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On the rebound: estimating direct rebound effects for Australian households*

Bianca Peters and Stephanie F. McWhinnie[†]

Reducing dependence on fossil fuels by decreasing energy consumption is a common environmental policy. One mechanism used to achieve this is to encourage increased energy efficiency. However, improving efficiency may have an opposing effect and cause an increase in energy consumption if the intensity of use changes. This phenomenon is known as the *rebound effect*. We estimate direct rebound effects for energy use in Australia based on both aggregate residential energy use data and on household energy expenditure data. Our approach implements a new methodology developed by Hunt and Ryan (2014, Catching on the rebound: Why price elasticities are generally inappropriate measures of rebound effects. Surrey Energy Economics Discussion Paper Series SEEDS 148; 2015, *Energy Economics* 50, 273) that explicitly relates energy service use with energy source demand and directly incorporates measures of efficiency changes. The results indicate that the rebound effect is relatively high for energy use by Australian households. Due to the unique nature of our household data set, we can examine the influence of demographic and housing characteristics. We find that low-income households and households with vulnerable members have the largest rebound effects. The relatively large rebound effects found here suggest that consumers gain from efficiency by improved energy services, and thus, policy targeting energy efficiency is not likely to be successful at reducing energy consumption.

Key words: Australian households, energy, own-price elasticity, rebound effect.

1. Introduction

Reducing dependence on fossil fuels by reducing energy consumption is a key policy of many governments. A common instrument used to achieve this is to encourage increased energy efficiency of buildings and durable goods. However, energy consumption will only fall as a result of an increase in energy efficiency if the intensity of use remains the same. The *rebound effect* is when there is an increase in energy consumption due to an improvement in efficiency, which causes the real price of energy to fall as less fuel is required to produce the same level of energy services.

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† Bianca Peters and Stephanie F. McWhinnie (email: stephanie.mcwhinnie@adelaide.edu.au) are with the School of Economics, University of Adelaide, Adelaide, South Australia, Australia.

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In the Australian context, the 2015 Energy White Paper (Commonwealth of Australia, 2015b) identified increasing energy productivity to promote growth as one of the areas of energy priority. Increasing energy efficiency is included in this priority area. The National Energy Productivity Plan 2015–2030 (Commonwealth of Australia, 2015d) subsequently sets out specific measures to increase efficiency of housing through the National Construction Code; increase efficiency of appliances through the new Equipment Energy Efficiency (E3) prioritisation plan; cooperate internationally on efficiency through the International Partnership for Energy Efficient Cooperation; and deliver better energy productivity services for vulnerable consumers (indigenous, low-income, remote and elderly). Understanding how residential energy use responds to changes in efficiency is therefore important to know how effective these policy measures will be.

In this article, we estimate the direct rebound effect of residential energy use in Australia using both aggregate energy use data and household energy expenditure data. We conduct the analysis using a new method developed by Hunt and Ryan (2014, 2015). The advantage of this method is it is developed from a consumer utility model that explicitly ties utility from energy services to demand for energy sources and allows for changes in efficiency, even if these cannot be easily quantified. To our knowledge, this is the first article to use Australian household data to estimate the rebound effect.

The first part of the analysis uses aggregate state energy use data covering the period 1989 to 2015. We calculate rebound effects and price elasticities using several measures to capture changes in efficiency: a simple time trend to allow for technological progress; past energy prices to allow for changing incentives to invest in more efficient appliances; and an index of changes in appliance energy use. We find considerable rebound effects for both electricity and gas and other fuels and that electricity is more responsive than gas and other fuels.

The second part of our analysis uses household energy expenditure data from the Australian Household Expenditure Survey. We use data from four waves of this confidential survey across the period 1989–2010. We find that, like in the aggregate analysis, electricity exhibits larger rebound effects than gas and other. In addition, we take advantage of the unique nature of the data set to analyse rebound effects for households with different demographic characteristics; this analysis is uncommon in the literature. Rebound effects have been assumed to be higher for low-income households as they are likely to be further away from satiation of demand for energy than high-income households and our analysis supports this. We also find that households with children, elderly, pensioners or beneficiaries have higher rebound effects for both electricity and gas than households without. These results support the need to consider varying policy impacts on households with vulnerable consumers. The household data also allow us to explore the effects of different housing characteristics. We find that households in detached and semidetached homes respond significantly differently to those in flats and apartments, as do households who own their homes rather than renting. Knowing how different household types are able to respond, or not, to energy efficiency changes is important for understanding policy impacts and outcomes.

Evidence of the rebound effect is typically from household energy consumption and is limited to econometric studies based on energy sources data. The studies typically use data from the United States or United Kingdom, which may be difficult to apply to the Australian context due to different demographic and climatic characteristics. Sorrell *et al.* (2009) state that the direct rebound effect is generally less than 30 per cent for household energy services in the OECD. Sorrell (2007) conducted a review of the literature and found that marginal consumers have not been the focus of analysis. Analysis of energy use by households with different incomes is useful as the literature suggests rebound effects will be higher for lower income households as they are further away from satiation (Milne and Boardman 2000; Sorrell *et al.* 2009). We are able to compare rebound effects for low- and high-income households and households with different demographic profiles in this article due to the extensive variables included in the Household Expenditure Survey.

Estimating the size of the rebound effect is important for creating effective pollution reduction policies. When energy policy is being developed, rebound effects should be taken into consideration as nonprice regulations may not reduce energy demand. Regulations that do not control the level of prices may improve the efficiency of appliances; however, consumption of energy services may increase due to the fall in the real price, which may offset the impact of this efficiency gain. Carbon taxes and emission trading schemes may be a more effective way of countering rebound effects (Sorrell 2007). The results from this analysis suggest that rebound effects are important in the Australian context, particularly for households with more vulnerable occupants.

2. Theoretical framework

The direct rebound effect is when the efficiency for an energy service improves, causing the real price of that service to fall, which then results in an increase in the consumption of that energy service. For example, if air conditioners become more efficient, this will lower the real price of cooling. Hence, it is likely that demand will increase for the energy source used to provide cooling. Due to this price effect, energy consumption may not fall as much as expected, which is known as a rebound effect. In an extreme case, consumption of the energy source may actually increase more than the total potential energy savings from an improvement in efficiency, which is known as *backfire*.

The rebound effect was described using price elasticities by Khazzoom (1980), and the widely accepted measure is the elasticity of demand for energy services with respect to efficiency. Due to the problem that we do not typically observe direct measures of efficiency, many subsequent studies have estimated the rebound effect using price elasticities and assuming that each energy source produces one energy service and that efficiency does not change over time.

2.1 Measuring the direct rebound effect using price elasticities and accounting for efficiency changes

Hunt and Ryan (2014, 2015) developed an alternative model from which elasticities can be used to estimate rebound effects while allowing for efficiency to change over time and for multiple energy services to be produced from a single source. Explicitly incorporating energy efficiency allows the role of past energy prices to be recognised, that is, high energy prices are likely to foster energy efficient innovations and thus not accounting for this effect is likely to overestimate rebound effects.

The underlying model of Hunt and Ryan (2014) is explained in Hunt and Ryan (2015) but, as it provides an innovative justification for using elasticities to estimate rebound effects, we provide a short description here. They set up a consumer utility model of multiple energy sources (x_i) and multiple energy services (y_m) where households maximise their utility from consuming energy services subject to prices of energy services (p_m) and total energy expenditure. From this, demand equations and expenditure share equations for each service and, subsequently, each energy source as a function of source prices (p_i), total expenditure and service efficiencies (ε_m) are derived. From these share equations, which directly include efficiencies, Hunt and Ryan calculate the own- and cross-price elasticities for sources (i,j) as:

$$\eta_{ij} = \eta_{p_j}(x_i) = \frac{\partial x_i}{\partial p_j}\frac{p_j}{x_i} = -\delta_{ij} + \frac{1}{s_i}\frac{\partial s_i}{\partial \ln p_j} \quad \text{where } \delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases} \tag{1}$$

and the rebound effects for services (m,q) as:

$$\eta^*_{mq} = \eta_{\varepsilon_q}(y_m) = \frac{\partial y_m}{\partial \varepsilon_q}\frac{\varepsilon_q}{y_m} = \delta_{mq} - \frac{1}{s_{m^*}}\frac{\partial s_{m^*}}{\partial \ln p_{m^*}} \quad \text{where } \delta_{mq} = \begin{cases} 1 & \text{if } m = q \\ 0 & \text{if } m \neq q \end{cases} \tag{2}$$

Hunt and Ryan proceed to make a correspondence between (1) and (2) to show that:

$$\eta_{ij} = \eta_{p_j}(x_i) = -\sum_{m \in i} \frac{s_{m^*}}{s_i}\left[\sum_{q \in j} \eta^*_{mq}\right] \tag{3}$$

That is, the own-price and cross-price elasticities are linear combinations of direct and indirect rebound effects with weights being the (negative) ratios of expenditure shares of an energy source used to provide a particular service to the total expenditure share of that service. Thus, own-price elasticities can be used to calculate the combined rebound effect of services provided by an energy source. The two caveats are now that efficiency measures must be included in the estimation procedure for the share equations and interpretation of the rebound effect is a weighted average of the services.

2.2 Estimating price elasticities and rebound effects

We use a Deaton and Muellbauer (1980) Linear Almost Ideal Demand System (LAIDS) to estimate a system of expenditure share equations for our energy sources. This follows the approach of Hunt and Ryan and has the usual advantages of being: able to be aggregated over consumers; consistent with household expenditure data; and easily estimated. The system of energy source expenditure share equations (s_i) is derived as:

$$s_i = \alpha_i + \sum_j \gamma_{ij} \ln p_j + \beta_i(\ln B - \ln P) + \sum_i \mu_i \ln \varepsilon_i \tag{4}$$

subject to the usual demand system restrictions of adding up, homogeneity and symmetry:

$$\sum_i \alpha_i = 1, \quad \sum_i \gamma_{ij} = 0, \quad \sum_i \beta_i = 0, \quad \sum_i \mu_i = 0, \quad \gamma_{ij} = \gamma_{ji} \tag{5}$$

where $\ln P = \Sigma_i s_i \ln p_i$ is the Stone Price Index, B is total expenditure on all energy sources, and ε_i is a measure of efficiency of energy source i. From (1) and these estimating equations, we can use the coefficients to calculate the own- and cross-price elasticities as:

$$\eta_{ij} = -\delta_{ij} + \frac{1}{s_i}\frac{\partial s_i}{\partial \ln p_j} = -\delta_{ij} + \frac{\gamma_{ij}}{s_i} - \beta_i \frac{s_j}{s_i} \quad \text{where } \delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases} \tag{6}$$

and the combined rebound effect can be calculated from (3) and these estimating equations as:

$$R_{ij} = -\sum_{m \in i} \frac{s_{m^*}}{s_i}\left[\sum_{q \in j} \eta^*_{mq}\right] = -\sum_{m \in i} \frac{s_{m^*}}{s_i}\left[\sum_{q \in j} \delta_{mq} \sum_{q \in j} \frac{\gamma^*_{nq}}{s^*_m}\right] = \delta_{ij} - \frac{\gamma_{ij}}{s_i}$$
$$\text{where } \delta_{ij} = \begin{cases} 1 & \text{if } i = j \\ 0 & \text{if } i \neq j \end{cases} \tag{7}$$

From (7), we can describe the combined rebound effects as the average rebound effect across all energy services using a particular energy source, where if:

1. $R_{ij} = 0$ there is no rebound effect;
2. $0 < R_{ij} \leq 1$ there is a rebound effect; and
3. $R_{ij} > 1$ there is backfire.

3. Data

We use Australian residential energy data to estimate price elasticities and the rebound effect. We take advantage of two key data sources to conduct this analysis.

3.1 Aggregate energy use

First, we use annual aggregate state residential energy consumption of energy in petajoules by energy source from the Australian Energy Statistics (Commonwealth of Australia 2015c) data set. The data included in this article cover each year in 1989–2015 and each of the six states of Australia. Summary statistics are presented in Table 1 where it can be seen that residential energy expenditure on electricity is almost twice as large as expenditure on gas and other fuels. We use two groups of energy sources – electricity, and gas and other fuels – as we only have price measures for electricity and gas. Other fuels include wood, coal, kerosene, heating oil and barbeque gas and represent an average of 19 per cent of energy use over the aggregate sample but only 3 per cent of the total expenditure in the household sample.

Price index data for electricity and gas and other fuels are taken from the Consumer Price Index (Australian Bureau of Statistics, 2016), which is available quarterly for each of the Australian states from 1989. We take the

Table 1 Summary statistics: aggregate data

Variable	Mean	Std. Dev.	Min.	Max.
Exp share of electricity	0.648	0.084	0.471	0.800
Exp share of gas and other	0.352	0.084	0.200	0.529
Log of electricity price dollars/GJ	3.935	0.226	3.591	4.470
Log of gas and other price dollars/GJ	3.258	0.377	2.437	4.145
Total energy expenditure/state/year, millions dollars	2304	1671	375	8193
Average maximum temperature in February	27.81	3.45	19.38	35.67
Average maximum temperature in July	16.39	3.07	11.14	22.90
3-year electricity price growth rate	0.045	0.126	−0.173	0.357
5-year electricity price growth rate	0.061	0.175	−0.235	0.541
3-year gas and other price growth rate	0.072	0.093	−0.093	0.395
5-year gas and other price growth rate	0.121	0.149	−0.109	1.016
Appliance energy use % change	−18.36	12.15	−36.06	0
Observations	161 for all except appliance energy use (132)			

Sources: Australian Bureau of Statistics, 2016; Australian Energy Market Commission, 2013; Bureau of Meteorology 2016; Commonwealth of Australia, 2015a,c; Energy Rating, 2016. Summer temperature data from the station used for Queensland are missing in 1992.

mean of the quarterly price index data across the relevant financial years to calculate annual price index series. The price index series for gas and other fuels only began in the third quarter of 1989. This does not affect the price indexes directly but, to allow starting the analysis in 1989, a simple prediction function was used to backcast earlier prices from which growth rates prior to 1989 are calculated. Real energy prices have risen significantly over the period that has been evaluated in this article, as can be seen in Figure 1, which shows the Australian average series.

To convert the energy consumption data to energy expenditure, we combine the price indexes with data from the Australian Energy Market Commission (2013) on electricity prices and the Commonwealth of Australia (2015a) on gas prices. This gives us real energy price series for each state from 1989. Converting to real prices allows us to capture variation in energy prices across states, as well as through time. The energy price indexes for each state alone do not allow this as they use a common base of 100 in the year 2012.

The weather data are from the Bureau of Meteorology (2016). We use average maximum temperatures of the hottest (February) and coldest (July) months in the capital city of each state to capture the extremes of Australian weather across the six states. We also consider alternative specifications to measure temperature including using the mean of the hottest and coldest 30 days of the year and the number of two-day spells of maximums above 35 or below 15.

We use three measures to capture efficiency in this analysis. First, we simply include a time trend. Second, we follow Hunt and Ryan (2014) and include once-lagged, three-year and five-year price growth rates. Third, we incorporate an index of household appliance energy use. Energy Rating (2016) provides a measure of energy used for and sales of five large household

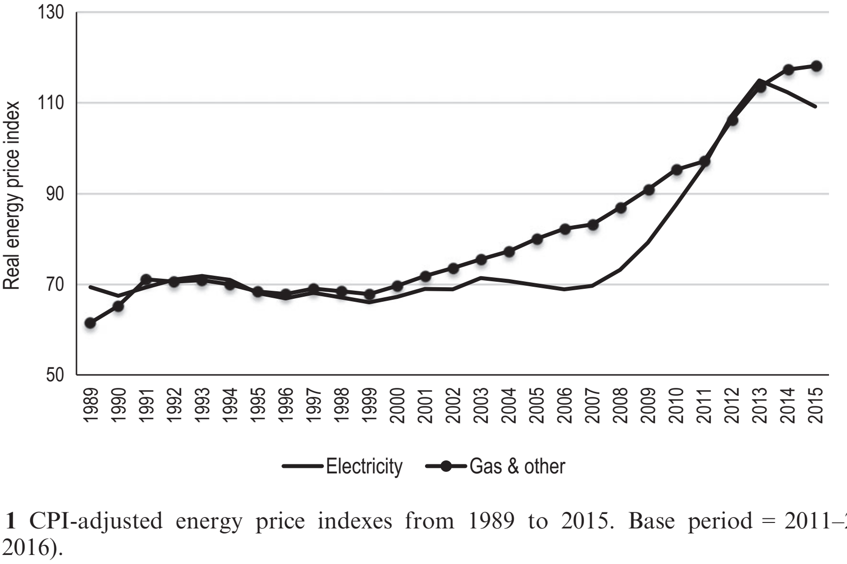

Figure 1 CPI-adjusted energy price indexes from 1989 to 2015. Base period = 2011–2012 (ABS, 2016).

appliances from 1993 in each state: refrigerators, freezers, washers, driers and dishwashers (Tasmania is not separately reported, and thus, we assign the energy efficiency index calculated for Victoria to all Tasmanian observations). We calculate an appliance energy use series by calculating the percentage change in energy use compared to 1993 for each appliance. Since 1993, the national average energy use of refrigerators, freezers and dishwashers has each fallen slightly more than 40 per cent, while the energy use of washers fell 20 per cent and driers fell slightly less than 10 per cent. We then create an aggregate series for each state by weighting each appliance's change by its sales share. On average, refrigerators, freezers and dishwashers account for 54 per cent of the sales, washers account for 33 per cent and driers for 13 per cent. We further create an average of the percentage change in energy use over the preceding 5 years to partly allow for durability of these appliances. The disadvantage of these series is that they only begin in 1993 or 1997, which restricts our sample.

The advantage of the aggregate consumption data is it corresponds well to the approach taken by Hunt and Ryan (2014) and allows us to see how residential energy use has changed over a period of 27 years and across six states. Across this time, however, household energy demand has changed, as seen in Figure 2. The chart suggests that households have changed their energy sources over this period, particularly changing from other fuels to electricity and gas. It is difficult to determine what has caused these changes in energy use by households, as they may be a result of preferences, price or availability of appliances. A likely contributing factor is air conditioner ownership, which has risen from around 10 per cent of Australian households in the early 1960s to more than 60 per cent by the mid-2000s (Energy Rating 2006). Energy prices have also increased sharply, particularly towards the end

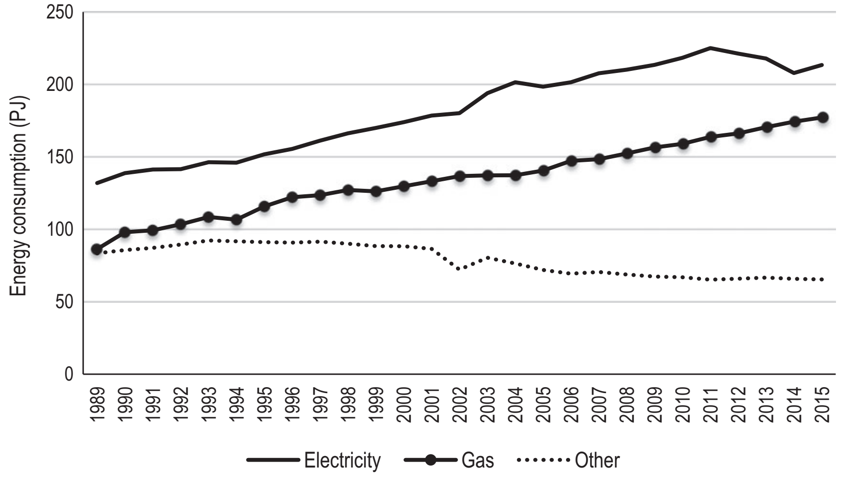

Figure 2 Residential energy consumption 1989–2015 (Commonwealth of Australia, 2015c).

of our sample, which should be taken into consideration when interpreting the results of this article.

3.2 Household energy expenditure

The second part of our analysis uses Confidentialised Unit Record File (CURF) data from the Household Expenditure Survey (HES). The data included in this article cover four periods: 1988–1989, 1998–1999, 2003–2004 and 2009–2010 (Australian Bureau of Statistics, 1989, 1999, 2004, 2012) with a total of 27,394 observations with full information. Summary statistics of all variables used in this part of the analysis are presented in Table 2. Households in the Australian Capital Territory and the Northern Territory were excluded because they are reported together in the HES thus cannot be assigned different temperatures and prices. In addition, observations were dropped if they did not have expenditure data (573), had total expenditure on energy not within 1 per cent of the sum of reported components (80) and had negative disposable income (78) or disposable income higher than $125,000 per quarter (7).

The unique nature of the HES data set has enabled us to explore demographic concepts that have not been investigated in depth, for instance, income, household composition and dwelling characteristics. Comparison between rebound effects of households of different income levels has not been

Table 2 Summary statistics: household data

Variable	Mean	Std. Dev.	Min.	Max.
Exp share of electricity	0.783	0.234	0	1
Exp share of gas and other	0.217	0.234	0	1
Log of electricity price dollars/GJ	3.86	0.16	3.60	4.19
Log of gas and other price dollars/GJ	3.15	0.38	2.46	3.90
Total expenditure on energy dollars/week	22.58	16.43	0.08	262.1
Average maximum temperature in February	28.2	2.6	21.9	33.9
Average maximum temperature in July	16.6	2.8	12.4	21.7
Average maximum temp interview quarter	22.6	4.5	13.6	33.1
3-year electricity price growth rate	0.01	0.07	−0.12	0.13
5-year electricity price growth rate	0.01	0.09	−0.18	0.19
3-year gas and other price growth rate	0.07	0.10	−0.06	0.50
5-year gas and other price growth rate	0.20	0.51	−0.09	3.12
Appliance energy use % change	−21.03	10.34	−34.68	−6.49
Income dollars/week	637	603	0	8,796
Number of persons in HH (6 = 6 or more)	2.53	1.34	1	6
HH with members <5, 65+ or pens. or beneficiaries	0.632	0.482	0	1
HH in detached or semidetached houses	0.895	0.306	0	1
HH that own their home with or without a mortgage	0.712	0.453	0	1
Observations	27,394 for all except appliance energy use (20,998)			

Sources: Australian Bureau of Statistics, 1989, 1999, 2004, 2012, 2016; Australian Energy Market Commission, 2013; Bureau of Meteorology 2016; Commonwealth of Australia, 2015a,c; Energy Rating, 2016.

widely investigated in the literature. We compare estimated rebound effects of the lowest 40 per cent and highest 40 per cent of income households. We also use information on having children aged under five or persons aged 65 or more or persons receiving a pension or welfare benefit to compare effects for households with and without these types. We include type of dwelling characteristics to calculate rebound effects for households that are detached or semidetached compared to flats or apartments. Finally, we consider the nature of ownership by calculating rebound effects for households that own their home, with or without a mortgage, compared to households that rent.

We augment the weather data in the household analysis to include the average daily maximum temperature in the quarter in which the household completed the HES. The survey sampling is conducted evenly across the year so the observations are annually representative but we control for the quarter to allow for any additional seasonality.

It should be noted that while the data are at the household level, it is not a complete panel so the observations in our demand system estimation can be thought of as many individuals within a particular market. Hence, the estimates of elasticity and rebound effects are not direct individual household responses to price or efficiency changes. To get an individual household response to changes in efficiency, data on the types of appliances in use or having been replaced and usage would be needed. As such, our household analysis uses aggregate efficiency changes as described in the previous section.

4. Empirical framework and analysis

4.1 Empirical model

As described in Section 2.2, to calculate own-price elasticities and rebound effects (Eqns 6, 7), we need estimates for the parameters γ_{ij} and β_i. We estimate these using a LAIDS of energy source demand. The base model estimates a traditional version, excluding efficiency measures, of the expenditure share of energy source i in period t in state r (s_{itr}) as follows:

$$s_{itr} = \alpha_i + \sum_j \gamma_{ij} \ln p_{jtr} + \beta_i(\ln B_t - \ln P_t) + \theta_i WS_{rt} + \lambda_i WW_{rt} + I_r + e_{itr} \quad (8)$$

where: $i,j = 1,2$ are the energy sources ($i,j = 1$ for electricity, =2 for natural gas and other fuels); t is the year; r is the state in which the household is located; B_t is total expenditure on the two energy sources; p_{jtr} is the price of the jth energy source in time t and state r; $\ln P_t$ is the Stone Price Index which is equal to $\ln P_t = \Sigma_j s_{jt} \ln p_{jt}$; WS_{rt} and WW_{rt} are weather related variable for summer and winter in each state r; I_r is an indicator for each state r to capture any unobserved differences in energy source provision across states; and e_{itr} is an error term.

As we have two energy sources, there are two expenditure share equations (8). We use the demand system restrictions from (5) to estimate a constrained regression of the electricity share equation. We use these estimated coefficients and system restrictions to determine the coefficients for the gas and other fuels share equation. The rebound effects are then calculated using these coefficients in equation (7).

The theory described in Section 2.2 tells us that the rebound effect can only be accurately estimated if energy efficiency is included in the model. We account for changes in energy efficiency using three approaches. The first approach accounts for efficiency changes over time by simply amending the base model to include a quadratic time trend, and the second includes this time trend and once-lagged, three-year and five-year price growth rates for each energy source. The time-trend model assumes technological improvements in efficiency are exogenous and not driven by prices. The model with price growth rates assesses whether efficiency is dependent on past energy prices. The theory suggests that if energy prices are rising, households have an incentive to invest in more energy efficient appliances. Our third approach uses the appliance energy use series for each state as described in Section 3.1. We conduct our analysis using all three approaches, with a main focus on the second as using the appliance energy use series restricts our sample to observations from 1993 onwards.

4.2 Results and analysis – aggregate data

The full set of regression results are presented in Tables A1 and A2 in Appendix S1 for reference where we note that likelihood ratio tests indicate that the models with price growth rates or appliance energy use are statistically preferred to the base model and the model with only the time trend. The results we are most interested in are the calculations of price elasticities and rebound effects using coefficients from the empirical models described above. Table 3 gives these calculations with the ranges of elasticities and rebound effects calculated using the lower and upper 95% confidence interval estimates of the coefficients shown in brackets.

The size of the rebound effects from the main model, with time trend and price growth rates, is estimated to be 0.74 for electricity and 0.51 for gas and other. Recall from Section 2.2 that the rebound effect confounds energy savings policy if it calculated as greater than zero and if it is calculated as being greater than one, there is backfire. Thus, our estimates indicate that increasing efficiency does reduce consumption but by less than would be expected from a constant energy services model.

The own-price elasticity for electricity is calculated as −0.60 and for gas and other is −0.65, which means that aggregate energy use is inelastic. The cross-price elasticity for these two energy sources is calculated to be negative, indicating that these energy sources are complementary in aggregate use.

The rebound effects differ when measures of appliance energy use change are used: the estimates for rebound effects are lower when estimated using the percentage change from 1993 and higher when using the previous five-year average percentage change since 1993. We note, however, that these versions

Table 3 Average estimated price elasticities and rebound effects: aggregate data

Specification	Own-price elasticity electricity	Own-price elasticity gas and other	Cross-price elasticity	Rebound effect electricity	Rebound effect gas and other
Base model	−0.79 [−0.81, −0.78]	−0.09 [−0.10, −0.08]	−0.49 [−0.50, −0.49]	—	—
With time trend	−0.61 [−0.62, −0.59]	−0.89 [−0.90, −0.89]	−0.06 [−0.06, −0.05]	0.82 [0.82, 0.83]	0.68 [0.66, 0.69]
Main model	−0.60 [−0.62, −0.58]	−0.65 [−0.66, −0.64]	−0.19 [−0.19, −0.18]	0.74 [0.73, 0.75]	0.51 [0.50, 0.53]
Appliance energy use % change	−0.63 [−0.65, −0.61]	−0.51 [−0.51, −0.50]	−0.27 [−0.27, −0.26]	0.70 [0.69, 0.70]	0.44 [0.43, 0.46]
5-year appl. energy use % change	−0.67 [−0.69, −0.65]	−0.75 [−0.76, −0.75]	−0.14 [−0.14, −0.13]	0.80 [0.79, 0.81]	0.63 [0.61, 0.64]
Mean hottest and coldest 30 days	−0.60 [−0.62, −0.58]	−0.66 [−0.67, −0.65]	−0.19 [−0.19, −0.18]	0.74 [0.73, 0.75]	0.52 [0.50, 0.53]
Heat waves and cold snaps	−0.60 [−0.62, −0.59]	−0.67 [−0.68, −0.66]	−0.18 [−0.18, −0.17]	0.74 [0.74, 0.75]	0.53 [0.51, 0.55]

Note: All specifications include indicator variables for the state and specifications considering temperature effects also include both the time trend and price growth rate variables. Numbers in brackets represent calculations based on lower and upper 95% confidence intervals of coefficient estimates. No rebound effects are calculated for the base model as no efficiency terms are included in that specification.

reduce the sample size from 161 observations to 132 and 108 as the appliance energy use series only begins in 1993.

Reverting to the full sample, the final two rows in Table 3 consider alternative measures of temperature. First, we replace the mean maximum temperatures for February and July with the mean maximum temperatures for the hottest and coldest 30 days in each year. Second, we instead use the number of spells of two consecutive days with the maximum temperature above 35 degrees or two consecutive days with the maximum temperature below 15 degrees. The estimates for the rebound effects are the same as those from the main model for electricity and slightly higher for gas and other.

4.3 Results and analysis – household data

We now turn to the household expenditure data so that we can examine the impact of differing demographic and housing characteristics. To allow comparison to the aggregate data analysis, we initially consider the same specifications as in the previous section augmented with the quarterly temperature measure. As can be seen in the top section of Table 4, the main model gives rebound effects of 0.89 for electricity and 0.60 for gas and other, and similarly for the model with only the time trend. Using the measures of appliance energy use changes increases the estimated rebound effects, particularly for gas, although with the 1989 wave of observations omitted.

Table 4 Average estimated price elasticities and rebound effects: household data

Specification	Own-price elasticity electricity	Own-price elasticity gas and other	Cross-price elasticity	Rebound effect electricity	Rebound effect gas and other
Base model	−0.94	−1.29	0.08	—	—
With time trend	−0.78	−0.74	−0.07	0.90	0.62
Main model	−0.77	−0.72	−0.08	0.89	0.60
Appliance energy use % change	−0.80	−0.82	−0.05	0.92	0.70
5-year appliance energy use % change	−0.81	−0.84	−0.04	0.92	0.73
With household characteristics	−0.73	−0.75	−0.07	0.89	0.59
Lowest 40% income	−0.77	−0.83	−0.05	0.91	0.68
Highest 40% income	−0.74	−0.64	−0.10	0.87	0.52
H/H with children, elderly, pensioners	−0.76	−0.74	−0.07	0.89	0.61
H/H without children, elderly, pensioners	−0.77	−0.65	−0.10	0.87	0.55
Detached and semidetached H/H	−0.79	−0.83	−0.05	0.92	0.70
Flats, apartments and other	−0.55	0.10	−0.31	0.66	−0.21
H/H who own with/without mortgage	−0.77	−0.76	−0.07	0.90	0.63
H/H who rent	−0.77	−0.66	−0.09	0.88	0.55
Mean hottest and coldest 30 days	−0.79	−0.79	−0.06	0.91	0.67
Heat waves and cold snaps	−0.74	−0.62	−0.06	0.86	0.50

Note: All specifications include indicator variables for the state and all specifications considering demographic, housing and temperature effects also include both the time trend and price growth rate variables. To preserve space, ranges are not presented here. Instead, shaded entries indicate that calculations based lower and upper 95% confidence intervals of coefficient estimates are the same as the estimates presented; not shaded indicates the range is at most 0.01 lower or higher, except for own-price elasticity and rebound effect for gas and other for flats and apartments which ranged 0.09 to 0.12 and −0.23 to −0.20, respectively.

The range of estimates for the rebound effect of electricity based on household data, 0.87–0.92, is higher than the estimates based on aggregate expenditure data, 0.70–0.80. The rebound estimates for gas and other, 0.60–0.73, are also higher compared to estimates from the aggregate data, 0.44–0.63. The estimates for own-price elasticity range from −0.81 to −0.77 for electricity and from −0.84 to −0.72 for gas and other. These are also larger than the estimates from the aggregate analysis indicating a higher responsiveness of individuals to price changes. Finding that households are more responsive than state aggregates is not surprising; however, recall that the HES data do not report the efficiency of appliances actually used by households. As many energy-intensive appliances are durable, households are likely to retain less efficient appliances and associated energy use habits for periods longer than 5 years. Thus, our estimates using household observations are potentially overstating the responsiveness of consumers to changes in efficiency. Keeping this caveat in mind, we now turn to considering demographic and housing characteristics.

In the first specification in the second section of Table 4, we simply include demographic and housing characteristics as additional regressors and find limited impact on rebound effects. This might lead us to conclude that these characteristics are not important with respect to rebound effects. However, these calculations are giving an overall rebound effect for the full sample and may be disguising key differences.

In the rest of the second section, we divide the data into subsamples based on demographic characteristics. The gap between the rebound effects is largest between lowest 40 per cent and highest 40 per cent of income households: 0.91 compared to 0.87 for electricity and 0.68 compared to 0.52 for gas and other and note that the upper and lower estimates based on the upper and lower 95% confidence interval estimates of the rebound effects for these groups do not overlap. These results support the hypothesis that lower income households are further away from satiation of energy demand so are more likely to respond to increased efficiency by increasing energy service use. For instance, lower income households are likely to achieve a more comfortable room temperature or expand heating or cooling to the whole house. However, as higher income households reach optimal levels of thermal comfort, further improvements in efficiency are unlikely to lead to more heating or cooling.

Households with and without children under five, persons 65 and older, or pensioners or beneficiaries (63 per cent of households) also have different rebound effects, particularly for gas and other with 0.61 compared to 0.55. This suggest that households with more vulnerable members respond to changes in efficiency by taking advantage of the increase in available energy service provision to achieve positive health and well-being outcomes rather than by decreasing energy expenditure.

The third section of Table 4 presents results for groups based on housing characteristics. The 90 per cent of households that live in detached or semidetached houses have much larger rebound effects than the households that live in flats or apartments. In fact, the estimated rebound effect for gas and other is negative. As households in flats and apartments are less likely to be able to choose their gas-fuelled heating and cooking appliances (and may pay for gas as part of rent or building fees), it is certainly conceivable that they will have a lower rebound effect. However, we suggest caution in applying this result to building owners or managers overall. The 71 per cent of households that own, with or without a mortgage, are observed to have higher rebound effects than households that rent. This is also likely due to the reduced ability to choose appliances in rental accommodation.

The final section of Table 4 shows the effects of using alternative temperature measures, analogously to the aggregate data. The rebound effects are higher when replacing February and July mean daily maximums with means of the hottest and coldest 30 days and are lower when using the number of times when the daily maximum was greater than 35 for two consecutive days or less than 15 for two consecutive days. These differences highlight the need for policymakers and energy source providers to understand how households adjust their behaviour differently to average temperatures and periods of temperature extremes. For instance, during heat waves or cold snaps, consumers may be using cooling or heating appliances to their maximums, regardless of efficiency. Thus, changes in efficiency will lead to a greater reduction in energy use during these extreme periods. During regular seasonal temperatures, households with more efficient appliances have more leeway for responding by altering their energy service demand.

4.4 Limitations

Interpreting these estimates of rebound effects should be done with caution for several reasons. There are variables that are not taken into consideration when estimating elasticities that may vary over time, such as government policies. Households may respond differently to the level of prices if they expect changes in future prices or government policy. While our household data are rich in demographic detail and large in sample size, they are not annual data. The aggregate data are annual, but being at the state level limits the possible policy variation. Thus, we are unable to directly consider the impact of specific energy policies, such as the energy star rating scheme or the home insulation scheme. Future work considering specific energy policy changes in efficiency would be interesting.

Price elasticities may be overestimated in the household analysis if the true prices faced by consumers are lower than the average prices used here, for instance, some consumers may be able to take advantage of discounts for early or direct payment and increase demand accordingly. We would attribute these quantity changes to the smaller aggregate price changes.

The elasticities may also be overstated as no differences in quality of energy sources are accounted for. The elasticities we have calculated here use the standard price method that assumes that expenditure is simply price multiplied by quantity for a standardised undifferentiated good (McKelvey 2011). Household surveys, however, give data on groups of related goods that may be of different quality, with different prices for each of these qualities and with the ability of consumers to substitute between different quality levels in response to price changes. Thus, to calculate the responsiveness of quantity demanded with respect to price, differences in quality should first be accounted for otherwise the quantity response will be overstated (see McKelvey 2011; Gibson and Kim 2013, 2016). In our case, the variation in quality of energy sources is likely to be limited. For instance, electricity generated from coal or hydroelectricity provides the same amount heating or lighting. Future work that examines the responsiveness of use of energy sources with different quality levels or with characteristics that affect consumer perception about quality, such as pollution intensity of the source would add an interesting further dimension to developing effective energy policy.

Some households, such as the 41 per cent that currently only report using electricity, may be restricted in their ability to switch fuel depending upon their location and type of dwelling. Other households, such as the 58 per cent that report both sources, may be able to substitute more easily between fuel types. Figure 1 shows that prices have risen similarly across the period so the variation needed to cause fuel switching would need to come from differences in efficiency changes. Our empirical variation in responses comes from aggregate and interhousehold differences; a study of household level data that include direct measures of the types, use and efficiency of appliances and dwellings would be needed to shed further light on intrahousehold changes. Finally, our rebound effects are average effects across all energy services that use the same energy source so we cannot capture differences in efficiency changes across different services.

4.5 Comparison to previous studies

Comparing our rebound estimates to those for the United Kingdom (Hunt and Ryan 2014), we find that our results using aggregate exhibit similar rebound effects for electricity and lower for gas and other fuels. For example, Hunt and Ryan estimate a rebound effect of 0.72 in their equivalent to our main model, where our estimate is 0.74. Their estimate for gas is 0.75 and for other fuels is 0.63, whereas our combined estimate is 0.51. Our estimates based on household data give higher rebound effects for electricity (0.89) and lower for gas and other fuels (0.60). Comparing own-price elasticities also give different results with Hunt and Ryan's estimate for electricity as −0.43 in the main model, −0.92 for gas and −0.75 for other fuels. This means that Australian consumers are more responsive to price changes in electricity (−0.60 using aggregate data or −0.77 using household data) and less responsive to price changes in gas and other (−0.65 using aggregate data or −0.72 using household data). The larger responsiveness for electricity is likely to be caused by expanding air conditioner use and lower prevalence of gas heating in Australia compared to the United Kingdom. This demonstrates that care needs to be taken in applying estimates across different countries and facing different price paths.

To our knowledge, this article is the first study of Australian rebound effects. Fan and Hyndman (2011), however, study price elasticity of electricity demand in South Australia. Their elasticity estimates for annual median demand range from −0.36 to −0.43, which are smaller than our results for Australia. Their study is only on electricity but they compare winter and summer demand and find that responsiveness is 30–40 per cent higher in winter, which they attribute to the ability to switch heat sources. Our study includes all six states, with different energy policies and infrastructure and includes gas and other fuels, and therefore can allow for switching, which may explain why our elasticities are different.

5. Conclusion

This article uses two different data sources to estimate rebound effects for energy sources in the Australian context. Using aggregate data for residential energy use from 1989 to 2015 in six states, we estimate the rebound effect for electricity use to be between 0.70 and 0.80 and between 0.44 and 0.63 for gas and other fuels. We complement this aggregate analysis using household level expenditure data from 1989, 1999, 2004 and 2010. The average estimates of the rebound effect for electricity range from 0.86 to 0.92 and from 0.50 to 0.73 for gas and other fuels. In the context of increasing Australia's energy productivity, these results suggest that increased efficiency leads to increased residential energy service provision, more than decreased energy source use. Hence, energy efficiency policies are likely to have limited effectiveness in reducing energy consumption.

We use the household level data to pursue the impact of differences in demographic and housing characteristics. These results indicate that lower income households are more responsive than higher income households to efficiency changes. Similarly, households with young children, elderly persons, pensioners or beneficiaries have larger rebound effects than those households without. Households with more control over the energy service appliance choices (those in detached and semidetached homes or those that own rather than rent) are also more responsive. We note that the rebound estimates based on household data are higher than those conducted on the aggregate data. Thus, interpretations of the levels should be done cautiously. However, differences across demographic and housing characteristic groups merit consideration. In particular, if government policies to encourage efficiency are implemented with a primary goal of reducing energy use, this will be relatively unsuccessful if targeted at lower income household or household with more vulnerable members. Alternatively, if the goal of policy is to improve health and well-being outcomes of vulnerable consumers, then energy efficiency measures are likely to induce positive change.

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Supporting Information

Additional Supporting Information may be found in the online version of this article:

Appendix S1.

Table A1. Electricity share equation regression: aggregate data

Table A2. Electricity share equation regression: household data

Table A3. Electricity share equation regression: household data with demographic characteristics

Table A4. Electricity share equation regression: household data with housing characteristics and temperature variations