Price and income elasticities of residential electricity demand: the Australian evidence

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Abstract

This paper estimates country-wide and state-level price and income elasticities of Australian residential electricity demand, between 1970 and 2011, using an error-correction model. We find that the signs of all elasticity parameters are theoretically consistent, with long-run elasticities higher in magnitude than short-run elasticities. We also find strong evidence of structural breaks in the long-run elasticity estimates, with all (long-run) elasticities declining in magnitude over the past three decades. Finally, we document state-based heterogeneity in long-run cross-price and income elasticities, though there are few state-based differences in either long-run own-price elasticities, or short-run elasticities. These findings have important policy implications, including the need to consider potential structural breaks in price and income elasticities when forecasting and undertaking future scenario analyses.

Keywords: electricity demand, error correction,income elasticity, price elasticity, structural break
JEL Classification: O13, Q40, Q41

1 Introduction

This paper estimates price and income elasticities of Australian residential electricity demand, between 1970 and 2011, using country-wide and state-level data. Economic theory argues that the own-price elasticity of demand is negative, reflecting the "law" of

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downward-sloping demand, while the income elasticity of demand for electricity is positive, as electricity is a "normal" good.[1]

While the price elasticity of demand for electricity may be negative, its elasticity is likely to be low, due to the lack of substitutes.[2] However, price elasticities theoretically increase in value with the time horizon, reflecting the greater likelihood of substitutes, and the greater propensity for changes in consumer behaviour, in the medium- to longer-term. The focus of this paper is to estimate short- and long-run price and income elasticities to test the validity of these theories of consumer behaviour.

To the best of our knowledge, this is the first Australian-based study to: (i) estimate short- and long-run elasticities; (ii) estimate these parameters over a sufficiently long time span (three to four decades); and (iii) use both state-based and Australia-wide data. Existing Australian-based studies fulfil one or two of these attributes, but not all three. Consequently, our study provides a new contribution to the electricity demand literature.

There are three key findings. First, the signs of all elasticity parameters are theoretically consistent, with long-run elasticities higher in magnitude than short-run elasticities, as expected by economic theory. Second, there is evidence of structural breaks in the long-run elasticity estimates, potentially induced by economic policy changes, such as the easing in credit constraints during the 1980s and (more recently) greater consumer awareness of the need to limit (fossil-fuel-generated) electricity consumption. Over the past 42 years, the magnitude of long-run elasticities has fallen, at both the state level and for Australia overall. For example, own-price elasticity has fallen from -0.5 to -0.3, cross-price elasticity fell from 1.0 to 0.13, and income elasticity decreased from 1.7 to around 0.3 (all Australia-wide parameter estimates). In contrast, there is no evidence of structural breaks in short-run elasticities.

Third and final, there is strong evidence of state-based heterogeneity in the long-run cross-price and income elasticities, though little statistical difference between states' own-price elasticities. In addition, the ranking of state-level long-run cross-price and income elasticities is sample-dependent; for example, prior to 2003 – the year in which a structural break occurred – South Australia (SA) had the highest cross-price elasticity (0.97), with New South Wales (NSW) second lowest (0.25) of the states. In contrast, after 2003, NSW has the highest cross-price elasticity (0.26), with SA second lowest (0.18).

In contrast, there is relatively little state-based variation in short-run elasticity estimates. Where significant, state-based heterogeneity occurs in cross-price and income elasticity estimates. Of the six Australian states we examine, Tasmania and South Australia have the largest cross-price elasticity estimates (of 0.1-0.2), while Queensland and Tasmania have the highest income elasticity estimates (of around 0.4).

These price and income elasticity estimates reveal that households' residential energy

[1] Broadly, there are two types of goods – normal goods and "inferior" goods. The latter have a negative income elasticity, and include goods perceived to be low-quality or low-value.

[2] The magnitude of the price elasticity of demand is determined in part by the availability of rival goods; the greater (lower) the number of rivals, the greater (lower) is the magnitude.

demand is price and income inelastic, consistent with the view that electricity is a necessity with limited substitutes.

Section 2 outlines the data and empirical methodology used in this paper, with the results for the Australia-wide and state-specific data discussed in Section 3 and 4, respectively. Section 5 places this paper's results in the context of related Australian literature, with concluding remarks in Section 6.

2 Data and empirical methodology

2.1 Data

This paper uses annual data, between 1969/70 and 2010/11 (42 years), on six variables: (i) residential electricity consumption (in terawatt hours (TWh); real residential electricity prices; (iii) real residential gas prices; (iv) real household income; (v) the number of heating degree days (HDDs); and (vi) the number of cooling degree days (CDDs). The choice of variables are based on those used in the literature (see Silk and Joutz (1997)); for example, natural gas is a substitute to electricity for residential activities like heating and cooking. Due to its substitutability for electricity, natural gas prices are a determinant of the price elasticity of electricity demand, in both the short- and long-term.

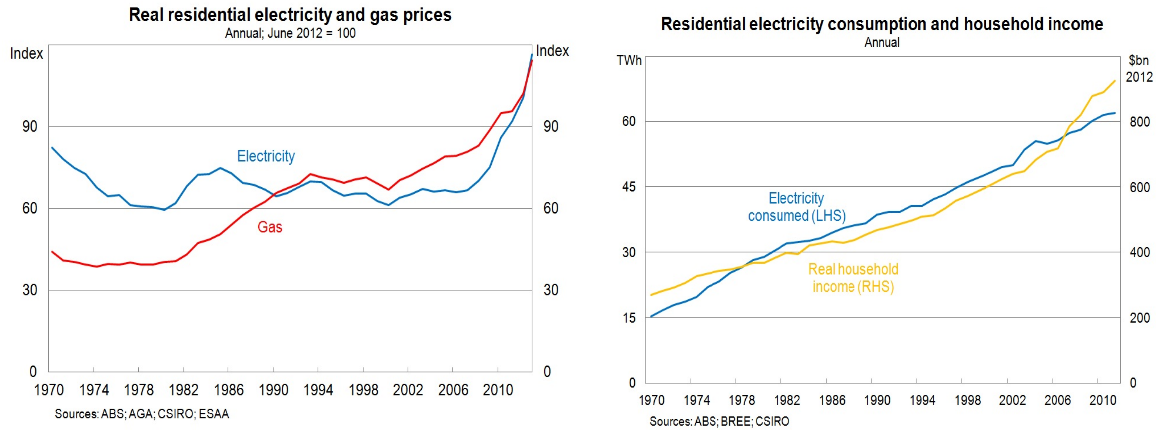
The choice of annual frequency is based on the availability of electricity price and consumption data. While higher frequency data (such as daily) are available, they are only available over the past decade, which precludes examining both short- longer-term elasticities, which are the focus of this paper.

Residential electricity consumption data are from the Bureau of Resource and Energy Economics (BREE). Nominal residential electricity price and household income data are from the Australian Bureau of Statistics (ABS). Nominal residential gas prices are obtained from the ABS after 1989 and, prior to 1989, from the Australian Gas Association (AGA). HDDs and CDDs are calculated using daily maximum and minimum temperatures, from the Bureau of Meteorology (BOM), for six selected Australian capital cities: Adelaide, Brisbane, Hobart, Melbourne, Perth, and Sydney. All the price and income data are deflated into real prices and values, using consumer price index (CPI) data from the ABS.

The above data are obtained for Australia collectively, and for six Australian states (South Australia, Queensland, Tasmania, Victoria, West Australia, and New South Wales). For the state-specific data, prices are deflated using the CPI of the corresponding capital city. However, due to the unavailability of state-specific household income prior to 1980/81, the sample period for the state-specific analysis is from 1980/81 to 2010/11 (31 years). Figure 1 shows the evolution of four of the above variables, over the 1969/70-2010/11 period, Australia-wide.

In real terms, residential electricity and gas prices are at their highest levels in four decades, having grown by 91 and 71 per cent, respectively, since 2000 (Figure 1, LHS). For residential electricity, this real price growth reversed all of the decline between the 1970s

Figure 1: **Evolution of selected variables**



and 1990s. Residential gas prices have recorded strong growth over the past four decades, having more than doubled (260 per cent) since 1970.

A discusses real electricity and gas price indices for the six capital cities.

2.2 Empirical methodology

To estimate the elasticities we use an error-correction model (ECM). An ECM relates the short-term relationship between variables to the longer-term relationship between these variables. More precisely, an ECM models the speed at which variables return to their long-run relationship, given the occurrence of a (short-term) deviation from its longer-run relationship. ECMs are therefore useful for estimating both short term and long term effects of multiple variables – for example, electricity price and household income – on another variable (electricity consumption). An ECM requires that a common order of integration exists between the nonstationary variables (that is, they are 'co-integrated') such that there exists (at least) one linear combination of these variables that is stationary.[3]

Applying an ECM to this paper leads to the following pair of equations:

$$\begin{aligned} \Delta q_t &= \beta_0 + \beta_1 \Delta p_t^{elec} + \beta_2 \Delta p_t^{gas} + \beta_3 \Delta y_t + \beta_4 \Delta HDD_t + \beta_5 \Delta CDD_t + \beta_6 z_{t-1} \\ z_t &= q_t - \alpha_0 - \alpha_1 p_t^{elec} - \alpha_2 p_t^{gas} - \alpha_3 y_t - \alpha_4 HDD_t - \alpha_5 CDD_t \end{aligned} \tag{1}$$

q_t, p_t^{elec}, p_t^{gas}, and y_t are, respectively, the (time-t) residential electricity consumed, real residential electricity price, real residential gas price, and real household income. HDD_t

[3]A stochastic process, $\{y_t\}$, is (weakly) 'stationary' if it has a finite mean, and a finite autocovariance which is independent of lag length; if either moment is not finite, then $\{y_t\}$ is 'nonstationary'. $\{y_t\}$ is 'integrated' of order d, or $I(d)$, if it needs to be differenced d-times in order to render it stationary. Hence, any $I(0)$ process is stationary.

and CDD_t are the (time-t) heating and cooling degree days respectively. All variables are transformed into (natural) logarithms which allows all the parameters in equation (1) to be interpreted as elasticities.

The first line in equation (1) is a model for estimating short-run elasticities; it describes how changes in electricity consumed reflect changes in the other variables, plus the extent to which q_t deviates from its long-run relationship with the other variables. $\beta_1 - \beta_5$ are the short-run parameters; β_1, β_2, and β_3 are, respectively, the short-run own-price elasticity, cross-price elasticity, and income elasticity, of electricity demand. β_6 indicates the "adjustment speed" of the system; given a deviation from its long-run relationship (i.e. $z \neq 0$), β_6 represents the speed at which electricity consumed adjusts back to its long-run relationship.

The second equation in equation (1) is the long-run model; α_1, α_2, and α_3 are, respectively, the long-run own-price elasticity, cross-price elasticity, and income elasticity, of electricity demand, and z_t is the (time-t) deviation of q_t from its long-run relationship.

The ECM estimates both equations simultaneously, using the Johansen (1995) procedure. This procedure is econometrically superior to the two-step approach of Engle and Granger (1987), in which the second equation in (1) is estimated first, and, using these parameter estimates, then estimates the first equation. In contrast, the Johansen approach estimates both equations simultaneously.

3 Australia-wide results

In order to establish that an ECM is appropriate for modelling the selected variables, unit root tests and tests of cointegration were conducted prior to estimating the ECM. As these tests' results are not the central focus of this paper, the output is discussed in B. Below, we present the parameter estimates for the long- and short-run models, starting with the long-run model (i.e. the second equation in (1)).

3.1 Long-run model

Table 1 contains the parameter estimates for the long-run ("cointegrating") equation, using the Australia-wide data.

The sign of the elasticity estimates are theoretically consistent and statistically significant (at the 1% significance level). There are four key findings to emerge from Table 1. First, the long-run own-price elasticity of demand ($\hat{\alpha_1}$) is estimated to be -0.75, indicating that, over the past four decades, residential electricity demand was price *inelastic*[4] This value indicates that a one percent rise in residential electricity prices led to a 75 basis point decline in electricity consumption. The value of $\hat{\alpha_1}$ is within the range of (U.S.-based)

[4]Price-inelastic demand is the term used when the price elasticity value is between zero (perfectly inelastic demand) and -1 ("unit" elasticity).

Table 1: **Parameter estimates for the long-run model**

The table reports parameter estimates and, in brackets, t-statistics for the (long-run) co-integrating equation. The t-statistics for the elasticity and weather coefficients are one-sided. $\bar{R}^2$ is the adjusted R^2 The estimated model uses annual Australia-wide data, from 1969/70 to 2010/11 (42 years).

$\hat{\alpha_0}$	$\hat{\alpha_1}$	$\hat{\alpha_2}$	$\hat{\alpha_3}$	$\hat{\alpha_4}$	$\hat{\alpha_5}$
-0.299	-0.748	0.273	0.952	0.001	-0.001
(-0.41)	(-5.44)	(2.18)	(8.02)	(0.51)	(-0.64)
		$\bar{R}^2$ = 0.96			

elasticity estimates reported in Bohi and Zimmerman (1993); using a variety of U.S.-wide datasets between the 1950s and 1970s, Bohi and Zimmerman (1993) reported that own-price elasticities ranged from -0.3 to -1.5, and income elasticities ranged from 0.3 to 1.1.

Second, the long-run cross-price elasticity of electricity demand ($\hat{\alpha}_2$) is positive and significant, indicating that a one per cent increase in residential natural gas prices leads to a 27 basis point increase in residential electricity consumption. The sign of $\hat{\alpha}_2$ is consistent with the substitutability between electricity and natural gas; a rise in natural gas prices leads households to substitute towards electricity.

Third, the long-run income elasticity of electricity demand ($\hat{\alpha}_3$) is positive and strongly significant, indicating that a one per cent increase in household income leads to a 95 basis point rise in residential electricity consumption. The value of $\hat{\alpha}_3$ is also within the range of (U.S.-based) estimates in Bohi and Zimmerman (1993). Fourth and final, the model has a high degree of explanatory power, with an $\bar{R}^2$ of 0.96.

Given the long time span of the dataset (42 years), it is possible that the long-run model may have undergone structural breaks, due to a sustained change in household consumption behaviour. For example, Australian financial system deregulation between the late 1970s and early 1980s may have eased credit constraints on households and possibly led to a change in price and income elasticities. More recently, greater energy efficiency initiatives by households may also have changed price and income elasticities.

3.1.1 Structural change

In this section, we analyse the potential for structural change, by partitioning the 42-year sample into two sub-samples, and testing whether the estimated coefficients for the first sub-sample model are statistically significantly different from the second sub-sample model's estimates. As the partition year is unknown, we nominate 1980 as the partition year and apply a Chow test to determine whether or not the differences between coefficients' estimates are statistically significant. If the differences are not significant, we use 1981 as the partition year and re-apply the Chow test to the new sub-samples. This recursive procedure is carried out until the Chow test indicates a statistically significant difference in the coefficient estimates, or the year 2001 is reached, whichever occurs earlier.

This "sequential" Chow test indicates that only one structural break occurred, in 1982, over the 1970-2011 period. Table 2 presents the parameter estimates for the long-run model for each sub-sample period.

The Chow test rejected (at the 1% significance level) the hypothesis that the respective

Table 2: **Parameter estimates for sub-sample analysis**

The table reports parameter estimates and, in brackets, t-statistics for the (long-run) co-integrating equation. The t-statistics for the elasticity and weather coefficients are one-sided. $\bar{R}^2$ is the adjusted R^2 The estimated model uses annual Australia-wide data, from 1969/70 to 2010/11 (42 years).

$\hat{\alpha_0}$	$\hat{\alpha_1}$	$\hat{\alpha_2}$	$\hat{\alpha_3}$	$\hat{\alpha_4}$	$\hat{\alpha_5}$
Panel A: 1969/70 – 1980/81 period					
-0.842	-0.524	1.018	1.674	0.001	-0.002
(-2.33)	(-2.89)	(3.78)	(11.73)	(1.51)	(-1.76)
$\bar{R}^2 = 0.99$					
Panel B: 1981/82 – 2010/11 period					
-0.343	-0.354	0.129	0.765	-0.001	-0.001
(-0.31)	(-2.03)	(3.19)	(5.51)	(-0.33)	(-0.87)
$\bar{R}^2 = 0.99$					

elasticity parameters were equal across the two sub-samples. For the first sub-sample, the estimates of own-price and cross-price elasticities, $\hat{\alpha_1}$ and $\hat{\alpha_2}$, respectively, were -0.52 and 1.02, significantly higher in magnitude than the estimates for the second sub-sample (-0.35 and 0.13, respectively). This indicates that households have become less responsive to price changes (i.e. their demand has become more inelastic). Income elasticity estimates ($\hat{\alpha_3}$) were also lower in the post-1981 period, falling from 1.67 to 0.77.[5]

Having identified 1982 as the (first) breakpoint year, we test for whether a second structural break occurred after 2001, using an indicator function, D_t^T, where T is the specified break year, with $D_t^T = 1$ when $t \geq T$.[6] Incorporating D_t^T and the 1982 break point (captured by D_t^{1982}) into the second equation in equation (1) leads to the following equation:

$$\begin{aligned} q_t = {} & \alpha_0 + \alpha_1 p_t^{elec} + \alpha_2 p_t^{gas} + \alpha_3 y_t + \alpha_4 HDD_t + \alpha_5 CDD_t \\ & + \eta_0 D_t^{1982} + \eta_1 D_t^{1982} p_t^{elec} + \eta_2 D_t^{1982} p_t^{gas} + \eta_3 D_t^{1982} y_t \\ & + \rho_0 D_t^T + \rho_1 D_t^T p_t^{elec} + \rho_2 D_t^T p_t^{gas} + \rho_3 D_t^T y_t + z_t \end{aligned} \tag{2}$$

We consider the potential for a second break during the 2000s, starting with T=2002 (see C). We found that a second break occurred during 2006, coinciding with the strong

[5] As was the case in Table 1, both weather coefficients ($\hat{\alpha_4}$ and $\hat{\alpha_5}$) were statistically insignificant, in each sub-period, with an insignificant difference between the estimated coefficients across the two sub-samples.

[6] We do not use the Chow test to test for a post-2000 break, as this would mean having few data points in the second sub-sample relative to the number of parameters estimated. An insufficient number of observations can induce bias and inefficiency in the estimators.

surge in real residential electricity and gas prices (see Figure 1) and a greater awareness of electricity (and, more broadly, energy) efficiency and the environmental impact of (fossil-fuel-generated) electricity consumption. We found evidence of a second structural break, particularly for income elasticity (α_3); as noted above, in the pre-1982 period $\hat{\alpha_3}$ was 1.7, but was less than half this (0.8) in the post-1983 period ($\hat{\alpha_3} + \hat{\eta_3}$). The income elasticity fell further during the post-2006 period, to around 0.3 ($\hat{\alpha_3} + \hat{\eta_3} + \hat{\rho_3}$). This finding is consistent with the potential for greater consumer awareness of climate change and electricity efficiency issues, so that a given rise in income leads to a smaller increase in electricity consumption.

In contrast, there is no statistically significant change in the other elasticity parameters during the post-2006 period; the value of $\hat{\rho}_1$ (own-price elasticity) and $\hat{\rho}_2$ (cross-price elasticity) are statistically insignificant.

To summarise, over the past 42 years, the magnitude of long-run income and price elasticities have fallen, potentially due to both economic policy changes and energy efficiency initiatives. Own-price elasticity has fallen from -0.5 to -0.3, cross-price elasticity has fallen from 1.0 to 0.13, and income elasticity has fallen from 1.7 to around 0.3. The decline in the magnitude of own-price elasticities since 2003 has coincided with an increase in real electricity prices, implying a (standard) convex-shaped demand curve, in which higher prices lead to less elastic demand.

Having discussed estimates of the long-run elasticities, we turn to the short-run elasticity estimates.

3.2 Short-run model

Table 3 contains the parameter estimates for the short-run model; the first equation in (1). There are three findings from Table 3. First, the short-run elasticity parameter estimates ($\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$) are lower in value than the corresponding estimates of long-run elasticities (see Table 1); for example, the estimate of short-run own-price elasticity (-0.5) is smaller in magnitude than the long-run parameter estimate (-0.75). This is consistent with economic theory, which argues that elasticities for goods increase with the time horizon.[7] The short-run elasticity estimates are also in the range of U.S.-based estimates in Bohi and Zimmerman (1993).

Second, the negative sign of $\hat{\beta}_6$ is theoretically consistent, implying that electricity consumption reverts to its long-run relationship, given a positive (negative) short-run deviation from this relationship. $\hat{\beta}_6$ is also economically and statistically significant; it implies that 20% of any deviation in electricity consumption from its long-run equilibrium level is corrected in the subsequent year.

Third and final, the overall fit of the short-run model is quite high; the $\bar{R}^2$ is 0.55. Furthermore, there is no evidence that the residuals are not a white noise process; the residuals

[7] The model was estimated without any lagged dependent variables, as these were found to be statistically insignificant.

Table 3: **Parameter estimates for the short-run model**

The table reports parameter estimates and, in brackets in the second row, t-statistics for the (short-run) error correction model. t-statistics for the elasticity and weather coefficients are one-sided. $\bar{R}^2$ is the adjusted R^2, JB is the Jarque-Bera test for normality in the residuals ($\{z\}$), BPG is the Breusch-Godfrey-Pagan test for autocorrelation in $\{z\}$, and $ARCH(1)$ is the Lagrange Multipler test for (first-order) conditional homoscedasticity in $\{z\}$. p-values for these tests are in brackets. The ECM is based on annual Australia-wide data, from 1969/70 to 2010/11 (42 years).

$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$	$\hat{\beta}_6$
0.033	-0.447	0.121	0.244	0.012	0.011	-0.191
(4.74)	(-2.82)	(0.91)	(2.05)	(1.65)	(0.36)	(-3.81)
$\bar{R}^2 = 0.55$				$JB = 1.55$ (0.62)		
$BPG = 2.81$ (0.83)				$ARCH(1) = 0.96$ (0.50)		

appear to be unautocorrelated (on the basis of the BPG test), normally distributed (on the basis of the JB test), and homoscedastic (on the basis of the ARCH test).

3.2.1 Structural change

As with the long-run model, it is possible that the short-run model may have undergone structural breaks. We used the same approach as that in Section 3.1 to investigate the potential for structural change in the short-run model. In contrast to the long-run model, we found weak evidence of a structural break in the short-run model. Notably, the highest p-value of the sequential Chow test was 0.06, when 1983 was the break year. Furthermore, using 1983 as the partition year, the hypothesis that the respective short-run elasticity parameters were equal across subsamples, was not rejected at the 5% level (p-value was 0.09). These results are available on request.

4 State-based results

Hitherto, the econometric analysis has been based on Australia-wide data, which has provided estimates of short- and long-run elasticities for Australia overall. This section analyses whether there are state-specific differences in the estimated parameters. One potential reason for state-based parameter heterogeneity could be variation in states' endowments of natural gas and input fuels for electricity, which can affect the degree of substitutability between electricity and gas even in the presence of inter-state trade of gas and electricity. State-based parameter heterogeneity is modelled by applying state-specific intercept and interaction dummy variables to equation (1):

$$
\begin{aligned}
\Delta q_{i,t} &= \beta_0 + \beta_1 \Delta p^{elec}_{i,t} + \beta_2 \Delta p^{gas}_{i,t} + \beta_3 \Delta y_{i,t} + \beta_4 \Delta HDD_{i,t} + \beta_5 \Delta CDD_{i,t} + \beta_6 z_{i,t-1} \\
&\quad + \cdot D_{j,t} + (\beta_1 \cdot D_{j,t}) \cdot \Delta p^{elec}_{j,t} + (\beta_2 \cdot D_{j,t}) \cdot \Delta p^{gas}_{j,t} + (\beta_3 \cdot D_{j,t}) \cdot \Delta y_{j,t} \\
&\quad + (\beta_4 \cdot D_{j,t}) \cdot \Delta HDD_{j,t} + (\beta_5 \cdot D_{j,t}) \cdot \Delta CDD_{j,t} + (\beta_6 \cdot D_{j,t}) \cdot z_{j,t-1} \\
z_{i,t} &= q_{i,t} - \alpha_0 - \alpha_1 p^{elec}_{i,t} - \alpha_2 p^{gas}_{i,t} - \alpha_3 y_{i,t} - \alpha_4 HDD_{i,t} - \alpha_5 CDD_{i,t} \\
&\quad + \cdot D_{j,t} - (\alpha_1 \cdot D_{j,t}) \cdot \Delta p^{elec}_{j,t} - (\alpha_2 \cdot D_{j,t}) \cdot \Delta p^{gas}_{j,t} - (\alpha_3 \cdot D_{j,t}) \cdot \Delta y_{j,t} \\
&\quad - (\alpha_4 \cdot D_{j,t}) \cdot HDD_{j,t} - (\alpha_5 \cdot D_{j,t}) \cdot CDD_{j,t}
\end{aligned} \tag{3}
$$

where i indexes all six states, j indexes all states except NSW, and $D_{j,t}$ is an indicator (step) function with a value of one for state j, and value of zero for state $i_{i \neq j}$.

4.1 Long-run model

Estimating the full (36-parameter) long-run model reveals evidence of state-based heterogeneity in the intercept (α_0), cross-price elasticity (α_2), and income elasticity (α_3) parameters. We find no evidence of state-based heterogeneity in own-price elasticities (α_1) or the weather-related parameters (α_4, α_5). On the basis of the parameter estimates from the full model, a more parsimonious model is estimated, in which state-based heterogeneity is allowed only in the intercept, cross-price elasticity and income elasticity parameters (a total of 21 parameters). The results are reported in Table 4.

Cross-price elasticity estimates vary between 0.01 (Queensland) and 0.90 (Tasmania), with intermediate values (around 0.3) for each of NSW and South Australia.[8] There is relatively less variation in income elasticities, with estimates ranging from 0.75 (NSW) to 0.94 (South Australia), with Queensland, Western Australia and Tasmania having similar income elasticities (around 0.8). In contrast, the estimate of own-price elasticity ($\hat{\alpha_1}$) is around -0.3, with statistically insignificant differences between states. This estimate is consistent with that for Australia-wide data post-1980 (-0.35), from Table 2.

As the above heterogeneity highlights, the hypothesis that the dummy variables jointly equal zero is strongly rejected, with a p-value of less than 0.01. Furthermore, the model's explanatory power is high, with an $\bar{R}^2$ close to 1.0, and the model's residuals show no evidence of autocorrelation, as indicated by the Durbin-Watson statistic (DW).

4.1.1 Structural change

A Chow test is again used to test for the possibility of structural change in the model, proceeding sequentially from the year 1981 to 2000. However, no structural break was found during this period, likely reflecting the fact that the state-level data are from 1981,

[8]State j's cross-price elasticity estimate ($\alpha_{\hat{2},j}$) equals: $\hat{\alpha_2} \cdot \left(1 + \hat{D_j}\right)$, when $\hat{D_j}$ is statistically significant (at the 5% level); otherwise, $\alpha_{\hat{2},j} = \hat{\alpha_2}$.

Table 4: **Parameter estimates for the (state-based) long-run model**

The table reports parameter estimates and, in brackets, t-statistics for the (long-run) co-integrating equation. t-statistics for the elasticity and weather coefficients are one-sided. State-based heterogeneity is modelled using dummy variables as both intercept and interaction terms; for the latter, the interacting parameters are the estimated cross-price elasticity ($\hat{\alpha_2}$) and income elasticity ($\hat{\alpha_3}$). $\bar{R}^2$ is the adjusted R^2, F-test tests whether the dummy variables are jointly equal to zero (p-value is in brackets), and DW is the Durbin-Watson statistic. The estimated model uses annual data for six Australian states, from 1980/81 to 2010/11 (a total of 186 observations).

$\hat{\alpha_0}$	$\hat{\alpha_1}$	$\hat{\alpha_2}$	$\hat{\alpha_3}$	$\hat{\alpha_4}$	$\hat{\alpha_5}$	$\hat{D_{VIC,t}}$	$\hat{D_{QLD,t}}$	$\hat{D_{WA,t}}$	$\hat{D_{TAS,t}}$	$\hat{D_{SA,t}}$
-0.026	-0.316	0.350	0.746	0.072	0.023	1.300	0.654	-0.202	-3.093	-0.914
(-0.60)	(-3.37)	(1.96)	(9.64)	(2.09)	(1.47)	(2.82)	(1.87)	(-0.52)	(-6.63)	(-2.18)

$\alpha_2 \cdot \hat{D}_{VIC,t}$	$\alpha_2 \cdot \hat{D}_{QLD,t}$	$\alpha_2 \cdot \hat{D}_{WA,t}$	$\alpha_2 \cdot \hat{D}_{TAS,t}$	$\alpha_2 \cdot \hat{D}_{SA,t}$	$\alpha_3 \cdot \hat{D}_{VIC,t}$	$\alpha_3 \cdot \hat{D}_{QLD,t}$	$\alpha_3 \cdot \hat{D}_{WA,t}$	$\alpha_3 \cdot \hat{D}_{TAS,t}$	$\alpha_3 \cdot \hat{D}_{SA,t}$
-0.301	-0.339	-0.218	0.545	-0.073	-0.073	0.121	0.104	0.111	0.194
(-2.47)	(-3.84)	(-2.13)	(4.47)	(-0.52)	(-1.40)	(2.85)	(2.34)	(1.94)	(2.61)

$\bar{R}^2 = 0.998$	F-test $= 38.98$ (0.00)	$DW = 1.85$

and so cover a period during which much of the regulatory and economic policy reforms – the likely source of the structural break (see Section 3.1) – had come into effect. Mirroring the analysis in Section 3.1, time dummy variables were used to test for a potential structural break during the 2000s. For brevity, only the findings from this analysis are reported, with the results available on request.

Similar to the Australia-wide analysis, we found strong evidence that a structural break in the state-level analysis, with the break year being 2004 (similar to the break-year for the Australia-wide analysis). The break affected all three elasticity parameters, for all states, though to varying degrees of economic and statistical significance. For all states, the elasticity parameters declined in magnitude, as was the case with the Australia-wide analysis. For the sake of brevity, Table 5 provides the parameter estimates for only the three price and income elasticity parameters, for each state. As was the case in Table 4, we found no evidence of state-based heterogeneity in the own-price elasticity estimates.

Table 5 reveals that, similar to the Australia-wide data, state-level price and income elasticities were lower during the post-20004 period, compared to pre-2004. However, the extent of these declines vary considerably by state. For example, while cross-price elasticities for Victoria fell from 0.63 to 0.22, the decline was greater for Tasmania; $\alpha_{2,\hat{T}AS}$ fell from 0.97 to 0.18.

To summarise, the magnitude of long-run income and price elasticities have fallen during the 2000s, with the declines observed in all of the selected six states. This phenomenon mirrors the findings based on Australia-wide data.

4.2 Short-run model

Estimating the full (36-parameter) short-run model reveals evidence of state-based heterogeneity in the cross-price elasticity (β_2), and income elasticity (β_3) parameters. As with the long-run model's parameter estimates, we find no evidence of state-based heterogeneity in short-run own-price elasticities (β_1) or the two weather-related parameters (β_4 and β_5). Using these results, a more parsimonious model is estimated, in which state-based heterogeneity is allowed only in the cross-price elasticity and income elasticity parameters (a total of 17 parameters). Table 6 contains the parameter estimates.

There are four key findings. First, similar to the Australia-wide data, the short-run elasticity parameter estimates ($\hat{\beta}_1$, $\hat{\beta}_2$ and $\hat{\beta}_3$) are lower in magnitude than the corresponding estimates of long-run elasticities (see Table 4); for example, the estimate of short-run own-price elasticity ($\hat{\beta}_1$) is -0.12, compared to the estimate of the long-run parameter ($\hat{\alpha_1}$) of -0.32. These findings are consistent with theory. Second, the negative sign of the error-correction estimate ($\hat{\beta}_6 = -0.25$) is also theoretically consistent, and implies that 25% of any deviation in residential electricity consumption from its long-run level is corrected in the subsequent year.

Third, in terms of state-based elasticity heterogeneity, only Tasmania (0.16) and South Australia (0.11) have statistically significant cross-price elasticity estimates; the other

Table 5: **Parameter estimates for the (state-based) long-run model with a structural break**

The table reports parameter estimates and, in brackets, t-statistics for the (long-run) price and income elasticities. t-statistics for the (non-interacting) own-price elasticity and weather coefficients are one-sided. State-based heterogeneity is modelled using dummy variables as both intercept and interaction terms; for the latter, the interacting parameters are the estimated cross-price elasticity ($\hat{\alpha_2}$) and income elasticity ($\hat{\alpha_3}$). $\bar{R}^2$ is the adjusted R^2, F-test tests whether the respective elasticity coefficients are equal across the two sample periods (p-value is in brackets), and DW is the Durbin-Watson statistic. The estimated model uses annual data for six Australian states, from 1980/81 to 2010/11 (a total of 186 observations).

Panel A: 1980/81-2002/03 period

$\hat{\alpha_1}$	$\alpha_{2,\hat{NSW}}$	$\alpha_{2,\hat{VIC}}$	$\alpha_{2,\hat{QLD}}$	$\alpha_{2,\hat{WA}}$	$\alpha_{2,\hat{TAS}}$	$\alpha_{2,\hat{SA}}$	$\alpha_{3,\hat{NSW}}$	$\alpha_{3,\hat{VIC}}$	$\alpha_{3,\hat{QLD}}$	$\alpha_{3,\hat{WA}}$	$\alpha_{3,\hat{TAS}}$	$\alpha_{3,\hat{SA}}$
-0.460	-0.250	0.771	0.633	0.320	0.221	0.971	0.270	0.794	0.927	0.949	0.978	0.962
(-3.13)	(1.99)	(2.33)	(2.09)	(1.91)	(2.19)	(4.11)	(1.89)	(2.23)	(2.13)	(2.56)	(2.75)	(2.55)

Panel B: 2003/04-2010/11 period

$\hat{\alpha_1}$	$\alpha_{2,\hat{NSW}}$	$\alpha_{2,\hat{VIC}}$	$\alpha_{2,\hat{QLD}}$	$\alpha_{2,\hat{WA}}$	$\alpha_{2,\hat{TAS}}$	$\alpha_{2,\hat{SA}}$	$\alpha_{3,\hat{NSW}}$	$\alpha_{3,\hat{VIC}}$	$\alpha_{3,\hat{QLD}}$	$\alpha_{3,\hat{WA}}$	$\alpha_{3,\hat{TAS}}$	$\alpha_{3,\hat{SA}}$
-0.097	-0.262	0.134	0.217	0.048	0.040	0.176	0.062	0.547	0.457	0.599	0.263	0.459
(-1.89)	(1.88)	(2.63)	(1.91)	(0.68)	(0.39)	(0.42)	(1.48)	(2.11)	(1.88)	(2.65)	(1.99)	(1.88)

$\bar{R}^2 = 0.995$	F-test $= 27.98$ (0.00)	$DW = 1.92$

states' $\hat{\beta}_2$ estimates are insignificantly different from zero. Similarly, only Queensland (0.35) and Tasmania (0.47) have statistically significant $\hat{\beta}_3$ values; the other states' income elasticity estimates are insignificantly different from zero. While the evidence of state-level parameter heterogeneity is modest compared to that of the state-level long-run model and the Australia-wide short-run model, there is sufficient heterogeneity to reject the hypothesis that the dummy variables jointly equal zero; the p-value of the F-test statistic is less than 0.01.

Fourth and final, the ECM's explanatory power is reasonable ($\bar{R}^2 = 0.26$) though not as high as for the prior models, and the residuals appear to be neither autocorrelated (using the DW and BPG test statistics) nor heteroscedastic (using the ARCH test statistic).

4.2.1 Structural change

Echoing the findings for the Australia-wide analysis, we found no evidence of a structural break in the short-run state-level elasticity parameters, using a sequential Chow test to analyse the potential for structural change in the short-run model. For the state-level data, the highest p-value of the sequential Chow test was 0.09, when 1985 was the break year. To summarise, both the Australia-wide and state-level data provide no evidence of structural breaks in the (short-run) price and income elasticities of electricity demand. The only evidence of structural change having occurred is for the long-run elasticity parameters.

5 Related Australian literature

To the best of our knowledge, the only publicly-available studies using Australia-wide data are Productivity Commission (2011), NIEIR (2002), and Narayan and Smyth (2005). Over the period 1975-2008, Productivity Commission (2011) reported long-run own-price elasticities ranging between -0.2 and -0.7 for Australia, within the range of estimates reported here (see Table 1). However, the estimates from Productivity Commission (2011) are likely to be statistically biased, as its model omits cross-price and income elasticities. NIEIR (2002) used data from 1980-1995 and estimated that the long run price elasticity for the Australian residential sector was -0.25, broadly in line with the estimate of α_1 (of -0.35) reported in Table 2.[9]

The paper that comes closest in theoretical formulation to ours is Narayan and Smyth (2005), whose model is similar to the second equation in (1), containing own- and cross-price variables, and income and temperature variables. Using Australia-wide data from 1969 to 2000, Narayana and Smyth report values of $\hat{\alpha}_1$ and $\hat{\alpha}_2$ of -0.54 and 0.32, respectively, with $\hat{\alpha}_3$ and $\hat{\alpha}_4$ each insignificantly different from zero. Estimates of the short-run

[9]Similar to Productivity Commission (2011), NIEIR (2002)'s model omits income and cross-price variables, potentially biaising its estimates of own-price elasticities.

Table 6: **Parameter estimates for the state-based short-run model**

The table reports parameter estimates and, in brackets, t-statistics for the ECM. t-statistics for the elasticity and weather coefficients are one-sided. State-based heterogeneity is modelled using dummy variables that interact with cross-price elasticity ($\hat{\beta}_2$) and income elasticity ($\hat{\beta}_3$) parameters. $\bar{R}^2$ is the adjusted R^2, F-test tests whether the (interaction) dummy variables are jointly equal to zero, DW is the Durbin-Watson statistic, JB is the Jarque-Bera test for normality in the residuals ($\{z\}$), BPG is the Breusch-Godfrey-Pagan test for autocorrelation in $\{z\}$, and $ARCH(1)$ is the Lagrange Multipler test for (first-order) conditional homoscedasticity in $\{z\}$. p-values for each test statistic is in brackets. The ECM uses annual data for six Australian states, from 1981/82 to 2010/11 (a total of 180 observations).

$\hat{\beta}_0$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	$\hat{\beta}_5$	$\hat{\beta}_6$
0.019	-0.123	-0.025	0.107	0.067	0.016	-0.252
(5.73)	(-2.71)	(-0.22)	(0.68)	(4.18)	(2.11)	(-4.08)

$\beta_2 \cdot \hat{D}_{VIC,t}$	$\beta_2 \cdot \hat{D}_{QLD,t}$	$\beta_2 \cdot \hat{D}_{WA,t}$	$\beta_2 \cdot \hat{D}_{TAS,t}$	$\beta_2 \cdot \hat{D}_{SA,t}$	$\beta_3 \cdot \hat{D}_{VIC,t}$	$\beta_3 \cdot \hat{D}_{QLD,t}$	$\beta_3 \cdot \hat{D}_{WA,t}$	$\beta_3 \cdot \hat{D}_{TAS,t}$	$\beta_3 \cdot \hat{D}_{SA,t}$
0.086	-0.014	0.108	0.183	0.137	-0.110	0.243	0.073	0.364	0.120
(0.51)	(-1.15)	(0.74)	(1.99)	(2.65)	(-0.52)	(1.96)	(1.01)	(1.96)	(0.56)

$\bar{R}^2 = 0.258$	F-test = 46.76 (0.00)	$DW = 1.92$
$JB = 9.35$ (0.01)	$BPG = 25.40$ (0.08)	$ARCH(1) = 0.08$ (0.78)

elasticities are -0.27 (for $\hat{\beta}_1$), and zero (for each of $\hat{\beta}_2$ and $\hat{\beta}_3$). The statistically insignificant estimates for the short- and long-run cross-price elasticities are inconsistent with the estimates reported by us, as is the insignificant value for short-run income elasticity.

Intriguingly, Narayan and Smyth (2005) find no evidence of a structural break in either the long-run or short-run elasticity parameters, in contrast to the strong evidence we documented above.[10] Consequently, Narayana and Smyth's estimates of α_1 (-0.54) and α_2 (0.32) are for their entire 32-year sample, whereas our estimates decline over the sample period, reflecting the structural change that has occurred over the past three decades.

In terms of state-level analyses, an early study is Weyman-Jones (1975), whose sample period (1953-1971) slightly overlaps with ours. Over this period, Weyman-Jones reports own-price elasticity estimates ranging from -0.69 (for Western Australia) to -1.51 (for Victoria), with NSW's estimate at -0.97 (and zero for Tasmania). Income elasticity estimates range from 0.98 (South Australia) to 1.47 (Western Australia), with estimates for Tasmania, Victoria and Queensland each around 1.13. These estimates are materially larger in magnitude than those reported in this paper, with $\hat{\alpha_1}$ = -0.42 (for all states) and $\hat{\alpha_3}$ ranging from 0.75 (NSW) to 0.94 (South Australia). These differences likely reflect: (i) differing sample periods; (ii) structural change – elasticity estimates were higher in the early part of the 1970-2011 period than over the past three decades (see Section 3.1); and (iii) Weyman-Jones (1975)'s estimates may be statistically biased as his model omits electricity substitutes.

Using data for the 1980-1995 period, NIEIR (2002) reported estimates of $\hat{\alpha_1}$ for Victoria of -0.38, consistent with our estimate of -0.46 (see Table 5) over a similar sample period.

The paper that comes closest in empirical application to ours is KPMG Econtech (2010). Using state-level data between 1987 and 2007, KPMG estimated long- and short-run own-price, cross-price and income elasticities of residential electricity demand, by state. Table 7 compares our short- and long-run elasticity estimates with those of KPMG.

The key finding from Table 7 is that our elasticity estimates, both long-run and short-run, are typically larger in magnitude (both economically and statistically) than those reported in KPMG Econtech (2010).[11] Furthermore, in terms of the long-run parameters, there are occasionally large differences (both economically and statistically) between our estimates and those from KPMG Econtech (2010). For example, while both papers report the same value of $\alpha_{1,\hat{N}SW}$ (-0.32), KPMG Econtech (2010) reports statistically insignificant values of $\hat{\alpha_1}$ for the other states; in contrast, for *all* states, we find statistically significant values of $\hat{\alpha_1}$.

Furthermore, for some states, long-run elasticity parameters are either not estimated

[10] Narayana and Smyth use two residuals-based tests (cumulative sum of recursive residuals (CUSUM); and CUSUM of squared residuals (CUSUMSQ)) for structural change. However, as the CUSUM/CUSUMQ tests are known to have low statistical power, compared to the Chow test, these tests are unlikely to reject a false null hypothesis (of no structural change).

[11] For consistency, our long-run estimates in Table 7 do not account for structural breaks (that is, the values are from Table 4), as KPMG Econtech (2010) do not consider the possibility of structural breaks.

Table 7: **A comparison of short-run and long-run price elasticity estimates**

The table reports short- and long-run elasticity estimates by state, taken from two studies: (i) KPMG Econtech (2010) (denoted 'KPMG'); and (ii) our paper (denoted 'Rai et al.'). For the latter study, the estimates are from Table 4, though with (insignificant) state differences in α_1 incorporated into the estimates. For each elasticity estimate, t-statistics are provided in brackets below the estimate. Panel A notes the sample period used in each study, Panel B contains the long-run elasticity estimates, and Panel C contains short-run elasticity estimates. '–' denotes estimates not reported in KPMG Econtech (2010).

Panel A: Sample period

KPMG	1987-2007
Rai et al.	1981-2011

Panel B: Long-run elasticity estimates

KMPG	NSW	VIC	QLD	WA	TAS	SA
$\hat{\alpha_1}$	-0.32	-0.04	-0.09	$-0.31^{(a)}$	-0.31	-0.21
	(-2.03)	(-0.24)	(-1.10)	(0)	(-1.04)	(-1.72)
$\hat{\alpha_2}$	–	0.15	–	–	0.48	0.30
	–	(0.71)	–	–	(2.00)	(1.52)
$\hat{\alpha_3}$	0.29	0.80	0.21	0.19	0.84	0.72
	(1.72)	(13.93)	(2.81)	(1.74)	(4.45)	(3.70)
Rai et al.	NSW	VIC	QLD	WA	TAS	SA
$\hat{\alpha_1}$	-0.32	-0.29	-0.35	-0.28	-0.35	-0.27
	(-3.37)	(-2.24)	(-4.15)	(-3.00)	(-2.98)	(-2.77)
$\hat{\alpha_2}$	0.35	0.05	0.01	0.13	0.90	0.28
	(1.96)	(0.84)	(0.13)	(2.47)	(3.87)	(3.12)
$\hat{\alpha_3}$	0.75	0.67	0.87	0.85	0.86	0.94
	(9.64)	(7.40)	(5.85)	(4.34)	(7.94)	(8.61)

Panel C: Short-run elasticity estimates

KMPG	NSW	VIC	QLD	WA	TAS	SA
$\hat{\beta}_1$	-0.17	-0.04	-0.00	-0.92	-0.18	-0.16
	(-1.35)	(-0.67)	(-0.02)	(-2.88)	(-0.90)	(-1.18)
$\hat{\beta}_2$	–	0.70	–	–	–	0.14
	–	(5.17)	–	–	–	(0.51)
$\hat{\beta}_3$	0.39	0.46	0.28	–	0.49	0.22
	(2.28)	(3.07)	(1.19)	–	(1.17)	(0.65)
Rai et al.	NSW	VIC	QLD	WA	TAS	SA
$\hat{\beta}_1$	-0.51	-0.58	-0.45	-0.48	-0.61	-0.49
	(-2.71)	(-2.40)	(-2.17)	(-2.99)	(-3.03)	(-2.66)
$\hat{\beta}_2$	-0.02	0.03	-0.02	0.06	0.16	0.11
	(-0.21)	(0.29)	(-0.27)	(0.57)	(1.92)	(2.52)
$\hat{\beta}_3$	0.11	0.00	0.35	0.17	0.47	0.23
	(0.68)	(0.17)	(2.65)	(1.01)	(2.58)	(1.27)

Notes: (a) This coefficient was not estimated; instead, a pre-specified value was used.

(for example, $\hat{\alpha_2}$ and $\hat{\beta}_2$ are not estimated for NSW, Queensland or Western Australia) or pre-specified (such as $\alpha_{1,\hat{W}A}$) by KPMG, with little explanation by KPMG given for such actions.

In terms of the short-run elasticity estimates, we find no significant state-based variation in $\hat{\beta}_1$, the own-price elasticity estimate, whereas KPMG Econtech (2010) find significant state-based variation in $\hat{\beta}_1$ (a statistically significant range of -0.92). However, both we and KMPG find that state-level short-run estimates are typically statistically insignificant, and have lower significance (both economically and statistically) than the Australia-wide short-run elasticity estimates.

Potential reasons for differences between our estimates and those of KPMG Econtech (2010) are:

1. sample size – our sample covers an additional 11 years of data);
2. choice of conditioning variables – we use the same variables in each state-level regression, whereas KPMG Econtech (2010) exclude gas prices for some states (as noted above), and pre-assign elasticities for other states. This creates the potential for statistical bias in KPMG's estimates; and
3. choice of household income income variable – KPMG Econtech (2010) used Gross State Product (GSP), rather than state-level household income. While GSP is related to household income, the two are not perfectly correlated as GSP contains (state-level) non-household items like business investment and state government expenditure.

In summary, our Australia-wide and state-level results provide new contributions to the Australian literature on residential electricity demand. Accounting for structural breaks, the price and income elasticity estimates reveal that households' residential energy demand is price and income inelastic, consistent with the view that electricity is a necessity with limited substitutes.

6 Concluding comments

This paper has estimated price and income elasticities of Australian residential electricity demand, between 1970 and 2011, both country-wide and at the state level. There were three key findings in this paper. First, the signs of all elasticity parameters were theoretically consistent, with long-run elasticities higher in magnitude than short-run elasticities, as expected by economic theory.

Second, there was strong evidence of structural breaks in the long-run elasticity estimates, potentially induced by economic policy changes, such as the easing in credit constraints during the 1980s and (more recently) greater consumer awareness of the need to limit (fossil-fuel-generated) electricity consumption. Over the past 42 years, the magnitude of long-run elasticities have fallen, at both the state-level and for Australia overall. For example, own-price elasticity fell from -0.5 to -0.3, cross-price elasticity fell from 1.0 to 0.13, and income elasticity decreased from 1.7 to around 0.3 (all Australia-wide parameter estimates). In contrast, there was no evidence of structural breaks in the short-run elasticities.

Third and final, there was strong evidence of state-based heterogeneity in the long-run cross-price and income elasticities, though little statistical difference between states' own-price elasticities. The uniformity of own-price elasticities is interesting and differs from prior Australian literature, which revealed large state-based heterogeneity in own-price elasticities. In addition, the ranking of state-level long-run cross-price and income elasticities was sample-dependent; for example, prior to 2003 – the year in which a structural break occurred – South Australia (SA) had the highest cross-price elasticity (0.97), with New South Wales (NSW) second lowest (0.25) of the states. In contrast, after 2003, NSW had the highest cross-price elasticity (0.26), with SA second lowest (0.18).

In contrast, there was relatively little state-based variation in short-run elasticity estimates, with statistically significant heterogeneity observed in only one quarter of the parameters estimated. Where significant, state-based heterogeneity occurred in cross-price and income elasticity estimates, with own-price elasticity estimates insignificantly different between states. Tasmania and South Australia had the largest cross-price elasticity estimates (of 0.1-0.2), while Queensland and Tasmania had the highest income elasticity estimates (around 0.4).

Collectively, these findings have important policy implications, including the need to allow for state-specific elasticities and allow for potential structural breaks in elasticity estimates when conducting longer-run analyses of the impact of changes in (relative) energy prices on residential demand. Furthermore, the potential for future structural breaks suggests caution when using historical elasticity estimates for predictive purposes. At a minimum, suitably designed sensitivity tests should be undertaken to assess how robust predictions are to changes in price and income elasticities.

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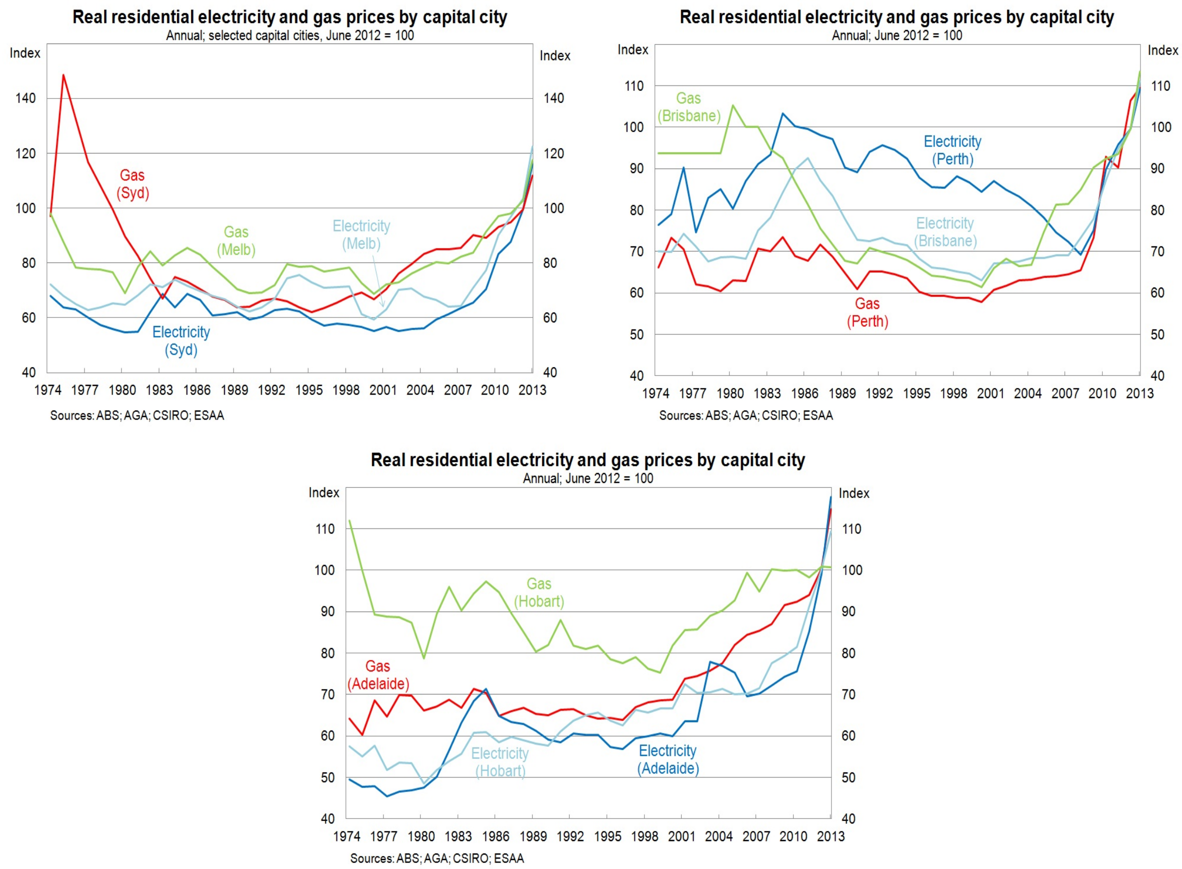
A State-specific prices

The figures below display real residential electricity and gas price indices for each of six Australian capital cities: Adelaide, Brisbane, Hobart, Melbourne, Perth, and Sydney.

Since 2000, real residential electricity prices in Sydney, Melbourne and Adelaide have

Figure A1: **Real residential electricity and gas prices**



doubled, with the lowest price growth recorded in Perth (29 per cent). Over the same period, residential gas prices in Sydney, Melbourne and Adelaide rose around two-thirds, with the lowest price growth recorded in Hobart (23 per cent). For all capital cities, the post-2000 growth in real residential electricity and gas prices reversed all of the declines recorded prior to 2000, and current real prices are at four-decade highs.

Furthermore, the profile of prices prior to 2000 differ quite markedly across capital cities; for example, Sydney gas prices fell sharply, in real terms, between the mid-1970s and 1980s, while Adelaide gas real prices were flat during this period. This differing price profile suggests the possibility that consumption responses to price changes (i.e. price elasticities) may differ across states; this possibility is empirically tested in Section 4.

B Order of integration

Prior to estimating the ECM, unit root tests that were conducted to determine which variables are non-stationary and whether a common order of integration exists between the nonstationary variables.[12] Table B1 presents the results of tests where the null hypothesis is that each corresponding variable is a nonstationary, $I(1)$ process.[13]

Table B1 reveals that the null hypothesis of nonstationarity is rejected, at the 5%

Table B1: **Unit root tests for order of integration**

The table reports test statistics and, in brackets, two-sided p-values under the null hypothesis (H_0) that each variable is $I(1)$ (i.e. nonstationary). The alternate hypothesis is that the process is (trend) stationary. For each variable, the regression includes a constant; a linear trend is also included for electricity consumption (q) and real household income (y). p^{elec} and p^{gas} are, respectively, the real electricity and gas price (residential); HDD and CDD are heating degree days and cooling degree days, respectively. The tests use annual Australia-wide data, from 1969/70 to 2010/11 (42 years).

H_0	q	p^{elec}	p^{gas}	y	HDD	CDD
$I(1)$	-1.75	-3.94	-4.19	-1.85	-4.89	-3.81
	(0.71)	(0.04)	(0.03)	(0.50)	(0.02)	(0.04)

significance level, for all variables, except electricity consumption (q) and household income (y). Further analysis revealed that q and y were integrated of order one. The question now is whether a linear combination of all these variables exists that is stationary.

As noted above, the Johansen (1995) approach is used to test for the presence of cointegration; Table B2 presents the results from a multivariate cointegration test on the six variables employed in this study. In each row, the null hypothesis tested is whether no more than the specified number of stationary linear combinations ("cointegrating vectors") exists.

There are two ends of this spectrum: (i) when no stationary linear combinations exist, the appropriate model is one in which all the variables are differenced; that is, $\beta_6 = 0$ in the first line of equation (1); and (ii) when every linear combination is stationary, then the appropriate model has all the variables in levels. Table B2 displays the test statistics for hypothesis tests within these two extremes.

Table B2 reveals that the null hypothesis of zero cointegrating vectors is strongly rejected, with a p-value of less than 0.01. In fact, Johansen (1995)'s trace statistic suggests

[12] As Campbell and Perron (1991) note, a cointegrating relationship can exist among both stationary and nonstationary variables, provided that all the nonstationary variables have a common order of integration. In other words, a cointegrating relationship does not require *all* variables to have the same order of integration.

[13] The test used is the Augmented Dickey Fuller (ADF) test of Said and Fuller (1984).

Table B2: **Tests for the number of cointegrating vectors**

In each row, test statistics and two-sided p-values are reported, that test the null hypothesis (H_0) that no more than the specified number of cointegrating vectors (denoted by R) exists. The test statistics are based on the inclusion of an intercept in the cointegrating relation, and a linear trend in the data. 'Trace' is the test statistic developed in Johansen (1995), and the data are Australia-wide, from 1969/70 to 2010/11 (42 annual observations).

H_0	Trace	p-value
$R = 0$	159.83	0.001
$R \leq 1$	115.58	0.001
$R \leq 2$	80.97	0.005
$R \leq 3$	44.12	0.07
$R \leq 4$	24.87	0.11
$R \leq 5$	13.51	0.10

the presence of three cointegrating vectors between the variables.[14] The finding that the variables are cointegrated implies that the ECM developed in Section 1 is appropriate for estimating the long- and short-run elasticities.

C Additional structural break tests

Table C3 reports the parameter estimates for the long-run model, allowing for two structural breaks in the co-integrating equation (see equation (2)).

Table C3: **Two structural breaks in the long-run model**

The table reports parameter estimates and, in brackets, t-statistics for equation (2). The t-statistics for the (non-interacting) own-price elasticity and weather coefficients are one-sided. $\bar{R}^2$ is the adjusted R^2. The estimated model uses annual Australia-wide data, from 1969/70 to 2010/11 (42 years).

$\hat{\alpha_0}$	$\hat{\alpha_1}$	$\hat{\alpha_2}$	$\hat{\alpha_3}$	$\hat{\alpha_4}$	$\hat{\alpha_5}$	$\hat{\eta_0}$	$\hat{\eta_1}$	$\hat{\eta_2}$	$\hat{\eta_3}$	$\hat{\rho_0}$	$\hat{\rho_1}$	$\hat{\rho_2}$	$\hat{\rho_3}$
-0.71	-0.52	1.01	1.68	0.00	0.00	0.34	0.17	-0.88	-0.87	2.24	0.14	-0.06	-0.48
(-2.54)	(-3.81)	(4.94)	(15.56)	(0.39)	(1.39)	(-1.16)	(2.33)	(-4.25)	(-7.30)	(2.35)	(1.06)	(-0.12)	(-2.05)
						$\bar{R}^2 = 0.99$							

[14] This statement uses the fact that the trace statistic rejects $H_0 : R \leq 2$, but does not reject $H_0 : R \leq 3$.