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Dynamic demand for residential electricity in Taiwan under seasonality and increasing-block pricing

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ABSTRACT

This paper studies the dynamic demand for residential electricity in Taiwan employing a monthly panel data set, composed of 19 counties and spanning the period from 2007:01 to 2013:12. The partial adjustment model used addresses the endogeneity of the electricity price that results from the increasing-block pricing. The estimated results show that there is a significant seasonal difference in the demand for electricity between the summer and non-summer periods. Both the adjustment speed and own price elasticity during the summer months are found to be lower than those in the non-summer months due to the hot weather in summer. It is easier for consumers to adjust their electricity consumption in response to the changes in electricity pricing during the non-summer time. The estimated inelastic short-run and long-run income effects show that electricity is a necessity for consumers. Moreover, the controversial electricity-conservation policies are found to be ineffective measures for reducing electricity consumption in Taiwan.

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1. Introduction

Energy-related resources are scarce in Taiwan. The indigenous energy supply accounts for only around 2% of the total and the remaining 98% must be imported (Bureau of Energy, Taiwan). Around half of the energy consumption in this island is in the form of electricity. Electricity consumption per capita was as high as 10,500 kWh in 2013, having grown by 100% over the previous two decades. To resolve the problems that result from the huge shortage of indigenous energy in the market, increasing and volatile international energy costs, CO_2 emissions, and the huge financial deficits recorded by the public electricity utilities among other things, the government has attempted to improve the demand-side management of electricity consumption by modifying electricity policies.

In terms of residential electricity demand, policies such as increasing the electricity tariff, providing a tariff discount based on energy conservation, launching the energy efficiency rating and labeling system, and subsidizing the purchase of energy-conservation appliances, have been advocated and implemented. These policies and proposals, in particular increasing the electricity tariff and the "Power Tariff Discount on Energy Conservation Incentive Measures," have, however, stirred up widespread controversy and led to conflicts among the government, the general population, industries, and the electric utility.

The electricity price is regulated in Taiwan. It has been adjusted upward several times in the past few years mainly to respond to the increasing and volatile production costs and is planned to be floating in the very near future. On the one hand, the rising electricity price has been criticized for aggravating the living burden faced by the general public and its effect in term of conserving electricity has been questioned. On the other hand, the "Power Tariff Discount on Energy Conservation Incentive Measures" have allowed those households whose average daily electricity consumption has fallen below that in the same period for the previous year to be entitled to certain tariff discounts. This policy has been aimed at promoting residential electricity conservation and at reducing the impact of and resistance to the enforcement of the rise in the electricity price. Nonetheless, the actual effect of this policy on electricity conservation is unclear. This is because it provides the conservation incentive only to existing (not new) electricity users and it might become harder and harder to further conserve electricity over time. In addition, because of the tariff discounts, this policy is associated with a revenue loss which worsens the already serious

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problem of the financial deficit generated by the utility. Exactly what the empirical effect of this policy might be deserves further research. Therefore, the unknown effects of the price and discount-incentive policies motivate us to estimate the empirical demand for electricity. The price and income elasticities of demand for electricity are essential measures describing the behavior of consumers and the empirical results can be used to examine the policy effects as well as provide us with useful policy implications.

There exist few studies that estimate the electricity demand function for the case of Taiwan. Holtedahl and Joutz (2004) used Taiwan annual time-series data for the period 1955–1995 to estimate the residential electricity demand. Su et al. (2011) used a household data set with monthly average variables for the period from January 2009 to August 2010. Hsueh (1988) pooled household data from 1982 and 1986 (summer and winter, respectively) to perform the estimation. This paper aims to improve the literature from the points of view of data collection, the treatment of seasonality, the endogeneity of the electricity price, and the specifications of the empirical model.

First, the samples that the above three papers applied are either based on time series or cross-sectional data sets. In this study, we instead collect a panel data set composed of monthly county-level aggregate data spanning the period from January 2007 to December 2013. This large and richer data set allows us to explore the electricity demand both over time and across regions. In particular in recent years, the economic and energy environments and relevant policies have varied dramatically in Taiwan and around the world. Our newer data set is able to offer more accurate information on consumer behavior and allow us to examine the effects of recently implemented electricity-conservation policies.

Second, by taking advantage of monthly data, we can study the seasonality of electricity consumption. Because the peak of electricity consumption in a year is concentrated in the summer months, the regulated rates in June, July, August, and September (called the summer rates hereafter) have been higher than those in the non-summer months (called the non-summer rates hereafter) since 1989. This pricing structure aims to reduce the possible waste of electricity consumption in the summer months in addition to reflecting the higher marginal production costs. Under different electricity prices and weather conditions, it is reasonable to expect that the residential electricity consumption patterns differ between the summer and non-summer months. It is thus crucial to distinguish the demand function in the summer months from that in the non-summer months, or biased estimates may result.

Third, the rate structure in Taiwan is increasing-block pricing (see Table 1 for the rate structures promulgated within the time span of our data set). The co-determination of the price and consumption of electricity will yield biased and inconsistent estimates when ordinary least squares (OLS) is used. In this paper, an instrumental variable approach proposed by Billings (1982) is employed to deal with the simultaneity bias.[1] This IV method creates a set of constant IVs for each legal rate structure that corresponds to the Taylor–Nordin specification of the marginal price and difference parameters (see Nordin (1976) and Taylor (1975)). It assumes that consumers, instead of taking the effort to learn how a rate structure works and which block they are applying at each moment in time, will roughly estimate the whole rate structure from a linear regression of the theoretical electricity bills to obtain the price information and consume electricity accordingly. Because the IVs are predetermined and vary over the rate structures (and not over the quantities consumed), no feedback regarding the effect of quantity on price can be obtained. This IV method appears to be appropriate for the case of Taiwan. The reason is that because the rate structure enforced on the island is very complicated, it is impossible for households to fully understand what is the exact marginal price they are charged. In addition, the IVs can reflect the differences in rate structures among seasons and years and avoid the problem of simultaneity bias.[2]

Table 1
Legal rate structures in 2007–2013.

Time span	Electricity blocks (kWh per month)	Summer rate (NT$/kWh)	Non-summer rate (NT$/kWh)
2007.01–2008.06	1–110	2.10	2.10
	111–330	2.73	2.415
	331–500	3.64	2.90
	501 and above	3.74	
2008.07–2008.09	1–110	2.10	2.10
	111–330	2.87	2.54
	331–500	3.85	3.09
	501–700	4.11	3.24
	701 and above	4.47	3.48
2008.10–2012.05	1–110	2.10	2.10
	111–330	3.02	2.68
	331–500	4.05	3.27
	501–700	4.51	3.55
	701 and above	5.10	3.97
2012.06–2013.09	1–120	2.10	2.10
	121–330	3.02	2.68
	331–500	4.39	3.61
	501–700	4.97	4.01
	701 and above	5.63	4.50
2013.10–2013.12	1–120	2.10	2.10
	121–330	3.02	2.68
	331–500	4.39	3.61
	501–700	5.44	4.48
	701–1000	6.16	5.03
	1001 and above	6.71	5.28

Notes: 1. Summer denotes the time period from Jun. 1 to Sep. 30; Non-summer denotes all other days of the year.
2. In 2013, NT$ 29.77 = US$ 1 (Central Bank, Taiwan).

Finally, we specify a dynamic panel data model to estimate the balanced panel data set that covers the county-level, monthly data for 19 counties in Taiwan. It is recognized that household consumption may be governed by habits. A partial adjustment model of household electricity consumption appears to be more suitable and this model allows for serial correlation in the error term.

In sum, in this paper we wish to estimate the price and income elasticities of the demand for electricity in Taiwan and to examine the empirical effects of electricity-conservation policies which are now unclear and controversial. We use a newer and larger panel data set, consider the seasonality and the endogeneity of the electricity price, and specify a dynamic panel data model in our estimation.

The remainder of this paper is organized as follows. In Section 2, we offer a brief review of the literature. Section 3 discusses our model specification and related econometric issues. Section 4 describes the data. The empirical estimation results are discussed in Section 5. Section 6 concludes.

[1] See Section 4 for the details. This IV method is also applied by some recent papers to estimate the residential water demand with increasing block pricing (see Agthe and Billings (1996), Dharmaratna and Harris (2012), Martínez-Espiñeira (2003), and Martínez-Espiñeira and Nauges (2004)).

[2] The price variable used by Holtedahl and Joutz (2004) was the annual average real price of electricity per kilowatt hour for all sectors, which was not specific to the residential sector. The price variable employed by Su et al. (2011) was the ex post average electricity price that was obtained with the electricity expenditure divided by electricity consumption. The price variable so derived tends to distort the actual rate structures. Because the electricity consumption and expenditure are influenced by various factors, e.g., weather conditions, in addition to the electricity price, this gives rise to an uncertainty that the average price in the summer months might not be higher than that in the non-summer months, as implied by the actual rate structures. Hsueh (1988) applied the IV procedure used by Henson (1984) to deal with the simultaneity bias arising from the use of the marginal price. However, the rate structures in the summer and non-summer months were the same during the sample period. The only variation in price between seasons came from the CPI deflator.

2. Literature review

By using different data sets and price variables for the case of Taiwan, Holtedahl and Joutz (2004), Su et al. (2011), and Hsueh (1988) obtained very different elasticity estimates. The estimated price elasticities ranged from −1.7 to −0.15 and income elasticities ranged from 0.026 to 1.04 (see Table 2). It is interesting to know the estimated elasticities by using a recent panel data set.

In addition, the price elasticity in the non-summer months (off-peak electricity demand) was found to be larger than that in the summer months (peak electricity demand) in absolute value terms. However, Hsueh (1988)'s estimates were very elastic while Su et al. (2011)'s were inelastic. Filippini and Pachauri (2004) applied three seasonal data sets, i.e., winter, monsoon, and summer, to examine the households' demand for electricity in urban India. The results showed that electricity demand was both income- and price-inelastic in all three seasons. The absolute value of the price elasticity in summer (peak electricity demand) was lower than that in the other two seasons. Paul et al. (2009) employed a state-level panel of monthly observations to estimate the U.S. electricity demand. The estimates of the price elasticities for the summer, winter, and spring/fall seasons were very inelastic and exhibited a narrow range of variation.[3] From the above literature review, it is shown that the estimated results of the seasonal price elasticities vary with the regions and data sets applied.

With respect to the problem of simultaneity caused by the increasing-block pricing, although it is a very important issue in the study of the demand for residential electricity or water with decreasing/increasing block pricing (see, e.g., Wilder and Willenborg (1975), McFadden et al. (1977), Billings (1982), Henson (1984), Deller et al. (1986), Nieswiadomy and Molina (1989), and Hewitt and Hanemann (1995)), most recent papers use the average or marginal price without considering the endogeneity of the price variable. Their main contributions lie in the application of more advanced econometric techniques and more complete data to estimate the electricity demand in different country/region cases.[4] Alberini and Filippini (2011) argued that, at the aggregate level, the potential for the average price to be endogenous is mitigated by the presence of many different pricing levels and schemes in different locales. In Alberini and Filippini (2011) and Alberini et al. (2011), the endogeneity of price is not considered, while they instrument for price to deal with the problem of measurement error. Two recent papers, Kamerschen and Porter (2004) and Reiss and White (2005), considered the simultaneity bias problem explicitly. The former employed a simultaneous equation model and the latter used a model of endogenous sorting to conduct the estimation.

In this paper, we apply the instrumental variable approach proposed by Billings (1982) to deal with the problem of simultaneity bias. The IVs are predetermined by the rate structure and do not vary over the quantities consumed, which also largely overcome the bias occurring due to errors of measurement of quantity (mis-measurement of quantity might result in incorrect price obtained under the increasing-block pricing). The IVs can also reflect the differences in rate structures among seasons, years, and regions.

For the estimation of a dynamic panel data model, most of the previous literature used fixed or random effect models to control for unobserved heterogeneity. Some recent papers, for example, Alberini and Filippini (2011), Alberini et al. (2011), Filippini (2011), and Blázquez et al. (2013), were concerned with the inconsistent and biased estimates of the LSDV (least squares dummy variable) estimator especially when N (the number of groups) is large and T (the number of time periods) is small. They turned to apply the generalized method of moments (GMM; see Arellano and Bond (1991) and Blundell and Bond (1998)) and the corrected least squares dummy variable (LSDVC; see Kiviet (1995)) estimator to estimate the dynamic model. In this paper, after taking the characteristics of the data set into consideration, the estimators of GMM and LSDVC are not used. We apply the pooled mean group (PMG) estimator introduced by Pesaran et al. (1999) to perform the estimation. The PMG specifies a common long-run coefficient without requiring identical dynamics in each group.

3. Model specification and econometric approaches

According to the household production theory, households purchase electricity with appliances to produce services such as cooling/warming the house, heating the water, and lighting. By maximizing the household utility subject to its budget constraint, the optimal consumption of electricity is a function of its own price and the prices of related energies, household income, household characteristics, and climatic variables, etc. This desired, or long-run, demand for electricity (E_{it}^*) may be expressed in log form as:

$$\ln E_{it}^* = \alpha_0 + \alpha_1 \ln P_{it} + \alpha_2 \ln I_{it} + \gamma' \ln \mathbf{X}_{it} + u_{it}, \quad i = 1, \ldots, N, \quad t = 1, \ldots, T \tag{1}$$

where P_{it}, I_{it}, and $\mathbf{X}_{it}$ are the electricity price, household income, and the vector of other explanatory variables, respectively; α_1 and α_2 are the long-run own price and income elasticities, respectively; and u_{it} denotes the error term that may be serially correlated.

However, actual electricity consumption (E_{it}) may differ from the long-run equilibrium consumption because the equipment stock/electricity-using habit cannot be adjusted immediately. The change in actual demand between any two periods of $t-1$ and t is therefore only some fraction ($0<\lambda<1$) of the difference between the actual demand in period $t-1$ and the long-run equilibrium demand in period t.[5] That is,

$$\ln E_{it} - \ln E_{it-1} = \lambda(\ln E_{it}^* - \ln E_{it-1}). \tag{2}$$

The lower the value of the adjustment speed λ is, the longer the electricity consumption takes to adjust to its long-run optimal level. By substituting $\ln E_{it}^*$ from Eq. (1) into Eq. (2) and rearranging, we obtain the short-run partial adjustment model:

$$\ln E_{it} = \beta_E \ln E_{it-1} + \beta_0 + \beta_1 \ln P_{it} + \beta_2 \ln I_{it} + \delta' \ln \mathbf{X}_{it} + \varepsilon_{it}, \tag{3}$$

where $\beta_E = 1-\lambda$, $\beta_0 = \lambda\alpha_0$, $\beta_1 = \lambda\alpha_1$, $\beta_2 = \lambda\alpha_2$, $\delta' = \lambda\gamma'$, and $\varepsilon_{it} = \lambda u_{it}$. In Eq. (3), β_1 and β_2 are the short-run own price and income elasticities, respectively. The long-run elasticities of α_1 and α_2 can be recovered by $\alpha_1 = \beta_1/(1-\beta_E)$ and $\alpha_2 = \beta_2/(1-\beta_E)$.

Eqs. (1) and (2) can also be rearranged into the following equation:

$$\Delta \ln E_{it} = \phi[\ln E_{it-1} - (\alpha_0 + \alpha_1 \ln P_{it} + \alpha_2 \ln I_{it} + \gamma' \ln \mathbf{X}_{it})] + \varepsilon_{it}, \tag{4}$$

where $\phi = -\lambda$ (minus the adjustment speed) and the coefficients in the parentheses are the long-run coefficients.

[3] There was some earlier literature which estimated the U.S. monthly/bimonthly residential electricity demand in the national or state-level data set under declining-block tariffs. The estimates of the price elasticities in Murray et al. (1978), Acton et al. (1980), Parti and Parti (1980), and Garbacz (1984) exhibited a greater range of variation from inelastic to elastic in a year, while those of Archibald et al. (1982) exhibited a narrower range of variation with inelastic estimates. There was no consentaneous conclusion for the difference in seasonality.

[4] See for example, Nakajima and Hamori (2010) for case of the United States; Bernard et al. (2011) for Canada; Blázquez et al. (2013), Moral-Carcedo and Vicéns-Otero (2005), and Pardo et al. (2002) for the case of Spain; Hondroyiannis (2004) for Greece; Filippini (2011) for the case of Switzerland; Narayan and Smyth (2005) for the case of Australia; Nakajima (2010) for the case of Japan; Holtedahl and Joutz (2004) for the case of Taiwan; Sa'ad (2009), Yoo et al. (2007), and Jung (1993) for the case of South Korea; Filippini and Pachauri (2004) and Bose and Shukla (1999) for the case of India; Chaudhry (2012) for the case of Pakistan; and Ziramba (2008) for the case of South Africa, among others.

[5] See Alberini and Filippini (2011) for the details.

Table 2
Selected empirical studies and price/income elasticities.

Study	Type of data coverage	Own price elasticity	Income electricity
Holtedahl and Joutz (2004)	Taiwan annual aggregate data from 1955 to 1995	Short-run: −0.15 Long-run: −0.16	Short-run: 0.23 Long-run: 1.04
Su et al. (2011)	Household-level data with time-series (Jan. 2009 to Aug. 2010) average, Taiwan	Summer: −0.303 Non-summer: −0.526 to −0.366	Summer: 0.407 to 0.434 Non-summer: 0.407 to 0.527
Hsueh (1988)	Pooled household data from 1982 and 1986, Taiwan	Summer: −1.32 to −1.089 Winter: −1.7	Summer: 0.046 to 0.08 Winter: 0.026 to 0.25
Alberini and Filippini (2011)	Annual aggregate data at the state level for 48 U.S. states from 1995 to 2007	Short-run: −0.15 Long-run: −0.73	0.05[&]
Alberini et al. (2011)	Nationwide household-level data for the U.S. from 1997 to 2007	Short-run: −0.736 Long-run: −0.814	Short-run: 0.009 Long-run: 0.01
Nakajima and Hamori (2010)	Six types of panel data for 48 U.S. states and the District of Columbia from 1993 to 2008	−0.34 to −0.12	0.33 to 1
Paul et al. (2009)	State-level panel of monthly observations for 48 U.S. states and the District of Columbia from Jan. 1990 to Dec. 2006	Short-run summer: −0.15 Short-run winter: −0.11 Short-run spring/fall: −0.12 Long-run summer: −0.52 Long-run winter: −0.32 Long-run spring/fall: −0.35	0.11
Reiss and White (2005)	Household-level cross-sectional data, 1993 and 1997, California, USA	−0.39	0.00
Kamerschen and Porter (2004)	Nationwide annual data from 1973 to 1998, USA	−0.94 to −0.85	0.65 to 0.69
Bernard et al. (2011)	Four independent household surveys conducted in 1989, 1994, 1999, and 2002, Quebec, Canada	Short-run: −0.51 Long-run: −1.32	Short-run: 0.08 Long-run: 0.2[&]
Blázquez et al. (2013)	Aggregate panel data at the province level for 47 Spanish provinces from 2000 to 2008	Short-run: −0.07 Long-run: −0.19	Short-run: 0.23 Long-run: 0.61
Hondroyiannis (2004)	Monthly aggregate data for Greece from 1986 to 1999	−0.41	1.56
Filippini (2011)	Aggregate data at the city level for 22 Swiss cities from 2000 to 2006	Short-run peak: −0.778 Long-run peak: −2.266 Short-run off-peak: −0.652 Long-run off-peak: −1.652	Short-run peak: 0.035[&] Short-run off-peak: −0.106[&]
Narayan and Smyth (2005)	Annual aggregate data for Australia as a whole from 1969 to 2000	Short-run: −0.271 to −0.263 Long-run: −0.541 to −0.474	Short-run: 0.012[&] to 0.042[&] Long-run: 0.323 to 0.408
Nakajima (2010)	Panel data for 46 prefectures from 1975 to 2005, Japan	−1.204 to −1.127	0.602 to 0.651
Sa'ad (2009)	Nationwide time series data from 1973 to 2007, South Korea	−0.27	1.33
Yoo et al. (2007)	Cross-sectional household data for Seoul, South Korea, 2005	−0.246	0.059
Filippini and Pachauri (2004)	Three cross-sectional urban Indian household-level data sets in 1993–1994 for the winter, summer, and monsoon seasons, respectively	Winter: −0.42 Summer: −0.29 Monsoon: −0.51	Winter: 0.64 Summer: 0.63 Monsoon: 0.60
Bose and Shukla (1999)	Time series data for 9 years (1985/86–1993/94) pooled over 19 Indian states	−0.65	0.88
Ziramba (2008)	Annual aggregate data from 1978 to 2005, South Africa	Short-run: −0.02[&] Long-run: −0.04[&]	Short-run: 0.30 Long-run: 0.31

Note: [&] indicates that the figure is not significant at the 10% level.

To estimate the dynamic panel data demand, there are a number of alternative estimation methods that vary from the degree of parameter heterogeneity. At one extreme are the pooled estimators where slope coefficients and error variances are constrained to be the same. These estimators include fixed effects (FE), random effects (RE), GMM, and LSDVC estimators among others. At the other extreme, one can estimate separate equations for each group—provided that the time-series dimension is sufficiently large. All coefficients are fully heterogeneous and the mean of the estimates is of particular interest. This includes the mean group (MG) estimator proposed by Pesaran and Smith (1995). In between the two extremes is the PMG estimator introduced by Pesaran et al. (1999). This intermediate estimator allows the intercepts, short-run coefficients (including the adjustment speed), and error variances to differ freely across groups, but constrains the long-run coefficients to be the same.

Which estimator is more appropriate to use depends strongly on the sizes of N and T. The panel data set used in this paper covers $N = 19$ and $T = 84$ for the whole sample, and $T = 28$ for the summer subset and $T = 56$ for the non-summer subset if we separate the sample according to the seasonality. These samples are characterized by that both N and T are quite large. For this kind of data set, the choice among alternative estimators faces a general trade-off between consistency and efficiency. The pooled estimators dominate the heterogeneous estimators in terms of efficiency if the slope coefficients are identical. If they are not, the pooled estimators can give inconsistent and potentially highly misleading estimates of the coefficients (see Blackburne and Frank (2007), Loayza and Rancière (2006), Pesaran and Smith (1995), and Pesaran et al. (1999)).

We employ the FE and PMG estimators to estimate the dynamic panel data demand. First, the FE estimator is used because it is commonly applied by many studies in the existing literature to estimate residential electricity demand. The estimated results are of reference value. In the dynamic panel data model, the variable $\ln E_{t-1}$ is frequently correlated with the lagged ε_{it}. This leads the OLS and FE estimators of β_E to be biased and inconsistent and the bias does not vanish as N increases. However, as T grows, the FE estimator becomes consistent (the endogeneity bias → 0 as $T \to \infty$). The value of T is large in our sample. In fact, the FE estimates are found to outperform the other estimators, in terms of the root mean square error (RMSE) criterion. On this see, for example, Judson and Owen (1999),[6] Baltagi et al. (2000), Baltagi et al. (2002), and Flannery and Hankins (2013). It is therefore worth the effort to estimate the FE results for the electricity demand.

[6] Using a Monte Carlo approach, Judson and Owen (1999) found that the LSDVC outperforms other estimators. If the LSDVC cannot be implemented, when $T = 30$, FE performs just as well or better than the viable alternatives. In addition, according to their simulation results (Table 2), in the cases where $N = 20$ and $T = 20$ or 30, the average bias of FE is smaller than that of GMM (one-step and two-step estimations) and OLS while bigger than that of the LSDVC and Anderson and Hsiao estimator; the RMSE of FE is basically lower than all other estimators apart from that for the LSDVC. However, it should be noted that the bias of LSDV can be sizeable even when $T = 20$.

Second, the PMG estimator allows us to estimate a common long-run coefficient without making the less plausible assumption of identical dynamics in each county.[7] Therefore, the adjustment speed can be different among counties in addition to the intercepts. In the long run, because all counties are close to each other in geographic conditions, are regulated by similar electricity policies, and share common conservation information and technologies, there are good reasons to expect that the long-run equilibrium relationships are similar across counties. The PMG estimator is efficient and consistent if the long-run coefficients are in fact equal across counties; inconsistent, otherwise. The MG estimator is consistent in either case. We use the Hausman test to compare the PMG and MG estimates. The result does not reject the long-run homogeneity and the PMG estimator is preferred.

It should be mentioned that several estimators such as the difference and system GMM estimators and the LSDVC are also applied to estimate the dynamic electricity demand in some recent papers (see, e.g., Alberini and Filippini (2011), Alberini et al. (2011), Filippini (2011), and Blázquez et al. (2013)). However, because both GMM estimators are designed for situations with small T and large N panels (see Arellano and Bond (1991), Blundell and Bond (1998), and Roodman (2009a)), we do not employ them to estimate our data set.[8] On the other hand, we have employed the LSDVC method to estimate the electricity demand. However, because of the low within variations in some explanatory variables, such as the two policy dummy variables and the characteristics of the house and household, these variables are discarded by the estimation software automatically. In addition, several coefficients are not significant—a similar finding by Blázquez et al. (2013). We therefore do not apply the estimated results of the LSDVC.[9]

4. Data description

In this study, we compiled a balanced panel data set, including 19 cities and counties in Taiwan, spanning the period from January 2007 to December 2013.[10] Monthly residential electricity consumption figures for each city/county were downloaded from the website of the Environmental Protection Administration.[11] These figures were divided by the number of electricity-using households in each city/county to yield the variable for electricity consumption per household (E).

There are ten rate structures, as shown in Table 1, that were applied in the sample period. Following Billings (1982), the IVs for the marginal price and difference variable (denoted by P_{IV} and D_{IV}, respectively) were obtained. This was done by first calculating the theoretical electricity bills (TEB) for each rate structure over the range of household electricity consumption encountered in the data set. For example, the range of E in our data set is 157 to 645 kWh. Based on 2 kWh increments from 157 to 645 kWh, we obtained 245 $(=(645-157)/2+1)$ observations of Es (157, 159,..., 645) and the correspondingly calculated TEBs. These values of TEB were then regressed against their corresponding E values to give the fitted values:

$$\hat{TEB} = \hat{a} + \hat{b}E.$$

The estimated intercept ($\hat{a}$) represents D_{IV} and the slope estimate of $\hat{b}$ ($dTEB/dE$) reflects P_{IV}. Table 3 presents the corresponding IVs for each rate structure. It can be seen that the differences in P_{IV} between the time periods were around NT$0.2; the differences in P_{IV} between the summer and non-summer months were around NT$0.7.

This IV method appears to be appropriate for the case of Taiwan. The first reason is that the rate structure enforced on the island is very complicated (see Table 1), and it is therefore impossible for households to fully understand what is the exact marginal price they are charged. In addition, the accumulated consumption of electricity, bimonthly-charged bills, and the setting up of electricity meters outside residences exacerbate the difficulty of knowing the correct marginal price in real time. Moreover, incentives for consumers to search for the marginal price might be weak because the ratio of electricity expenditure to income is quite low in Taiwan.[12]

The second reason is that the commonly used average price in the literature is not an appropriate price measure in the case of Taiwan since the electricity utility, the Taiwan Power Company (Taipower), only publishes the annual average price for all households. Not only are its between variations negligible and caused only by the CPI deflator, but its within variations are also not large relative to the variable P_{IV}. This price measure can neither reflect the price difference between the non-summer and summer months, nor is it consistent with consumers' perceptions. Although the households do not know the exact marginal price, they are fully informed of the rate structure that is higher in the summer months, since this rate discrimination has been enforced for more than two decades. On the other hand, as indicated in Footnote 2, the average price which divides the electricity expenditure by electricity consumption is also inappropriate. This average price does not necessarily reflect a higher tariff in the summer months than that in the non-summer months as the actual rate structures suggest.[13]

On the contrary, the IVs are predetermined by the rate structures which can reflect the differences in rates among seasons and years. They can also avoid the endogeneity problem of back feeding the effect of quantity on price and the problem of measurement error in the electricity consumption variable.[14]

[7] The xtpmg command of Stata is used to estimate Eq. (4).

[8] "A weakness of IV and GMM estimators is that their properties hold when N is large, so they can be severely biased and imprecise in panel data with a small number of cross-sectional units." (Bruno, 2005, p. 474). In addition, "…as T rises, the instrument count can easily grow large relative to the sample size, making some asymptotic results about the estimators and related specification tests misleading." (Roodman, 2009b, p. 139).

[9] We employ the procedure of xtlsdvc of the Stata software to obtain the LSDVC estimates. The calculation of bias approximations necessitates the use of a preliminary consistent estimator. The initial values required by the xtlsdvc are derived from Anderson and Hsiao (1982) (AH) or GMM estimators (Arellano and Bond, 1991, AB or Blundell and Bond, 1998, BB). We choose the AH estimator to initialize the correction procedure (the AB and BB are also applied, a memory problem resulting from a large T for both GMM estimators interrupts the program). The estimated coefficients of the lagged dependent variables are equal to 0.633 and 0.401 for the summer and non-summer months, respectively. The corresponding FE estimates (with the same explanatory variables) are equal to 0.607 and 0.386, respectively. The above two sets of outcomes are similar.

[10] Before 2010, there were 25 cities and counties included in the administrative area of the Taiwan government. There was a large-scale rezoning of some cities and counties that commenced on December 25, 2010. In this rezoning, Taipei County was upgraded into a special municipality (New Taipei City), Taichung City and County were merged into a special municipality (Taichung City), Tainan City and County were merged into a special municipality (Tainan City), and Kaohsiung City and County were merged into a special municipality (Kaohsiung City). For this research, three offshore counties, Penghu, Kinmen, and Lienchiang, were excluded. Thus, there were only 19 cities and counties included in the sample. It should be noted that all variables have been adjusted adequately to be consistent both before and after the rezoning.

[11] Data source: http://ecolife.epa.gov.tw/Cooler/effect/Electricity_Area.aspx. Data on the website are provided by the Taiwan Power Company (Taipower) to the Environmental Protection Administration, Taiwan.

[12] The ratios of electricity expenditure to final consumption expenditure per household are 1.38%, 1.35%, 1.42%, 1.43%, 1.39%, 1.31%, and 1.37% for the years 2007 to 2013, respectively (Taipower: http://info.taipower.com.tw/#). It could be expected that the ratio for electricity expenditure to income per household should be even lower.

[13] In a preliminary analysis, we applied the marginal price (without instruments) and sample average price as the price variable to estimate the electricity demand. We also tried to use the lagged marginal prices of one and two periods and the lagged average prices of one and two periods, respectively, as the instruments of the current electricity price. The estimated results show positive price elasticities for both price variables and all those IVs. This implies that those lagged marginal and average prices are likely to be invalid instruments and the marginal and average prices (without instruments) are inappropriate when it comes to estimating Taiwan's electricity demand.

[14] Ohsfeldt (1983) noted that the two-part tariff approximation procedure used by Billings (1982) does not delete the errors-in-variables problem in demand models with multi-part tariff schedules. Consequently, OLS estimates of demand coefficients tend to be biased. He suggested that if OLS is used, an errors-in-variables test should be applied to determine if coefficient estimates are significantly biased. The presence of significant errors requires ones using alternative estimating procedures such as the maximum likelihood method of Burtless and Hausman (1978), in which the likelihood function is modified to account for the truncation in the error term.

Table 3
Instrumental variables for each legal rate structure.

Time span	Summer rate (NT$/kWh)	Non-summer rate (NT$/kWh)
2007.01–2008.06	$P_{IV} = 3.399$ $D_{IV} = -242.507$	$P_{IV} = 2.760$ $D_{IV} = -123.562$
2008.07–2008.09	$P_{IV} = 3.623$ $D_{IV} = -280.954$	$P_{IV} = 2.963$ $D_{IV} = -158.803$
2008.10–2012.05	$P_{IV} = 3.851$ $D_{IV} = -319.387$	$P_{IV} = 3.159$ $D_{IV} = -189.834$
2012.06–2013.09	$P_{IV} = 4.118$ $D_{IV} = -398.577$	$P_{IV} = 3.427$ $D_{IV} = -265.624$
2013.10–2013.12	$P_{IV} = 4.219$ $D_{IV} = -428.579$	$P_{IV} = 3.527$ $D_{IV} = -295.627$

The income variable (I) is defined by the monthly virtual income, which is computed by subtracting the negative D_{IV} from the monthly disposable income of households. The Nordin difference variable signifies the difference between the amount a household actually pays for electricity and the amount the household would pay if all its electricity consumption were charged at the marginal price ($D_{IV} = \hat{a} = TEB - \hat{b}E$). It can be regarded as a subsidy from the government when the rate structure is increasing-block pricing.[15] From the aspect of the income effect, it is expected that the higher the income (subsidy), the higher the electricity consumption will be.

Two climatic variables, the mean temperature (MT) and mean relative humidity (MRH), are considered to control for the electricity consumption.[16] The climate in Taiwan is marine tropical. The entire island experiences hot, humid weather from June through September due to the monsoon season and typhoons. The weather is warmer than that for the South China coastal area because of the effect of the warm ocean current. Since the weather conditions will affect the electricity consumption through the electrical appliances, the average numbers of air conditioners and dehumidifiers owned per household (denoted by AC and DH, respectively), are taken into account. Their interactive terms with the climatic variables are included in the estimation equation.[17]

The price of residential LPG (liquified petroleum gas), P_G, is included as an explanatory variable. Electricity and gas are the two main energies consumed in Taiwan's households for cooking, heating water and the house, and drying clothes. To some extent, they might be substitutes for each other. The family size (FS) and house size (HS) are taken into consideration as well. They are expected to have a positive effect on electricity consumption if no effect of economies of scale exists. We include the quadratic terms of these two variables to help explain the possible effect of such scale economies.

Finally, two dummy variables for the electricity-conservation policy (ECP) are included in the analysis. Since July 1, 2008, the Ministry of Economic Affairs, Taiwan and Taipower have carried out the "Power Tariff Discount on Energy Conservation Incentive Measures" (denoted by ECP_1). Those households whose average daily electricity consumption falls below that in the same period of the previous year are entitled to have tariff discounts. There are two main purposes of this measure. The first one is to promote residential electricity conservation. The second one is to reduce the impact and resistance of the enforcement of the increasing rate structure by the government at that time. Another measure referred to as "Energy Conservation Competitions in Counties and Cities" (denoted by ECP_2) has been in place since July 1, 2010. Under this measure, customers living in the cities or counties that win the top 3 prizes in the nationwide electricity-conservation competition could enjoy an additional discount of 5%, 10% or 15% in addition to the basic discounts from the ECP_1. The government hopes this measure could further increase households' willingness to engage in electricity conservation. It is very important to know whether these ECPs work or not. These policy effects on electricity conservation are controversial because they have resulted in a huge loss of electricity revenue, which has further worsened Taipower's financial deficit.[18]

Table 4 shows the descriptive statistics for all variables,[19] where all nominal variables have been deflated by the consumer price index (CPI) with 2006 as the base year. On average, the electricity consumption, electricity and LPG prices, income, mean temperature, and mean relative humidity are all higher in the summer months than during the non-summer months.

5. Empirical results

Table 5 presents the empirical results. First, by using the entire sample without considering the seasonality, we estimate Eq. (3) with the FE estimator and Eq. (4) with the PMG estimator and the results are shown in the column "Whole". The estimates of own price elasticity are significantly positive regardless of whether the FE or the PMG estimator is used, which violates the law of demand. In Taiwan, the peak period for electricity consumption occurs in the summer months. To reduce the possible waste of electricity consumption and to reflect the higher marginal production costs of electricity in the summer months, the government sets a higher rate structure in the summer months. This positive relationship between the electricity price and quantity consumed seems to result in the significantly positive estimate of the price elasticity. It appears to be necessary to distinguish summer months from non-summer months. We then separate the whole data into the summer (months including June to September) and non-summer (months consisting of the remaining months) subsets. These two subsets are estimated separately and their parameter estimates are shown in the columns for "Summer" and "Non-Summer".[20]

Note that the coefficient estimates of the FE model belong to the short-run results, while those of the PMG model are the long-run estimates. The coefficients of the lagged variable, price, and income are all significant with the expected signs for both models and both subsets. The FE estimates of the adjustment speed are 0.395 ($=1 - 0.605$) for the summer period and 0.650 ($=1 - 0.350$) for the non-summer period. These estimates are similar to those of the PMG estimates ($|-0.399|$ and $|-0.645|$). Both FE and PMG estimates show that the adjustment speed in the summer months is slower than that in the non-summer

15 It is worth mentioning that the variable for the monthly disposable income of households for cities/counties is not available, and only annual data are available. By applying the proportional relationships of national GDP among quarters, we adjust the annual household disposable income to quarterly figures. We then divide the quarterly household disposable income by 3 to obtain the monthly figures.

16 In the literature, cooling degree days (CDD) and heating degree days (HDD) are two commonly applied weather variables. However, these two variables are not available in the Climatological Data Annual Report published by the Central Weather Bureau, Taiwan.

17 Because of the problem of multicollinearity, other electrical appliances such as computers, refrigerators, and dryers, are not considered.

18 Although the government declared that these conservation measures had saved 4.1% of average electricity consumption per household per month from 2007 to 2011, some news reported that the total and per household electricity consumptions were in fact increasing and the resulting loss of revenue to Taipower amounted to around NT$30 billion from 2008 to 2011.

19 Because the data set has been separated into summer and non-summer months and two policy variables which are in essence year dummies have been included in the model, we do not further include time dummies (year and monthly dummies) as explanatory variables to avoid the problem of multicollinearity.

20 In fact, we have tested the hypothesis that there is no structural change between the two subsets. Let D be a seasonal dummy ($D = 0$ for summer months; $D = 1$, otherwise). We then estimate the following model:

$$\ln E_{it} = \varsigma_0 + \varsigma_1 \ln P_{IVit} + \varsigma_2 \ln I_{it} + \varsigma_3 \ln E_{it-1} + \varsigma' \ln \mathbf{X}_{it} + \xi_0 D + \xi_1 D \ln P_{IVit} + \xi_2 D \ln I_{it} + \xi_3 D \ln E_{it-1} + \xi' D \ln \mathbf{X}_{it} + \varepsilon_{it}$$

and test whether all ξ are simultaneously equal to zero. The p-value of the F test statistic is very close to zero, such that the null hypothesis of no structural change is rejected. We are led to conclude that the coefficients of the demand for electricity in the summer months differ from those in the non-summer months. This supports the separation of the entire sample into summer and non-summer portions.

Table 4
Descriptive statistics of variables.

Variable	Description	Unit	Mean	SD	Min.	Max.	Data source
E	Household monthly electricity consumption (= city monthly residential electricity consumption/the number of city household electricity users)	kWh	289.924[a] 335.754[b] 267.009[c]	76.099[a] 84.962[b] 59.216[c]	157.000[a] 189.000[b] 157.000[c]	645.000[a] 645.000[b] 546.000[c]	City monthly electricity consumption: Taiwan EPA website, http://ecolife.epa.gov.tw/Cooler/effect/Electricity_Area.aspx. Number of city household electricity users: provided by Taipower
P_{IV}	Instrumental variable for marginal price of electricity	NT$/kWh	3.166[a] 3.590[b] 2.955[c]	0.342[a] 0.171[b] 0.164[c]	2.619[a] 3.189[b] 2.619[c]	3.798[a] 3.798[b] 3.225[c]	Derived from the legal rate structures of electricity
I	Monthly household disposable income	NT$	67,147.9[a] 67,156.1[b] 67,143.8[c]	13,683.9[a] 13,673.6[b] 13,695.4[c]	44,010.3[a] 44,435.3[b] 44,010.3[c]	111,520.5[a] 109,412.8[b] 111,520.5[c]	Report on the Survey of Family, Income and Expenditure, 2007–2013, Directorate-General of Budget, Accounting and Statistics, Taiwan
FS	Family size	Person	3.233[a]	0.256[a]	2.540[a]	3.750[a]	Same as the above
HS	House size	Ping	46.513[a]	7.593[a]	30.620[a]	59.247[a]	Same as the above
AC	Annual average number of air conditioners owned per household	One	1.927[a]	0.363[a]	1.088[a]	2.982[a]	Same as the above
DH	Annual average number of dehumidifiers owned per household	One	0.364[a]	0.284[a]	0.028[a]	1.054[a]	Same as the above
MT	Monthly mean temperature	°C	23.351[a] 28.095[b] 20.979[c]	4.522[a] 1.556[b] 3.546[c]	12.500[a] 21.600[b] 12.500[c]	30.600[a] 30.600[b] 28.000[c]	Climatological Data Annual Report, 2007–2013, Central Weather Bureau, Taiwan
MRH	Monthly mean relative humidity	%	75.961[a] 76.571[b] 75.656[c]	4.655[a] 4.458[b] 4.723[c]	60.000[a] 65.000[b] 60.000[c]	93.000[a] 89.000[b] 93.000[c]	Same as the above
P_G	Monthly average price of residential LPG	NT$/20 kg	731.949[a] 733.480[b] 731.184[c]	73.877[a] 65.760[b] 77.637[c]	522.945[a] 535.766[b] 522.945[c]	939.843[a] 918.164[b] 939.843[c]	Bureau of Energy, Taiwan: http://web3.moeaboe.gov.tw/oil102/
ECP_1	Dummy for the first electricity-conservation policy. $ECP_1 = 1$ for the time period of July, 2008 to June, 2010; $=0$ otherwise						
ECP_2	Dummy for the second electricity-conservation policy. $ECP_2 = 1$ for the time period since July, 2010; $=0$ otherwise						

Notes: 1. [a], [b], and [c] denote figures for the whole sample, summer months (June, July, August, and September), and non-summer months (other remaining months), respectively.
2. For the unit of house size (HS), one ping = 3.3058 square meters.
3. All nominal variables have been deflated by the CPI to be real terms (base year = 2006).

Table 5
Parameter estimates of the electricity demand function.

	Whole		Summer		Non-Summer	
Variables	FE	PMG	FE	PMG	FE	PMG
$\ln E_{t-1}$	0.453***	−0.496***[a]	0.605***	−0.399***[a]	0.350***	−0.645***[a]
	(7.31)	(−18.35)	(6.42)	(−6.35)	(5.43)	(−12.44)
$\ln P_{IV}$	0.451***	0.992***	−0.454***	−1.130**	−0.857***	−1.270***
	(11.57)	(12.18)	(−3.01)	(−2.43)	(−8.81)	(−7.65)
$\ln I$	0.150	0.156*	0.291**	0.890***	0.205*	0.161**
	(1.70)	(1.67)	(2.21)	(3.83)	(1.84)	(2.15)
ECP_1	−0.047***	−0.113***	0.026	0.061	0.106***	0.144***
	(−4.80)	(−6.20)	(1.34)	(1.28)	(5.81)	(6.32)
ECP_2	−0.041***	−0.106***	0.041	0.099	0.112***	0.146***
	(−3.46)	(−4.81)	(1.70)	(1.52)	(4.91)	(6.04)
$\ln P_G$	0.016	0.028	−0.024	−0.124	0.039	0.086
	(0.72)	(0.40)	(−0.57)	(−0.72)	(1.55)	(1.34)
$\ln MT$	0.311***	0.657***	1.089***	3.159***	0.270***	0.420***
	(10.95)	(15.80)	(5.06)	(5.59)	(7.62)	(13.72)
$\ln MT \times \ln AC$	−0.033**	−0.061*	−0.016	−0.056	−0.042**	−0.032
	(−2.43)	(−1.75)	(−0.71)	(−0.72)	(−2.24)	(−1.13)
$\ln MRH$	0.027	−0.060	0.089	0.443	−0.047	−0.097
	(0.48)	(−0.61)	(0.50)	(1.55)	(−0.94)	(−1.16)
$\ln \mathrm{MRH} \times \ln DH$	−0.015***	−0.023***	−0.007	−0.020	−0.005	−0.003
	(−3.57)	(−2.70)	(−1.60)	(−1.00)	(−1.20)	(−0.43)
$\ln FS$	−2.006***	−3.518*	−0.832	−2.792	−1.362***	−2.090
	(−3.76)	(−1.73)	(−1.55)	(−0.78)	(−3.07)	(−1.21)
$(\ln FS)^2$	0.979***	1.728*	0.300	1.043	0.613***	0.962
	(4.11)	(1.91)	(1.31)	(0.66)	(3.31)	(1.26)
$\ln HS$	−1.389	−0.010	−0.946	4.922	−0.135	1.436
	(−0.53)	(−0.00)	(−0.72)	(0.35)	(−0.10)	(0.28)
$(\ln HS)^2$	0.162	−0.019	0.110	−0.660	0.001	−0.212
	(0.47)	(−0.02)	(0.63)	(−0.36)	(0.01)	(−0.32)
Intercept	3.645	1.443***	−1.627	−8.577***	2.600	1.525***
	(0.71)	(18.61)	(−0.54)	(−6.35)	(0.91)	(11.96)

Notes: 1. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
2. For the FE estimator, the figures in parentheses are t values; for the PMG estimator, they are z values.
3. [a] indicates that the figure is the estimate of the adjustment coefficient (ϕ).

months. This difference implies that during summer months experiencing high temperatures, the use of air conditioners is necessary, which requires the consumption of a large amount of electricity. It is difficult for households to adjust their electricity consumption habits. Conversely, the weather is relatively cool in the non-summer months. It is thus easier for people to adjust their electricity consumption habits during those months. For example, people can increase the pre-set temperatures of their refrigerators, choose to wear more clothes and stay inside the house to keep themselves warm without relying on heating equipment. The foregoing measures help save electricity.

Table 6 shows that the estimated FE short-run and long-run own price elasticities are −0.454 and −1.149 (=−0.454/(1 − 0.605)) respectively for the summer months. For the non-summer months, they are −0.857 and −1.318 (=−0.857/(1 − 0.350)) respectively. The PMG estimates of the short-run and long-run own price elasticity are −0.451 (= − 1.130 × | − 0.399|) and −1.130 respectively for the summer months; −0.819 (− 1.270 × | − 0.645|) and −1.270 respectively for the non-summer months. It is shown that the estimates of price elasticities from the FE and PMG are similar. Although the FE estimator is hampered by the problem of endogeneity bias under the specification of dynamic panel data model, this bias seems not a serious problem for our sample whose number of time periods is quite large. The endogeneity bias vanishes as T grows.

The estimated price elasticities are higher for the non-summer months than for the summer months. This result is similar to those of Su et al. (2011) and Hsueh (1988) for the case of Taiwan and Filippini and Pachauri (2004) for the case of India. For the summer months, because of the higher temperatures that require the intense use of air conditioners and air ventilators, the own price elasticity is less than that for the non-summer months. However, it is interesting to see that the long-run difference between the magnitudes of non-summer and summer price elasticities is less than that exhibited in the short run. This indicates that although it is harder to reduce electricity consumption in response to a price increase in summer in the short run, the electricity conservation can be elastic as the equipment stock and electricity-using habits can adjust in the long run.

On the other hand, the estimates of price elasticities are inelastic for the short run and elastic for the long run. Although these estimates look higher than those in most previous studies on the residential demand for electricity, they are similar to the findings in Hsueh (1988), Bernard et al. (2011), and Nakajima (2010) (see the review in Table 2).[21] The higher estimates of the own price elasticity may be attributed to the frequent upward adjustments in rates in the past few years. During our sample period, the first rate structure, which was applied for the period 2007:01 to 2008:06, was initiated on July 1, 2006. Before the rates were raised, people had become used to the low rates. Later, the rates were adjusted twice within a very short time span (2008:07–2008:10) in addition to the new specification of higher-priced blocks. Households expected that the rates would possibly be further increased in response to the soaring oil price and the huge loss faced by Taipower. In addition, the electricity price will be allowed to float in the very near future. Facing these changes, people will be more willing to change their habits in terms of electricity usage and switch to electricity-saving appliances. Hence, in the long run, the effect of price on the electricity consumption may therefore be large. However, we cannot exclude that this result may be due to the low between variation of the price variable and the IV approach used in the empirical analysis. Therefore, these values of price elasticities should be considered carefully.[22]

Table 6
Short-run and long-run elasticities.

		FE		PMG	
		Short-run	Long-run	Short-run	Long-run
Own price elasticity	Summer	−0.454	−1.149	−0.451	−1.130
	Non-summer	−0.857	−1.318	−0.819	−1.270
Income elasticity	Summer	0.291	0.737	0.355	0.890
	Non-summer	0.205	0.315	0.104	0.161

The estimated FE short-run and long-run income elasticities are found to be 0.291 and 0.737 (=0.291/(1 − 0.605)) respectively for the summer months and 0.205 and 0.315 (=0.205/(1 − 0.350)) respectively for the non-summer months. The PMG estimates of the short-run and long-run income elasticity are 0.355 (= 0.890 × | − 0.399|) and 0.890 respectively for the summer months; 0.104 (0.161 × | − 0.645|) and 0.161 respectively for the non-summer months (see Table 6). These estimates are consistent with the previous literature. The estimated inelastic short-run and long-run income effects indicate that electricity is a necessity in people's everyday lives. It is worth mentioning that there is a seasonal difference in the income effects. The income effect in summer months is higher compared to that in the non-summer months, implying that the increase in income is likely to result in greater electricity consumption in the summer months.

As mentioned previously, the performance of the two electricity-conservation policies (ECP_1 and ECP_2) is controversial. After controlling for other factors, our estimates show that the electricity consumptions are higher during the two periods of time in which the *ECP*s are implemented, although the effect in the summer months is not significant.

It is worth noting that these *ECP*s do not provide any electricity-conservation incentive for new household electricity users. Thus, if the increase in the electricity consumption of the new as well as some old users outweighs the reduction resulting from some old users, the electricity consumption increases overall. In the summer months, because the electricity is more expensive, the policies are likely to provide more incentives to households to save electricity. However, in the non-summer months, the incentive becomes weaker due to the cheaper price of electricity so that the *ECP*s fail to have the expected effects in terms of reducing average household electricity consumption. In addition, due to the fact that it is harder and harder for households to conserve electricity year after year, the electricity consumed in the period for ECP_2 is a little higher than that in the period for ECP_1 (although the difference is tested to be insignificant). In sum, the *ECP*s are found to be ineffective in reducing household electricity consumption and there are seasonal differences between the summer and non-summer months.

Turning to the effects of climatic variables on electricity consumption, it is shown that the higher the temperature, the higher the electricity consumption, while the significantly positive effects are relatively small in the non-summer months. The weather in Taiwan is hot even in some of the non-summer months, where the mean temperature is as high as 21 °C.[23] Such a high temperature drives people to switch on their air conditioners, air ventilators, and other electrical appliances to lower the temperature, which stimulates electricity consumption. The relative humidity, however, does not have a significant effect on the electricity consumption. The interactive terms of temperature and the number of air conditioners owned per household and humidity and the number of dehumidifiers owned per household are each insignificant in both the summer and non-summer months as well. This may indicate that these two variables fail to be good proxies for explaining electrical appliance usage. The number of appliances neither reflects

[21] In Table 2, the estimates of price elasticity in Filippini (2011) are large. Nonetheless, his elasticity estimates are not suitable for comparison with our own due to the fact that what Filippini (2011) estimated was the daily time-of-use price elasticity. Households can substitute between peak and off-peak electricity consumption in a day without reducing the total electricity demand. We thank an anonymous referee for emphasizing this point.

[22] We thank an anonymous referee for pointing out this problem.

[23] Note that the non-summer period covers eight months, including different weather patterns. During months close to the summer months, the average temperature is high. In the winter time, although the average temperature is lower, the minimum mean temperature is as high as 12.5 °C (see Table 4).

their performance, nor the amount of time that they are used. Unfortunately, these characteristics are not available for the aggregate-level data.

The effect of family size on electricity consumption is mixed in the literature. Yoo et al. (2007) and Jung (1993) find evidence of a significantly positive effect, Blázquez et al. (2013) and Filippini and Pachauri (2004) arrive at a significantly negative effect, and Filippini (2011) indicates that the effect is indeterminate. We therefore conjecture that the relationship between electricity consumption and family size may not be linear and hence specify a quadratic form of family size. The outcomes support the view that there is indeed a U-shaped relationship between the two variables, but it is only significant during the non-summer months. The turning point occurs at 3 persons per family, which is a little lower than the average family size in the sample. This result indicates that the economies of scale merely apply to small families of up to 3 persons. The variable for house size has no significant effect on the consumption of electricity.

Finally, the price of residential LPG, P_G, does not have a significant effect on electricity consumption, irrespective of the summer and non-summer months. In Taiwan, gas is mainly used for cooking and heating water for baths. Because the price of electricity is much higher than the price of gas, the substitution effect of electricity for gas when the price of gas is increasing tends to be weak.

6. Conclusion

In this empirical study, we have examined the residential demand for electricity in Taiwan, where 98% of the energy supply is imported and electricity-related policies and regulations are experiencing a transition. A number of controversies and conflicts have arisen in the past few years as to whether the building of the fourth nuclear power plant should be continued, or whether electricity and petroleum prices should be further increased, as well as how effective the electricity-conservation measures that have been introduced in fact are. This research may provide important and useful information to policy-makers with regard to the price and income elasticities of demand for electricity.

This paper employs a panel data set composed of 19 county-level aggregate monthly data sets spanning the period from January 2007 to December 2013. We specify a partial adjustment model with an endogenous electricity price that results from the implementation of increasing-block pricing. The use of monthly data and instrumental variables for different electricity rate structures (rather than the commonly-used annual average electricity price) allows us to study the seasonal effects of electricity demand.

Our empirical results confirm that there are significant seasonal differences in the demand for residential electricity between the summer and non-summer months. Both the speed of adjustment and own price elasticity during the summer time are found to be lower than those in the non-summer time due to the high temperatures. The results suggest that if the carbon tax is considered in combination with the electricity price, the government might impose a higher carbon tax in the non-summer months to effectively reduce electricity consumption and curb CO_2 emissions since CO_2 is a pollutant that accumulates. Meanwhile, by doing so the government is able to smooth the electricity expenditure of households over the course of a year because the electricity price is lower (higher) in the non-summer (summer) months. In addition, the estimated elastic long-run own price elasticities indicate that it is possible for governments to effectively reduce residential electricity consumption by increasing electricity prices in the long run. The estimated inelastic income effects imply that electricity is a necessity for households. However, the income effect in the summer months is higher than that in the non-summer months.

Finally, it would be well worth building a large household-level panel data set on the consumption of electricity in order to generate more accurate empirical results that help in enhancing the allocative efficiency of electricity consumption. Specifically, the collection of data related to electricity-using habits, electrical appliances, conservation measures, and perceptions of the electricity price, etc. is recommended due to their being intimately associated with electricity consumption. Other IV variables, IV approaches, and more advanced econometric methods could also be employed to deal with the endogeneity of the price variable under the increasing-block pricing framework.

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