This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

Consumption effects of an electricity decarbonization policy: Hong Kong

C.K. Woo[a,*], A. Shiu[b], Y. Liu[a], X. Luo[a], J. Zarnikau[c]

[a] Department of Asian and Policy Studies, Education University of Hong Kong, Tai Po, Hong Kong

[b] School of Accounting and Finance, Hong Kong Polytechnic University, Hung Hom, Hong Kong

[c] Department of Economics, University of Texas at Austin, Austin, Texas 78713, USA

Keywords: Electricity decarbonization, retail demands for electricity and town gas, price elasticity estimation, Hong Kong

[*] Corresponding author. Email: chiwoo@eduhk.hk (C.K. Woo); phone: + 852 2948 7495.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

Abstract

This paper estimates the consumption effects of an electricity rate increase triggered by an electricity decarbonization policy's implementation. Underscoring its real-world relevance is the policy's net impact on CO_2 emissions, the sum of (a) the supply-side impact attributable to using generation resources with low emissions to displace those with high emissions, and (b) the demand-side impact caused by energy consumption changes in response to the electricity rate increase. For Hong Kong, the changes in (b) are decreases in electricity consumption and increases in town gas consumption. Using a sample of monthly data for the period of 1981-2016, we document the low price responsiveness of Hong Kong's electricity and town gas demands by customer class (residential, commercial and industrial). Hence, the 40% projected electricity rate increase due to Hong Kong's adopted electricity decarbonzation policy may only have a small demand-side impact on CO_2 emissions. Finally, the electricity demands' low price responsiveness has two important policy implications. First, Hong Kong's demand-side-management should rely more on energy efficiency improvement than price-induced consumption reductions. Second, restructuring Hong Kong's electricity industry to introduce wholesale competition should consider the potential for large electricity price spikes and market power abuse in connection to price-inelastic electricity demands.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

1. Introduction

The world's electricity industry has seen three transformative events in the last three decades. The first event is market restructuring to introduce wholesale competition in Europe, North America, South America, Australia, New Zealand, and Asia [1-3], leading to bilateral trading enabled by open transmission access and centralized power exchanges administered by independent system operators [4-8]. Wholesale electricity market prices are highly volatile with large spikes,[1] triggering extensive research in price behavior and dynamics, forward contracts and tolling agreements, derivatives and risk management, product differentiation, system operation, and integrated resource planning [9-49]. Further, an electricity market reform's ability to deliver reliable service at stable and reasonable rates requires demand price responsiveness that mitigates price spikes and market power of generators [2-3, 50-54].

The second event is large-scale renewable energy development, thanks to the global potential of solar and wind resources [55-57], as well as government policies such as feed-in-tariff (FIT), easy transmission access, renewable portfolio standard, low-cost financing, and tax subsidies [58-66]. Due to their zero fuel costs, renewable

[1] Wholesale electricity prices are inherently volatile due to: (a) daily fuel-cost variations, especially for the natural gas that is widely used by combustion turbines and combined-cycle gas turbines; (b) hourly weather-sensitive demands with intra-day and inter-day fluctuations, which must be met in real time by generation and transmission already in place; (c) planned and forced outages of electrical facilities; (d) hydro conditions for systems with significant hydro resources; (e) carbon-price fluctuations affecting thermal generation that uses fossil fuels; (f) transmission constraints that cause transmission congestion and generation re-dispatch; and (g) lumpy capacity additions that can only occur with long lead times.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

resources like solar and wind displace thermal generation via the merit order effect that reduces wholesale market prices in Europe (e.g., Denmark, Germany and Spain), North America (e.g., the Northwestern states, California, Texas, and the Northeastern states) and Australia [67-84]. As a result, renewable resources benefit electricity consumers, unless their per MWh procurement costs far exceed the market prices (e.g., Germany, Spain and Ontario that had used high FIT rates to promote renewable generation development).

The third event is deep decarbonization [85], underscored by the international commitments made in the 2015 Paris Climate Change Summit and the China-U.S. bilateral agreement ratified in the 2016 G20 Summit in Hangzhou China. Despite the Trump administration's withdrawal of the U.S. committed reduction in CO_2 emissions, China continues its pursuit of decarbonization through renewable energy development and carbon trading, which are a clean electricity future's critical components that have attracted extensive research attention [86-113].

Against the backdrop of the above transformative events, this paper's primary objective is to estimate the consumption effects of an electricity decarbonization policy. To underscore this objective's real-world relevance, consider ($A + B$), the policy's projected net impact on a region's CO_2 emissions. This net impact is the supply-side impact A attributable to using generation resources with

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

low CO_2 emissions to displace those with high CO_2 emissions, plus the demand-side impact *B* due to energy consumption changes in response to the policy's ensuing electricity rate increase.

We choose Hong Kong as our case study for the following reasons. First, Hong Kong is an international metropolis with a population of ~7.3 million, larger than the individual population sizes of 38 American states, eight Canadian provinces and eight OECD countries. Its economic performance rivals OECD countries', with a per capita GDP of about US$43,000 per year and an unemployment rate of 3.4% in 2016.[2] Such a performance could not have been possible *sans* a superbly reliable electricity supply [114]. Second, Hong Kong is experiencing deteriorating air quality. Besides transportation, the major source of local emissions, including CO_2, is the 6,608 MW of coal-fired generation that accounts for 52.3% of Hong Kong's 12,625 MW of total generation capacity [115-117]. Finally, the Hong Kong government has recently made two important policy decisions that shape Hong Kong's electricity future [118-119]. The first decision rejects reforming Hong Kong's electricity industry due to concerns of limited competition among the likely few sellers. Its further justification is the low electricity demand price responsiveness, as evidenced by the own-price elasticity estimate of -0.155 reported

[2] http://www.censtatd.gov.hk/hkstat/hkif/index.jsp

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

in [120]. The second decision adopts a fuel mix that uses natural gas and renewable energy to displace coal consumed by Hong Kong's local generation. Importantly, the adopted fuel mix's projected 40% electricity rate increase is found to be publicly acceptable [117].

To achieve the paper's primary objective, we use a sample of newly constructed monthly data for the 192-month period of January 1981 to December 2016 to estimate the price elasticities of Hong Kong's retail electricity and town gas demands by customer class (residential, commercial and industrial).[3] The price elasticity estimates reported herein help answer three substantive questions:

- What is the estimated reduction in Hong Kong's total electricity demand due to the projected 40% electricity rate increase? This question is relevant and important because declining electricity consumption reduces Hong Kong's local emissions [120-121]. When electricity demands are highly price-sensitive, a supply-side policy that leads to electricity rate increases can achieve a greater emissions reduction than what the policy anticipates.
- What is the estimated increase in Hong Kong's town gas consumption due to the projected 40% electricity rate increase? According to [122-123], electricity and town gas are substitutes in Hong Kong. Hence, the decremental emissions

[3] Unlike cities in Europe and North America that use natural gas, Hong Kong uses "[t]own gas produced from naphtha and natural gas". (https://www.towngas.com/Eng/Corp/AbtTG/HKBus/Production.aspx).

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

of declining electricity consumption are weakened by the incremental emissions of rising town gas consumption.

- Are Hong Kong's electricity demands highly price-inelastic? If yes, introducing competition via an electricity market reform in Hong Kong is challenging because low demand price responsiveness tends to exacerbate price spikes and market power of generators [2-3, 50-54].

While specific to Hong Kong, the above questions are equally relevant to other regions that likely see substantial changes in their electricity generation resources. The first case in point is California's newly enacted renewable portfolio standard, mandating that 50% of the state's electricity sales be met by 2030 by qualifying renewable resources such as solar, wind or geothermal.[4] The second case is nuclear plant retirements in Europe in the wake of Japan's 2011 Fukushima disaster, as well as the vast development of renewable resources in Europe and North America [124-127]. The third case is China's ambitious plan to cut its greenhouse gas emissions by reducing its consumption of coal, the dominant fuel used in China's electricity generation [86-113].[5]

Our demand estimation uses a constant-elasticity-of-substitution (CES) specification described in Appendix C to:

---

[4] http://www.energy.ca.gov/portfolio/
[5] http://www.bbc.com/news/science-environment-33040965

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

- Detect demand price responsiveness when the substitutability among electricity and town gas is expected to be low in Hong Kong;[6]
- Exploit the publicly available data, while accounting for the effects of weather on energy consumption [128-133]; and
- Offer up-to-date price elasticity estimates to enrich the only empirical evidence that we have found, the residential electricity price elasticity estimate of -0.155 reported in [120].

Our paper's main contributions are as follows. First, it shows how to use the monthly tariff information in Appendix A to construct monthly energy price data by customer class that match the publicly available quarterly price data. Detailed in Appendix B, the resulting monthly price data yield a larger and more granular sample than those based on quarterly or annual data.

Second, it presents a CES system of electricity and town gas demands to comprehensively estimate class-specific price elasticities. This formulation is applicable to cities and regions where aggregate data are available but disaggregate data are either unavailable or costly to collect. Even if disaggregate data were available, our approach could still offer a reality check of the findings from a

[6] There are four reasons for our expectation of low substitutability. First, electricity has many end-uses (e.g., air conditioning, cooking, lighting, motors and drives, ventilation, refrigeration, water heating, and other plug loads like computers and electronics). Second, town gas is mainly for cooking and water heating. Third, all households and firms in Hong Kong have universal access to electricity, which is not the case for town gas because the Hong Kong China Gas Company's (HKCGC's) distribution network's geographic coverage is less extensive than that of Hong Kong Electric's (HEC's) and China Light Power's (CLP's) distribution networks.

disaggregate demand analysis.

Third, it documents the effects of monthly weather on Hong Kong's electricity and town gas consumption. After an extensive exploration of such weather variables as monthly mean temperatures, rainfall, bright sunshine hours, relative humidity, and wind speed, it finds energy demands by customer class move with cooling degree month (CDM = max(monthly mean of daily maximum temperatures – 18C, 0)) and heating degree month (HDM = max(18C - monthly mean of daily minimum temperatures, 0)).

Fourth, it documents small price elasticity estimates of -0.01 to -0.02 for Hong Kong's class-specific electricity demands and -0.06 to -0.23 for the related town gas demands. To the best of our knowledge, these estimates are new, filling a glaring informational gap in the extant studies of Hong Kong's retail energy consumption.

Finally, it applies the price elasticity estimates to calculate the demand-side impact on Hong Kong's CO_2 emissions due to the government's fuel mix decision's projected 40% electricity rate increase. While the price-induced electricity consumption decline reduces the natural gas used by electricity generation, the electricity rate increase also raises Hong Kong's town gas consumption. The net change is an annual reduction of ~44,007 (0.24%) metric tons in the total CO_2

emissions attributable to Hong Kong's electricity and town gas consumption. This demand-side estimate of CO_2 emissions reduction complements those found via energy system modeling of renewable energy development in Hong Kong [115].

The rest of this paper proceeds as follows. Section 2 briefly reviews the energy demand literature, describes our data sample and presents our model specification and estimation strategy. Section 3 reports the regression results and price elasticity estimates. It also uses the elasticity estimates to compute the net change in Hong Kong's CO_2 emissions. Section 4 concludes.

2. Material and methods

2.1 Literature review

To contextually link our empirical analysis to the vast literature of energy demand estimation, this section reviews retail demand studies of electricity and natural gas for three customer classes: residential, commercial and industrial. As there are hundreds of such studies, we necessarily rely on extant surveys [134-141]. These surveys indicate that own- and cross-price elasticity estimates are typically developed from the data for a given type of energy (e.g., electricity or natural gas) consumed by a particular customer class (e.g., residential or commercial). Relatively rare are the price elasticity estimates found using a single data file that encompasses multiple energy types and customer classes. Our paper shows how to overcome the

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

empirical challenges of assembling such data and performing the associated estimation.

With electricity as the dominant focus of research, residential demand studies are based on the theory of consumer behavior [142]. Studies of non-time-differentiated kWh consumption often use a linear or double-log specification in a single-equation setting, thanks to the specification's easy estimation and theoretical validity [143-144]. Appendix D documents our estimation of the linear and double-log demand models, finding these models inappropriate for characterizing our sample's underlying data generation process (DGP).

Enabled by smart metering, electricity demand response under dynamic pricing can improve an electric grid's economic and operational efficiencies [48, 49, 145]. Focusing on peak load reduction, a residential time-of-use (TOU) electricity study typically estimates a demand system of peak and off-peak kWh consumption [146-156]. Besides the CES specification [157-158], two commonly used functional forms are the Translog [159] and Generalized Leontief (GL) [160], with the latter being more suitable when the TOU demands exhibit low elasticities of substitution [161-163].

A useful message from the TOU demand studies is that the CES and GL specifications can parsimoniously parameterize a retail energy demand system for a given customer class, chiefly because electricity and natural gas likely have low substitutability that leads to small cross-price elasticity estimates.[7] Further, they offer a formal test of the null hypothesis of zero substitution. If this hypothesis is rejected, estimating CO_2 emissions reduction due to an electricity rate increase should consider price-induced changes in natural gas consumption. Appendix D documents our estimation of the CES and GL demand models, finding that the CES model is an empirically reasonable representation of our sample's DGP.

Non-residential energy demands are based on the theory of firm behavior [164]. While linear and double-log specifications are popular in the single-equation setting, they lack the theoretical rigor of an energy demand system parameterized by a suitably chosen functional form, as exemplified by [165-169]. Our paper demonstrates how to estimate a CES system that is relatively easy to implement.

Meta analyses suggest that retail energy demand studies have vastly different attributes, yielding highly diverse price elasticity estimates [139-140]. It is difficult to use extant studies to project price-induced consumption changes, as selecting the "right" price elasticity estimates can be both challenging and controversial [170-172]. Hence, an empirically reasonable computation of the price-induced

[7] The relative versatility of these two energy types explains their low substitutability. To see this point, consider a household's consumption of end-use services (e.g., clothes and dish washing, cooking, refrigeration, lighting, space cooling, space heating, and water heating). While electricity is a versatile energy input for the domestic production of such end-use services, natural gas is mainly for cooking and water heating.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

consumption changes should preferably use an estimated demand system based on a unified framework implemented with a single data file, as demonstrated by our demand estimation reported below.

Finally, our paper is closely related to a 2011 study that uses residential and regional own-price elasticity estimates to assess the effect of price-induced electricity consumption reductions on CO_2 emissions in the U.S.A. [173]. Based on a panel of annual data by state for the 15-year period of 1990-2004, the study's double-log demand estimation yields elasticity estimates of -0.20 to -0.25. For a 10% increase in retail electricity rates, the projected CO_2 emissions reduction is about 0.86%. However, [173] only considers the electricity rate increase's effect on electricity consumption, unlike our paper that considers the electricity rate increase's effect on both electricity and town gas consumption.

2.2 Data description

Our sample contains Hong Kong's monthly data for the 192-month period of January 1981 to December 2016. The period's ending month reflects the data available at the time of our writing. We exclude the data before 1981 because of the sharp and abrupt structural change in Hong Kong's economy triggered by China's economic reform that began in 1978.

Unlike the U.S.A. where monthly data are readily available from the Energy

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

Information Agency, the Hong Kong government publishes the following data:

- Monthly electricity and town gas consumption data by customer class available from the Census and Statistics Department.[8]
- Quarterly utility-specific tariffs by customer class for electricity in the various issues of Hong Kong Energy Statistics Quarterly Report (Quarterly Report hereafter),[9] or Hong Kong Energy Statistics Annual Report (Annual Report hereafter) published by the Census and Statistics Department.[10,11] Appendix B details how we use the electricity tariff information to construct the average electricity prices by customer class. We cannot use the published quarterly and annual average prices in Quarterly and Annual Reports because such prices are not differentiated by customer class and unavailable for our entire sample period.[12]

---

8 http://www.censtatd.gov.hk/hkstat/sub/sp90.jsp?tableID=127&ID=0&productType=8

9 Appendix A reproduces the utility-specific tariffs for electricity and town gas reported in the 1st Quarter 2017 Report of Hong Kong Energy Statistics.

10 http://www.censtatd.gov.hk/hkstat/sub/sp90.jsp?productCode=B1100001 and http://www.censtatd.gov.hk/hkstat/sub/sp90.jsp?productCode=B1100002

11 While CLP reported “Domestic tariff” and “General service tariff” for the entire sample period, HEC reported “Domestic tariff”, “Commercial and miscellaneous tariff” and “Small industrial tariff” before 2002 and merged the last two categories into “Commercial, industrial and miscellaneous tariff” in subsequent years.

12 Annual and Quarterly Reports provide the average prices of electricity and town gas for 1981-2000 and 2001Q1-2006Q3, respectively. There are no reported figures on average prices in both reports since 2006Q4.We calculated subsequent figures by dividing quarterly total sales revenue by quarterly local consumption for electricity and town gas, which are available in Tables 4.1, 4.2 and 4.3 of the Quarterly reports. There is only slight discrepancy between the reported and our calculated values in the overlapping period of 2006Q1-Q3.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

- Quarterly town gas tariff data in different issues of Quarterly and Annual Reports. We incorporate the monthly fuel cost adjustments to the published tariff data and calculate the average prices by customer class.[13]
- Quarterly real GDP available in Hong Kong Economic Reports.[14] We convert the quarterly real GDP to monthly real GDP = quarterly GDP × (number of days within the month / total calendar days within the quarter).[15]
- Weather data published by the Hong Kong Observatory, which include monthly temperatures, rainfall, bright sunshine hours, relative humidity and wind speed.[16] We use the monthly means of daily maximum and minimum temperatures to derive the CDM and HDM.

The average price variables are endogenous under nonlinear tariffs [174 - 175]. To see this point, consider a random shock (e.g., a typhoon which causes residents to stay home) that increases residential electricity consumption and therefore the residential average price because of the residential tariff's increasing block rate structure. The positive correlation between the random shock and average price may cause unintended bias in our demand estimation [176]. To overcome this

[13] HKCGC only reported "General tariff" for residential, commercial and industrial classes. This tariff data is available in the 1980-1981 issues of Annual Report and data for 1982 and onwards is available in the Quarterly Reports.
[14] http://www.hkeconomy.gov.hk/en/reports/archive.htm
[15] Recognizing the number of days in each calendar month, the January real GDP is the Q1 GDP times 0.344 [= 31 days / (31 days + 28 days + 31 days)]. The February and March real GDP data are derived in the same manner.
[16] http://www.hko.gov.hk/cis/monthlyExtract_e.htm?y=2015

This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

bias, we use the stepwise autoregressive (STEPAR) method in PROC FORECAST of SAS [177] to develop the monthly predicted prices that highly correlated with the actual prices ($r > 0.85$).[17] As the predicted prices in month t are driven by the actual prices in prior months, they do not depend on the consumption levels in month t. Hence, the predicted prices are exogenous and serve as instrumental variables in our demand estimation.

Panel A of Table 1 reports our data sample's descriptive statistics. We use the Phillips-Perron (PP) test for a unit root [178] to find residential electricity and town gas consumption, real GDP and weather are stationary at the 5% significance level, not so for the remaining series. Hence, using these data directly in our demand estimation raises concerns of spurious regressions [176]. Further, the relatively low coefficients of variation indicate that all data series have relatively small dispersion, presaging the empirical challenge in detecting Hong Kong's electricity and town gas demands' price sensitivity.

Panel B of Table 1 reports the constructed data series for estimating an energy demand system based on the CES specification. With relatively large coefficients of variation, the first-differenced data series are stationary at the 5%

---

[17] As a quick and automatic way to generate forecasts for many time series, the STEPAR method combines a "time trend regression with an autoregressive model and uses a stepwise method to select the lags to use for the autoregressive process" [177]. In short, the monthly price predictions are automatically produced by PROC FORECAST *sans* additional modeling efforts by the authors.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

significance level.

Table 2 shows the correlation coefficients for the first-difference of logged data series used in the estimation. We explain these coefficients as follows:

- The likely low substitution between electricity and town gas consumption implies that the logged consumption ratios are weakly correlated with the logged price ratios.
- The logged consumption ratios are positively correlated with logged GDP, as rising GDP tends to increase Hong Kong's stock and utilization of major electricity-consuming durables (e.g., air conditioners, refrigerators, cooking ranges, and water heaters), more so than those of major town-gas-consuming durables (e.g., cooking stoves and water heaters).
- The logged consumption ratios are positively correlated with CDM but negatively correlated with HDM. This reflects Hong Kong's large air conditioning loads that are mainly weather driven. Electricity consumption is high in the summer months with high CDM but low HDM (e.g., June - October), not so in the winter months with low CDM and high HDM (e.g., November – February). In contrast, town gas consumption is largely weather insensitive because Hong Kong has mild winter weather and does not use town gas as the primary fuel for space heating.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

While the correlation coefficients in Table 2 are informative, they do not quantify Hong Kong energy demands' price responsiveness. Thus, we use a regression analysis to identify and quantify this responsiveness.

2.3 Regression specification

After extensive trials of different functional forms and model specifications reported in Appendix D, we find that the CES specification is an empirically plausible representation for our sample's DGP. To specify our regression model, let X_k = electricity consumption (MWh) at price E_k and Y_k = town gas consumption (GJ) at price G_k for customer class k = 1 for residential, 2 for commercial and 3 for industrial.

A CES system for the three customer classes comprises the following equations:

$$\Delta\ln(X_1/Y_1) = \alpha + \alpha_{EG}\,\Delta\ln(E_1/G_1) + \alpha_Y\,\Delta\ln(\mathrm{GDP}) + Z_1; \qquad (1.a)$$

$$\Delta\ln(X_2/Y_2) = \beta + \beta_{EG}\,\Delta\ln(E_2/G_2) + \beta_Y\,\Delta\ln(\mathrm{GDP}) + Z_2; \qquad (1.b)$$

$$\Delta\ln(X_3/Y_3) = \phi + \phi_{EG}\,\Delta\ln(E_3/G_3) + \phi_Y\,\Delta\ln(\mathrm{GDP}) + Z_3. \qquad (1.c)$$

In the above equations, Z_k denotes the total effect of non-price drivers, assumed to be a linear function of the weather variables (ΔCDM and ΔHDM), as well as binary indicators for months of the year.

Electricity and town gas are substitutes when the coefficients α_{EG}, β_{EG} and

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

ϕ_{EG} are all negative. If these coefficients are equal to zero, the corresponding energy demands are completely price-insensitive. Omitted here for brevity, the derivation of the price elasticities is given in Appendix C.

2.4 Estimation strategy

Affixing an additive random error to each equation yields a system of seemingly unrelated regressions (SUR), thanks to these errors' likely contemporaneous correlation.[18] We use the iterative SUR (ITSUR) method of PROC MODEL in SAS [177] to estimate the CES system. We use robust standard errors to gauge the regression coefficient estimates' precision and statistical significance, thereby circumventing the need to specify the AR order and form of heteroscedasticity of the random errors [179].

We perform three final checks of our results. First, we use the PP test to determine that the regression residuals do not follow a random walk, thus allaying concerns of spurious regressions [176]. Second, we re-estimate the CES system after adding an interaction term of $\Delta\ln(\text{GDP}) \times \Delta\ln(E_k/G_k)$ to allow for the price elasticities' possible dependence on GDP. As the re-estimation yields the anomalous finding that electricity and town gas are not substitutes, we exclude this interaction

[18] The two reasons for the errors' contemporaneous correlation are as follows. First, the energy demand regressions for a given customer class reflect the consumption decisions of the same class. Second, a random shock (e.g., storms) can affect the energy demands of all three customer classes.

This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

term in our final specification.[19] Finally, we construct quarterly data to re-estimate the CES system. The resulting coefficient estimates are similar to those reported in Table 3. Since the use of quarterly data reduces the sample size and masks the monthly variations in energy prices and consumption, we decide not to use quarterly data for our demand analysis.

3. Results

3.1 Regression results

Table 3 reports the ITSUR regression results. The three regressions have adjusted R^2 values of 0.43 to 0.79, indicating their empirically reasonable fit with the noisy monthly first-differenced data.

The estimates for α_{EG}, β_{EG} and ϕ_{EG} are all negative, lending support to our expectation that electricity and town gas are substitutes in Hong Kong. Their small sizes, however, suggest low price sensitivities. Except for the commercial class, these estimates are statistically insignificant (*p*-value > 0.1). Taken together, these findings' main inference is that Hong Kong energy demands are highly price-inelastic.

The positive coefficient estimates for $\Delta\ln(\text{GDP})$ indicate that rising GDP tends to raise the consumption ratio. This makes sense because an increase in GDP

[19] A theoretically valid energy cost function is concave in energy prices, implying that in our two-input case, electricity and town gas should be substitutes [164].

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

likely has a greater impact on electricity consumption due to the increasing use of air conditioning and other end-uses (e.g., electronics and refrigeration) than town gas consumption that is mainly for cooking and water heating. Coefficient estimates for ΔCDM and ΔHDM confirm that Hong Kong's electricity and town gas demands move with weather.

3.2 Elasticity estimates

Table 4 reports the own-price elasticity estimates for electricity, which are -0.0214, -0.0207 and -0.0113 for the residential, commercial and industrial class, respectively. Hence, the aggregate elasticity estimate is small at -0.0194. The estimates for town gas are -0.0648 for the residential class, -0.1972 for the commercial class and -0.2287 for the industrial class, implying an aggregate own-price elasticity estimate of -0.1275. These estimates indicate that Hong Kong's electricity and town gas demands by customer class are highly price-inelastic.

3.3 Net change in CO_2 emissions

This section assesses the demand-side impact of the 40% electricity rate increase on Hong Kong's CO_2 emissions. Fig.1 shows that this assessment entails the following steps:

- Step 1: Use the own-price elasticity estimates to compute the percentage change in class-specific electricity consumption.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

- Step 2: Use the results from Step 1 and the 2016 annual data to find the change in total electricity consumption of the three customer classes.
- Step 3: Use the result from Step 2 to find the change in natural gas used in electricity generation at an assumed marginal heat rate of ~7 MMBtu/MWh based on CLP's combined cycle gas turbines.
- Step 4: Use the cross-price elasticity estimates to find the percentage change in class-specific town gas consumption.
- Step 5: Use the results from Step 4 and the 2016 annual data to find the change in total town gas consumption of the three customer classes.
- Step 6: Compute the changes in CO_2 emissions based on the results from Steps 3 and 5, thereby quantifying the net change in CO_2 emissions caused by the 40% electricity rate increase.

As the own- and cross-price elasticity estimates are key parameters in the above steps, we explore three plausible scenarios of interest:

- Scenario 1 (zero price responsiveness): All price elasticities are zero to reflect a complete lack of price responsiveness. Absent price-induced consumption changes, this scenario's demand-related CO_2 emissions reductions by customer class are zero.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

- Scenario 2 (expected price responsiveness): The price elasticities are the estimates reported in Table 4. Fig.2. shows that the 40% electricity rate increase would decrease Hong Kong's total electricity consumption, while increasing Hong Kong's total town gas consumption. The net reduction in annual CO_2 emissions is ~44,007 metric tons, or 0.24% of Hong Kong's total CO_2 emissions due to natural-gas-fired generation and town gas consumption.
- Scenario 3 (higher-than-expected price responsiveness): The own- and cross-price elasticities are larger in size than those in Scenario 2. Hence, we assume the own-price (cross-price) elasticities are the lower (upper) bounds of the 95% confidence intervals for the estimates reported in Table 4. Fig.3. shows that the net reduction in annual CO_2 emissions remain small at ~48,141 metric tons, or 0.27% of Hong Kong's total CO_2 emissions due to natural-gas-fired generation and town gas consumption.

Based on the three scenarios' empirical findings, the 40% electricity rate increase is expected to have a small demand-side impact on Hong Kong's total CO_2 emissions.

4. Conclusion

We conclude by answering the three questions posed in Section 1. First, what is a 40% electricity rate increase's effect on Hong Kong's total electricity demand? Based on the own-price elasticity estimates in Table 4, this effect is small, only

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

-0.81% of Hong Kong's total electricity demand.

Second, what is the projected increase in town gas consumption resulting from the 40% electricity rate increase? Based on town gas' cross-price elasticity estimates, the change in Hong Kong's total town gas consumption is 5.12%, thus offsetting the CO_2 emissions reduction noted above. Based on Fig.2, the net impact is a 0.24% reduction in Hong Kong's CO_2 emissions due to the price-induced changes in electricity and town gas consumption.

Finally, are the estimated electricity demands price-inelastic? The answer is "yes" because the class-specific elasticity estimates have sizes well below 1.0. These price-inelastic electricity demands caution the introduction of an electricity market reform in Hong Kong, due chiefly to the potential for large price spikes and market power abuse by electricity suppliers.

The above findings have two important policy implications. First, the low price responsiveness reported herein suggests Hong Kong's demand-side management should rely more on energy-efficiency improvements than price-induced demand reductions to cut its total electricity consumption [e.g., 9]. It also supports the government's decision to decarbonize Hong Kong's electricity supply, as the supply-side impact is not weakened by the demand-side impact on Hong Kong CO_2 emissions.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

Second, mitigating market power abuse in a deregulated electricity market in Hong Kong necessitates electricity forward trading [180] and market surveillance of and regulatory sanctions against non-competitive behavior [2-3, 181-182]. This requires reform prerequisites that Hong Kong does not currently have (e.g., legislative mandates for vertical and horizontal divestiture, as well as the establishment of an independent system operator and a public utilities commission). Hence, HEC and CLP should continue to be integrated utilities, operating under the recently signed 15-year regulatory contracts between the Hong Kong government and these two electric utilities.[20]

Acknowledgements

Major funding of this paper comes from the Hong Kong Research Grants Council's General Research Fund (Project number: 18665516) awarded to the first author. Without implications, all errors are ours.

[20] http://www.enb.gov.hk/sites/default/files/en/node66/new_HKE_SCA_eng.pdf; http://www.enb.gov.hk/sites/default/files/en/node66/new_CLP_SCA_eng.pdf

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

Appendix A: Tariffs reproduced from the 1st Quarter 2017 Report of Hong Kong Energy Statistics

電力一般價目 (1)

General tariff for electricity (1)

	每千瓦小時港元 HK$/kWh
I. 香港電燈有限公司 The Hongkong Electric Company, Limited	2017年1月1日至 2017年3月31日 For the period 1.1.2017 - 31.3.2017
(a) 住宅價目 Domestic tariff	
首20 千瓦小時最低收費 (港元) Minimum charge for the first 20 kWh (HK$)	13.00
用電超過20 千瓦小時 For consumption exceeding 20 kWh	
首150 千瓦小時 For the first 150 kWh	0.688
以後的 For the next	
150 千瓦小時 kWh (151 - 300)	0.827
200 千瓦小時 kWh (301 - 500)	0.966
200 千瓦小時 kWh (501 - 700)	1.202
300 千瓦小時 kWh (701 - 1 000)	1.341
500 千瓦小時 kWh (1 001 - 1 500)	1.480
超過1 500 千瓦小時 For over 1 500 kWh	1.619
(b) 商業、工業及雜項價目 Commercial, industrial and miscellaneous tariff	
首30 千瓦小時最低收費 (港元) Minimum charge for the first 30 kWh (HK$)	32.10
用電超過30 千瓦小時 For consumption exceeding 30 kWh	
首500 千瓦小時 For the first 500 kWh	1.071
以後的 For the next	
1 000 千瓦小時 kWh (501 - 1 500)	1.111
18 500 千瓦小時 kWh (1 501 - 20 000)	1.222
超過20 000 千瓦小時 For over 20 000 kWh	1.249

註釋： (1) 指基本電價 + 燃料價條款調整 + 燃料費特別回扣 + 地租及差餉特別回扣。

從2017年1月1日至2017年3月31日，燃料價條款調整、燃料費特別回扣和地租及差餉特別回扣，分別為每千瓦小時+0.234港元，-0.179港元和 -0.040港元。

電力公司會給予大用量使用者特惠價目。

Notes : (1) Refers to basic charge + fuel clause adjustment + special fuel rebate + special rent and rates rebate.

From 1.1.2017 to 31.3.2017, the fuel clause adjustment, special fuel rebate, and special rent and rates rebate were +HK$0.234/kWh, -HK$0.179/kWh and -HK$0.040/kWh respectively.

Bulk tariff schemes are available in the electricity company to large quantity consumers.

This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

電力一般價目[(1)]
General tariff for electricity [(1)]

	每千瓦小時港元 HK$/kWh
II. 中華電力有限公司 CLP Power Hong Kong Limited	
	2017年1月1日至 2017年3月31日 For the period 1.1.2017 - 31.3.2017
(a) 住宅價目 Domestic tariff	
每兩個月最低收費 (港元) Minimum charge per every two months (HK$)	36.00
首400 千瓦小時 For the first 400 kWh	1.065
以後的 For the next	
600 千瓦小時 kWh (401 - 1 000)	1.199
800 千瓦小時 kWh (1 001 - 1 800)	1.357
800 千瓦小時 kWh (1 801 - 2 600)	1.665
800 千瓦小時 kWh (2 601 - 3 400)	1.894
800 千瓦小時 kWh (3 401 - 4 200)	1.998
超過 4 200 千瓦小時 For over 4 200 kWh	2.010
(b) 一般服務價目 General service tariff	
每月最低收費 (港元) Minimum charge per month (HK$)	36.00
首5 000 千瓦小時 For the first 5 000 kWh	1.230
超過5 000 千瓦小時 For over 5 000 kWh	1.222

註釋 : (1) 指基本電費 + 燃料調整費。

從2017年1月1日至2017年3月31日，燃料調整費為每千瓦小時+0.210港元。

電力公司會給予大用量使用者特惠價目。

Notes : (1) Refers to basic charge + fuel cost adjustment.

From 1.1.2017 to 31.3.2017, the fuel cost adjustment was +HK$0.210 /kWh.

Bulk tariff schemes are available in the electricity company to large quantity consumers.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

煤氣一般價目
General tariff for gas

	每百萬焦耳港元 HK$/megajoule
香港中華煤氣有限公司 The Hong Kong and China Gas Company Limited	
	2017年1月1日至 2017年3月31日 For the period 1.1.2017 - 31.3.2017
(a) 一般價目 General tariff	
每月最低收費 (港元) Minimum charge per month (HK$)	20.00
首500 百萬焦耳 For the first 500 megajoules	0.2390
以後的 For the next	
2 000 百萬焦耳 megajoules (501 - 2 500)	0.2380
5 000 百萬焦耳 megajoules (2 501 - 7 500)	0.2376
10 000 百萬焦耳 megajoules (7 501 - 17 500)	0.2366
15 000 百萬焦耳 megajoules (17 501 - 32 500)	0.2356
25 000 百萬焦耳 megajoules (32 501 - 57 500)	0.2343
50 000 百萬焦耳 megajoules (57 501 - 107 500)	0.2333
50 000 百萬焦耳 megajoules (107 501 - 157 500)	0.2324
50 000 百萬焦耳 megajoules (157 501 - 207 500)	0.2314
50 000 百萬焦耳 megajoules (207 501 - 257 500)	0.2305
超過257 500百萬焦耳 For over 257 500 megajoules	0.2295

(b) 燃料調整費
Fuel cost adjustment

	1月 Jan.	2月 Feb.	3月 Mar.
2017	0.0190	0.0196	0.0194

註釋 : 1 百萬焦耳 = 10^6 焦耳。

煤氣公司會給予大用量使用者特惠價目。

Notes : 1 megajoule = 10^6 joules.

Bulk tariff schemes are available in the gas company to large quantity consumers.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

Appendix B: Price data construction

The biggest challenge in our monthly demand analysis is the lack of suitable monthly price data for Hong Kong's electricity and town gas consumption. To construct the price data, we first verify each tariff in the Quarterly and Annual Reports of Hong Kong Energy Statistics, ensuring that the tariff's volumetric charges contain the quarterly and monthly fuel cost adjustments.[21] If the tariff's volumetric charges have excluded the fuel cost adjustments, we add the adjustments to the volumetric charges, resulting in the effective charges paid by the end-use customers. We ignore the monthly customer charges because they do not vary with consumption and their small sizes should not affect a customer's service-connection decision. The tariffs' nonlinearity motivates us to consider two different approaches to construct the price data.

To illustrate these approaches, we use a hypothetical 3-block tariff to construct the monthly data for price variable P_1 for a given customer class of HEC. Using a 4- or 5-block tariff complicates our illustration, without the benefit of additional insights.

Suppose the tariff's first block is Q_1 kWh, second block is Q_2 kWh, and third block is Q_3 kWh for a customer's monthly billing kWh in excess of (Q_1 + Q_2).

[21] While the Annual Reports from 1980 to 2001 show information of quarterly fuel cost adjustments for HEC, CLP and HKCGC, those from 2002 to 2014 show only the annual fuel cost adjustments. Quarterly Reports from 2001Q2 to 2016Q4, however, show monthly fuel cost adjustments for HEC, CLP and HKCGC.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

Further suppose that the three volumetric charges (HK$/kWh) are VC_1, VC_2 and VC_3. Based on this 3-block tariff, the first approach is simple averaging so that each month's $P_1 = (VC_1 + VC_2 + VC_3) / 3$. It generates a reasonable P_1 when the tariff is almost linear with approximately equal VC_1, VC_2 and VC_3.While easy to implement, it ignores the tariff's block quantities. As some tariffs in the Quarterly Reports are highly nonlinear, we decide to abandon this approach.

We adopt the second approach of block-weighted averaging. Under this approach, we assume each month's average price estimate for the customer class is $P_1 = (VC_1 Q_1 + VC_2 Q_2) / (Q_1 + Q_2)$, which excludes the volumetric charge VC_3 to which we cannot attach a kWh weight *sans* data on a customer's monthly billing kWh. When VC_1, VC_2 and VC_3 are close, block-weighted and simple averaging should yield nearly identical P_1 values.

We recognize that an accurately calculated average price for a given class should be P_1' = (VC_1 * Class kWh sales at VC_1 + VC_2 * Class kWh sales at VC_2 + VC_3 * Class kWh sales at VC_3) ÷ (Class kWh sales at VC_1 + Class kWh sales at VC_2 + Class kWh sales at VC_3). Unfortunately, we do not have the necessary utility-specific data on monthly class sales by variable charge to compute P_1'.

For each customer class, we now have two electricity prices: P_1 (HK$/MWh) for Hong Kong Island (HKI) served by HEC and P_2 (HK$/MWh) for Kowloon and

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

New Territory (KNT) served by CLP.[22] We derive Hong Kong's average monthly electricity price E as a weighted average of P_1 and P_2 based on CLP's and HEC's annual sales by customer class.

When compared to P_1', P_1 is likely biased. So are our other similarly constructed prices. Hence, we scale all of our constructed prices using the following factor: λ = Actual AP / Constructed AP, where Actual AP = Hong Kong's quarterly actual average electricity price and Constructed AP = Hong Kong's quarterly constructed average electricity price.

We use the following steps to compute λ:

(1) Find Hong Hong's quarterly total sales in the government report.[23] We use the monthly data in the report to compute the quarterly sum of total sales.

(2) Compute the quarterly weighted average of HEC's and CLP's constructed prices by customer class. For a given customer class, this price is (HEC's share of Hong Kong's *annual* total class sales * HEC's quarterly average class-specific constructed price + CLP's share of Hong Kong's *annual* total class sales * CLP's quarterly average class-specific constructed price). Because the Quarterly Report does not have quarterly utility-specific sales data, we can only use the *annual* class sales data from the annual reports of HEC and CLP to compute the annual utility-specific class sales shares.

(3) Estimate Hong Hong's quarterly total electricity revenue as Sum (over customer classes) of Hong Kong's total quarterly electricity sales by customer

---

[22] A map of Hong Kong that shows HKI and KNT is available at: http://www.travelchinaguide.com/map/hongkong/

[23] http://www.censtatd.gov.hk/hkstat/sub/sp90.jsp?tableID=127&ID=0&productType=8

class from Step 1 * Weighted quarterly average electricity price by customer class from Step 2.

(4) Find Hong Kong's quarterly constructed *AP* as Result from Step 3 ÷ Result from Step 1.

(5) Find λ for the following cases when *AP* are derived from different sources:

- Case 1: Hong Kong's quarterly actual *AP* is reported in the Quarterly Report. For the period of 2001Q1 to 2006Q4, we find λ = Hong Kong's quarterly actual *AP* in the Quarterly Report ÷ Result from Step 4.
- Case 2: Hong Kong's quarterly actual *AP* is derived by dividing quarterly total sales revenue by quarterly local electricity consumption. For the period of 2007Q1 to 2014Q4, we find λ = Hong Kong's quarterly actual *AP* derived by the above-mentioned method ÷ Result from Step 4.
- Case 3: Hong Kong's quarterly actual *AP* is not reported in the Quarterly Report. For the period of 1981Q1 to 2000Q4, λ = (Hong Kong's annual actual *AP* (expand to quarterly actual *AP*) ÷ Result from Step 4), where Hong Kong annual actual *AP* = (HEC's annual sales * HEC's annual system average price + CLP's annual sales * CLP's annual system average price) ÷ (HEC's annual sales + CLP's annual sales).

The scaling factors have a sample mean of 0.930, indicating the constructed average prices are moderately above the actual average prices.

We use the GDP price deflator to convert the nominal prices to real prices in constant 2014 dollar.[24] We multiply the real electricity prices by 1000 to obtain their

[24] The quarterly GDP price deflator data are available at http://www.censtatd.gov.hk/hkstat/sub/sp250.jsp?tableID=030&ID=0&productType=8. We use linear

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

HK$/MWh values. We also multiply the real town gas prices by 1000 to obtain their HK$/GJ value.

Appendix C: The CES energy cost function

This appendix derives the regression specification in the main text. Consider a retail customer with a CES energy cost function: $C = A^{1/\rho}\, Q = EX + GY$, where $A = [\lambda\, E^{\rho} + (1 - \lambda)\, G^{\rho}]$, E= electricity price (\$/MWh), G = town gas price (\$/GJ), and Q = intermediate output index, an increasing function of end-use needs (e.g., heating, lighting, …, etc.) [158]. Invoking Shephard's Lemma [164], the electricity demand is $X = \partial C/\partial E = A^{1/\rho - 1} \lambda\, E^{\rho - 1} Q$ and the town gas demand is $Y = \partial C/\partial G = A^{1/\rho - 1}\,(1 - \lambda)\, G^{\rho - 1} Q$. Absent data on Q, the estimable equation is $\ln(X / Y) = \alpha + \beta \ln(E / G)$, with $\alpha = [\lambda / (1 - \lambda)] > 0$ and $\beta = (\rho -1) < 0$ when electricity and town gas are substitutes. To account for the energy consumption ratio's dependence on non-price variables, we assume the intercept α to be a linear function of logged income, weather and binary indicators for months of the year.

To find the own-price elasticity, consider the electricity cost share $S_X = EX / C = \lambda\, E^{\rho} / A$. The effect of an electricity price change on ln$X$ is $\partial \ln X / \partial E = \partial \ln C / \partial E + (\rho - 1) / E - (\rho / A)\, \lambda\, E^{\rho - 1}$. As $S_X = (\partial \ln C / \partial E)\, E = \lambda\, E^{\rho} / A$ and $\beta = (\rho - 1)$, $\partial \ln X / \partial \ln E = \beta\,(1 - S_X) = \beta\, S_Y$ because $(S_X + S_Y) = 1$. Finally, $\partial \ln X / \partial \ln E + \partial \ln X / \partial \ln G = 0$

---

interpolation to find the monthly deflator series.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

because the CES cost function is homogenous of degree one in energy prices.

Appendix D: Summary of empirical explorations

This appendix summarizes our explorations that lead to our finally chosen CES formulation shown in Section 2. By no means exhaustive, these explorations employ several commonly used approaches to find empirically plausible elasticity estimates.

We first use the Generalized Leontief (GL) demand system, which is suitable for estimating energy demands with small elasticity of substitution [163, 165]. We first-difference the data as the raw data series are non-stationary at the 5% significance level. We apply the ITSUR method of PROC MODEL in SAS [177] to estimate the GL system under the restrictions of positive coefficient estimates for the square-rooted price ratios, as required by a well-behaved energy cost function that is concave in energy prices [160]. Based on the monthly actual price data, all restrictions are rejected at the 5% significance level. Based on the monthly predicted price data, two out of three non-negative restrictions are rejected at 5% level. Further, the regression residual for the industrial electricity demand is non-stationary. As part of the estimation process, we test AR(n) (n = 1, 2, and 3) errors and try additional weather variables like rainfall, bright sunshine hours, relative humidity, and wind speed. None of these efforts leads to empirically plausible own-price elasticity

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

estimates that should be negative.

After abandoning the GL specification, we estimate the popular double-log model:[25] ln(energy consumption) = $\alpha + \beta \times$ ln(real actual *or* predicted price) + non-price effects (e.g., ln(real GDP), ln(weather variables)) + AR(1) error. Estimating the six energy demand equations (= electricity and town gas for three customer classes) yields positive own-price elasticity estimates for all customer classes. Re-estimation with different weather variables fails to remedy the anomalous elasticity estimates. We also try the linear demand specification, yielding positive own-price elasticity estimates. Repeating the estimation process using the first-differenced data does not yield empirically plausible results.

After rejecting the double-log and linear specifications, we estimate a CES system in level form. With the actual monthly price data, the coefficient estimates for the logged price ratio variables are positive, suggesting that the two energy types are not substitutes. With the predicted monthly price data, only one coefficient estimate for the logged price ratio variable is negative. Further, the industrial class' regression residuals are non-stationary. Finally, changing the combination of regressors does not solve the problems of implausible price elasticity estimates and non-stationary residuals.

---

[25] For a discussion on the theoretical basis of the double-log and linear demand equations for the residential class, see [143].

This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

We then estimate a CES system in first-difference form, yielding empirically plausible coefficient estimates that are consistent with the properties of a theoretically valid energy cost function. As a result, we report this system's regression results in the main text.

References

[1] Sioshansi FP. Evolution of Global Electricity Markets: New Paradigms, New Challenges, New Approaches. San Diego, California: Elsevier, 2013.

[2] Woo CK, Chow LCH, Lior N (editors). Electricity market reform and deregulation. Energy 2006; 31: 745-1114.

[3] Woo CK, Lloyd D, Tishler A. Electricity market reform failures: UK, Norway, Alberta and California. Energy Policy 2003; 31: 1103-1115.

[4] Bohn RE, Caramanis MC, Schweppe FC. Optimal pricing in electrical networks over space and time. Rand Journal of Economics 1984; 15: 360-376.

[5] Hogan W. Contract networks for electric power transmission. Journal of Regulatory Economics 1992; 4: 211-242.

[6] Stoft S. Power System Economics: Designing Markets for Electricity. New York, New York: Wiley-IEEE Press, 2002.

[7] Woo CK, Horowitz I, Martin J. Reliability differentiation of electricity transmission. Journal of Regulatory Economics 1998; 13: 277–292.

[8] Woo CK, Lloyd-Zannetti D, Horowitz I. Electricity market integration in the Pacific Northwest. The Energy Journal 1997; 18(3): 75-101.

[9] Baskette C, Horii B, Kollman E, Price S. Avoided cost estimation and post-reform funding allocation for California’s energy efficiency programs. Energy 2006; 31: 1084-1099.

[10] Benth FE, Koekebakker S. Stochastic modeling of financial electricity contracts. Energy Economics 2008; 30: 1116–1157.

[11] Bessembinder H, Lemmon M. Equilibrium pricing and optimal hedging in electricity forward markets. Journal of Finance 2002; 57: 1347–1382.

[12] Bessembinder H, Lemmon M. Gains from trade under uncertainty: the case of electric power markets. Journal of Business 2006; 79: 1755–1782.

[13] Burger M, Bernhard K, Muller A, Schindlmayr G. A spot market model for pricing derivatives in electricity markets. Quantitative Finance 2004; 4(1): 109–122.

[14] Camona R, Ludkovski M. Pricing asset scheduling flexibility using optimal switching. Applied Mathematical Finance 2008; 15(5-6): 405-447.

[15] Deng SJ, Johnson B, Sogomonian A. Exotic electricity options and valuation of electricity generation and transmission. Decision Support Systems 2001; 30(3): 383–392.

[16] Deng SJ, Oren SS. Electricity derivatives and risk management. Energy 2006; 31: 940–953.

[17] Deng SJ, Xia Z. A real options approach for pricing electricity tolling agreements. International Journal of Information Technology & Decision Making 2006; 5(3): 421–436.

[18] Douglas SM, Popova JN. Econometric estimation of spatial patterns in electricity prices. The Energy Journal 2011; 32(2): 81–105.

[19] Eydeland A, Wolyniec K. Energy and Power Risk Management: New Development in Modeling, Pricing and Hedging. Hoboken, New Jersey: John Wiley & Sons, 2003.

[20] Gal N, Milstein I, Tishler A, Woo CK. Fuel cost uncertainty, capacity investment and price in a competitive electricity market. Energy Economics 2017; 61: 233-240.

[21] Guthrie G, Videbeck S. Electricity spot price dynamics: beyond financial models. Energy Policy 2007; 35: 5614–5621.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

[22] Haldrup N, Nielsen MO. A regime switching long memory model for electricity prices. Journal of Econometrics 2006; 135: 349–376.

[23] Janczura J, Weron R. An empirical comparison of alternate regime-switching models for electricity spot prices. Energy Economics 2010; 32: 1059–1073.

[24] Johnsen TA. Demand, generation and price in the Norwegian market for electric power. Energy Economics 2001; 23(3): 227–251.

[25] Huisman R, Mahieu R, Schlichter F. Optimal peak/off-peak allocations. Energy Economics 2009; 31(1): 169–174.

[26] Karakatsani NV, Bunn DW. Intra-day and regime-switching dynamics in electricity price formation. Energy Economics 2008; 30: 1776–1797.

[27] Kleindorfer PR, Li L. Multi-period VAR-constrained portfolio optimization with applications to the electric power sector. The Energy Journal 2005; 26(1): 1–26.

[28] Knittel CR, Roberts MR. An empirical examination of restructured electricity prices. Energy Economics 2005; 27: 791–817.

[29] Li Y, Flynn PC. Electricity deregulation, spot price patterns and demand-side management. Energy 2006; 31: 908–922.

[30] Longstaff FA, Wang AW. Electricity forward prices: a high-frequency empirical analysis. Journal of Finance 2004; 59: 1877–1900.

[31] Lucia JJ, Schwartz ES. Electricity prices and power derivatives: evidence from the Nordic Power Exchange. Review of Derivatives Research 2002; 5(1): 5–50.

[32] Marckhoff J, Wimschulte J. Locational price spreads and the pricing of contracts for difference: evidence from the Nordic market. Energy Economics 2009; 31: 257–268.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

[33] Moore J, Woo CK, Horii B, Price S, Olson A. Estimating the option value of a non-firm electricity tariff. Energy 2010; 35: 1609-1614.

[34] Mount TD, Ning Y, Cai X. Predicting price spikes in electricity markets using a regime-switching model with time-varying parameters. Energy Economics 2006; 28: 62–80.

[35] Park H, Mjelde JW, Bessler DA. Price dynamics among U.S. electricity spot markets. Energy Economics 2006; 28: 81–101.

[36] Redl C, Haas R, Huber C, Bohm B. Price formation in electricity forward markets and relevance of systematic forecast errors. Energy Economics 2009; 31: 356–364.

[37] Ryabchenko V, Uryasev S. Pricing energy derivatives by linear programming: tolling agreement contracts. Journal of Computational Finance 2011; 14(3). Available at: http://www.ise.ufl.edu/uryasev/files/2011/11/PRICING_ENERGY_DERIVATIVES_BY_LINEAR_PROGRAMMING.pdf (Accessed on 23 June, 2015)

[38] Thompson M. Optimal economic dispatch and risk management of thermal power plants in deregulated markets. Operation Research 2013; 61: 791–809.

[39] Tishler A, Milstein I, Woo CK. Capacity commitment and price volatility in a competitive electricity market. Energy Economics 2008; 30: 1625-1647.

[40] Wangensteen I, Botterud A, Flatabo N. Power system planning and operation in international markets - perspectives from the Nordic region and Europe. Proceedings of the IEEE 2005; 93(11): 2049-2059.

[41] Weron R. Modeling and Forecasting Electricity Loads and Prices. New York: John Wiley, 2006.

[42] Woo CK, Karimov R, Horowitz I. Managing electricity procurement cost and risk by a local distribution company. Energy Policy 2004; 32: 635-645.

[43] Woo CK, Horowitz I, Horii B, Karimov R. The efficient frontier for spot and forward purchases: an application to electricity. Journal of the Operational Research Society 2004; 55: 1130-1136.

[44] Woo CK, Horowitz I, Olson A, Horii B, Baskette C. Efficient frontiers for electricity procurement by an LDC with multiple purchase options. OMEGA 2006; 34: 70–80.

[45] Woo CK, Horowitz I, Toyama N, Olson A, Lai A, Wan R. Fundamental drivers of electricity prices in the Pacific Northwest. Advances in Quantitative Analysis of Finance and Accounting 2007; 5: 299–323.

[46] Woo CK, Ho ST, Leung HY, Zarnikau J, Cutter E. Virtual bidding, wind generation and California’s day-ahead electricity forward premium. The Electricity Journal 2015; 28(1): 29-48.

[47] Sreedharan P, Miller D, Price S, Woo CK. Avoided cost estimation and cost-effectiveness of permanent load shifting in California. Applied Energy 2012; 96: 115-121.

[48] Woo CK, Greening L (editors). Demand response resources. Energy 2010; 35(4): 1518-1614.

[49] Woo CK, Sreedharan P, Hargreaves J, Kahrl F, Wang J, Horowitz I. A review of electricity product differentiation. Applied Energy 2014; 114: 262-272.

[50] Borenstein S. The trouble with electricity markets: understanding California’s restructuring disaster. The Journal of Economic Perspectives 2002; 16(1): 191-211.

[51] Borenstein S, Bushnell JB, Wolak FA. Measuring market inefficiencies in California's restructured wholesale electricity market. American Economic

Review 2002; 92(5): 1376-1405.

[52] Woo CK. What went wrong in California's electricity market? Energy 2001; 26: 747-758.

[53] Tishler A, Milstein I, Woo CK. Capacity commitment and price volatility in a competitive electricity market. Energy Economics 2008; 30: 1625-1647.

[54] Milstein I, Tishler A. Can price volatility enhance market power? The case of renewable technologies in competitive electricity markets. Resource and Energy Economics 2015; 41: 70-90.

[55] Hoogwijk M, de Vries B, Turkenburg W. Assessment of the global and regional geographical, technical and economic potential of onshore wind energy. Energy Economics 2004; 26: 889-919.

[56] Lu X, McElroy MB, Kiviluoma J. Global potential for wind-generated electricity. Proceedings of National Academy of Sciences 2009; 106(27): 10933-10938.

[57] Marini S, Strada C, Villa M, Berrettoni M, Zerlia T. How solar energy and electrochemical technologies may help developing countries and the environment. Energy Conversion and Management 2014; 87: 1134-1140.

[58] Alagappan L, Orans R, Woo CK. What drives renewable energy development? Energy Policy 2011; 39: 5099-5104.

[59] Barroso LA, Rudnick H, Sensfuss F, Linares P. The green effect. IEEE Power and Energy Magazine 2010; 8(5): 22-35.

[60] Green R, Yatchew A. Support schemes for renewable energy: an economic analysis. Economics of Energy and Environmental Policy 2012; 1(2): 83-98.

[61] Haas R, Meyer NI, Held A, Finon D, Lorenzoni A, Wiser R, Nishio K. Promoting Electricity from Renewable Energy Sources – Lessons Learned

from the EU, U.S. and Japan. Berkeley, California: Lawrence Berkeley National Laboratory, 2008. Available at: http://escholarship.org/uc/item/17k9d82p (Accessed on 23 June, 2015).

[62] Palmer K, Burtraw D. Cost-effectiveness of renewable electricity policies. Energy Economics 2005; 27: 873-894.

[63] Schmalensee R. Renewable Electricity Generation in the United States. Cambridge, Massachusetts: MIT, 2009. Available at: http://dspace.mit.edu/bitstream/handle/1721.1/51715/2009–017.pdf?sequence1 (Accessed on 23 June, 2015)

[64] Woo CK, Chow LCH, Owen A (editors). Renewable energy policy and development. Energy Policy 2011; 39: 3883-4050.

[65] Yatchew A, Baziliauskas A. Ontario feed-in-tariff programs. Energy Policy 2011; 39: 3885–3893.

[66] Zarnikau, J. Successful renewable energy development in a competitive electricity market: a Texas case study. Energy Policy 2011; 39: 3906–3913.

[67] Sudeshna R, Jesper M, Poul EM, Anne-Franziska S, Pöyry AS. Wind Energy and Electricity Prices: Exploring the Merit Order Effect. Brussels, Belgium: European Wind Energy Association, 2010. Available at: http://www.ewea.org/fileadmin/ewea_documents/documents/publications/reports/MeritOrder.pdf (Accessed on 4 February, 2014)

[68] Cutler NJ, MacGill IF, Outhred HR, Boerema ND. High penetration wind generation impacts on spot prices in the Australian national electricity market. Energy Policy 2011; 39: 5939-5949.

[69] Gelabert L, Labandeira X, Linares P. An ex-post analysis of the effect of renewable and cogeneration on Spanish electricity prices. Energy Economics 2011; 22: 559-565.

[70] Gil HA, Gomez-Quiles C, Riquelme J. Large-scale wind power integration and wholesale electricity trading benefits: estimation via an ex post approach. Energy Policy 2012; 41: 849-859.

[71] Gil HA, Lin J. Wind power and electricity prices at the PJM market. IEEE Transactions on Power Systems 2013; 28: 3945-3953.

[72] Jacobsen HK, Zvingilaite E. Reducing the market impact of large shares of intermittent energy in Denmark. Energy Policy 2010; 38: 3403-3413.

[73] Ketterer JC. The impact of wind power generation on the electricity price in Germany. Energy Economics 2014; 44: 270-280.

[74] Morales J, Conejo A. Simulating the impact of wind production on locational marginal prices. IEEE Transactions on Power Systems 2011; 26(2): 820-828.

[75] Munksgaard J, Morthorst PE. Wind power in the Danish liberalised power market - policy measures, price impact, and investor incentives. Energy Policy 2008; 36: 3940-3947.

[76] Paraschiv F, Erni D, Pietsch R. The impact of renewable energies on EEX day-ahead electricity prices. Energy Policy 2014; 73: 196-210.

[77] Sensfuβ F, Ragwitz M, Genoese M. The merit-order effect: a detailed analysis of the price effect of renewable electricity generation on spot market prices in Germany. Energy Policy 2008; 36: 3086-3094.

[78] Woo CK, Zarnikau J, Moore J, Horowitz I. Wind generation and zonal-market price divergence: evidence from Texas. Energy Policy 2011; 39: 3928-3938.

[79] Woo CK, Ho T, Zarnikau J, Olson A, Jones R, Chait M, Horowitz I, Wang, J. Electricity-market price and nuclear power plant shutdown: evidence from California. Energy Policy 2014; 73: 234-244.

[80] Woo CK, Moore J, Schneiderman B, Ho T, Olson A, Alagappan L, Chawla K,

Toyama N, Zarnikau J. Merit-order effects of renewable energy and price divergence in California's day-ahead and real-time electricity markets. Energy Policy 2016; 92: 299-312.

[81] Woo CK, Horowitz I, Moore J, Pacheco A. The impact of wind generation on the electricity spot-market price level and variance: the Texas experience. Energy Policy 2011; 39: 3939-3944.

[82] Zarnikau J, Woo CK, Baldick R. Did the introduction of a nodal market structure impact wholesale electricity prices in the Texas (ERCOT) market? Journal of Regulatory Economics 2014; 45: 194-208.

[83] Woo CK, Zarnikau J, Kadish J, Horowitz I, Wang J, Olson A. The impact of wind generation on wholesale electricity prices in the hydro-rich Pacific Northwest. IEEE Transactions on Power Systems 2013; 28(4): 4245-4253.

[84] Woo CK, Moore J, Schneiderman B, Olson A, Jones R, Ho, T, Toyama N, Wang J, Zarnikau J. Merit-order effects of day-ahead wind generation forecast in the hydro-rich Pacific Northwest. The Electricity Journal 2015; 28(9): 52-62.

[85] Williams JH, DeBenedictis A, Ghanadan R, Mahone A, Moore J, Morrow WR, Price S, Torn MS. The technology path to deep greenhouse gas emissions cuts by 2050: the pivotal role of electricity. Science 2012; 335(6064): 53-59.

[86] Hasanbeigi A, Morrow W, Sathaye J, Masanet E, Xu T. A bottom-up model to estimate the energy efficiency improvement and CO_2 emission reduction potentials in the Chinese iron and steel industry. Energy 2013; 50: 315-325.

[87] Lin B, Moubarak M, Quyang X. Carbon dioxide emissions and growth of the manufacturing sector: evidence for China. Energy 2014; 76: 830-837.

[88] Li H, Wei Y. Is it possible for China to reduce its total CO_2 emissions? Energy 2015; 83: 438-446.

[89] Zhou W, Jian D, Chen D, Griffy-Brown C, Zhu B. Capturing CO_2 from cement plants: a priority for reducing CO_2 emissions in China. Energy 2016; 106: 464-474.

[90] Gui S, Mu H, Li N. Analysis of impact factors on China's CO_2 emissions from the view of supply chain paths. Energy 2014; 74: 405-416.

[91] Li H, Mu H, Zhang M, Gui S. Analysis of regional difference on impact factors of China’s energy – related CO_2 emissions. Energy 2012; 39: 319-326.

[92] Yang M, Fan Y, Yang F, Hu H. Regional disparities in carbon dioxide reduction from China's uniform carbon tax: a perspective on interfactor/interfuel substitution. Energy 2014; 74: 131-139.

[93] Chang K, Zhang C, Chang H. Emissions reduction allocation and economic welfare estimation through interregional emissions trading in China: evidence from efficiency and equity. Energy 2016; 113: 1125-1135.

[94] Pao H, Fu H, Tseng C. Forecasting of CO_2 emissions, energy consumption and economic growth in China using an improved grey model. Energy 2010; 40: 400-409.

[95] Jin H, Gao L, Han W, Hong H. Prospect options of CO_2 capture technology suitable for China. Energy 2010; 35: 4499-4506.

[96] Kaivo-oja J, Luukkanen J, Panula-Ontto J, Vehmas J, Auffermann B. Are structural change and modernisation leading to convergence in the CO_2 economy? Decomposition analysis of China, EU and USA. Energy 2014; 72: 115-125.

[97] Zou W, Zhu B, Chen D, Zhao F, Fei W. Technoeconomic assessment of China’s indirect coal liquefaction projects with different CO_2 capture alternatives. Energy 2011; 36: 6559-6566.

[98] You CF, Xu XC. Coal combustion and its pollution control in China. Energy 2010; 35: 4467-4472.

[99] Zhang N, Lior N, Jin H. The energy situation and its sustainable development strategy in China. Energy 2011; 36: 3639-3649.

[100] Cui X, Hong J, Gao M. Environmental impact assessment of three coal-based electricity generation scenarios in China. Energy 2012; 35: 952-959.

[101] Zhang H, Zhang B, Bi J. More efforts, more benefits: air pollutant control of coal-fired power plants in China. Energy 2015; 80: 1-9.

[102] Chang K, Chang H. Cutting CO_2 intensity targets of interprovincial emissions trading in China. Applied Energy 2016; 163: 211-221.

[103] Dai H, Mischke P, Xie X, Xie Y, Masui T. Closing the gap? Top-down versus bottom-up projections of China’s regional energy use and CO_2 emissions. Applied Energy 2016; 162: 1355-1373.

[104] Dai H, Xie X, Xie Y, Liu J, Masui T. Green growth: the economic impacts of large-scale renewable energy development in China. Applied Energy 2016; 162: 435-449.

[105] Huang W, Ma D, Chen W. Connecting water and energy: assessing the impacts of carbon and water constraints on China’s power sector. Applied Energy 2017; 185: 1497-1505.

[106] Jiang J, Xie D, Ye B, Shen B, Chen Z. Research on China’s cap-and-trade carbon emission trading scheme: overview and outlook. Applied Energy 2016; 178: 902-917.

[107] Li W, Jia Z. The impact of emission trading scheme and the ratio of free quota: a dynamic recursive CGE model in China. Applied Energy 2016; 174: 1-14.

[108] Li Y, Lukszo Z, Weijnen M. The implications of CO_2 price for China's power sector decarbonization. Applied Energy 2015; 146: 53-64.

[109] Li Y, Lukszo Z, Weijnen M. The impact of inter-regional transmission grid expansion on China's power sector decarbonization. Applied Energy 2016; 183: 853-873.

[110] Shan Y, Liu J, Liu Z, Xu X, Shao S, Wang P, Guan D. New provincial CO_2 emission inventories in China based on apparent energy consumption data and updated emission factors. Applied Energy 2016; 184: 742-750.

[111] Tang K, Yang L, Zhang J. Estimating the regional total factor efficiency and pollutants' marginal abatement costs in China: a parametric approach. Applied Energy 2016; 184: 230-240.

[112] Wu R, Dai H, Geng Y, Xie Y, Masui T, Tian X. Achieving China's INDC through carbon cap-and-trade: insights from Shanghai. Applied Energy 2016; 184: 1114-1122.

[113] Zhang YJ, Hao JF, Song J. The CO_2 emission efficiency, reduction potential and spatial clustering in China's industry: evidence from the regional level. Applied Energy 2016; 174: 213-223.

[114] Woo CK, Ho T, Shiu A, Cheng YS, Horowitz I, Wang J. Residential outage cost estimation: Hong Kong. Energy Policy 2014; 72: 204-210.

[115] Ma T, Ø stergaard PA, Lund H, Yang H, Lu L. An energy system model for Hong Kong in 2020. Energy 2014; 65: 301-310.

[116] Woo CK, Shiu A, Cheng YS, Li R, Ho T, Horowitz I, Wang J. Residential willingness-to-pay for reducing coal-fired generation's emissions in Hong

Kong. Electricity Journal 2014; 27(3): 50-66.

[117] Cheng YS, Cao KH, Woo CK, Yatchew A. Residential willingness to pay for deep decarbonization of electricity supply: contingent valuation evidence from Hong Kong. Energy Policy 2017; 109: 218-227.

[118] HKSAR Government. Planning Ahead for a Better Fuel Mix – Future Fuel Mix for Electricity Generation. Hong Kong, 2014. Available at: http://www.gov.hk/en/residents/government/publication/consultation/archives.htm (Accessed on 20 November, 2016)

[119] HKSAR Government. Public Consultation on the Future Development of the Electricity Market. Hong Kong, 2015. Available at: http://www.gov.hk/en/residents/government/publication/consultation/archives.htm (Accessed on 20 November, 2016)

[120] Lam JC. Climatic and economic influences on residential electricity consumption. Energy Conversion and Management 1998; 39: 623-629.

[121] To WM, Lai TM, Lo WC, Lam KH, Chung WL. The growth pattern and fuel life cycle analysis of the electricity consumption of Hong Kong. Environmental Pollution 2012; 165: 1-10.

[122] Lai TM, To WM, Lam KH, Lo WC, Chung WL. Electricity consumption in Hong Kong: trend analysis and greenhouse gases emission. HKIE Transactions 2014; 21(2): 81-88.

[123] Tso GFK, Yau KKW. A study of domestic energy usage patterns in Hong Kong. Energy 2003; 28: 1671-1682.

[124] Woo CK, Horowitz I, Horii B, Orans R, Zarnikau J. Blowing in the wind: vanishing payoffs of a tolling agreement for natural-gas-fired generation of electricity in Texas. The Energy Journal 2012; 33(1): 207-229.

[125] Woo CK, Ho T, Zarnikau J, Olson A, Jones R, Chait M, Horowitz I, Wang J.

This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

Electricity-market price and nuclear power plant shutdown: evidence from California. Energy Policy 2014; 73: 234-244.

[126] Woo CK, Horowitz I, Zarnikau J, Moore J, Schneiderman B, Ho T, Leung E. What moves the ex post variable profit of natural-gas-fired generation in California? Energy Journal 2016; 37(3): 29-57.

[127] Milstein I, Tishler A. Intermittently renewable energy, optimal capacity mix and prices in a deregulated electricity market. Energy Policy 2011; 39(7): 3922-3927.

[128] Lam JC. Residential sector air conditioning loads and electricity use in Hong Kong. Energy Conversion and Management 2000; 41: 1757-1768.

[129] Bojic M, Yik F, Sat P. Energy performance of windows in high-rise residential buildings in Hong Kong. Energy and Buildings 2002; 34: 71-82.

[130] Fung WY, Lam KS, Hung WT, Pang SW, Lee YL. Impact of urban temperature on energy consumption of Hong Kong. Energy 2006; 31: 2623-2637.

[131] Lam JC, Tang HL, Li DHW. Seasonal variations in residential and commercial sector electricity consumption in Hong Kong. Energy 2008; 33: 513-523.

[132] Cheung CT, Mui KW, Wong LT, Yang KC. Electricity energy trends in Hong Kong residential housing environment. Indoor and Built Environment 2014; 23(7): 1021-1028.

[133] Auffhammer M, Mansur ET. Measuring climatic impacts on energy consumption: a review of the empirical literature. Energy Economics 2014; 46: 522-530.

[134] Hartman RS. Frontiers in energy demand modeling. Annual Review of Energy 1979; 4: 433-466.

[135] Bohi D, Zimmerman ME. An update on econometric studies of energy demand behavior. Annual Review of Energy 1984; 9: 105-154.

[136] Al-Sahlawi MA. The demand for natural gas: a survey of price and income elasticities. The Energy Journal 1989; 10(1): 77-90.

[137] Berndt ER. The practice of econometrics: structural and time series approaches. Boston, Massachusetts: Addison Wesley; 1991, chapter 7.

[138] Dahl C. A Survey of Energy Demand Elasticities in Support of the Development of the NEMS. MPRA Paper No. 13962; 1993.

[139] Dahl C, Roman C. Energy Demand Elasticities – Fact or Fiction: A Survey. Golden, Colorado: Colorado School of Mines; 2004.

[140] Espey JA, Espey M. Turning on the lights: a meta-analysis of residential electricity demand elasticities. Journal of Agricultural and Applied Economics 2004; 36: 65-81.

[141] Suganthia L, Samuel AA. Energy models for demand forecasting - a review. Renewable and Sustainable Energy Reviews 2012; 16(2): 1223-1240.

[142] Deaton A, Muellbauer J. Economics and Consumer Behavior. Cambridge, Massachusetts: Cambridge University Press; 1980.

[143] Hausman JA. Exact consumer's surplus and deadweight loss. The American Economic Review 1981; 71(4): 662-676.

[144] Woo CK, Zarnikau J, Kollman E. Exact welfare measurement for double-log demand with partial adjustment. Empirical Economics 2012; 42(1): 171-180.

[145] Joskow PL, Wolfram CD. Dynamic pricing of electricity. The American Economic Review 2012; 102(3): 381-385.

[146] Faruqui A, Malko JR. The residential demand for electricity by time-of-use: a survey of twelve experiments with peak load pricing. Energy 1983; 8(10): 781-796.

[147] Aigner DJ. The welfare econometrics of peak load pricing for electricity. Journal of Econometrics 1984; 26(1-2): 1-15.

[148] Aigner DJ. The Residential Electricity Time-of-Use Pricing Experiments: What Have We Learned? In: Hausman JA, Wise DA, editors. Social experimentation, Chicago, Illinois: University of Chicago Press; 1985.

[149] DOE. Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them: A Report to the United States Congress Pursuant to Section 1253 of the Energy Policy Act of 2005. Washington D.C.: Department of Energy; 2006.

[150] FERC. Assessment of Demand Response & Advanced Metering. Washington D.C.: Federal Energy Regulatory Commission; 2008.

[151] Newsham GR, Bowker BG. The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: a review. Energy Policy 2010; 38: 3289-3296.

[152] Faruqui A, Sergici S. Household response to dynamic pricing of electricity: a survey of 15 experiments. Journal of Regulatory Economics 2010; 38(2): 193-225.

[153] Faruqui A, Palmer J. The Discovery of Price Responsiveness - A Survey of Experiments Involving Dynamic Pricing of Electricity. San Francisco, California: Brattle Group; 2012.

[154] Aigner DJ, Hausman JA. Correcting for truncation bias in the analysis of experiments in time-of-day pricing of electricity. The Bell Journal of Economics 1980; 11(1): 131-142.

[155] Aigner DJ, Ghali K. Self-selection in the residential electricity time-of-use pricing experiments. Journal of Applied Econometrics 1989; 4(S1): 131-144.

[156] Train K, Mehrez G. Optional time-of-use prices for electricity: econometric analysis of surplus and Pareto impacts. The Rand Journal of Economics 1994; 25(2): 263-283.

[157] Caves DW, Christensen LR, Herriges JA. Consistency of residential customer response in time-of-use electricity pricing experiments. Journal of Econometrics 1984; 26(1-2): 179-203.

[158] Woo CK, Li R, Shiu A, Horowitz I. Residential winter kWh responsiveness under optional time-varying pricing in British Columbia. Applied Energy 2013; 108: 288-297.

[159] Christensen LR, Jorgenson DW, Lau LJ. Transcendental logarithmic utility functions. The American Economic Review 1975; 65(3): 367-383.

[160] Diewert WE. An application of the Shephard duality theorem: a Generalized Leontief production function. Journal of Political Economy 1971; 79(3): 481-507.

[161] Parks RW, Weitzel D. Measuring the consumer welfare effects of time-differentiated electricity prices. Journal of Econometrics 1984; 26(1-2): 35-64.

[162] Caves DW, Christensen LR, Herriges JA. The neoclassical model of consumer demand with identically priced commodities: an application to time-of-use electricity pricing. The Rand Journal of Economics 1987; 18(4): 564-580.

[163] Woo CK, Zarnikau J, Shiu A, Li R. Winter residential optional dynamic pricing: British Columbia, Canada. Energy Journal 2017; 38(5): 99-111.

[164] Varian H. Microeconomics Analysis. New York: Norton; 1992.

[165] Woo CK. Demand for electricity of small nonresidential customers under time-of-use pricing. The Energy Journal 1985; 6(4): 115-127.

[166] Tishler A, Lipovesky S. The flexible CES-GBC family of cost functions: derivation and application. Review of Economics and Statistics 1997; 79(4): 638-646.

[167] Zarnikau J. Functional forms in energy demand modeling. Energy Economics 2003; 25(6): 603-613.

[168] Xiao N, Zarnikau J, Damien P. Testing functional forms in energy modeling: an application of the Bayesian approach to US electricity demand. Energy Economics 2007; 29(2): 158-166.

[169] Zarnikau J, Hallett I. Aggregate industrial energy consumer response to wholesale prices in the restructured Texas electricity market. Energy Economics 2008; 30(4): 1798-1808.

[170] Fisher FM, Fox-Penner PS, Greenwood JE, Moss WG, Phillips A. Due diligence and the demand for electricity: a cautionary tale. Review of Industrial Organization 1992; 7(2): 117-149.

[171] Wade SH. Price Responsiveness in the AEO2003 NEMS Residential and Commercial Building Sector Models. Washington D.C.: Department of Energy; 2003.

[172] Orans R. Direct Testimony, 2008 Long Term Acquisition Plan, Appendix E. Vancouver, British Columbia: B.C. Hydro; 2008.

[173] Azevedo I, Morgan MG, Lave L. Residential and regional electricity consumption in the U.S. and EU: how much will higher prices reduce CO_2 emissions? Electricity Journal 2011; 24(1): 21-29.

This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

[174] Ito K. Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing. The American Economic Review 2014; 104(2): 537-563.

[175] Reiss PC, White MW. Household electricity demand, revisited. The Review of Economic Studies 2005; 72: 853-883.

[176] Davidson R, MacKinnon JG. Estimation and Inference in Econometrics. Oxford: Oxford University Press; 1993.

[177] SAS. SAS/ETS® 9.1 User's Guide. Cary, North Carolina: SAS Institute; 2004.

[178] Phillips PCB, Perron P. Testing for a unit root in time series regression. Biometrika 1988; 75: 335-346.

[179] Wooldridge JM. Econometric Analysis of Cross Section and Panel Data. Cambridge, Massachusetts: MIT Press; 2010.

[180] Allaz B, Vila J. Cournot competition, forward markets and efficiency. Journal of Economic Theory 1993; 59(1): 1-16.

[181] Woo CK, King M, Tishler A, Chow LCH. Costs of electricity deregulation. Energy 2006; 31: 747-768.

[182] Woo CK, Cheng YS, Law A, Zarnikau J, Ho ST, Leung HY. Consumer support for a public utilities commission in Hong Kong. Energy Policy 2015; 76: 87-97.

This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

Nomenclature

FIT	Feed-in-tariff
CES	Constant-elasticity-of-substitution
HKCGC	Hong Kong China Gas Company
HEC	Hong Kong Electric
CLP	China Light Power
CDM	Cooling degree month
HDM	Heating degree month
DGP	Data generation process
TOU	Time-of-use
GL	Generalized Leontief
Quarterly Report	Hong Kong Energy Statistics Quarterly Report
Annual Report	Hong Kong Energy Statistics Annual Report
STEPAR	Stepwise autoregressive
PP test	Phillips-Perron test
SUR	Seemingly unrelated regressions
ITSUR method	Iterative SUR method
HKI	Hong Kong Island
KNT	Kowloon and New Territory

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

Table 1

Descriptive statistics for Hong Kong energy data; sample period = Jan-1981 – Dec-2016.

Panel A: Raw data series

Data type	Variable (unit)	Stationary at 5% level?	Mean (M)	Standard deviation (SD)	Coefficient of variation = SD / M	Minimum	Maximum
Residential consumption	Electricity X_1 (MWh)	Yes	650180.68	351169.55	0.54	151666.67	1647777.78
	Town Gas Y_1 (GJ)	Yes	930412.04	425378.83	0.46	137000.00	1898000.00
Commercial consumption	Electricity X_2 (MWh)	No	1583121.14	730083.00	0.46	307222.22	2972500.00
	Town Gas Y_2 (GJ)	No	735918.98	269516.87	0.37	135000.00	1117000.00
Industrial consumption	Electricity X_3 (MWh)	No	397484.57	121791.60	0.31	191944.44	688611.11
	Town Gas Y_3 (GJ)	No	70851.85	32876.78	0.46	14000.00	152000.00
Actual residential price	Electricity ($/MWh)	No	821.97	230.43	0.28	552.71	1358.35
	Town Gas ($/GJ)	No	183.39	64.69	0.35	86.70	301.35
Actual commercial price	Electricity ($/MWh)	No	821.50	202.67	0.25	539.71	1146.40
	Town Gas ($/GJ)	No	183.39	64.69	0.35	86.70	301.35
Actual industrial price	Electricity ($/MWh)	No	794.85	189.63	0.24	525.45	1104.17
	Town Gas ($/GJ)	No	183.39	64.69	0.35	86.70	301.35
Predicted residential price	Electricity E_1 ($/MWh)	No	821.55	228.69	0.28	449.58	1355.37
	Town Gas G_1 ($/GJ)	No	183.50	64.62	0.35	75.40	300.31
Predicted commercial price	Electricity E_2 ($/MWh)	No	821.62	202.53	0.25	480.20	1147.73
	Town Gas G_2 ($/GJ)	No	183.50	64.62	0.35	75.40	300.31
Predicted industrial	Electricity E_3 ($/MWh)	No	794.92	189.45	0.24	482.61	1105.64

This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

price	Town Gas G_3 ($/GJ)	No	183.50	64.62	0.35	75.40	300.31
Weather	Cooling degree days CDM	Yes	7.92	4.77	0.60	0.00	16.40
	Heating degree days HDM	Yes	0.79	1.42	1.80	0.00	6.70
Gross Domestic Product	Real GDP ($M)	Yes	135681.57	42867.26	0.32	53592.51	221349.77

Panel B: Constructed data series used in the estimation

Data type	Variable	Stationary at 5% level?	Mean (M)	Standard deviation (SD)	Coefficient of variation = SD / M	Minimum	Maximum
First-differenced natural log of energy consumption ratio	$\Delta\ln(X_1/Y_1)$	Yes	-0.0017	0.2902	-170.7059	-1.2741	0.6750
	$\Delta\ln(X_2/Y_2)$	Yes	0.0001	0.1193	1193.0000	-0.2685	0.3083
	$\Delta\ln(X_3/Y_3)$	Yes	-0.0042	0.1113	-26.5000	-0.3567	0.4990
First-differenced natural log of predicted energy price ratio	$\Delta\ln(E_1/G_1)$	Yes	-0.0002	0.0298	-149.0000	-0.2635	0.2288
	$\Delta\ln(E_2/G_2)$	Yes	-0.0008	0.0242	-30.2500	-0.1378	0.1589
	$\Delta\ln(E_3/G_3)$	Yes	-0.0009	0.0235	-26.1111	-0.1430	0.1584
First-differenced natural log of GDP	$\Delta\ln(\text{GDP})$	Yes	0.0030	0.0624	20.8000	-0.1272	0.1840
First-differenced weather variables	ΔCDM	Yes	0.0065	2.7219	418.7538	-7.1000	7.4000
	ΔHDM	Yes	-0.0079	1.3101	-165.8354	-6.5000	4.8000

This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

Table 2

Correlation coefficients for the constructed data series used in the estimation; sample period = Jan-1981 – Dec-2016.

Variable	First-differenced natural log of predicted energy price ratio			First-differenced natural log of GDP	First-differenced weather variables	
	Residential: $\Delta\ln(E_1/G_1)$	Commercial: $\Delta\ln(E_2/G_2)$	Industrial: $\Delta\ln(E_3/G_3)$	$\Delta\ln(GDP)$	ΔCDM	ΔHDM
$\Delta\ln(X_1/Y_1)$	0.03	-0.03	-0.01	0.20	0.67	-0.13
$\Delta\ln(X_2/Y_2)$	0.02	-0.05	0.00	0.46	0.73	-0.40
$\Delta\ln(X_3/Y_3)$	0.01	-0.03	-0.01	0.43	0.47	-0.34

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

Table 3

ITSUR regression results for the CES system; sample period = Jan-1981 – Dec-2016; adjusted R^2 in [ ]; clustered autocorrelation-heteroscedasticity-consistent standard errors in ( ); "***" = 1% significance, "**" = 5% significance, "*" = 10% significance.

Variable	Residential class: j = 1 [0.7888]	Commercial class: j = 2 [0.7769]	Industrial class: j = 3 [0.4267]
$\Delta\ln(E_j/G_j)$	-0.0861 (0.1944)	-0.2178* (0.1162)	-0.2400 (0.1983)
$\Delta\ln(\text{GDP})$	1.6455*** (0.2994)	0.3373** (0.1684)	0.0245 (0.2430)
ΔCDM	0.0288*** (0.0065)	0.0136*** (0.0028)	0.0022 (0.0039)
ΔHDM	0.0399*** (0.0085)	0.0047 (0.0044)	-0.0215*** (0.0063)

Note: For brevity, this table omits the estimates for the intercepts and coefficients of the binary indicators for months.

This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

Table 4

Own-price elasticity estimates based on ITSUR regression results; sample period = Jan-1981 – Dec-2016; standard errors in ( ); "***" = 1% significance, "**" = 5% significance, "*" = 10% significance.

Energy type	Residential	Commercial	Industrial	Aggregate
Electricity	-0.0214 (0.0482)	-0.0207* (0.0110)	-0.0113 (0.0093)	-0.0194 (0.0150)
Town gas	-0.0648 (0.1462)	-0.1972* (0.1052)	-0.2287 (0.1890)	-0.1275 (0.0985)

Note: The cross-price elasticity estimates are not shown here because the sum of the own price and cross price elasticity estimates is equal to zero, see Appendix C. The aggregate elasticity is the weighted average of the class-specific estimates, with each weight equal to the class-specific consumption share.

This is the pre-published version published in Energy, available online at: https://doi.org/10.1016/j.energy.2017.12.074.

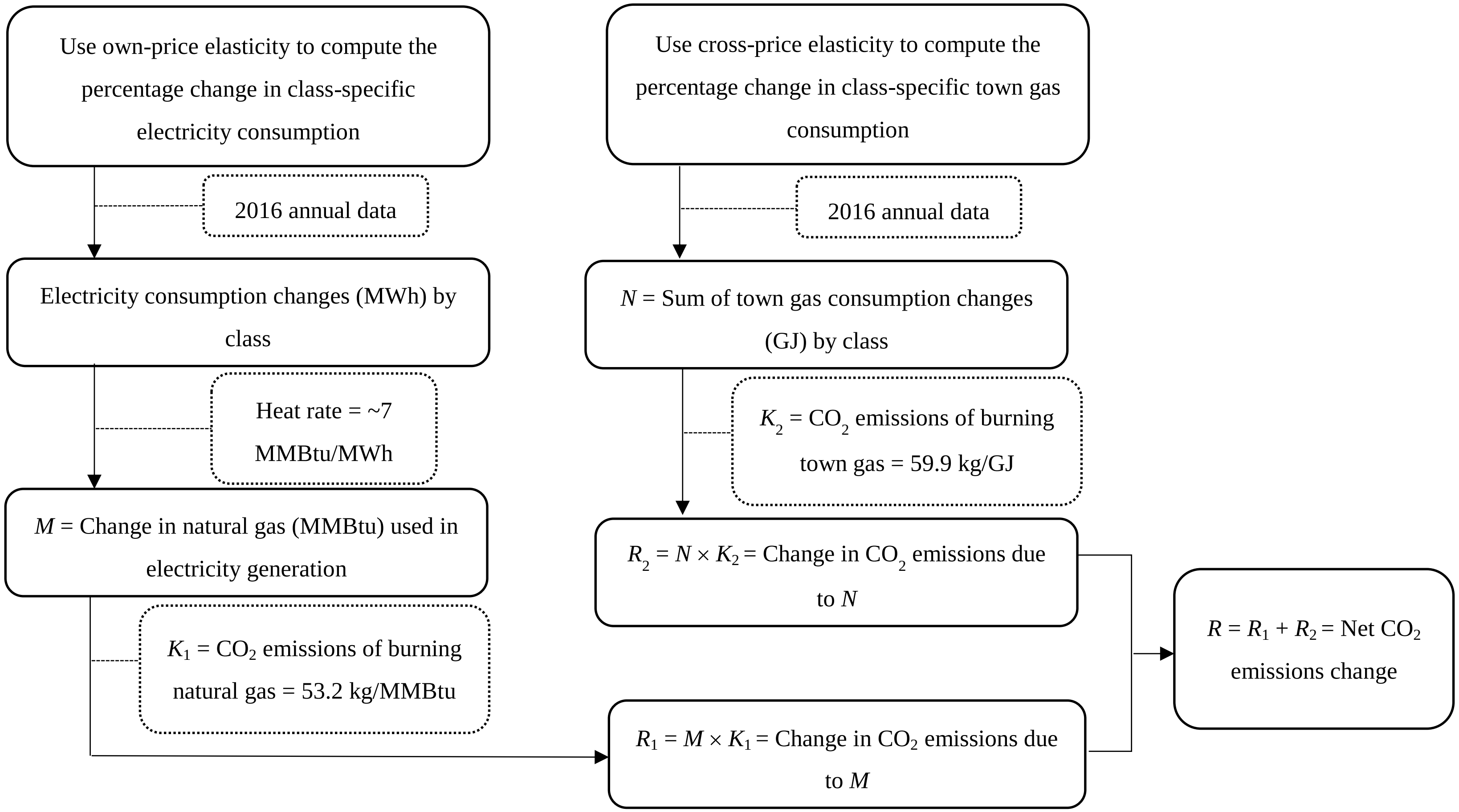

Fig. 1. Assessment of the net change in CO_2 emissions due to the projected 40% electricity rate increase triggered by Hong Kong's electricity decarbonization policy

This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

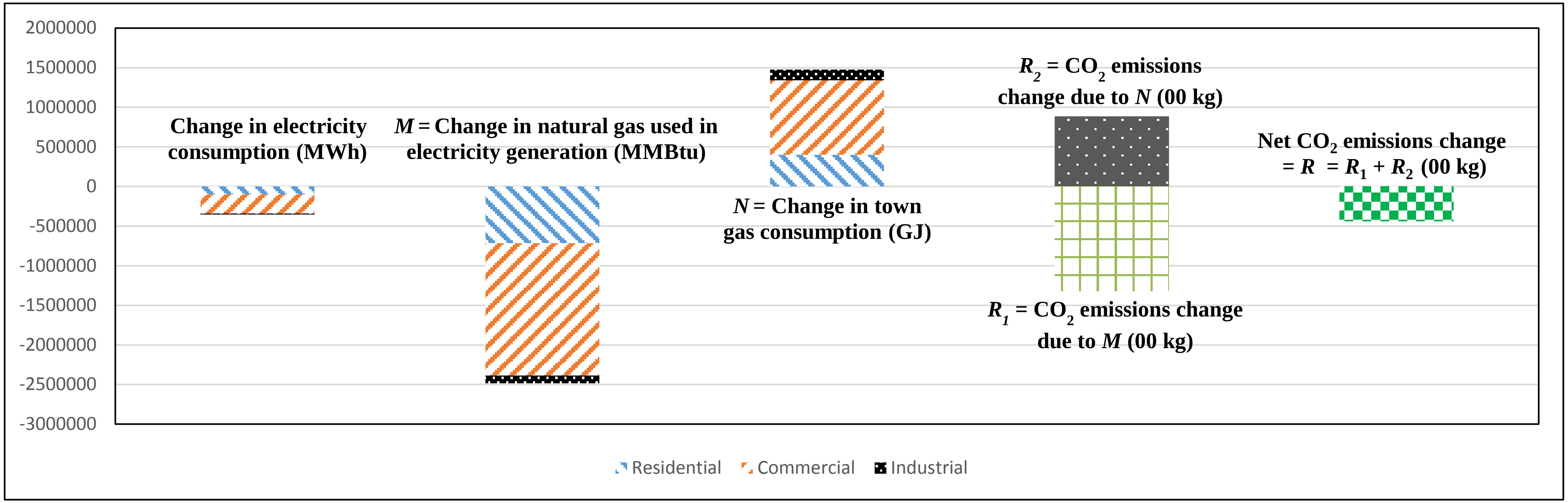

Fig. 2. The net change in CO_2 emissions due to the 40% electricity price increase based on the annual consumption data in 2016 under the expected price responsiveness scenario.

Note: Using the CO_2 content information available at https://www.eia.gov/tools/faqs/faq.php?id=73&t=11, this figure's construction is as follows. Let M_j = change in natural gas usage (MMBtu) in electricity generation = CCGT's heat rate of ~7 MMBtu / MWh × MWh change in customer class j's price-induced electricity consumption decline (= class j's own-price elasticity estimate for electricity × 40% × class j's annual MWh consumption in 2016). The total change in electricity generation's natural gas usage is $M = M_1 + M_2 + M_3$. The CO_2 emissions change due to M is $R_1 = M \times K_1$ where K_1 = CO_2 emissions of burning natural gas = 53.2 kg / MMBtu. Let N_j = class j's change in town gas consumption (GJ) = class j's cross-price elasticity estimate for town gas × 40% × class j's annual GJ consumption in 2016. The total change in town gas consumption is $N = N_1 + N_2 + N_3$. The CO_2 emissions change due to N is $R_2 = N \times K_2$ where K_2 = CO_2 emissions of burning town gas = 59.9 kg / GJ based on the information available at https://www.towngas.com/en/Social-Responsibility/Environmental-Protection/Carbon-Management. Finally, the net CO_2 emissions change is $R = R_1 + R_2$.

This is the pre-published version published in Energy, available online at:
https://doi.org/10.1016/j.energy.2017.12.074.

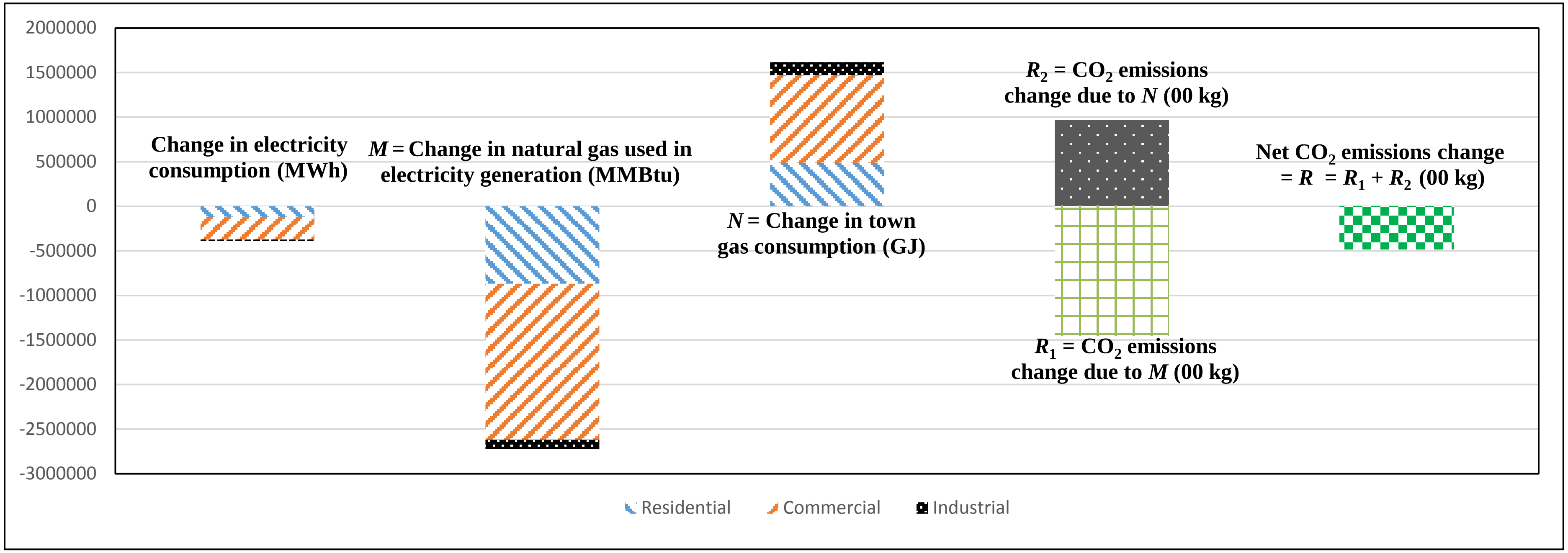

Fig. 3. The net change in CO_2 emissions due to the 40% electricity price increase based on the annual consumption data in 2016 under the higher-than-expected price responsiveness scenario.

Note: This figure's construction is the same as Fig.2's.