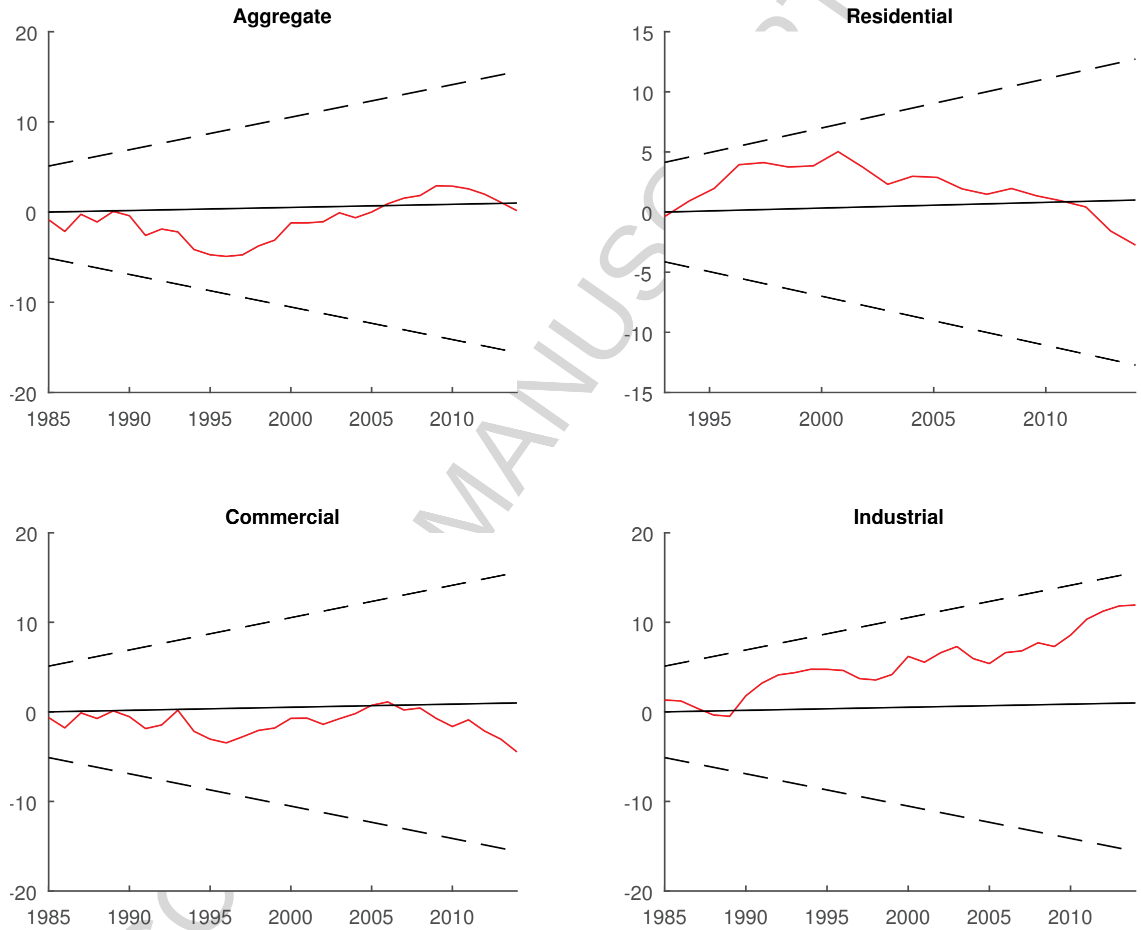

Figure 5: Plot of cumulative sum (CUSUM) residuals. Dashed lines represent critical bounds at the 5 per cent level of significance.

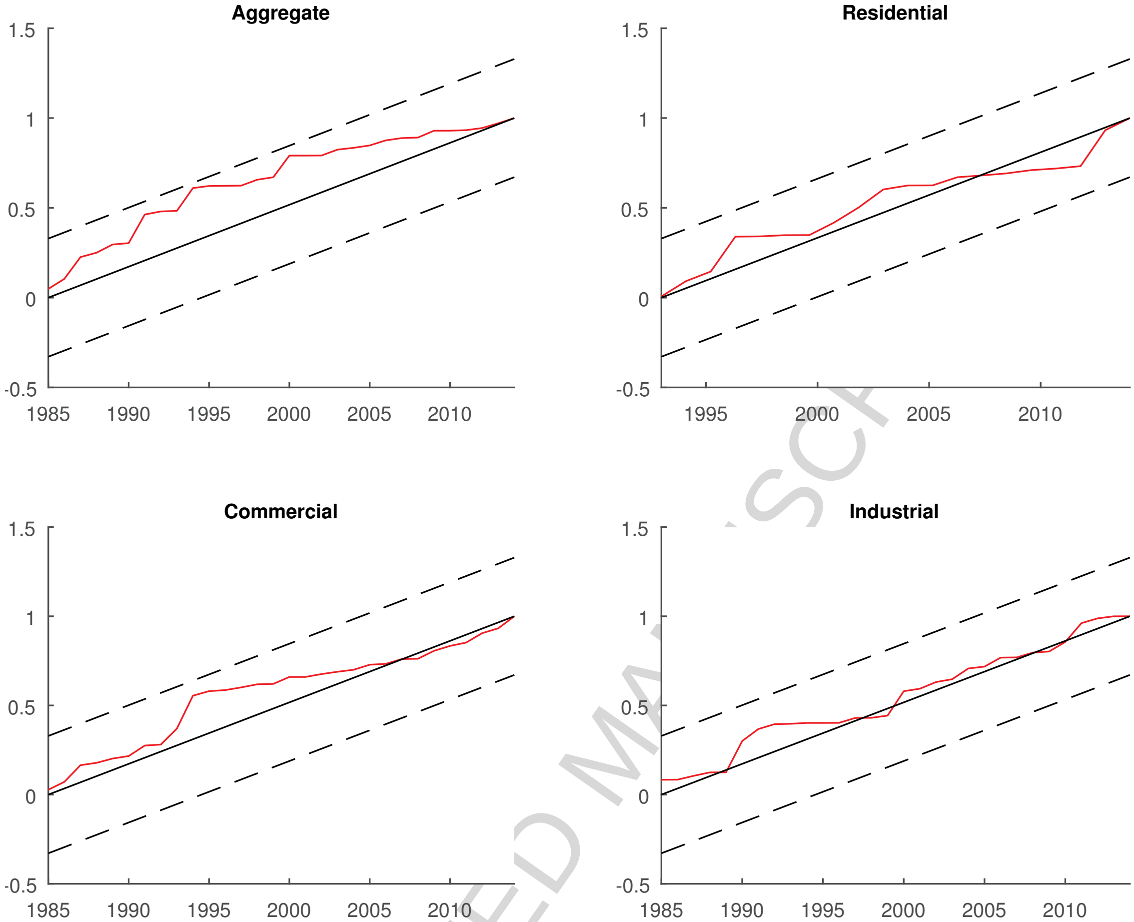

Figure 6: Plot of cumulative sum of squares (CUSUMQ) residuals. Dashed lines represent critical bounds at the 5 per cent level of significance.

6 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). This is especially true in the case where the estimates are derived using the average rather than the marginal price and is likely to have some element of endogeneity bias. However, the longer time span examined, the improved approach to testing the long-run relationship among variables, 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.

One such factor that could cause substantial changes in demand behaviour over time is the increased penetration of renewable energy technology. As distributed wind and solar energy becomes more widely used and displaces grid-supplied electricity, consumers are likely to become more responsive to electricity price changes in the long run. Additionally, the introduction of smart metering technology will provide consumers with more flexibility in managing electricity demand usage. Furthermore, the 2011 amendments to the All-Island Electricity Licence to make provisions for the introduction of net metering and power wheeling is likely to encourage greater investment among consumers and stimulate major changes in their demand behaviour when those programmes become fully operational.

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References

Amusa, H., Amusa, K. & Mabugu, R. (2009). Aggregate demand for electricity in South Africa: An analysis using the bounds testing approach to cointegration. *Energy Policy*, *37*(10), 4167–4175.

Anderson, K. P. (1973). Residential demand for electricity: Econometric estimates for california and the united states. *The Journal of Business*, *46*(4), 526–553.

Asafu-Adjaye, J. (2000). The relationship between energy consumption, energy prices and economic growth: Time series evidence from Asian developing countries. *Energy Economics*, *22*(6), 615–625.

Athukorala, P. W. & Wilson, C. (2010). Estimating short and long-term residential demand for electricity: New evidence from Sri Lanka. *Energy Economics*, *32*, S34–S40.

Bailey, J., Janson, N. & Espinasa, R. (2013). *Pre-Feasibility Study of the Potential Market for Natural Gas as a Fuel for Power Generation in the Caribbean*. Inter-American Development Bank. Retrieved from https://publications.iadb.org/handle/11319/6015?locale-attribute=en

Banerjee, A., Dolado, J. & Mestre, R. (1998). Error-correction mechanism tests for cointegration in a single-equation framework. *Journal of Time Series Analysis*, *19*(3), 267–283.

Bernstein, M. A. & Griffin, J. M. (2006). *Regional differences in the price-elasticity of demand for energy*. National Renewable Energy Laboratory.

Bewley, R. A. (1979). The direct estimation of the equilibrium response in a linear dynamic model. *Economics Letters*, *3*(4), 357–361.

Blázquez, L., Boogen, N. & Filippini, M. (2013). Residential electricity demand in Spain: New empirical evidence using aggregate data. *Energy Economics*, *36*, 648–657.

Bose, R. K. & Shukla, M. (1999). Elasticities of electricity demand in india. *Energy Policy*, *27*(3), 137–146.

Briguglio, L. (1995). Small island developing states and their economic vulnerabilities. *World Development*, *23*(9), 1615–1632.

Brown, R. L., Durbin, J. & Evans, J. M. (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society. Series B (Methodological)*, *37*(2), 149–192.

Chen, S.-T., Kuo, H.-I. & Chen, C.-C. (2007). The relationship between GDP and electricity consumption in 10 Asian countries. *Energy Policy*, *35*(4), 2611–2621.

De Vita, G., Endresen, K. & Hunt, L. C. (2006). An empirical analysis of energy demand in Namibia. *Energy Policy*, *34*(18), 3447–3463.

De Vita, G. & Trachanas, E. (2016). 'nonlinear causality between crude oil price and exchange rate: A comparative study of China and India – a failed replication (negative Type 1 and Type 2). *Energy Economics*, *56*, 150–160.

Dickey, D. A. & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427–431.

Edward Seaga Research Institute. (2016). National income and product. Retrieved from http://macrodata.org/#/app/discovermain

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987–1007.

Engle, R. F. & Granger, C. W. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica: Journal of the Econometric Society*, 251–276.

Glasure, Y. U. & Lee, A.-R. (1998). Cointegration, error-correction, and the relationship between GDP and energy:: The case of South Korea and Singapore. *Resource and Energy Economics*, *20*(1), 17–25.

Halvorsen, R. (1975). Residential demand for electric energy. *The Review of Economics and Statistics*, 12–18.

Harris, N. & Fabricius, I. (2005). *Cities and structural adjustment*. Routledge.

Holtedahl, P. & Joutz, F. L. (2004). Residential electricity demand in Taiwan. *Energy Economics*, *26*(2), 201–224.

Ito, K. (2014). Do consumers respond to marginal or average price? evidence from nonlinear electricity pricing. *The American Economic Review*, *104*(2), 537–563.

Jamaica Public Service. (2004). JPS Rate Submission 2004: Volume I. Retrieved from http://www.our.org.jm/ourweb/sites/default/files/documents/sector_documents/jps_rate_subission_2004.pdf

Jamaica Public Service. (2013). Our History. Retrieved from http://www.myjpsco.com/about-us/our-history/

Jamaica Public Service. (2014). JPS Tariff Application: 2014–2019. Retrieved from http://www.our.org.jm/ourweb/sites/default/files/documents/sector_documents/jps_2014-2019_rate_review_application_742014-final.pdf

Jarque, C. M. & Bera, A. K. (1987). A test for normality of observations and regression residuals. *International Statistical Review/Revue Internationale de Statistique*, 163–172.

Johansen, S. (1991). Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models. *Econometrica*, *59*, 1551–1580.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control*, *12*(2), 231–254.

Kamerschen, D. R. & Porter, D. V. (2004). The demand for residential, industrial and total electricity, 1973–1998. *Energy Economics*, *26*(1), 87–100.

Khanna, M. & Rao, N. D. (2009). Supply and demand of electricity in the developing world. *Annu. Rev. Resour. Econ. 1*(1), 567–596.

Kwiatkowski, D., Phillips, P. C., Schmidt, P. & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, *54*(1), 159–178.

Lee, J. & Strazicich, M. C. (2003). Minimum lagrange multiplier unit root test with two structural breaks. *The Review of Economics and Statistics*, *85*(4), 1082–1089.

Ljung, G. M. & Box, G. E. (1978). On a measure of lack of fit in time series models. *Biometrika*, *65*(2), 297–303.

Ministry of Energy and Mining. (2009). Jamaica's National Energy Policy: 2009 - 2030. Retrieved from http://mstem.gov.jm/sites/default/files/National%20Energy%20Policy.pdf

Narayan, P. K. (2005). The saving and investment nexus for china: Evidence from cointegration tests. *Applied Economics*, *37*(17), 1979–1990.

Narayan, P. K. & Popp, S. (2010). A new unit root test with two structural breaks in level and slope at unknown time. *Journal of Applied Statistics*, *37*(9), 1425–1438.

Nationwide Newsnet. (2014). JPS Terminates Power Purchase Agreement. (June 26). Retrieved from http://nationwideradiojm.com/jps-terminates-power-purchase-agreement/

Office of Utilities Regulation. (2004). Jamaica Public Service Company Limited Tariff Review for period 2004–2009: Determination Notice. Retrieved from http://www.our.org.jm/ourweb/sectors/electricity/documents?type=72&page=1

Office of Utilities Regulation. (2010a). Generation Expansion Plan 2010. Office of Utilities Regulation.

Office of Utilities Regulation. (2010b). Request for Proposals for Supply of up to 480 MW of Base-Load Generating Capacity on a Build, Own and Operate(BOO) Basis. Office of Utilities Regulation.

Ouattara, B. (2004). *Modelling the long run determinants of private investment in Senegal*. Centre for Research in Economic Development and International Trade, University of Nottingham.

Paul, A. C., Myers, E. C. & Palmer, K. L. (2009). A partial adjustment model of US electricity demand by region, season, and sector. Retrieved from http://ssrn.com/abstract=1372228

Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. *Econometrica: Journal of the Econometric Society*, *57*(6), 1361–1401.

Pesaran, M. H. & Shin, Y. (1998). An autoregressive distributed-lag modelling approach to cointegration analysis. *Econometric Society Monographs*, *31*, 371–413.

Pesaran, M. H., Shin, Y. & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, *16*(3), 289–326.

Pesaran, M. H. & Timmermann, A. (2002). Market timing and return prediction under model instability. *Journal of Empirical Finance*, *9*(5), 495–510.

Ramcharran, H. (1990). Electricity consumption and economic growth in Jamaica. *Energy Economics*, *12*(1), 65–70.

Ramsey, J. B. & Schmidt, P. (1976). Some further results on the use of ols and blus residuals in specification error tests. *Journal of the American Statistical Association*, *71*(354), 389–390.

Reiss, P. C. & White, M. W. (2005). Household electricity demand, revisited. *The Review of Economic Studies*, *72*(3), 853–883.

STATIN. (2016). Understanding the Consumer Price Index. Retrieved from http://statinja.gov.jm/Economic%20Statistics/Brochures/CPI%20Brochure%20lastest%20update.pdf

Taylor, L. D. (1975). The demand for electricity: A survey. *The Bell Journal of Economics*, 74–110.

UN Department of Economic and Social Affairs. (2015). Sustainable Development Knowledge Platform. United Nations. Retrieved from https://sustainabledevelopment.un.org/content/dsd/dsd_aofw_sids/sids_members.shtml

United Nations Statistics Division. (2016a). Demographic Yearbook. Retrieved from http://unstats.un.org/unsd/demographic/products/dyb/dyb2014.htm

United Nations Statistics Division. (2016b). National Accounts Main Aggregates Database. Retrieved from http://unstats.un.org/unsd/snaama/selbasicFast.asp

US Energy Information Administration. (2016). International Energy Statistics. Retrieved from http://www.eia.gov/cfapps/ipdbproject/IEDIndex3.cfm?tid=2&pid=2&aid=7

Woodland, A. D. (1993). A micro-econometric analysis of the industrial demand for energy in nsw. *The Energy Journal*, *14*(2), 57–89.

World Bank. (1996). *Jamaica – Fourth Power Project.* (tech. rep. No. 15702). Retrieved from http://documents.worldbank.org/curated/en/909281468049808721/Jamaica-Fourth-Power-Project

World Bank. (2016). Enterprise Surveys. World Bank. Retrieved from http://www.enterprisesurveys.org

Ziramba, E. (2008). The demand for residential electricity in South Africa. *Energy Policy*, *36*(9), 3460–3466.

Appendices

A Robustness Analysis

As noted in Section 5, I estimate 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. An important first observation is that all coefficient estimates have the correct signs, though price and income are insignificant for the industrial sector model.

Table A.1: Log Difference Estimates of the Effect of Price and Income on Electricity Demand – Static Model

	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.

B 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:

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

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 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:

$$x_t = c_t + \delta t + u_t \tag{B.2}$$

$$c_t = c_{t-1} + \epsilon_t \tag{B.3}$$

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 around 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.

To test for unit root when there are structural changes, I run the following regression suggested by Perron (1989):

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + \alpha_2 t + \mu_2 d_u + \varepsilon_t \tag{B.4}$$

where α_0 is the intercept term, α_2 is the trend coefficient, and μ_2 is the coefficient of the level break dummy d_u such that $d_u = 1$ for $t > T_B$ and zero otherwise. The test is $H_0 : \alpha_1 = 1$ (unit root with break) against $H_1 : \alpha_1 < 1$ (broken trend stationary). The asymptotic distribution of the t-statistic is dependent on the location of the break measured by $\lambda = T_B/n$, where T_B is the break date and n is the total sample size.

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, KPSS, and Perron procedures are presented in Table B.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 results of the Perron (1989) unit root test confirm that in the presence of a break, all variables used in this analysis are $I(1)$ except the urban population share which was found to be stationary in levels.

Table B.2: Results of ADF, KPSS, and Perron Unit Root Tests.

Variable	ADF Levels	ADF 1^{st} differences	KPSS Levels	KPSS 1^{st} differences	Perron Levels	I(d)
Aggregate						
Electricity consumption	−1.47	−4.67***	0.25***	0.15**	−2.04	I(1)
Price	−2.23	−3.65**	0.27***	0.17**	−2.36	I(1)
Income	−3.36*	−5.03***	0.31***	0.10	−2.03	I(1)
Urbanisation	−3.31*	−1.55	0.17*	0.14*	−5.07***	I(0)
Residential						
Electricity consumption	−2.18	−4.94***	0.24***	0.15**	−1.85	I(1)
Price	−2.16	−3.87**	0.25***	0.13*	−1.96	I(1)
Income	−2.92	−4.37***	0.32***	0.09	−2.24	I(1)
Urbanisation	−3.31*	−1.55	0.17*	0.14*	−5.07***	I(0)
Commercial						
Electricity consumption	−1.21	−5.33***	0.23***	0.11	−2.15	I(1)
Price	−2.24	−3.71**	0.27***	0.15**	−2.70	I(1)
Income	−4.72***	−1.96	0.30***	0.12*	−2.09	I(1)
Urbanisation	−3.31*	−1.55	0.17*	0.14*	−5.07***	I(0)
Industrial						
Electricity consumption	−2.65	−4.53***	0.24***	0.09	−3.09	I(1)
Price	−2.53	−3.39*	0.29***	0.18*	−2.70	I(1)
Income	−2.50	−4.19***	0.21**	0.10	−2.70	I(1)
Urbanisation	−3.31*	−1.55	0.17*	0.14*	−5.07***	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. Perron (1989) critical values are -4.55, -3.94, and -3.66 from Table IV.B with the location of the structural break given by λ=0.4. 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.

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 2 , but choice of an appropriate lag length is important since the specification assumes serially uncorrelated errors. To determine the optimal lag length, Equation 2 is estimated by OLS for $q = 1, 2, 3$. The maximum lag length is restricted to 3 based on the common rule of thumb $\sqrt[3]{T}$, and the small sample size available. As the results of Table B.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.

Table B.3: Lag order selection and cointegration results.

Sector	Lag lengths	AIC	SBC	SC	F_{PSS}	W_{PSS}	t_{BDM}
Aggregate	1	16.69	39.58	0.65	5.92**	23.69**	−3.00
Residential	3	32.58	68.56	0.00	3.77	15.10	−2.69
Commercial	1	17.01	39.91	0.00	4.12*	16.49*	−1.96
Industrial	1	17.71	40.61	0.60	5.84**	23.34**	−4.88***

Notes: Optimal lag length is chosen from a maximum lag length of $\sqrt[3]{T}$ and SC is the serial correlation statistic. F_{PSS} and W_{PSS} are the respective modified F-test and Wald test proposed by Pesaran et al. (2001) while t_{BDM} is based on the Banerjee et al. (1998) t-test procedure. The pairs of critical values for F_{PSS} at 1%, 5%, and 10% are 4.98–6.42, 3.54–4.73, and 2.89–3.98 respectively, with $k = 3$ independent variables. The critical values for W_{PSS} are 19.92–25.68, 14.16–18.92, and 11.56–15.92 while the values for t_{BDM} are -2.57—3.46, -2.86—3.78, and -3.43—4.37, respectively. Critical values for F_{PSS} are from Case III of Narayan (2005) while those for W_{PSS} follow from the calculation outlined in Pesaran et al. (2001). Critical values for t_{BDM} are taken from Table CII (iii) of Pesaran et al. (2001).

C 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 Bewley (1979) method, if G is a transformation function and the random variable X has mean μ, $G(X)$ 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 the variance-covariance matrix of X.

Highlights

• Long-run price and income elasticities of electricity demand are estimated for residential, commercial, and industrial consumers in Jamaica.
• Residential and industrial consumers are found to be more responsive to price changes.
• Use of the price instrument would be more successful in slowing demand growth in the residential and industrial sectors.