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A meta-analysis on the price elasticity and income elasticity of residential electricity demand

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ABSTRACT

Price elasticity and income elasticity can quantitatively measure the impact of price volatility and income diversity on household electricity demand. To analyze household electricity demand and better identify the main factors affecting residential electricity demand elasticity in previous literature, a meta-analysis based on a comprehensive and systematic summary of 103 articles is presented in this study. The influencing factors are identified, with a weighed least squares (WLS) linear regression model to evaluate their strength. The price elasticities and income elasticities are discussed from three dimensions, namely short-term, long-term and unmarked. The results show that residential electricity demand is almost price-inelastic and income-inelastic in the short-term. But in the long-term, some residential electricity demand is price-elastic and income-elastic. The results also reveal that residential electricity demand elasticity is affected by many factors, such as time interval and sample period. These conclusions can support the formulation of more effective electricity price and energy policy.
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1. Introduction

Energy is an important driving force for social progress and development. Electricity is a kind of clean secondary energy, which refers to it is converted from primary energy that directly from the natural world, including raw coal, crude oil, and natural gas. It is closely related to the industrial development, national economy development and people's livelihoods. According to Energy Market Authority, 2017, more than 15% of the electricity was used for households, and most of the electricity is generated using imported natural gas in Singapore (Energy Market Authority, 2017). Similarly, China Energy Statistics 2017 shows that household electricity consumption accounts for 13% of total electricity consumption, of which 70% of electricity is generated by thermal power (China Energy Statistics, 2017). In some countries, the household sector is one of the main areas of electricity consumption. A large amount of electricity consumption exacerbates annual greenhouse gas emissions. In order to mitigate the negative impact of energy consumption on the environment, many measures have been taken, such as strengthening research on renewable energy and organic materials (Maroušek, 2012; Marousek et al., 2015), formulating appropriate environmental taxes (Ghaith and Epplin, 2017; Oderinwale and Weijde, 2016), and subsidizing environmentally friendly electricity production (Mardoyan and Braun, 2014; Maroušek et al., 2014).

Although renewable energy research and policy regulations are important ways to promote energy conservation and improve energy efficiency, more and more people are gradually realizing that behavioral factors are of great significance for achieving energy conservation (Zhou and Yang, 2016). Changes in household electricity consumption behavior can effectively achieve the household energy saving. At present, there are many studies that consider energy price and household income as some of the determinants of household electricity consumption behavior (Esmaeilimoakher et al., 2016; Silva et al., 2017). However, energy price is affected by various factors. For example, the ban of nuclear energy, public demand for renewable resources, and the formulation of environmental taxes. There are also significant differences in household income due to differences in work, education, and regions. The volatility of electricity prices and the diversity of household

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Nomenclature

Indices

i	The number of explanatory variables
n	The total amount of explanatory variables

Parameters

η	The price elasticity and income elasticity collected from previous studies
X_i	The set of potential independent variables
$\beta 0$	When all explanatory variables are zero
βi	Correlation coefficients
ε	Error term

Acronyms

WLS	Weighted least squares method
GLS	Generalized least squares method
OLS	Ordinary least squares method
IV	Instrumental variable method
ML	Maximum likelihood method
ECM	The error components model

incomes increase complexity of research problems. Price elasticity and income elasticity are quantitative indicators to measure the impact of price changes and income changes on electricity demand. Their introduction can evaluate the response of household electricity consumption to price changes and income changes. Ultimately, the consumption pattern can effectively support the regulation of residential electricity markets (Nakajima and Hamori, 2010), the formulation of energy policies (Kwon et al., 2016), residential electricity demand forecasts (Cabral et al., 2017), electricity infrastructure planning (Collins et al., 2017), and measuring the effectiveness of environmental taxes (Benavides et al., 2015).

In recent years, the field of economics has produced a large amount of residential electricity demand research literature, which provides considerable empirical evidence for the analysis of electricity demand (Romero-Jordán et al., 2016; Wang and Mogi, 2017). However, these studies establish different evaluation models, use different evaluation methods, and distinct types of data from different countries covering different periods, and draw conclusions in specific situations. The high heterogeneity of existing empirical studies hinders the general adaptive conclusions to be made that support for policy decisions.

Meta-analysis offers an effective and appropriate way to solve this problem (Labandeira et al., 2017). It is a review method based on statistical analysis, proposed by Glass in 1976, then introduced into the field of economics by Stanley and Jarrell (1989), to fill the gaps of the quantitative literature review method. Meta-regression is a popular meta-analysis method used in economics (Chen et al., 2015). Espey (1996) first proposed using meta-analysis to determine whether there are systematic factors affecting gasoline prices and income elasticity estimates in the US. His study considered the data characteristics, model structure, and estimation technique as explanatory variables. In his subsequent study, Espey (1998) used demand specifications, data characteristics, environmental characteristics, and the estimation method used as explanatory variables to estimate the global long-run and short-run gasoline prices and income elasticity. A considerable amount of subsequent research is based on this study. Espey and Molly (2004) used meta-analysis to quantitatively summarize previous studies of residential electricity demand by both GLS estimation and ML estimation. Labandeira et al. (2017) used meta-analysis methods to evaluate the price demand elasticity of a variety of energy goods, including electricity, natural gas, gasoline, and diesel. Other research uses meta-analysis focused on the demand elasticity of water (Houtven et al., 2017), food (Chen et al., 2015), transportation noise nuisance (Bristow et al., 2012), alcohol (Gallet, 2007), pesticides (Böcker and Finger, 2017), etc. On the whole, however, the use of meta-analysis to study elasticity estimates of electricity demand is still quite limited. Espey and Molly (2004) selected peer-reviewed journal articles published between 1971 and 2000 covering the time period from 1947 to 1997, lost the latest reference value. Labandeira et al. (2017) focused on a variety of energy goods, their research covering residential, industrial and commercial aspects. However, different energy goods have different performance levels and storage requirements, and can meet the needs of people under different scenarios. Therefore, there are differences in the factors that affect them. We exclude such energy sources as diesel and gasoline, and only select electricity as the object of the research. In comparison, the study of electricity demand in this paper is more accurate and precise.

We comprehensively collect the results of previous studies involving the demand elasticity of residential electricity. The meta-regression method is used to determine the following points. First, we need to determine how much elasticity estimates are sensitive to the demand specification, difference in data sources, background environment and estimation method. Second, whether short-term elasticity estimates differ from long-term estimates is determined. Third, we need to consider the different responses of price elasticity and income elasticity to a range of factors. Finally, we judge whether the price elasticity and income elasticity are elastic in the short- and long-term. To accomplish this, we summarize the elasticity of electricity demand, and identify the factors that influence electricity demand - extracting useful estimates from the latest academic articles. Then we take the price elasticity and income elasticity of residential electricity demand as dependent variables, with demand specification, estimation technique, data characteristics, and environmental characteristics as explanatory variables. A regression analysis of cross studies is conducted to obtain the determinants of residential electricity demand elasticity.

For the remainder of this article, Section 2 introduces our data sources; then we establish the meta-regression model and determine the explanatory variables in Section 3. Section 4 presents the empirical results, and Section 5 contains our concluding remarks.

2. Data sources

In order to complete relevant studies, empirical studies were obtained from a variety of databases, including the Web of Science, Chinese Journal Full-text Database, Google Scholar, and used the keywords “electricity” and “demand” and “price elasticity” or “income elasticity”. Then, a manual scanning of the abstracts was conducted. Articles that do not meet the research requirements were eliminated. Eventually, this paper summarizes the 103 articles on the theme of residential electricity demand. The articles used in the meta-analysis are shown in Table A.1 in Appendix A. These articles were published between 1990 and 2017 covering the period from 1950 to 2014. These studies yielded 175 and 196 short- and long-term price elasticity estimates respectively, 148 and 151 short- and long-term income elasticity estimates respectively, and 228 and 151 price and income elasticity estimates that did not specify short- or long-term.

Table 1 provides a statistical summary of the elasticities. The short-term price elasticity estimates range from −0.948 to 0.61 with a mean of −0.228. For the long-term price elasticity estimates, the mean is −0.577, range from −4.2 to 0.6. Short term income

Table 1
Statistics of price elasticities and income elasticities.

Variable	Observations	Mean	Minimum	Maximum
Short-term price	175	−0.228	−0.948	0.610
Long-term price	196	−0.577	−4.200	0.600
Unmarked price	228	−0.450	−3.735	3.290
Short-term income	148	0.239	−0.450	1.265
Long-term income	151	0.960	−0.890	4.450
Unmarked income	151	0.362	−1.257	1.950

elasticity estimates range from −0.45 to 1.265 with a mean of 0.239. For the long term income elasticity estimates, the mean is 0.960, with a maximum value of 4.45 and a minimum value of −0.89. Unmarked elasticity estimates range from −3.735 to 3.29 with a mean of −0.450 for price elasticity, and range from −1.257 to 1.95 with a mean of 0.362 for income elasticity.

In this study, we have collected the studies from various countries covering different periods to identify the factors, which affecting residential electricity demand elasticity in previous literature. In other words, the factors that lead to heterogeneity are identified. Differences in taxes and currency exchange rates can reflect the diverse responses of households to the changes in electricity prices in different countries. In order to reflect the significant differences in residential electricity consumption in different countries, we don't consider the differences in taxes and currency exchange rates.

Some studies contain multiple sets of estimated elasticity, and we determined whether the results are derived from the same data set and whether the same models and methods are used to make the estimates. Some studies carefully distinguish the different effects of seasonal, temperature, and time factors on the elasticity of electricity demand (Hung and Huang, 2015; Romero-Jordán et al., 2016). For these articles, we extracted the evaluation results overall or from different data sets, different estimation models and different estimation methods.

The probability density graphs of the price elasticities and income elasticities are provided in Fig. 1.

Fig. 1 shows the distribution of the estimates of demand elasticity. The Gaussian kernel function is used to represent the continuous density curves. As can be seen from Fig. 1, all probability density graphs are relatively concentrated and approximate normal distribution. The absolute values of price elasticities and income elasticities are almost all less than 1 in the short-term. This means that the residential electricity demand is almost inelastic in the short term. As for price elasticities and long-term income elasticities in the long-term, although the absolute values of most of the demand elasticities are less than 1, there are still a considerable amount of elasticity estimates whose absolute values are greater than 1. This shows that in the long term, some residential electricity demand is elastic to the changes in electricity price and household income. In addition, only a small amount of the absolute values of unmarked price elasticities and income elasticities are greater than 1.

3. Meta-regression model

A large number of literature focusing on the price elasticity and income elasticity of residential electricity demand were obtained. However, it is not clear that household will respond to the changes in electricity prices and household income under what circumstances and to what extent. Therefore, a research framework is proposed to explore potential determinants that influence residential electricity demand elasticity in Fig. 2.

As shown in Fig. 2, the research framework is divided into three phases. The first stage is data collection and extraction, which is what Section 2 has shown. The second stage is the establishment of a meta-regression model. The final stage is the regression results and analysis, including the identification of the determinants, and different responses of price elasticity and income elasticity between short and long-term. The following elaborates the establishment of a meta-regression model.

The following variables are considered as potential determinants, namely explanatory variables in the estimates: demand specification, data characteristics, environmental characteristics and estimation technique. The dependent variables are price elasticity and income elasticity. Elasticity itself has no unit, and is easy to compare and explain (Espey, 1998). The meta-regression model can be written as

$$\eta = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \varepsilon \quad (1)$$

We summed a series of explanatory variables from the four aspects of demand specification, data characteristics, environmental characteristics, and estimation technique. The descriptions of all explanatory variables are summarized in Table A.2 in the Appendix.

3.1. Demand specification

This covers functional form, lag structure, and whether it is double log model. Since most of the articles are expressed in linear form, we classify other form as a 'nonlinear form'. Lag structure is used to measure whether or not the dependent variable is affected by the variables from past periods. The partial adjustment model is the most common lag type. The static model means there is no significant adjustment to changes of price or income from past periods of the data. Since correlational observations are infrequent, all other lag structures are classified as 'other lags'. The use of a double logarithmic model in each study is another important factor affecting the outcome. Since the semi-logarithm model and the simple regression model are less used, we classify these as the 'non-double log model'.

3.2. Data characteristics

The data type used in empirical studies in meta-analysis is an important factor influencing the outcome (Labandeira et al., 2017), and hence experiments were performed using cross-sectional data, time-series data, and panel data to see the distinction. It is also important to consider that demand elasticity estimation uses monthly, quarterly, or annual data; and whether the data are macro or micro survey data.

3.3. Environmental characteristics

Different levels of data produce different elasticity results, which are mainly related to differences in regional climate and residential living habits. Whether the data is at the national level or at the state/provincial level is therefore an important analysis variable. Different economic development and energy policies have led to significant differences in household electricity consumption, so developed and developing countries are used as important dummy variables. The sample periods are classified as pre-1972, 1972–1981, 1982–2000, and post-2000. The division of these periods is related to energy market changes, energy economic crisis, and economic development. As is well known, crude oil occupies an important position in the energy consumption structure, and its price fluctuation is closely related to the macro economy (Ji and

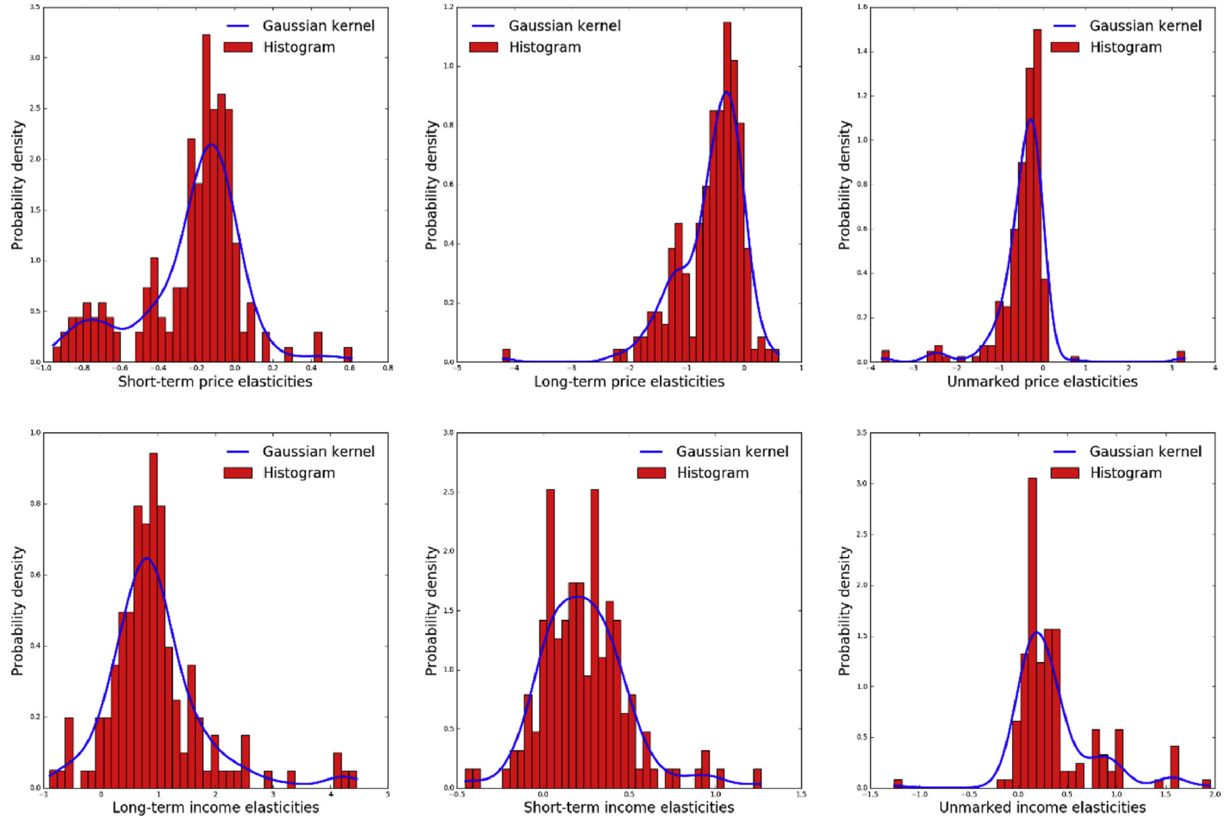

Fig. 1. Density of price elasticities and income elasticities on total samples.

Guo, 2015). Two energy crises occurred between 1972 and 1981, and oil prices soared. After 1981, the decline in demand caused by the recession led to lower crude oil prices. After 2000, the oil market share continued to decline, the share of other energy sources increased, and renewable energy has gradually become the main form of consumer energy.

3.4. Estimation technique

Practice has shown that different estimation methods have an obvious impact on the results. Many methods have been used to estimate residential elasticity of demand for electricity, the most popular being OLS, followed by the ECM, IV, and ML. Since other methods are only infrequently used, they were all classified as ‘other methods’.

In the current meta-analysis, OLS is the simplest method of evaluation. However, if there is heteroskedasticity, that is, random errors term have different variances, then the variance of the OLS estimates will not be guaranteed to be minimal. This may lead to bias estimation of the standard error of the coefficients. Sebri (2016) argued that the problem of heteroskedasticity is primarily due to the fact that effect size estimates used in meta-regression analysis are collected from empirical studies that are generally based on different sample sizes. In this paper, according to the quadratic distribution of the residual of explanatory variables, we judged that the model is likely to have heteroscedasticity. To reduce the heteroscedasticity, WLS is used. When using WLS, we chose to use the reciprocal of the standard deviation during the estimation as a weight.

Following Chen et al. (2015) approach, we use dummy variables instead of explanatory variables, that is, a set of variables describing the same characteristics take a value of 0 or 1. If each sample can only satisfy one of the characteristics of the set of variables, then this set of variables are mutexes. A variable is excluded from each set of mutexes (Espey and Molly, 2004), to improve the usefulness of the meta-analysis. At the same time, it is also possible to avoid highly correlation between explanatory variables, that is, multicollinearity. Since the four time periods of the sample period are not mutually exclusive, all are retained.

Heteroscedasticity tests, multicollinearity diagnosis, and WLS regression are all performed using IBM SPSS Statistics 22.

4. Results and discussions

In this section, a linear regression model based on the WLS method is used to evaluate all the explanatory variables, and the results are shown in Tables A.3 and A.4 in Appendix A. The mean values of variables included in the meta-analysis are shown in Table 2.

4.1. Price elasticity

From Table 2, there are obvious differences in the mean values of some explanatory variables that are used to describe the same feature. For short-term price elasticity, monthly data is more elastic than quarterly data and annual data, with quarterly data almost perfectly inelastic. This is related to the national background of the data we collected, with a relatively small number of articles using quarterly data to study the price elasticity, and mainly concentrated in the United Kingdom and Malaysia. The annual temperature differences in these two countries is small, resulting in quarterly data with almost no price elasticity. The monthly data is more elastic than the annual data, mainly related to the season, climate change, and different festivals. The price elasticity of the annual data is almost the same as the entire sample. Consistent with Labandeira et al. (2017), the micro survey data price elasticity is more

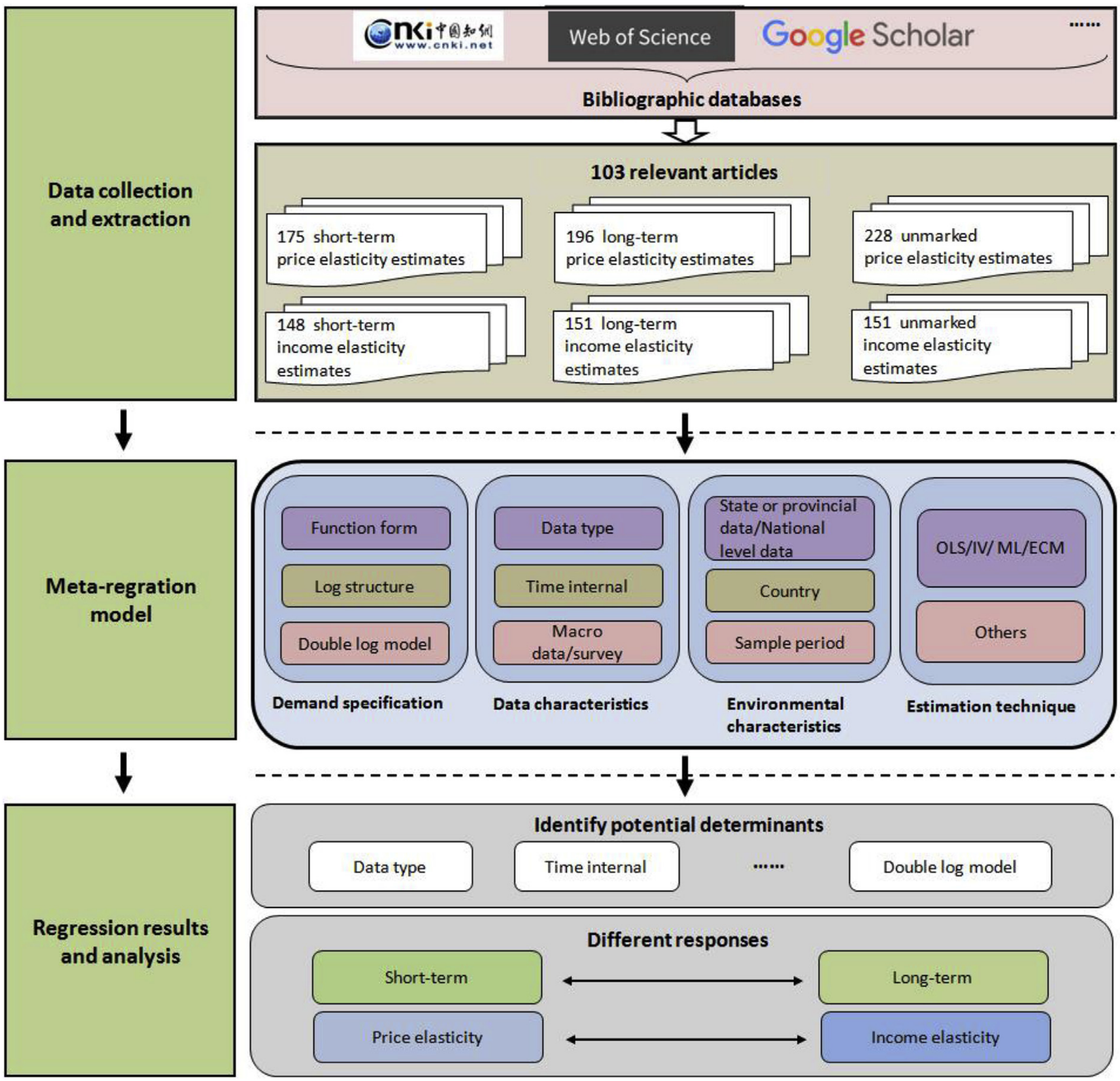

Fig. 2. Proposed research framework.

obvious than the macro data, mainly because the micro survey data contains more complex detail. Developing countries are also more price elastic than developed countries. The different economic conditions of the countries make people respond differently to changes in electricity prices. During the 1972–1981 sample period, changes in energy consumer behavior resulting from the energy crisis led to a reduction in both the short- and long-term price elasticity of electricity demand. Sarwar et al. (2017) also agreed with changes in oil prices, many countries are heavily dependent on electricity consumption to promote economic growth. After 2000, electricity demand has a higher price elasticity (in absolute values) than other sample periods. This may be related to an increased energy-saving awareness and the popularity of energy pricing policies (Wu and Zhang, 2017). The micro survey data price elasticity is also more significant where the price elasticity data is not specified as short or long term.

4.1.1. Demand specification

From Table A.3, we find that whether the functional form of price elasticity of electricity demand is linear has obvious statistical significance for short-term price elasticity, but not for long-term price elasticity. Likewise, whether the lag structure is a partial adjustment model has no statistical significance for short-term and long-term price elasticity. The static model also produces unapparent price estimates both for short-term and long-term. From Table 2, we find dynamic models generally produce much lower price elasticity (in absolute values) than static models, which is consistent with Espey and Molly (2004) conclusion. Using the double log model has a more obvious effect on long-term price elasticity.

4.1.2. Data characteristics

Both the time series data and panel data have statistical significance for short-term price elasticity. Compared to the time series data, the panel data generates higher elasticities (in absolute values). Espey (1998) thought that due to more detail and changes in the panel data, which may capture more subtle responses, resulting in more flexible estimates. Compared to the time series data, the panel data have statistically significant effects on long-term price elasticity. Studies using monthly or annual data still have obvious effects on short-term elasticity changes. Even though the difference is not large, it is still clear that the influence of

Table 2
Mean values of variables included in the price elasticity and income elasticity meta-analysis.

Variables	Short-term price	Long-term price	Unmarked price	Short-term income	Long-term income	Unmarked income
Demand specification						
Functional form						
Linear	−0.227	−0.578	−0.484	0.239	0.960	0.351
Nonlinear	−0.433	−0.442	−0.208	0.000	0.000	0.466
Lag structure						
Other lags	−0.138	−0.481	−0.198	0.200	1.003	0.504
Partial adjustment model	−0.214	−0.630	−0.534	0.293	0.935	1.432
Static model	−0.548	−0.867	−0.557	0.179	0.507	0.280
Double log model	−0.237	−0.621	−0.482	0.204	0.976	0.380
Non-double log model	−0.179	−0.293	−0.288	0.412	0.877	0.282
Data characteristics						
Time series	−0.178	−0.497	−0.187	0.273	1.238	1.150
Cross-sectional	−0.021	−0.815	−0.684	0.375	0.661	0.289
Panel data	−0.245	−0.582	−0.402	0.227	0.851	0.358
Time interval						
Monthly	−0.322	−0.557	−0.363	0.203	0.164	0.298
Quarterly	−0.046	−0.258	−0.362	0.641	1.978	0.390
Annual	−0.212	−0.593	−0.519	0.229	0.972	0.380
Macro data	−0.152	−0.489	−0.198	0.219	1.042	0.680
Survey	−0.370	−0.771	−0.557	0.273	0.752	0.258
Environmental characteristics						
State or provincial data	−0.193	−0.462	−0.470	0.299	0.604	0.289
National level data	−0.248	−0.618	−0.433	0.205	1.101	0.416
Country						
Developed	−0.220	−0.581	−0.341	0.209	0.919	0.333
Developing	−0.273	−0.555	−0.683	0.403	1.099	0.400
Sample period						
Pre −1972	−0.207	−0.537	−0.253	0.341	1.155	0.955
1972–1981	−0.132	−0.475	−0.290	0.257	1.016	0.492
1982–2000	−0.195	−0.495	−0.486	0.224	0.967	0.593
Post-2000	−0.237	−0.557	−0.418	0.199	0.979	0.343
Estimation technique						
OLS	−0.136	−0.548	−0.822	0.280	0.729	0.397
IV	−0.373	−0.893	−0.175	0.187	0.547	0.037
ML	−0.177	−1.062	−0.432	0.328	1.259	0.240
ECM	−0.107	−0.420	−0.385	0.189	1.079	0.383
Other methods	−0.416	−0.498	−0.364	0.244	0.822	0.601
Total	−0.228	−0.577	−0.450	0.239	0.960	0.362

monthly data is greater than annual data. This means that, consistent with Espey and Molly (2004) research, monthly data can more accurately measure the demand responses of price changes, compared to the broad and obscurant annual data. It also demonstrates the rapid short-term response of residential electricity demand. Moreover, both macro and micro-survey data have a significant impact on both short- and long-term price elasticity. This may be related to the significant differences in the price elasticity of the macro data and survey data shown in Table 2.

4.1.3. Environmental characteristics

Both national level and state/provincial data have a significant impact on short-term price elasticity estimates, but not long term. Compared to the national level data, the state/provincial level data contain more detailed information, such as climate, lifestyle, and economic status, and there is a clear impact on the demand response of price changes. Similarly, studies using developed country data to estimate the demand for electricity is more elastic in the short term than the long term. This shows that differences in economic development cause people to respond quickly to changes in price in the short-term. According to Table 2, developing countries are generally more sensitive to price changes than developed countries. Before 1972 and from 1982 to 2000 were no change in elasticity, indicating demand price elasticity to be relatively stable during these two periods, but otherwise with elasticity changes in the short and long term. Short-term price elasticity declined over time in 1972–1981 and after 2000. This may be related to the multiple energy crises occurring in between 1972 and 1981. Consistent with Sarwar's et al. (2017) research electricity, as a substitute for other energy forms, has been less sensitive to price changes in the short term. After 2000, economic growth has engendered increasing numbers of domestic appliances, slightly reducing short-term price elasticity.

4.1.4. Estimation technique

Using OLS and ML as the assessment methods, there were no significant effects on short- and long-term price elasticity. Compared to the short-term, the IV method indicates more long-term price elasticity. The use of the ECM has significant effect in short-term, but not in long-term. The reason for these different results may be related to the characteristics of evaluation data, or due to the methods themselves having slight differences. OLS is a common method to estimate the parameters in the model, the advantage of which is convenient and practical. But OLS may yield biased and inconsistent estimates (Hung and Huang, 2015). IV is applied to solve endogenous problems by introducing an exogenous variable which is associated with endogenous variable in the model. However, the choice of instrumental variables is difficult. ML tries to find the best parameters under the given model, so that makes the set of samples most likely to appear. ECM treats the error term in cointegration regression as an equilibrium error and makes up for the deficiency of long-term static model by establishing a short-term dynamic model.

Elasticity experiments that did not indicate short- or long-term effects were mostly excluded in previous articles using meta-analysis methods. As a result, the amount of assessment data is significantly reduced. But in the previous studies of demand elasticity analysis, there were some examples that do not distinguish long term and short term (Gallet, 2007). Therefore, we retain this part of the data, and the same use of WLS in the regression analysis. As Table A.3 demonstrates, unmarked price elasticity of electricity demand is sensitive to functional form, whether the country is developed, macro data is used, the sample period and the estimation technique involved.

4.2. Income elasticity

From Table 2, we can see that developing countries are more income elastic than developed countries. This means that people in developing countries are more sensitive to changes in income. The elasticity of the quarterly data is significantly higher than the monthly and annual data. Similar to price elasticity, the articles that used quarterly data to study income elasticity are mainly concentrated in Malaysia. The electricity demand and intensity in Malaysia are quite high among the five ASEAN founding economies, with rapid growth in its per capita electricity consumption (Solaymani et al., 2017), consistent with our conclusions. Income elasticity in developing countries is generally higher than developed countries indicating that, as the economy grows, the demand for electricity is gradually satisfied and income elasticity decreases.

4.2.1. Demand specification

For the long and short term, since all income elasticity functional forms are linear, the coefficient estimates are not significant. The partial adjustment model and static model has no significant effect on short- and long-term income elasticity. While the double logarithmic model has a great impact on the demand responses from income changes.

4.2.2. Data characteristics

The use of time series or panel data can have a significant impact on short term income elasticity measures, but not in the long term. Whether the data is monthly or annual can significantly change income elasticity, especially long-term elasticity. It is likely that response to changes in income may take some time to take place. Table 2 shows that there is no significant difference between monthly and annual income elasticity estimates in the short term. In the long term, however, annual data produce greater elasticity estimates, while monthly data produces relatively less elasticity estimates. This is consistent with Dahl and Sterner (1991) research, who argue that monthly and quarterly data are not suitable for long-term adjustments. Espey (1998) also argues that using monthly data is lower estimated. Previous research shows that the use of macro-economic or micro survey data has no significant impact on short- and long-term income elasticity changes.

4.2.3. Environmental characteristics

Contrary to price elasticity estimates, data at the national or state/provincial level both have a role in estimating long-term income elasticity, but are not significant in the short term. On the one hand, the different living habits and economic conditions of different states and provinces engender a different response to electricity demand. On the other hand, changes in income have little impact on short-term changes in electricity demand, indicating people's electricity demand elasticity to be relatively stable. Long-term electricity demand changes are likely to be related to the purchase and use of new appliances. Studies using developed country data have no significant impact on short term and long term income elasticity measures. Residential electricity demand before 1972 is responsive to revenue growth in the long term. This could be linked to a limited global supply of electricity and a growing electricity demand. The impact of changes in income on electricity demand in the short term was minimal before 1981, with a significant change in electricity demand elasticity in the short term after 1982, short-term income elasticity was declining during the 1982 to 2000 sample period, and has risen since 2000. Long-term income elasticity has grown rapidly after 2000.

4.2.4. Estimation technique

Table A.4 shows that using OLS as the assessment method, there was no significant effect on short- and long-term price elasticity. ML method can significantly change income elasticity both in short term and long term. Compared to the short-term, the IV method and ECM method indicate more long-term price elasticity. As with the price elasticity estimation, it is not possible to determine the specific impact of a method on the results and it is likely that the overall difference is still related to the data characteristics.

As for unmarked income elasticity, all variables can significantly affect it, include functional form, whether a double logarithmic model, data type, time interval, whether macro or micro-survey data, whether developed or developing country and data from the national levels or state and provincial levels, and sample period.

5. Conclusions

This paper provides a meta-analysis of empirical studies of the elasticity of residential electricity demand. The results of statistics analysis show that residential electricity demand is almost inelastic in the short term. However, in the long term, some residential electricity demand is price-elastic and income-elastic. In addition, a comparison of the mean of price elasticity and income elasticity reveals that the impact of income changes on electricity demand is greater than the price changes in the long term. Moreover, the WLS linear regression model was used to identify the factors that have impact on residential electricity demand elasticity. The results show that price elasticity is sensitive to data types, time intervals, and macro data. Environmental characteristics can also affect short-term price elasticity. Short-term income elasticity is sensitive to data types and time intervals. Long-term income elasticity is sensitive to time intervals, national level data, evaluation methods, and sample periods.

These findings are of great significance to government and some research communities. By identifying the factors that lead to heterogeneity of residential electricity demand elasticity, researchers can gain a deeper understanding of residential electricity demand characteristics. Based on the understanding of the characteristics of household electricity consumption, the government has the opportunities to make more effective governance. Our results confirm the feasibility of adjusting household electricity consumption through regulating electricity prices in a long-term. Energy economists formulate appropriate electricity prices based on household electricity demand characteristics. Behavioral economists consider the impact and extent of electricity prices on household consumption behavior. The government controls electricity prices by formulating energy policies to change household consumption behaviors and support the reduction and shift of loads. Ultimately, these approaches can promote energy conservation, environmental protection, and energy structure adjustment. In addition, the residents' responses to changes in income are more pronounced in the long term. The government's stimulation of the economy is likely to have a positive impact on electricity consumption. But encouraging growth promotion policies for renewable power generation and improving environmental tax policies may provide further mitigating solutions.

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Appendix A. Supplementary table

Table A.1
Studies used in the meta-analysis.

Author(s)	Year	Author(s)	Year
Dodgson et al.	1990	Chang & Yu	1991
Badri	1992	Herriges & King	1994
Hsing	1994	Filippini	1995
Maddala et al.	1997	Silk & Joutz	1997
Beenstock	1999	Bose & Shukla	1999
Tiwari	2000	Halvorsen &Larsen	2001
Munley et al.	2001	Chang et al.	2003
Dulleck &Kaufmann	2004	Filippini &Pachauri	2004
Filippini	2004	Hondroyiannis	2004
Holtedahl &Joutz	2004	Holtedahl & Joutz	2004
Khan & Abbas	2004	Reiss & White	2004
Narayan & Smyth	2005	Lijesen	2006
Atakhanova & Howie	2007	Boonekamp	2007
Narayan et al.	2007	Yoo	2007
Zachariadis & Pashourtidou	2007	Amarawickrama & Hunt	2008
Asadoorian et al.	2008	Dergiades & Tsoulfidis	2008
Dergiades & Tsoulfidis	2008	Ziramba	2008
Khan & Qayyum	2009	Paul et al.	2009
Sa'ad	2009	Tario et al.	2009
Athukorala & Wilson	2010	Bilgili et al.	2010
Filippini	2010	Fell et al.	2010
Ito	2010	Nakajima & Hamori	2010
Nakajima	2010	Alberini et al.	2011
Alberini et al.	2011	Alberini & Filippini	2011
Alter & Syed	2011	Azevedo	2011
Bernard et al.	2011	Bernstein & Madlener	2011
Casarin & Delfino	2011	Dilaver & Hunt	2011
Faruqui & Sergici	2011	Fan & Hyndman	2011
Filippini	2011	Lavín et al.	2011
Syed	2011	Carter et al.	2012
Ito	2012	Journal	2012
Jorgensen & Joutz	2012	Labandeira et al.	2012
Shi et al.	2012	Walke	2012
Blazquez et al.	2013	Dicembrino & Trovato	2013
El-Shazly	2013	Gomez et al.	2013
Jin & Zhang	2013	Okajima & Okajima	2013
Polemis & Dagoumas	2013	Saunoris & Sheridan	2013
Sudarshan	2013	Zhou & Teng	2013
Arisoy & Ozturk	2014	Chang et al.	2014
Feng	2014	Rapson	2014
Romerojordán et al.	2014	Cetinkaya et al.	2015
Filippini et al.	2015	Hung & Huang	2015
Krishnamurthy & Kristrom	2015	Liang & Cao	2015
Liu et al.	2015	Liu et al.	2015
Liu et al.	2015	Moshiri	2015
Solaymani et al.	2015	Yu & Li	2015
Zhang & Liu	2015	Feng & Wang	2016
Khanna et al.	2016	Romerojordán et al.	2016
Salari & Javid	2016	Wang & Lin	2016
Zhang et al.	2016	Liu et al.	2017
Schulte & Heindl	2017	Wang & Mogi	2017
Zhang et al.	2017		

Table A.2
Description of the explanatory variables in meta-regression model.

Variables	Description
Demand specification	
Functional form	The functional form of regression model.
Linear	Functional form is linear.
Nonlinear	Functional form is multiplicative or direct.
Lag structure	This variable is used to measure whether or not the dependent variable is affected by the variables from past periods.
Other lags	In addition to the partial adjustment model and the static model, other infrequent lay structures are classified as ‘other lags’.
Partial adjustment model	This variable means that the variables in the past periods partially adjusted the dependent variable of current period.
Static model	This variable means demand elasticity is no significant adjustment by variables from past periods.
Double log model	Both the independent variable and dependent variable are in logarithmic form.
Non-double log model	The semi-logarithm model and simple regression model..
Data characteristics	
Time series	The empirical studies included in meta-analysis used the data of certain object over time.
Cross-sectional	The empirical studies used data from different objects at a certain time.
Panel data	The empirical studies used the synthesized data from the cross-sectional data and the time series data.
Time interval	This variable is used to indicate that is monthly data, quarterly data or annual data used in the empirical studies included in meta-analysis.
Monthly	Monthly data is used.
Quarterly	Quarterly data is used.
Annual	Annual data is used.
Macro data	The empirical studies included in meta-analysis used overall macro data.
Survey	The empirical studies used micro survey data.
Environmental characteristics	
State or provincial data	The empirical studies used data belonging to a state/province.
National level data	The empirical studies used data from the national level.
Country	This variable is used to distinguish between developed and developing countries.
Developed	The empirical studies belong to developed countries.
Developing	The empirical studies belong to developing countries.
Sample period	The period of sample data used in empirical studies.
Pre −1972	The sample period is before 1972.
1972−1981	The sample period is 1972−1981.
1982−2000	The sample period is 1982−2000.
Post-2000	The sample is after 2000.
Estimation technique	
OLS	Ordinary least squares are used to estimate.
IV	Weighted least squares are used to estimate.
ML	Maximum likelihood method is used to estimate.
ECM	The error components model is used to estimate.
Other methods	In addition to the above methods are classified as "other methods".

Table A.3
Meta-analysis coefficient estimates: price elasticity of electricity demand.

Variable	Short-term price	Long-term price	Unmarked price
Demand specification			
Functional form			
Linear	0.622**	0.701	−0.659***
Lag structure			
Partial adjustment model	0.070	−0.059	−0.599**
Static model	−0.113	−0.187	−0.109
Double log model	−0.233	−0.930***	0.008
Data characteristics			
Time series	−0.399***	−0.585	−0.031
Panel data	−0.531***	−0.676*	0.165

Table A.3 (*continued*)

Variable	Short-term price	Long-term price	Unmarked price
Time interval			
Monthly	−0.427***	−0.233	−0.099
Annual	−0.349***	−0.348	−0.322
Macro data	0.242***	0.405**	0.328**
Environmental characteristics			
National level data	−0.168**	−0.049	0.166
Country			
Developed	0.206***	0.076	0.299***
Sample period			
Pre −1972	−0.077	−0.070	−0.565
1972–1981	0.118*	−0.072	0.826**
1982–2000	0.039	0.179	0.312*
Post-2000	0.137*	0.203	0.486***
Estimation technique			
OLS	0.010	−0.094	−0.439***
IV	−0.064	−0.377*	−0.057
ML	0.177	−0.120	−0.473*
ECM	0.135*	0.093	−0.144

*Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

Table A.4
Meta-analysis coefficient estimates: income elasticity of electricity demand.

Variable	Short-term income	Long-term income	Unmarked income
Demand specification			
Functional form			
Linear	–	–	−0.372***
Lag structure			
Partial adjustment model	−0.130	0.289	1.031***
Static model	0.000	0.118	−0.170**
Double log model	−0.629***	−1.152**	0.604***
Data characteristics			
Time series	−0.365*	−0.960	0.503*
Panel data	−0.403**	−0.969	−0.180*
Time interval			
Monthly	−0.345**	−1.797***	−0.270**
Annual	−0.340**	−1.475***	−0.312**
Macro data	0.119	0.030	0.280***
Environmental characteristics			
National level data	0.062	0.655***	0.234***
Country			
Developed	−0.129	−0.141	−0.191***
Sample period			
Pre −1972	0.037	0.652***	−0.337
1972–1981	−0.081	0.081	0.076
1982–2000	−0.198***	−0.092	−0.263**
Post-2000	0.113	1.006***	−0.070
Estimation technique			
OLS	0.074	0.003	0.117
IV	−0.047	0.762*	−0.274**
ML	0.368**	0.991***	−0.040
ECM	0.005	0.439*	0.267**

*Significant at the 10% level; **Significant at the 5% level; ***Significant at the 1% level.

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