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Conditional Convergence in Australia's Energy Consumption at the Sector Level

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Abstract:

We examine the convergence of energy consumption per capita at the sector level in Australia over the period 1973-74 to 2013-14. To do so, we employ recently developed LM and RALS-LM unit root tests that accommodate up to two endogenously determined structural breaks. The results provide significant support for energy consumption per capita convergence among sectors in Australia.

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1. Introduction

A small literature has evolved over the last few years that has applied unit root tests to test for stochastic conditional convergence in energy consumption. Most of the existing studies have applied unit root tests to test for stochastic conditional energy convergence among groups of countries (see Anoruo & Di Pietro, 2014; Meng et al., 2013; Mishra & Smyth, 2014). These studies have mostly found evidence of stochastic conditional convergence in energy consumption.

Recently, there have been several calls for studies to test for stochastic conditional convergence at the sector level for different countries. For example, Meng et al. (2013, p.545), who apply LM tests based on the residual augmented least squares (RALS) regression proposed by Lee et al. (2012) and Meng et al. (2014) to test for stochastic conditional convergence in energy consumption among OECD countries, suggest: "Future research can extend the methodological approach taken in this study [to] …. sector analysis of energy use convergence within a specific country as well as across countries". Similarly, Mishra and Smyth (2014, p. 184) propose: "Future research could consider convergence in disaggregated energy across sectors". Finally, in a recent review of econometrics developments in energy economics research, Smyth and Narayan (2015, p. 353) write: "Future research could examine convergence in energy consumption at the sector level within specific countries".

To this point, the only study, of which we are aware, that tests for stochastic conditional convergence at the sector level is Lean et al (2016). Lean et al. (2016) test for stochastic conditional convergence in aggregate and disaggregate petroleum consumption at the sector level for the United States using the Narayan and Popp

(2010) and Narayan et al. (2016) unit root tests. They find evidence of stochastic conditional convergence for just over half of the 45 series that they examine, including aggregate petroleum consumption for all five sectors. At the conclusion of their study, they suggest that future research "could examine conditional convergence in …. energy consumption …. at the sector level for [countries other than the United States]" (Lean et al., 2016, p. 16). In making this suggestion they note that, there are "reasonably good historical statistics on energy consumption per capita at the sector level for Australia and the United Kingdom" (Lean et al., 2016, p. 16).

In this study, we respond to this call and test for stochastic conditional convergence in energy consumption at the sector level for Australia. Australia is an interesting country in which to situate such a study. Australia has traditionally been one of the highest consumers of energy on a per capita basis in the world (Falk & Settle, 2011), although Australia's energy consumption has been falling since 2011-12 and in 2013-14 was similar to 2009-10 levels (Department of Industry and Science, 2015).

Most of Australia's energy consumption is from oil, including crude oil, liquefied petroleum gas and refined products, coal and natural gas. In 2013-14 oil constituted 38.4 per cent of Australia's energy consumption, coal constituted 31.7 per cent of Australia's energy consumption and natural gas constituted 24 per cent of Australia's energy consumption. Meanwhile, renewables represented just 5.9 per cent of Australia's energy consumption (Department of Industry and Science, 2015).

Table 1 shows the break down in energy consumption across sectors since 1980-81. Since 1980-81, electricity supply, manufacturing and transport have been responsible for the lion's share of final energy demand in Australia. In 2013-14 electricity supply, manufacturing and transport together accounted for just under three quarters (74.61 per cent) of final energy demand. In 2013-14, mining, residential, commercial and other each accounted for less than 10 per cent of final energy demand. Over time, there has been a decline in the final energy demand share of manufacturing from 30.07 per cent in 1980-81 to 20.34 per cent in 2013-14 and an increase in mining's share from 2.26 per cent in 1980-81 to 9.11 per cent in 2013-14. The drop in Australia's energy consumption in manufacturing over time is largely attributable to decline of the automobile sector in Australia (Productivity Commission, 2014).

[**INSERT TABLE 1**]

Australia's climate change policy has two platforms. The first is "Direct Action", which entails the Government operating a reverse auction process to allocate AUD 2.5 billion to fund emission reduction projects. The second is a 20 per cent renewable energy target, which requires electricity retailers to fund small-scale solar PV systems and increase the proportion of large-scale renewables in the overall electricity mix (see Nelson, 2015 for more details). At the United Nations Framework Convention on Climate Change Conference of the Parties (COP) in Paris, Australia stated that it will reduce greenhouse gas emissions by 26-28 per cent by 2030 compared to 2005 levels. In the commentary since, it is generally thought that "achieving these emission reductions will be challenging under current policy settings" (Nelson et al 2015).

The results from this study are important in this context because knowledge of the existence, or otherwise, of stochastic conditional convergence in energy consumption is useful in ascertaining whether policies designed to reduce the intensity of energy consumption are proving effective. Where policies are designed to reduce the intensity of fossil fuel consumption, as in Australia's case, this also carries implications for efforts designed to reduce greenhouse gas emissions. If there is evidence of stochastic conditional energy convergence, and growth rates are relatively modest, this implies that policies designed to curtail energy consumption are being effective. However, if there is no evidence of stochastic conditional convergence then alternative policy settings being mooted in Australia to reduce energy consumption may need to be considered. These include, among others, introduction of a carbon tax, specific performance standards establishing separate greenhouse gas limits for coal and gas generators as in the United States and use of alternative energy sources, such as uranium (see Climate Institute 2014; Nelson 2015).

We contribute to the literature on stochastic conditional convergence in energy consumption in the following ways. First, this is one of the first studies to examine stochastic conditional convergence in energy consumption at the sector level and it is the first to do so for a country other than the United States.

Second, from a methodological perspective, we follow Meng et al (2013) and employ LM and RALS-LM unit root tests with up to two endogenous breaks, proposed by Meng et al. (2014) and Lee et al. (2012).[1] These unit root tests have several advantages over other popular alternatives (see Lee et al., 2012; Meng et al., 2013, 2014, 2015; Payne et al., 2014, 2015). One, they do not depend on the nuisance parameter and allow for trend breaks under the null. Two, the RALS-LM unit root test utilizes information on non-normal errors that have been ignored in the literature on unit root tests. In contrast to nonlinear unit root tests, which lose power in the

[1] Other applications of the LM and RALS-LM unit root test to test for stochastic conditional convergence are Payne et al. (2014) (SO_2 emissions) and Payne et al. (2015) (health care expenditures).

presence of non-normal errors, the RALS-LM unit root tests actually gain power in the presence of non-normal errors with a linear-based testing procedure.

The remainder of the study proceeds as follows. The next section provides a brief review of the extant literature. Section 3 discusses the data and method. The results are presented, and discussed in section 4. The final section concludes.

2. Overview of the literature

Beginning with Narayan and Smyth (2007) a large number of studies examine the integration properties of energy consumption and production. Much of this literature is reviewed in Smyth (2013) and Smyth and Narayan (2015). More recent studies include Barros et al. (2013, 2013a, 2016) and Lean and Smyth (2013, 2014). While there are conflicting results, an emerging consensus in this literature is that energy consumption and production are stationary once one allows for multiple trend breaks.

A second, related, set of studies test for stochastic conditional convergence in CO_2 and SO_2 emissions (see eg. Aldy, 2007; Barrassi et al., 2008, 2011; Bulte et al., 2007; Evans & Kim, 2016; Nguyen Van, 2005; Lee & Chang, 2008; List, 1999; Nourry, 2009; Payne et al., 2014; Strazicich & List, 2003). Evans and Kim (2016) find evidence of conditional convergence in CO_2 emissions across 11 Asian countries. There is mixed evidence on stochastic conditional convergence for OECD countries. Barrassi et al. (2011) and Strazicich and List (2003) find evidence of conditional convergence in emissions, while Barrassi et al. (2008), Lee and Chang (2008), Nguyen Van (2005) and Nourry (2009) fail to find evidence of conditional convergence in emissions among OECD countries. Similarly, there is mixed evidence of stochastic conditional convergence in pollution emissions across states of the United States. For example, Bulte et al., (2007), List (1999) and Payne et al., (2014) find evidence of conditional convergence, but Aldy (2007) does not find any such evidence.

A third set of studies test for convergence in energy consumption, energy intensity and energy productivity using a range of methods (see eg. Apergis & Christou, 2016; Jakob et al., 2012; Liddle, 2009; Markandya et al., 2006; Maza & Villaverde, 2008; Miketa & Mulder, 2005; Mohammadi & Ram, 2012; Mulder & de Groot, 2012). Many of the earlier studies on energy convergence focus on β-convergence using cross-sectional data. However, a number of studies have noted the limitations on testing for β-convergence and advocate the application of unit root tests to test for stochastic conditional convergence (see eg. Evans & Karras, 1996; Quah, 1996). Indeed, as Meng et al. (2013) and Mishra and Smyth (2014) have noted, given that countries have different endowments, the Solow-Swan growth model (Solow, 1956; Swan, 1956) implies conditional, rather than absolute, convergence.

The embryonic literature that tests for stochastic conditional convergence in energy consumption, in many respects, extends on, and marries, the approaches in the first two sets of studies in order to address the limitations in the energy convergence literature focused on β-convergence. It extends the literature on the integration properties of energy consumption to consider stochastic conditional convergence in energy consumption. It extends the literature on stochastic conditional convergence in CO_2 and SO_2 emissions to the closely related topic of energy consumption.

The seminal study on stochastic conditional convergence in energy consumption is Meng et al. (2013). These authors tested for conditional convergence in energy consumption per capita among OECD countries employing the LM and RALS-LM unit toot tests. Their results supported the existence of convergence in per capita energy consumption for most of the countries, once allowance was made for structural breaks.[2] Mishra and Smyth (2014) also find evidence of stochastic conditional convergence applying the KPSS (Kwiatkowski et al, 1992) stationarity test with multiple breaks (Carrion-i-Silvestre et al. 2005) and the panel LM unit root test with endogenous breaks (Im et al., 2005) to the ASEAN-5 (Indonesia, Malaysia, Philippines, Singapore and Thailand). Anourou and DiPietro (2014) reach more mixed conclusions for a panel of 22 African countries, but still find evidence of conditional convergence for the panel, applying standard panel unit root tests.

As noted in the introduction, Lean et al (2016) is the only study that tests for stochastic conditional convergence at the sector level. That study tested for stochastic conditional convergence in aggregate and disaggregate petroleum consumption at the sector level for the United States using high frequency data, employing the Narayan and Popp (2010) and Narayan et al. (2016) unit root tests. Their results suggest that aggregate petroleum consumption converges at the sector level in the United States, but the results for disaggregated petroleum consumption were much more mixed.

To summarize, the literature on stochastic conditional convergence in energy consumption per capita at the sector level is limited to one study, which is for the United States. We contribute to the literature through examining stochastic conditional convergence in energy consumption per capita at the sector level in Australia. To do so, we employ LM and RALS-LM unit root tests, which have several advantages for this purpose over other popular alternatives in the literature.

[2] However, Fallahi and Voia (2015) reach more mixed results for the same sample of OECD countries using confidence intervals to test for stochastic convergence in per capita energy consumption.

3. Data and methodology

We utilize Department of Industry and Science (2015a) data on annual final energy demand in Australia by sector (GJ) over the period 1973-74 to 2013-14. Final energy demand is divided among the following seven sectors: electricity supply, transport, manufacturing, mining, residential, commercial and other. To convert final energy demand by sector into per capita figures, we use annual data on Australia's population from World Bank (2015). Table 2 contains descriptive statistics on energy consumption (GJ per capita) for the sample period (1973-1974 to 2013-2014) for each of the seven sectors. The mean final energy demand is highest in electricity supply, manufacturing and transport. The standard deviation is highest in electricity supply. Moreover, skewness is negative for all the sectors except mining and commercial. This suggests that while all the other sectors have a negatively skewed distribution, the mining and commercial sectors have a positively skewed distribution, indicating more weight on the right half of the distribution in these sectors.

[**INSERT TABLE 2**]

For each sector *i*, we examine the natural logarithm of the ratio of per capita energy consumption (PCEC), relative to the average for all sectors as follows:

$$y_{it} = ln(PCEC_{it} / \text{average } PCEC_t) \quad (1)$$

The two-step LM and three-step RAS-LM unit root tests developed by Lee et al. (2012) and Meng et al. (2014) are applied to the ratio in (1) to examine stochastic conditional convergence of energy consumption.[3] If relative energy consumption is found to be stationary, this suggests that energy consumption across the seven sectors

[3] Using this measure of convergence follows the approach in Meng et al (2013) and Mishra and Smyth (2014) as well as Payne et al. (2014, 2015).

is converging. As noted by Meng et al. (2013) and Mishra and Smyth (2014), (1) has the advantage that it removes the cross-sectional shocks that affect all the sectors in the panel. For instance, any positive shock to energy consumption across all the sectors will increase the average by the same proportion and hence leave the relative energy consumption series unchanged (Meng et al., 2013; Mishra & Smyth, 2014). This implies that any structural breaks identified will be sector specific.

In what follows we provide an overview of RALS-LM unit root test. A detailed explanation, including proofs, critical values and simulation results for the power of the test can be found in the original study by Meng et al (2014).

We follow the notation used by Meng et al (2014) to discuss the RALS-LM test.

Let us assume a data generating process is given as follows:

$$y_t = \psi + \xi t + x_t, \qquad x_t = \beta x_{t-1} + e_t \qquad (2)$$

The unit root procedures test for the null hypothesis of $\beta = 1$, against the alternative of $\beta < 1$. The parameters ψ and ξ represent the deterministic components of intercept and trend respectively. The model can be written in a more general form as follows:

$$y_t = z_t'\delta + x_t, \qquad x_t = \beta x_{t-1} + e_t \qquad (3)$$

such that z_t' denotes the deterministic terms, including any structural changes. For instance, in the presence of an intercept, trend and R structural breaks, z_t' will be denoted as $[1, t, D_{1t}, \dots\dots D_{Rt}]$, where $D_{jt} = 1$ for $t \geq T_{Bj} + 1, j = 1, \dots\dots, R$ and zero otherwise. One can perform the following regression to obtain the LM test statistics:

$$\Delta y_t = \delta' \Delta z_t + \phi \tilde{y}_{t-1} + \sum_{j=1}^{p} g_i \Delta \tilde{y}_{t-1} + e_t \qquad (4)$$

such that $\tilde{y}_t = y_t - \tilde{\psi} - z_t\,\tilde{\delta}, \;\; t = 2, \dots, T$; where $\tilde{\delta}$ is the vector of coefficients in the regression of Δy_t on ΔZ_t, and $\tilde{\psi}$ is the restricted maximum likelihood estimate of ψ

given by $y_1 - z_1\tilde{\delta}$; y_1 and z_1 denote the first observations of y_t and Z_t. The lagged differences $\Delta\tilde{y}_{t-j,}$ are included in the regression equation to control for autocorrelated errors. The LM test statistic, usually denoted by $\tilde{\tau}_{LM}$, which we report below, is the t-statistic of the null hypothesis testing $\phi = 0$ in the above regression.

Meng at al (2014) add another step on top of this procedure and utilize information present in the higher moments of non-normal errors to draw inferences on the nature and functional form of non-linearity. This is achieved by defining $\xi_t = \left(\Delta\tilde{y}_{t-1}, \Delta\tilde{y}_{t-2}, \dots, \Delta\tilde{y}_{t-p}\right)', f_t = (\tilde{y}_{t-1}, \xi_t')'$ and $F_t = (\Delta z_t', f_t')'$ and focussing on the following two moment conditions:

$$E[e_t \otimes F_t] = 0 \qquad (5)$$

$$E[(h(e_t) - K) \otimes F_t] = 0 \qquad (6)$$

e_t denotes the residuals from the LM regression presented in equation (4) above, $K = E(e_t)$ and $h(e_t)$ is a nonlinear function of e_t.

Following an approach similar to Im and Schmidt (2008), Meng et al (2014) define $h(\hat{e}_t^2, \hat{e}_t^3]'$, $\hat{K} = \frac{1}{T}\sum_{t=1}^{T} [\![h(\hat{e}]\!]_t)$, $\hat{D}_2 = \frac{1}{T}\sum_{t=1}^{T} h'(\hat{e}_t)$ and $m_j = T^{-1}\sum_{t=1}^{T} \hat{e}_t^j$ and augment the following term to the regression equation (4) above:

$$\hat{w}_t = [\hat{e}_t^2 - m_2, \hat{e}_t^3 - m_3 - 3m_2\hat{e}_t]' \qquad (7)$$

Giving the final regression equation for the RALS-LM unit root test as follows:

$$\Delta y_t = \delta'\Delta z_t + \phi\tilde{y}_{t-1} + \sum_{j=1}^{p} g_j\,\Delta\tilde{y}_{t-j} + \hat{w}_t'\gamma + u_t \qquad (8)$$

The RALS-LM test statistic is obtained through least squares estimation and the t-statistic associated with testing the null hypothesis for $\phi = 0$ is referred as τ_{RLM}. The moment conditions of asymptotic distribution of τ_{RLM} are discussed in Meng et al

(2014) and the asymptotic critical values for the RALS-LM test for various combinations T and ρ are also presented. It is to be noted that the RALS-LM test statistic does not depend on the break location parameter; hence the same critical values can be used irrespective of number of breaks in the series.

We follow a general to specific approach similar to that adopted in Meng et al (2013). We start with the LM and RALS-LM tests, allowing for a maximum of two structural breaks in the level and trend of the transformed series. The LM and RALS-LM tests determine the location of breaks using a $maxF$ test and also determine the significance of break dummies and optimal number of lags corresponding to the selected model. If one or more break dummies were not found to be significant at the 5 per cent level of significance, we went back to the previous step and estimated the LM and RALS-LM tests allowing for one structural break in the series. Our strategy was to continue with the same iterative procedure until all the breaks became significant or until the maximum number of breaks allowed in the estimation procedure became zero, although we did not need to go to the no-break case.[4]

Following an approach similar to Meng et al (2013) we set the trimming region to 10 per cent, thereby restricting the grid search of structural breaks in the range of 0.10 – 0.90 of the sample. Moreover, the breaks were restricted to be at least 0.1 of the sample apart. This ensured that there were enough data-points before and after breaks for the estimation. The optimum lag length was selected using a general to specific procedure, with the maximum lag length set at eight.[5]

[4] We, never the less, still report the no-break case below for completeness and to illustrate the effect of allowing for breaks.
[5] All the estimates were carried out using the RATS code for the LM and RALS-LM tests available from Junsoo Lee's homepage [https://sites.google.com/site/junsoolee/codes].

4. Results

The results from the two-break LM and two-break RALS-LM unit root tests for the period 1973-74 to 2013-14 are shown in Table 3 under the columns labelled τ^*_{LM} and $\tau^*_{RALS-LM}$. As the procedure for identifying the locations of the structural breaks and the optimal lags is common across both the tests, the break locations and optimal lags are reported only once. The null hypothesis of a unit root in relative energy consumption per capita is rejected at the 10 per cent significance level or better for all seven sectors using the LM test and six sectors using the RAS-LM test. Two structural breaks in the trend are significant for five sectors, while one structural break (the second structural break) is significant for the other two sectors.

[**INSERT TABLES 3 & 4**]

For mining and other the first structural break is not significant at the 5 per cent level and, hence, a one-break unit root test seems more suitable. To compare the effect of including two breaks instead of one, we give the results for the one-break LM and RALS-LM tests for all seven sectors. The results are presented in Table 4. The null hypothesis is rejected for the LM unit root test for six of the seven sectors at 10 per cent significance or better. The null hypothesis is rejected for the RALS-LM unit root test for five of the seven sectors at 10 per cent significance or better. For mining and other, the null hypothesis of a unit root in relative energy consumption per capita is rejected at the 1 per cent and 5 per cent levels respectively with the LM and RAS-LM unit root tests. The structural break in the trend is significant for all seven sectors.

[**INSERT TABLE 5]**

For completeness, in Table 5 we present the results for the Augmented Dickey Fuller (ADF), LM and RAS-LM unit root tests with no breaks. For the ADF test, the null hypothesis of a unit root is rejected for two sectors at the 10 per cent level or better.

For the LM and RAS-LM tests, the null hypothesis of a unit root is rejected for four sectors at the 10 per cent level or better. The results highlight that failure to accommodate structural breaks leads to failure to reject a false unit root hypothesis in five sectors, on the basis of the ADF test, and three sectors, on the basis of the LM and RAS-LM tests. The erroneous conclusions that would follow from failure to account for structural breaks in the LM and RAS-LM tests have important implications given that the three sectors for which these tests fail to reject the unit root null hypothesis are responsible for 75 per cent of final energy demand (see Table 1).

Our overall conclusion is that the LM test suggests that there is convergence in energy consumption per capita across all seven sectors at the 10 per cent significance level or better. The RAS-LM test suggests the same conclusion for six of the seven sectors, with residential being the exception. For five sectors (electricity supply, transport, manufacturing, residential and commercial), this conclusion is based on the results of the two-break tests presented in Table 3. For the other two sectors (mining and other), for which one of the two trend breaks in Table 3 is not significant, this conclusion is based on the results of the one break test reported in Table 4. Hence, our results provide considerable support for convergence. With the LM test it is all sectors and with the RAS-LM test the sectors for which we conclude that there is convergence in energy consumption per capita have consistently constituted in excess of 90 per cent of final energy demand over the period studied (see Table 1). These results are broadly consistent with the findings in Lean et al. (2016) for the United States.

Consistent with the findings in Lean et al. (2016), Meng et al. (2013) and Mishra and Smyth (2014), most of the breaks in Tables 3 and 4 can be linked to global events that have impacted global energy markets. The main events associated with the breaks in

Tables 3 and 4 are the decline in oil prices in the mid-1980s that foreshadowed the 1987 sock market crash; the oil price shock in 1990, coinciding with the first Gulf War; the Asian financial crisis (1997-99); the 2000 energy crisis; the 9/11 terrorist attacks in 2001, the oil price shock in the second gulf war in 2003 and the Global Financial Crisis (2007-08). Beyond these global events, many of the break dates can be attributed to domestic regulatory reform, such as the commencement of a National Electricity Market in 1998 and the establishment of a national energy regulator – the Australian Energy Regulator – and other industry reforms in the mid-2000s.

[**INSERT FIGURE 1]**

Following Meng et al. (2013), in order to visualise our empirical findings, we superimpose the level and trend breaks identified by the two-break test in Table 3 and plot the log of per capita energy consumption in each sector. Linear trends are estimated via OLS to connect the break points. The results, which are presented in Figure 1, show that the break dates coincide with the visualisation of the series.

5. Concluding remarks and policy implications

We have applied the LM and RAS-LM unit root tests to examine convergence in energy consumption per capita at the sector level in Australia. Our main conclusions are as follows. First, failure to accommodate structural breaks reduces the ability to reject a false unit root null hypothesis. Second, the number of sectors for which the null is rejected increases with the number of breaks. Third, most of the structural breaks coincide with shocks to global energy markets. Fourth, based on the optimal combination of one-break and two-break results, the LM test suggests that there is stochastic conditional convergence in energy consumption per capita for all sectors, while the RAS-LM test suggests the same conclusion for six of the seven sectors.

Meng et al (2013) make the point that in many OECD countries technological advancement in the energy sector has generated improvements in energy efficiency and that such improvements in energy efficiency have contributed to a decoupling of the relationship between economic growth and energy consumption. There is good reason to think this has been true of Australia, at least in recent years. Energy consumption in Australia has been falling since 2011-12 and in 2013-14 was similar to 2009-10 levels. At the same time, GDP growth over the same period has been positive and in 2013-14 was in excess of 2 per cent. In 2013-14 energy intensity, defined as the ratio of energy consumption to GDP, declined by 4 per cent. This decline reflects improvements in energy efficiency and a shift towards less energy-intensive sectors, such as services (Department of Industry and Science, 2015). It also reflects increasing awareness of climate change and the consequent need to reduce CO_2 and SO_2 emissions. For example, a recent poll found that 70 per cent of Australians who were surveyed thought that climate change was a reality. This figure was up from 64 per cent in a comparable poll in 2012 (Climate Institute, 2015).

Our findings have important implications for Australia's energy policy as it seeks to realize the emissions reductions to which it agreed in Paris. As noted above, most commentators are skeptical of Australia's capacity to achieve the targets to which it agreed in Paris under current policy settings (Climate Institute, 2014; Nelson et al 2015). This skepticism has been supported by emissions projections from Computable General Equilibrium Modeling (see eg. Adams et al., 2014). Our results, however, paint a more optimistic picture for Australia's commitments. That we find considerable evidence of stochastic conditional convergence in energy consumption per capita implies that policies designed to curtail energy consumption, and by extension pollution emissions, are being effective and that there is no pressing need to look at alternatives to current policies. In particular, we note that in 2014-15 34.7 per cent of emissions in Australia are due to electricity consumption alone, while a further 17.3 per cent were due to transport (Department of Environment, 2015) and our results suggest that energy consumption in both of these sectors is converging.

There are several avenues for future research. Some of these include the following (see also Lean et al. 2016). One, future research could build on Mishra and Smyth (2014), examining energy convergence in regional trade groupings. Two, future research could examine energy convergence at the province or state level within countries. Three, following Apergis & Christou (2016) future research could apply unit root tests to examine convergence in energy productivity or energy intensity. Four, following Fallahi and Voia (2015), future research could use alternative methods to examine conditional convergence in energy consumption per capita.

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Table 1: Percentage breakdown of final energy demand by each sector

Sector	1980-81	1990-91	2000-01	2010-11	2013-14
Electricity Supply	24.73	26.96	30.09	28.63	27.02
Transport	26.55	25.39	24.92	25.81	27.25
Manufacturing	30.07	27.19	23.71	22.68	20.34
Mining	2.26	4.17	5.07	6.86	9.11
Residential	8.35	8.3	7.94	7.69	7.7
Commercial	3.39	3.97	4.46	5.09	5.42
Other	4.65	4.02	3.82	3.25	3.16

Source: Department of Industry and Science (2015a), Table E and authors' calculations.

Table 2: Descriptive statistics for final energy demand at the sector level

Sector	Observations	Mean	Std. Dev.	Min.	Max.	Skewness
Electricity Supply	41	65.71	14.23	38.09	90.05	-0.14
Transport	41	61.87	5.74	51.08	70.00	-0.22
Manufacturing	41	61.52	3.77	51.29	68.61	-0.25
Mining	41	11.10	5.28	4.44	22.97	0.37
Residential	41	19.43	1.14	17.29	20.95	-0.23
Commercial	41	10.08	2.72	6.32	13.89	0.12
Other	41	9.70	0.59	7.97	10.68	-0.97

Source: Department of Industry and Science (2015a), Table E and authors' calculations.
Notes: (1). Sample consisted of annual data for the period 1973-74 to 2013-14. (2). Energy consumption is expressed as Giga Joules (GJ) per capita.

Table 3: Results using two-break LM and RALS-LM unit root tests.

Sector	LM	RALS-LM		$\hat{T}_B$		$\hat{k}$
	τ^*_{LM}	$\tau^*_{RALS-LM}$	$\hat{\rho}^2$			
Electricity Supply	-5.977***	-5.720***	0.951	1991	2007	6
Transport	-4.033*	-3.943*	0.813	1995	2007	5
Manufacturing	-5.295***	-6.233***	0.643	1985	2007	1
Mining	-5.594***	-7.866***	0.448	1985^n	1998	8
Residential	-4.120*	-3.917	0.981	1987	1991	0
Commercial	-6.303***	-6.381***	0.933	2000	2003	0
Other	-4.939***	-5.439***	0.758	1989^n	2004	0

Notes: (1.) Sample consisted of annual data for the period 1973-74 to 2013-14. (2.) $\hat{k}$ denotes the optimal number of lags selected using a general to specific procedure (3.) $\hat{T}_B$ denotes the location of structural breaks. Superscript "n" denotes lack of significance at 5% for the break dummies. (4.) τ^*_{LM} and $\tau^*_{RALS-LM}$ denote the test statistics for the LM and RALS-LM test. (5.) The test-statistics for the LM and RALS-LM tests are invariant to the location of breaks. (6.) Critical values for LM and RALS-LM test can be found in Meng et al (2014) or can be calculated using the critical values calculator RATS code available at https://sites.google.com/site/junsoolee/codes (7.) *, ** and *** denote significance at the 10%, 5% and 1% level of significance.

Table 4: Results using one-break LM and RALS-LM unit root tests.

Sector	LM	RALS-LM		$\hat{T}_B$	$\hat{k}$
	τ^*_{LM}	$\tau^*_{RALS-LM}$	$\hat{\rho}^2$		
Electricity Supply	-3.204*	-3.080	0.610	2007	3
Transport	-2.306	-2.340	0.969	2007	0
Manufacturing	-3.809**	-3.579**	0.570	2007	6
Mining	-4.397***	-7.759***	0.372	1994	8
Residential	-3.530*	-3.504*	0.974	2007	0
Commercial	-3.215**	-5.296***	0.269	1987	7
Other	-4.137**	-4.011**	0.871	2004	0

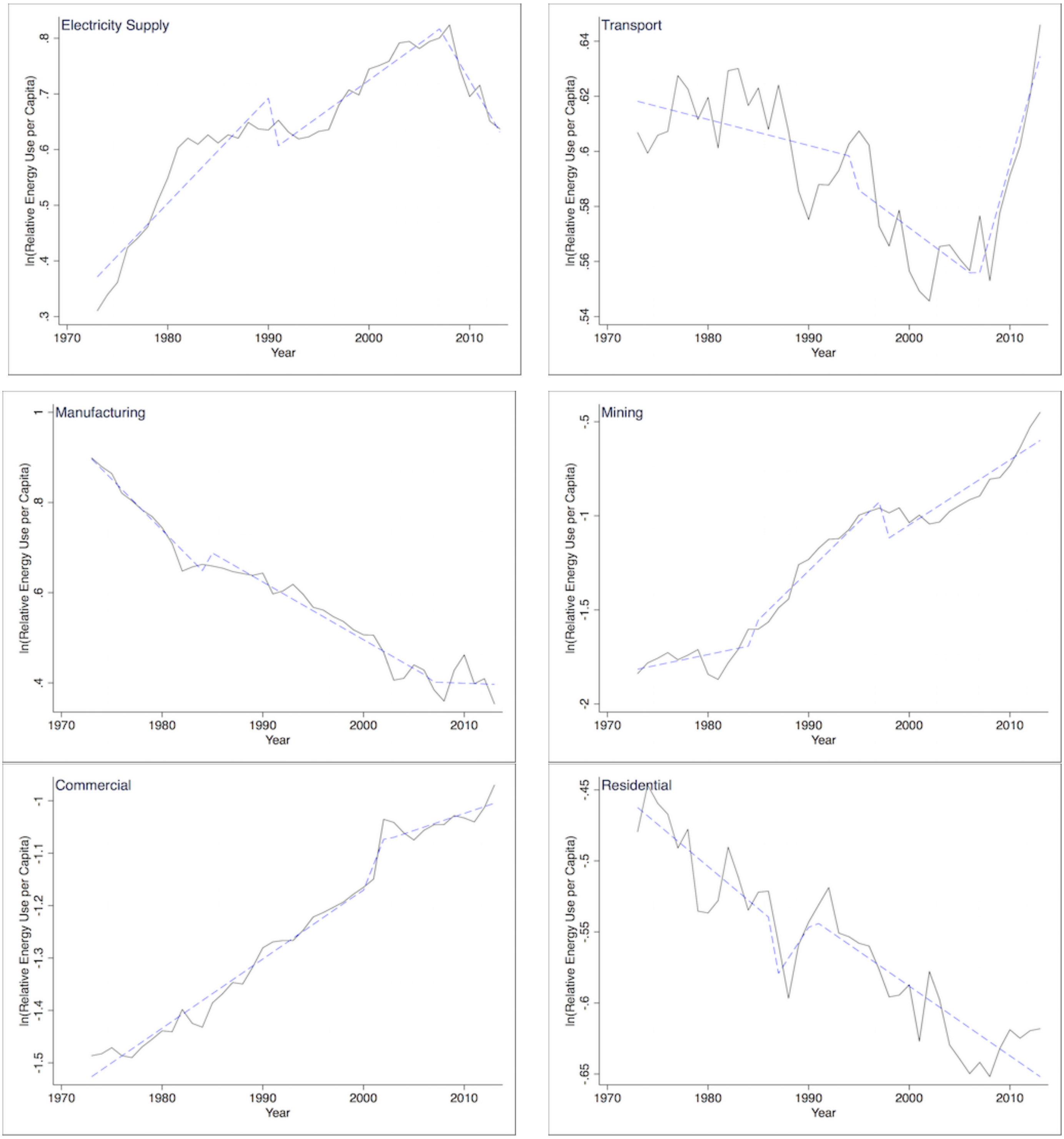
Notes: (1.) Sample consisted of annual data for the period 1973-74 to 2013-14. (2.) $\hat{k}$ denotes the optimal number of lags selected using a general to specific procedure (3.) $\hat{T}_B$ denotes the location of the structural break. All break dummies are significant at the 5% level or better. (4.) τ^*_{LM} and $\tau^*_{RALS-LM}$ denote the test statistics of the LM and RALS-LM test. (6.) The test-statistics for LM and RALS-LM tests are invariant to the location of breaks. (7.) Critical values for LM and RALS-LM test can be found in Meng et al (2014) or can be calculated using the critical values calculator RATS code available at https://sites.google.com/site/junsoolee/codes (8.) *, ** and *** denote significance at the 10%, 5% and 1% level of significance.

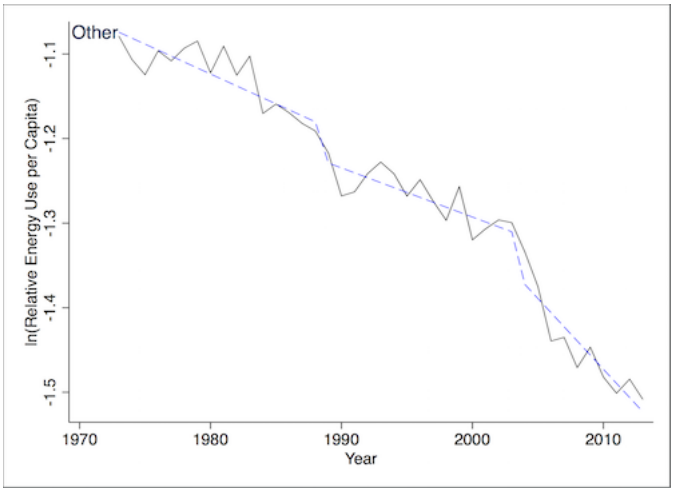
Table 5: Results using ADF test and no-break LM unit root tests.

Sector	ADF		LM	RALS-LM		$\hat{k}$
	τ_{ADF}	$\hat{k}$	τ_{LM}	$\tau^*_{RALS-LM}$	$\hat{\rho}^2$	
Electricity Supply	-1.464	3	-1.805	-1.560	0.781	3
Transport	-0.716	0	-1.420	-1.103	0.814	0
Manufacturing	-3.035	5	-1.928	-2.009	0.825	5
Mining	-5.479***	8	-5.156***	-9.625***	0.326	8
Residential	-3.333*	4	-3.201**	-3.321**	0.953	0
Commercial	-2.859	7	-2.573*	-3.673***	0.492	0
Other	-2.677	0	-2.742*	-2.922*	0.755	0

Notes: (1.) Sample consisted of annual data for the period 1973-74 to 2013-14. (2.) $\hat{k}$ denotes the optimal number of lags; selected by general to specific procedure (4.) τ^*_{LM} and $\tau^*_{RALS-LM}$ denote the test statistics for the LM and RALS-LM tests. ADF denotes the test statistic of the Augmented Dicky Fuller test. (5.) *, ** and *** denote significance at the 10%, 5% and 1% level of significance.

Figure 1: Log of per capita energy use relative to the mean.





Source: Department of Industry and Science (2015a), Table E and authors' calculations.
Notes: Sample consisted of annual data for the period 1973-74 to 2013-14.