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Impacts of shifting China's final energy consumption to electricity on CO_2 emission reduction

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Abstract

Electrification is advocated by both academics and the Chinese government to control air pollution and promote productivity. However, the problem remains to be solved of how to achieve the trade-off between reducing CO_2 emissions and maintaining economic growth when switching from various fuels to electricity under the policy support. In view of this, after analyzing the effects of exogenous shocks in various fuel demands based on impulse response functions of several vector autoregression models, this paper measures the current and long-term impacts of electrification on GDP and CO_2 emissions. Finally, some typical cases of replacement of fossil-fueled appliances by electrical counterparts encouraged by the government are assessed. The main findings are: (1) Almost all of the exogenous shocks in fuel

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demands have positive effects on both GDP and CO_2 emissions, while the gas shock has a slightly negative effect on GDP; (2) Carbon intensity decreases and even CO_2 emission reductions with increased GDP are potentially achieved, in both current and permanent periods, for coal-electricity and oil-electricity switching, while gas-electricity switching is not a wise choice in view of CO_2 emission reduction in the long run; (3) The alternative electric appliances for electrification have very different impacts on CO_2 emission reduction.

Keywords**:** Fuel-switching; Inter-fuel substitution; Electrification; CO_2 emissions; Economic growth.

1. Introduction

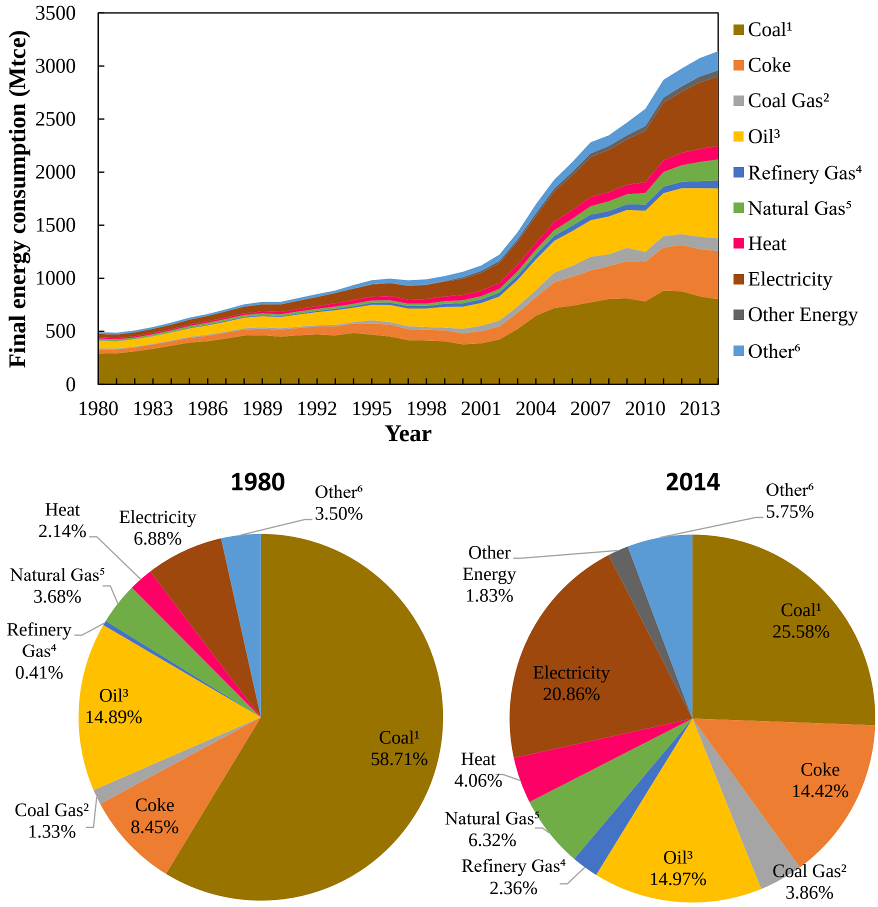
As a highly ordered form of energy with low entropy, electricity can be converted to useful work to a large extent. Electrical equipment and appliances tend to have significant efficiency advantages compared with their conventional counterparts fueled by fossil fuels, even accounting for efficiency losses in the delivery of electric power (Gellings and Yau, 1991). Electricity's high-energy density and precise control offer industries fast throughput, which reduces unit costs by spreading the costs of production factors over a larger production volume (Collard et al., 2004; Gellings, 2011). In addition, electricity is clean at the point of use, since its use involves no fumes or residues. Because of these efficiency and environmental reasons, electrification is an important fuel-switching measure to promote productivity and control air pollution.

As the largest energy consumer in the world, China[2] faces serious air pollution problems, such as smog appearing in many cities—mainly caused by coal burning and exhaust emissions of motor vehicles—while industrialization and urbanization are still rapidly advancing in the country. Although the share of electricity in final energy consumption has risen steadily, from 6.88% in 1980 to 20.86% in 2014, there is still considerable direct combustion of fossil fuels, especially coal products, in China (see Fig. 1). To reduce reliance on fossil fuels in end-use, the Chinese government has introduced a series of measures in some policy documents for the purpose of

[2] China specifically refers to the Chinese Mainland in this paper.

encouraging electrification; these measures include increasing the proportion of coal for electricity generation (National Development and Reform Commission, 2004), accelerating railway electrification (National Development and Reform Commission et al., 2006), and incentivizing new energy vehicle (NEV[3]) adoption (The State Council, 2012). Following the state-owned State Grid, the largest electric utility in the world, which has actively promoted the substitution of electricity for fossil fuels since 2013 (State Grid, 2013), the Chinese government has provided comprehensive policy support for this substitution since 2016. The support covers numerous fields, such as residential heating, transportation, and industrial and agricultural production (National Development and Reform Commission, 2016a).

[3] Here, NEVs largely include all-electric vehicles, plug-in hybrid electric vehicles, and fuel-cell vehicles.



1. Includes raw coal, washed coal and briquettes.
2. Includes coke oven gas, blast furnace gas, converter gas, etc.
3. Includes crude oil, gasoline, kerosene, diesel oil and fuel oil.
4. Includes LPG and other refinery gas.
5. Includes LNG and other natural gas.
6. Includes naphtha, lubricants, paraffin waxes, white spirit, bitumen asphalt and petroleum coke, which are primarily used for non-energy purposes.

Fig. 1. China total final consumption (TFC) from 1980 to 2014 by fuel, and fuel shares in 1980 and 2014 (Mtce: million tonnes of coal equivalent). Data source: China Energy Statistical Yearbook.

However, despite its efficiency and cleanliness, China's electricity is mainly from fossil fuels, which accounted for 74.82% of electricity generation in 2014 according to the World Development Indicators (WDI) databank. Especially, coal accounted for 72.63%. Even if the Chinese government's 2020 renewable electricity generation target of 27% of electricity generation from renewable sources (National Development and Reform Commission, 2016b) is achieved, the dominance of fossil fuel power will not be changed. Thus, the potential impacts on CO_2 emissions of fuel-switching for electrification are unclear, as yet. Meanwhile, global awareness of the issue of global warming is increasing, and China has committed to reducing greenhouse gas emissions to tackle this issue (Wang et al., 2016; Zhao et al., 2016). Several legal instruments have been successively ratified within the United Nations Framework Convention on Climate Change (UNFCCC); these include the Kyoto Protocol in 1997, the Doha Amendment to the Kyoto Protocol in 2012, and the Paris Agreement in 2015. Although the efficiency advantages of much electrical equipment and appliances may save primary energy and hence reduce emissions, not all appliances have these advantages. Furthermore, fuel-switching activity may indirectly set off a chain reaction of substitution and compensation between fuels, and even other production factors, which is often accompanied by industrial structural effects (Pereira and Pereira, 2010; Steenhof, 2006). This will have a dynamic effect on future economic growth and energy use and further affect either the carbon intensity or the absolute amount of CO_2 emissions. Thus, the dynamic effect on future CO_2 emission reduction of shifting final energy consumption to electricity is still a core issue for policy analysis.

Nevertheless, energy plays an important role in the national economy and drives almost all the socio-economic activities (Jr. et al., 2013; Lin et al., 2016; Tang et al., 2017). As key economic sectors, the energy sectors also contribute a large part of the overall economy. Due to its heavy dependence on energy, China would be profoundly affected by changes in the final energy consumption mix, especially when the changes involve electricity, which is very important for both the national economy and the livelihoods of the population (Yuan et al., 2008; Zhao et al., 2014). Accordingly, in addition to CO_2 emissions, the effects on economic growth of changes in each type of fuel demand and their being shifted to electricity should be assessed. After all, we do not want to reduce emissions at the expense of the economy. To sum up, this study aims to address the following specific questions:

(1) How do changes in each type of fuel demand dynamically affect GDP and CO_2 emissions in the future?

(2) What are the ideal fuel-switching states for electrification to achieve the trade-off between CO_2 emission reduction and economic growth maintenance?

(3) Can the current fuel-switching policies for electrification not only reduce CO_2 emissions but also maintain economic growth?

The main contribution to answering these three questions is reflected in several aspects: providing a quantitative decision-making foundation to promote switching from various non-electric fuels to electricity; helping to correct the economic forecasts, taking account of electrification policies; and calling on the climate change community to pay attention to the impacts of electrification policies on CO_2 emissions, even if these policies have some obvious advantages in controlling conventional air pollution, such as smog.

Since electrification is a kind of fuel-switching, we have reviewed the literature on impacts of fuel-switching, and we have found that the current studies mainly focus on two categories.

The first category regards fuel-switching as a factor influencing CO_2 emissions and measures its contribution by either index decomposition analysis (IDA) or econometric models. (Freitas and Kaneko, 2011) focuses on energy switching in Brazil, and the results from logarithmic mean Divisia index (LMDI) indicate that the transformation of the energy mix to cleaner sources is one of the main factors contributing to emissions' reduction. (Yuan et al., 2015) employs a new structural decomposition analysis (SDA) model to study indirect CO_2 emissions from residential consumption in China and points out that transformation of the consumption ratio reduces indirect emissions in all regions. (Özbuğday and Erbas, 2015) uses a linear heterogeneous panel data model that involves the share of renewable energy consumption in total energy consumption, and the results demonstrate that substituting renewable energy for non-renewable energy reduces CO_2 emissions in the long-run.

The second category employs accounting methods to investigate the benefits of substitution between two certain fuels. (Hayhoe et al., 2002) considers the changes in emissions of CO_2, CH_4, SO_2, and BC (black carbon) resulting from the substitution of natural gas for coal to evaluate the effects on global climate change, and concludes that higher temperatures will be produced initially, followed by a net decrease due to various contributions of these emissions in different periods. (Fuchigami et al., 2016) investigates the CO_2 emission reduction benefit of bio-coke, which is used as an alternative fuel for coal-coke.

Clearly, almost all the above-mentioned studies on the impacts of fuel-switching are from the standpoint of air pollution control and climate change mitigation, while ignoring the aggregate economic costs. In view of the importance of energy consumption and its mix for economic development, (Pereira and Pereira, 2010) uses some vector autoregressive (VAR) models and the corresponding impulse-response functions to estimate the long-term macroeconomic costs due to the reduction of each disaggregated final fuel demand and then evaluates the fuel-switching policy–induced abatement costs for CO_2 emissions. In fact, depending on the dynamic interaction and feedback mechanism among the considered variables, VAR can quantitatively estimate the long-term effects of fuel-switching on the economic growth and CO_2 emissions through simulating the aforementioned chain reaction of substitution and compensation between production factors. These long-term effect measurements provide more comprehensive policy-making information, rather than only focusing on the current effects of a fuel-switching policy. In view of this, this study also adopts VAR models to quantitatively estimate the impacts of switching from non-electric fuels to electricity. In addition, to fully estimate the changes in CO_2 emissions, this study includes the variable of CO_2 emissions into the VAR models to capture both the direct and indirect channels through which the production factors affect CO_2 emissions.

The rest of this paper is organized as follows: Section 2 describes the dataset used in this study, along with the data sources; Section 3 illustrates the model establishing process and the calculation methods of impact measurements; Section 4 presents the empirical results and discussions; and, finally, Section 5 concludes the paper and provides some policy implications.

2. Data description

This section describes the dataset used for model identifications and estimations in Section 3. Depending on the data availability, the required dataset includes annual observations of gross output, capital investment, and employment, as well as disaggregated final energy consumption and fossil-fuel carbon dioxide emissions from 1980 to 2014 in China. Gross output is represented by real GDP (1980 constant price), from the National Bureau of Statistics of China, while fossil-fuel CO_2 emission data are from the International Energy Agency (IEA).

Data on disaggregated final energy consumption are collected from the China Energy Statistical Yearbook, as shown in Fig. 1. In view of the characteristics of substitution between different types of final energy consumption, we follow (Pereira and Pereira, 2010), in which coke is merged into coal, while gas includes various coal gases, refinery gases, and natural gases. As heating is regarded as a final consumption process, according to energy balance tables, heat is reversely assigned to corresponding fuels which generate it. Since the data on other energy are incomplete and “other” (see

Fig. 1) is primarily used for non-energy purposes, neither other energy nor "other" is considered in this study. In other words, the disaggregated final energy consumption includes coal, oil, gas, and electricity in this paper.

Since the employment data from the National Bureau of Statistics of China exhibit an abnormal jump before and after 1989 due to the adjustment of statistical caliber, the labor force figures and the ratio of unemployment from WDI are collected, and the employment is calculated according to these. Capital investment is represented by gross capital formation at 1980 constant price, which are also calculated from related data of WDI.

The collected data on capital investment, labor (employment), GDP, and fossil-fuel CO_2 emissions are shown in Fig. 2. Like the energy consumption shown in Fig. 1, these variables increase considerably over the studied period. For the sake of brevity, unless otherwise specified, I, L, Y, and FC represent capital investment, labor, GDP, and fossil-fuel CO_2 emissions, respectively, in this paper, while C, O, G, and E represent the consumption of coal, oil, gas, and electricity, respectively. For instance, $\ln Y_t$ is just the GDP in log-level at time t.

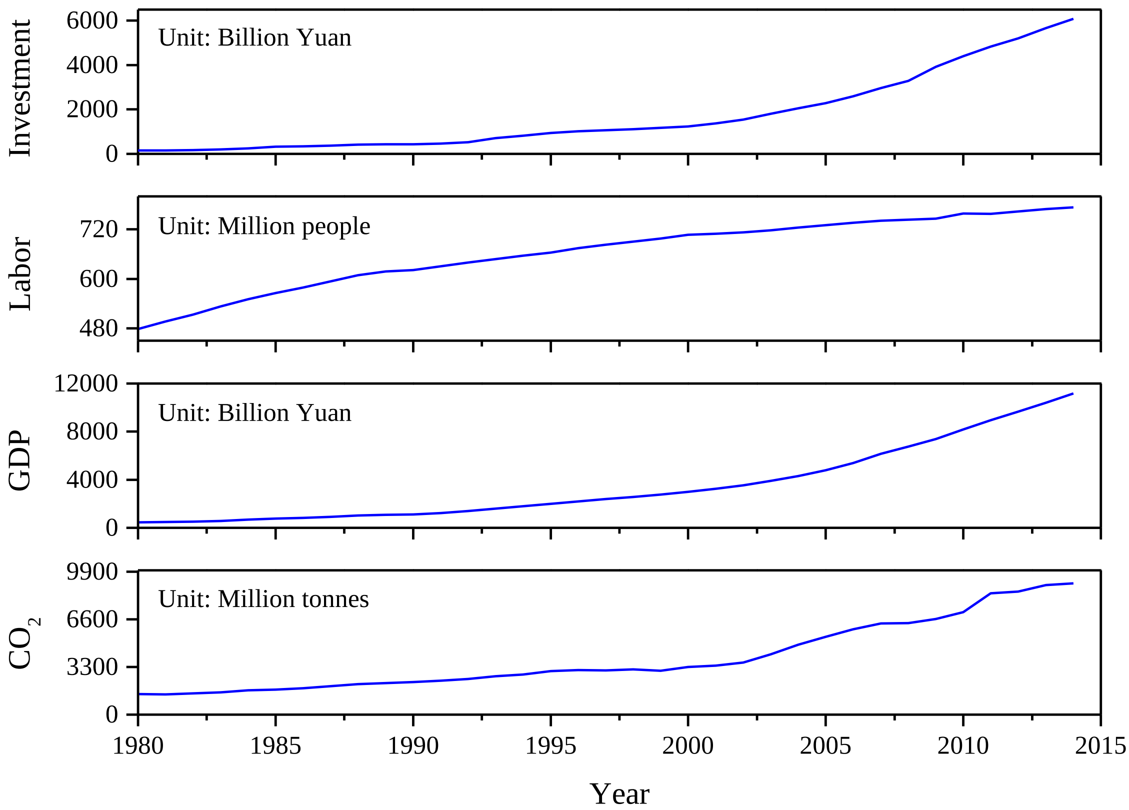


Fig. 2. Variables on capital investment, labor, GDP and fossil-fuel CO_2 emissions of China over the period of 1980-2014.

3. Methodology

Following the practice in (Pereira and Pereira, 2010), we will establish a vector autoregression (VAR) model for each type of fuel, which involves the variables on the focused fuel demand, capital investment, labor, and GDP. In particular, the variable on fossil-fuel CO_2 emissions is also included in these VAR models to measure the effects on it in comprehensive frameworks. Then, with the help of impulse-response functions based on these VAR models, the effect-measuring formulas of fuel-switching activities from non-electric fuels to electricity are introduced.

3.1. Unit root and cointegration analysis

As preliminary work for VAR modelling, the stationary properties of variables contained in the models are tested first. The Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) unit root tests are employed, and the test results are shown in Table 1, where the null hypothesis is that a unit root exists. As can be seen, the null hypothesis cannot be rejected at the 5% level of significance for all level variables. However, it can be rejected after these variables are differenced once, which suggests that the 1st differenced variables are stationary. Thus, these 1st differenced variables satisfy the precondition to establish VAR models.

Table 1
Results of ADF and PP tests for unit root.

Variable	ADF		PP	
	Level	1st difference	Level	1st difference
$\ln Y_t$	-0.0151	-4.2744	-0.3641	-3.4248
	(0.950)	(0.002)	(0.904)	(0.017)
$\ln I_t$	-0.9914	-4.0689	-0.3128	-4.1050
	(0.745)	(0.003)	(0.913)	(0.003)
$\ln L_t$	7.9249	-3.5003	4.1579	-2.6762
	(1.000)	(0.001)	(1.000)	(0.009)
$\ln C_t$	1.4722	-2.0792	2.7220	-2.0772
	(0.962)	(0.038)	(0.998)	(0.038)
$\ln O_t$	0.8461	-6.0236	0.8120	-6.9081
	(0.993)	(0.000)	(0.993)	(0.000)
$\ln G_t$	0.9712	-6.3978	1.1935	-6.5837

	(0.995)	(0.000)	(0.998)	(0.000)
$\ln E_t$	-0.3217	-3.0920	0.9303	-3.1616
	(0.911)	(0.037)	(0.995)	(0.032)
$\ln FC_t$	0.8420	-4.4934	0.7260	-4.5303
	(0.993)	(0.001)	(0.991)	(0.001)

Notes: For Labor and Coal, neither a constant nor a time trend is included in test equations, while a constant is included for the other variables. Values in parentheses indicate *p*-values.

Considering that all the above-mentioned series are I(1) (integrated of order one), we also test for cointegration among these variables in log-levels, including each one of the fuel demands ($\ln P_t, P \in \{C, O, G, E\}$), capital investment ($\ln I_t$), labor ($\ln L_t$), GDP ($\ln Y_t$), and fossil-fuel CO_2 emissions ($\ln FC_t$). Here, the Engle–Granger test is employed, since it is less vulnerable than the Johansen test to the small sample (such as ours) bias toward finding cointegration when it does not exist (Gonzaloa and Leeb, 1998; Pereira and Pereira, 2010).

For each of the four VAR modeling procedures corresponding to each type of fuel, five different cases are tested, each of which considers a different endogenous variable in the cointegration regression. The results of these cointegration tests are shown in Table 2, where the *p*-values of *t*-statistics suggest that we cannot reject the null hypothesis of no-cointegration on balance. Therefore, we only study the short-run dynamic interactions among the 1st differenced variables in ordinary VAR models instead of long-run relationships in vector error correction models (VECM).

Table 2
Results of Engle-Granger tests for no-cointegration.

Variable	*t*-statistic	Variable	*t*-statistic	Variable	*t*-statistic	Variable	*t*-statistic
$\ln C_t$	-3.4513	$\ln O_t$	-3.9419	$\ln G_t$	-2.8058	$\ln E_t$	-3.9750
	(0.410)		(0.223)		(0.706)		(0.213)
$\ln I_t$	-2.8697	$\ln I_t$	-3.8901	$\ln I_t$	-4.5070	$\ln I_t$	-4.0632
	(0.678)		(0.239)		(0.096)		(0.189)
$\ln L_t$	-2.9121	$\ln L_t$	-2.5376	$\ln L_t$	-2.4795	$\ln L_t$	-3.9438
	(0.659)		(0.811)		(0.830)		(0.229)
$\ln Y_t$	-3.2095	$\ln Y_t$	-3.8144	$\ln Y_t$	-3.1143	$\ln Y_t$	-3.6764
	(0.520)		(0.265)		(0.565)		(0.316)
$\ln FC_t$	-3.8388	$\ln FC_t$	-2.6292	$\ln FC_t$	-2.7480	$\ln FC_t$	-4.5078
	(0.257)		(0.777)		(0.730)		(0.092)

Values in parentheses indicate *p*-values.

3.2. VAR specifications and estimates

For further modeling in the following subsections, we need to establish four VAR models in this subsection; each of these models focuses on one of the four fuels and does not consider contemporaneous relations among variables for the moment. Previous studies have found a break point in energy consumption in China around 2002 (Zhang and Broadstock, 2016); this can be seen from Fig. 1, where the energy (especially coal and electricity) consumption level is abruptly elevated from 2002 onward.[4] Thus, for each the four fuel types, we first establish two candidate VAR models. One of these models does not consider the 2002 break point, whereas the other considers it through introducing an exogenous dummy variable DUM_t.

Following the standard procedure in the literature, these two candidate VAR models are estimated as follows (Chen, 2015):

$$\mathbf{y}_t = \mathbf{c} + \sum_{l=1}^{p} \mathbf{A}_l \mathbf{y}_{t-l} + \boldsymbol{\varepsilon}_t \tag{1}$$

$$\mathbf{y}_t = \mathbf{c} + \sum_{l=1}^{p} \mathbf{A}_l \mathbf{y}_{t-l} + \mathbf{H} \cdot DUM_t + \boldsymbol{\varepsilon}_t \tag{2}$$

where $\mathbf{y}_t = [\Delta \ln P_t, \Delta \ln I_t, \Delta \ln L_t, \Delta \ln Y_t, \Delta \ln FC_t]'$ is the vector of endogenous variables, $P \in \{C, O, G, E\}$ represents the focused type of fuel demand, Δ represents the difference operator, p is the lag order, $\mathbf{c}$ is a vector of constants, $\mathbf{A}_l$ is a 5×5 coefficient matrix, $\mathbf{H}$ is a five-dimensional vector, $\boldsymbol{\varepsilon}_t = [\varepsilon_{Pt}, \varepsilon_{It}, \varepsilon_{Lt}, \varepsilon_{Yt}, \varepsilon_{FCt}]'$ is a

[4] This can be mainly explained from two aspects (Zhang and Broadstock, 2016): 1) with the end of the Asian financial crisis and the market-oriented reform of the state-owned enterprises, the Chinese economy came back to a rapid economic development track from 1999, which was later enhanced by China's entry into the WTO (World Trade Organization) in December 2001; 2) the Chinese economy transitioned into a phase of "heavy industrialization" after 2000, resulting in an increase of energy intensity.

vector of zero mean residuals with a variance-covariance matrix $\mathbf{\Omega}$, and $E(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_s{}') = \mathbf{0}$ for $t \neq s$.

According to the practice in (Pereira and Pereira, 2010), we perform Bayesian information criterion (BIC) to determine the optimal lag order p; the test results are listed in Table 3, which indicates that p=1 is selected for all these VAR models. As shown in Fig. 3, all inverse roots of the characteristic AR polynomial for these VAR models lie inside unit circles, which means that the estimated models are all stable.

Table 3
BIC results for the VAR models.

Lag	VAR with							
	C	C&DUM	O	O&DUM	G	G&DUM	E	E&DUM
1	-21.3726*	-21.0690*	-21.6692*	-21.4121*	-19.6889*	-19.3867*	-23.5620*	-23.1919*
2	-20.5124	-20.2903	-20.5247	-20.2520	-18.5593	-18.3048	-22.7367	-22.4087
3	-20.5186	-20.7429	-19.8944	-19.6798	-17.5836	-17.4228	-22.0054	-21.9267

* indicates lag order selected by BIC.
Notes: For $P \in \{C, O, G, E\}$, P represents $\Delta \ln P_t$ is included in the model but DUM_t is not, while *P&DUM* represents both $\Delta \ln P_t$ and DUM_t are included in the model.

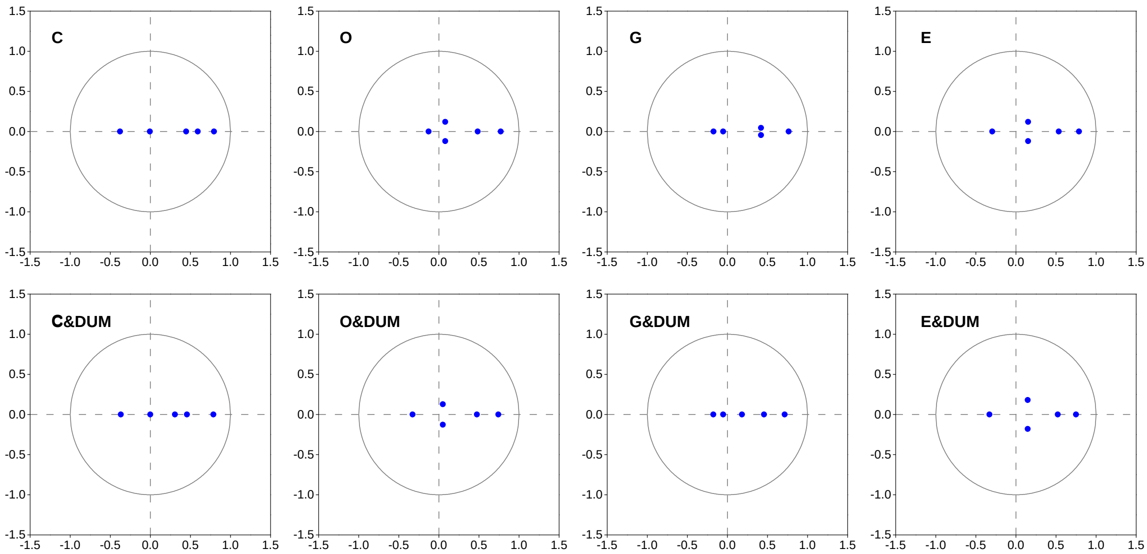


Fig. 3. Inverse roots of AR characteristic polynomial for the VAR models.

Furthermore, the VAR specifications without a dummy variable appear to be better than those with a dummy variable in terms of BIC results in Table 3 for all fuels. However, we still need to check whether the estimated residuals have no serial correlation, i.e., $E(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_s{}') = \mathbf{0}$ $(t \neq s)$, as mentioned before, to avoid so-called dynamic misspecification (Balestra, 1982). To this end, we employ the autocorrelation LM test under the null of no serial correlation at lag orders from 1 to 8. Its results (shown in Table 4) suggest that, if we do not want to reject the null hypothesis, even at the 10% level of significance, VAR models should include the dummy variable for coal and electricity, while this is not mandatory for oil and gas. Thus, the four VAR models for the four fuels adopt these specifications hereinafter, unless otherwise specified.

Table 4
Results of autocorrelation LM test for the VAR models.

Lag	VAR with							
	C	C&DUM	O	O&DUM	G	G&DUM	E	E&DUM
1	35.2152	33.2545	31.8855	23.0471	31.8844	29.3976	35.8310	34.1504
	(0.084)	(0.125)	(0.161)	(0.575)	(0.161)	(0.248)	(0.074)	(0.105)
2	32.7685	33.8034	22.1193	21.7852	26.1018	24.2748	23.4006	23.4492
	(0.137)	(0.112)	(0.629)	(0.648)	(0.402)	(0.504)	(0.554)	(0.551)
3	16.6399	15.1974	17.8655	16.7528	19.0441	19.5144	25.0331	24.5448
	(0.894)	(0.937)	(0.848)	(0.891)	(0.795)	(0.772)	(0.461)	(0.488)
4	27.0257	29.0666	18.1141	21.2773	26.7005	33.1111	33.9777	33.0723
	(0.355)	(0.261)	(0.838)	(0.677)	(0.371)	(0.128)	(0.108)	(0.129)
5	19.9751	23.0708	27.7297	29.1656	31.5370	31.4006	27.8312	27.9448
	(0.748)	(0.573)	(0.320)	(0.257)	(0.172)	(0.176)	(0.316)	(0.310)
6	13.8196	13.7160	16.5181	16.1503	20.0920	16.5817	21.3114	22.2740
	(0.965)	(0.966)	(0.899)	(0.910)	(0.742)	(0.896)	(0.675)	(0.620)
7	13.8126	15.4719	23.8705	23.2902	13.8084	16.3765	12.7333	18.1822
	(0.965)	(0.930)	(0.527)	(0.561)	(0.965)	(0.903)	(0.980)	(0.835)
8	21.0321	20.2691	19.0389	19.6036	27.7018	27.3138	15.4931	16.6707
	(0.691)	(0.733)	(0.795)	(0.767)	(0.322)	(0.340)	(0.929)	(0.893)

Values in parentheses indicate *p*-values.

3.3. Effect measurements of exogenous shocks in fuel demand variables

Based on the four estimated VAR models above, we can examine the effects of exogenous shocks in various types of fuel demand, respectively. To this end, the impulse-response function method is employed. This method is a type of innovation accounting analysis, which traces the effects of an exogenous shock to one of the innovations on the current and future values of the endogenous variables through dynamic feedbacks among these variables (Salahuddin et al., 2015).

Clearly, the key issue here is identifying truly exogenous shocks in each type of fuel demand that are not contemporaneously correlated with shocks in the remaining endogenous variables (Pereira and Pereira, 2010). Thus, we need to transform the estimated residuals in VAR models (1) or (2) to the following form:

$$\boldsymbol{\varepsilon}_t = \mathbf{P}\mathbf{e}_t \tag{3}$$

where $\mathbf{P}$ is a 5×5 matrix, while $\mathbf{e}_t = \mathbf{P}^{-1}\boldsymbol{\varepsilon}_t = [e_{Pt}, e_{It}, e_{Lt}, e_{Yt}, e_{FCt}]'$, and $E(\mathbf{e}_t\mathbf{e}_t^{'}) = \mathbf{I}$, i.e., an identity matrix. Then, each element in $\mathbf{e}_t$ is the identified exogenous shock of its corresponding variable. It is worth mentioning that, considering that the shocks in fuel demands are exogenously induced by the introduction of fuel-switching policies, we put the equation for the fuel demand in the first place for each VAR model. Then, the Cholesky decomposition is performed for the variance-covariance matrix $\boldsymbol{\Omega}$ to determine $\mathbf{P}$, as follows:

$$\boldsymbol{\Omega} = \mathbf{P}\mathbf{P}' \tag{4}$$

Here, $\mathbf{P}$ is called the Cholesky factor, which is a lower triangular matrix and ensures that $E(\mathbf{e}_t\mathbf{e}_t^{'}) = \mathbf{P}^{-1}E(\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t^{'})(\mathbf{P}^{-1})^{'} = \mathbf{P}^{-1}\boldsymbol{\Omega}(\mathbf{P}^{-1})^{'} = \mathbf{I}$. In fact, the Cholesky decomposition-based VAR model is equivalent to the recursive structural VAR (SVAR), which is widely used in energy studies (Chen et al., 2016; Lin and Liu, 2016; Wang and Mcphail, 2014; Wang et al., 2014). It should be noted that, according to the properties of Cholesky decomposition, effect measurements of a shock in the focused fuel demand on the other variables are independent from the order of these variables (Pereira and Pereira, 2010).

Accordingly, for the VAR model with $\Delta\ln P_t$, a shock in the focused fuel demand contemporaneously affects the remaining endogenous non-fuel variables, but not vice versa. Specifically, the responses of $\Delta\ln P_t$, $\Delta\ln Y_t$, and $\Delta\ln FC_t$ at the *h*th period to a shock in the focused fuel demand are computed as follows:

$$R_{Qh}(P) = \frac{\partial(\Delta\ln Q_{t+h})}{\partial(e_{Pt})},\ Q\in\{P,Y,FC\}, h=0,1,2,\ldots,H \tag{5}$$

where $P\in\{C,O,G,E\}$, and H is a user-specified number of periods.

Furthermore, the changes of $\ln P_t$, $\ln Y_t$, and $\ln FC_t$ at the *h*th period, induced by a shock in the focused fuel demand, can be computed, respectively, through accumulating the responses of $\Delta \ln P_t$, $\Delta \ln Y_t$ and $\Delta \ln FC_t$, as follows:

$$d_{Qh}(P) = \sum_{i=0}^{h} R_{Qi}(P),\ \ Q \in \{P, Y, FC\}, h = 0,1,2,\ldots,H \tag{6}$$

Then, the percentage changes of P_t, Y_t, and FC_t at the *h*th period are measured below:

$$\delta_{Qh}(P) = \left[\exp\left(d_{Qh}(P)\right) - 1\right] \times 100\%,\ \ Q \in \{P, Y, FC\}, h = 0,1,2,\ldots,H \tag{7}$$

Intuitively, these changes at the following H time horizons are caused by the change of the focused fuel demand P_t at the initial time, i.e., $\delta_{P0}(P)$ at period 0, which is originally caused by the shock in this fuel demand. We call $\delta_{Q0}(P)$ the current growth effect of its corresponding fuel demand shock. If the growth effect disappears at the *H*th period, i.e., the impulse-response function converges, we call $\delta_{QH}(P)$ the permanent growth effect of its corresponding fuel demand shock.

3.4. Impact measurements of fuel-switching activities

A fuel-switching activity can be treated as two independent parts, i.e., reduction in one fuel demand and increase in another fuel demand. Clearly, the fuel whose demand is reduced is the displaced fuel, i.e., any one of the three non-electric fuels, including coal, oil, and gas in this paper, while electricity is the fuel whose demand is increased. Let us define the percentage point reduction rate of the displaced fuel as the "substitution rate", which is specifically induced by a 1% growth in electricity demand at period 0 for the purpose of switching from that displaced fuel to electricity.

Then, we can study the impacts of a fuel-switching policy for electrification using the above-mentioned effect measurements of exogenous shocks in both reduced and increased fuel demand variables. Specifically, if we want to switch from one of the three non-electric fuels to electricity, given a substitution rate r_P for this displaced fuel ($P \in \{C, O, G\}$), the percentage changes of GDP and CO_2 emissions at the *h*th period caused by this fuel-switching are:

$$\begin{cases} D_{Yh}\left(P(r_P)\to E\right)=\left[\dfrac{\delta_{Yh}(E)}{\delta_{E0}(E)}-\dfrac{\delta_{Yh}(P)}{\delta_{P0}(P)}r_P\right]\times 100\% \\ D_{FCh}\left(P(r_P)\to E\right)=\left[\dfrac{\delta_{FCh}(E)}{\delta_{E0}(E)}-\dfrac{\delta_{FCh}(P)}{\delta_{P0}(P)}r_P\right]\times 100\% \end{cases}, P\in\{C,O,G\}, h=0,1,2,\ldots,H \quad (8)$$

Correspondingly, we call $D_{Y0}\left(P(r_P)\to E\right)$ and $D_{YH}\left(P(r_P)\to E\right)$ the current and the permanent growth effects, respectively, of this kind of fuel-switching activity on GDP, while $D_{FC0}\left(P(r_P)\to E\right)$ and $D_{FCH}\left(P(r_P)\to E\right)$ are, respectively, the current and the permanent growth effects on CO_2 emissions.

4. Results and discussions

Using the four VAR models that are specified and estimated above, this section obtains the final results to answer the three questions raised in the Introduction section. Specifically, Section 4.1 measures the effects of exogenous shocks in various fuel demand variables, which answers the question of how changes in each type of fuel demand dynamically affect future GDP and CO_2 emissions; Section 4.2 measures the impacts of various types of fuel-switching for electrification, which answers the question of what the ideal fuel-switching states for electrification to achieve the trade-off between CO_2 emission reduction and economic growth maintenance are; and Section 4.3 measures some typical substitution cases encouraged by the government, which answers the question of whether the current fuel-switching policies for electrification can not only reduce CO_2 emissions but also maintain economic growth.

4.1. Effect measurements of exogenous shocks in fuel demand variables

According to (5) and (6), the responses and accumulated responses of GDP and CO_2 emissions to one standard-deviation (S.D.) shock in various types of fuel demand are calculated, and the results are presented in Fig. 4. From the panels in Fig. 4, we can see that a shock in each type of fuel demand has a positive impact on both CO_2 emissions and the fuel demand, with statistical significance. Apart from the gas demand, shocks in various types of fuel demand also have positive impacts on GDP, and the coal and electricity shocks have statistically significantly impacts.

The slightly negative impact of the gas shock may be related to China's distorted natural gas price mechanism, while natural gas is the main part of the gas. For a long time, the industrial gas price has been much higher than the residential gas price in China, while the cost of residential gas, in contrast, has been higher than the cost of industrial gas. In addition, as an important importer of natural gas, China's natural gas import prices are often higher than the domestic prices, which creates huge losses for the natural gas industry (Wei et al., 2016). Thus, this negative impact is not surprising, since an increase in the natural gas price would have a negative impact on GDP in China (Zhang et al., 2017). Furthermore, the higher import risks involved in the increasingly large amount of imported gas also have a negative impact on economic output (Dong and Kong, 2016).

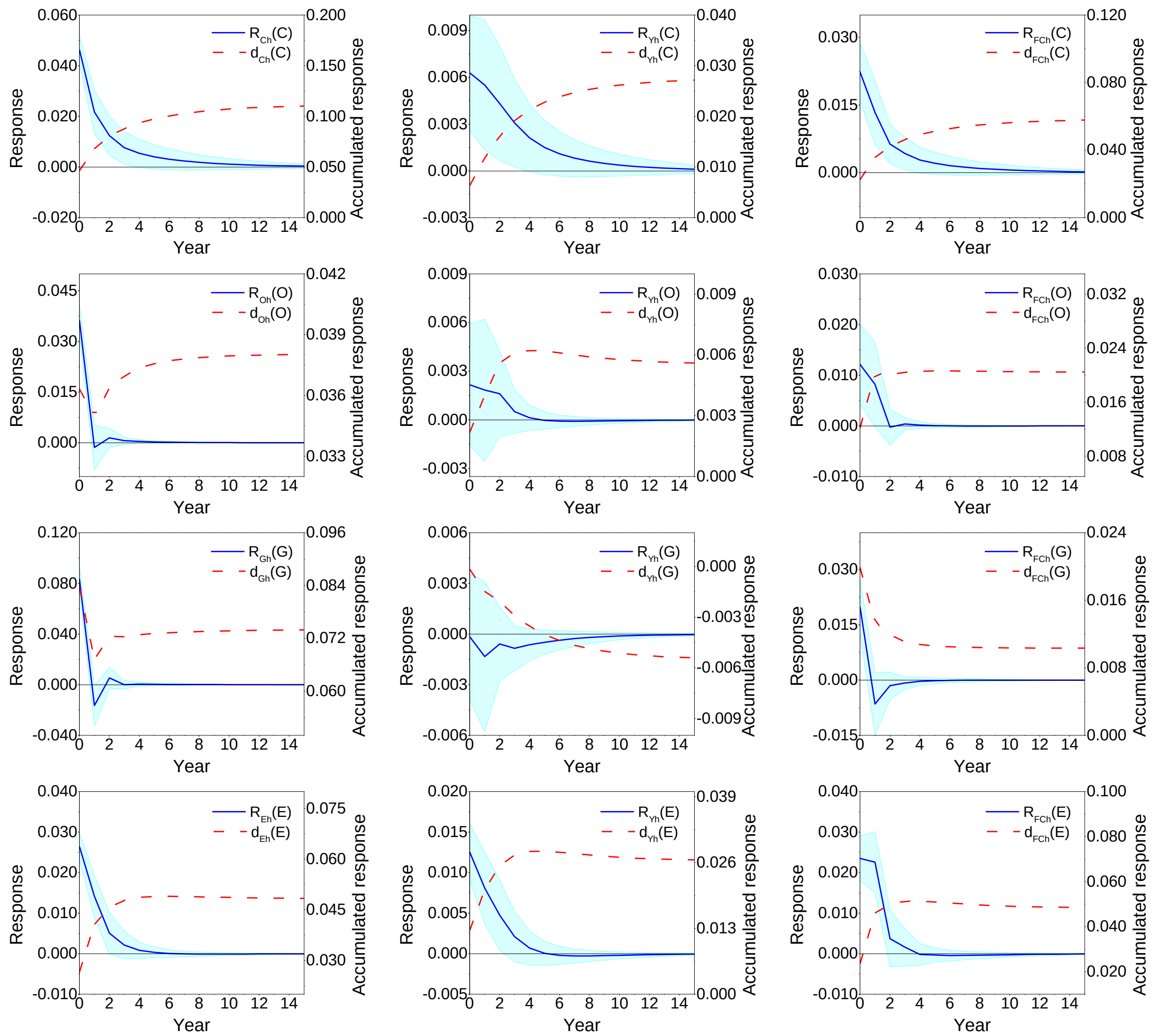


Fig. 4. Responses and accumulated responses of GDP and CO_2 emissions to a shock in each type of fuel demand. Notes: The error bands with 68% posterior probability are adopted as recommended by (Pereira and Pereira, 2010) and (Sims and Zha, 1999), which are represented by cyan shades.

Meanwhile, without exception, the accumulated response functions converge after 10 years and even 5 years; thus, there is no harm in regarding the changes at the 15th period as the permanent changes. In particular, the responses ($R_{Qh}(P)$) and the accumulated responses ($d_{Qh}(P)$), along with the percentage changes ($\delta_{Qh}(P)$) at the current period ($h=0$) and the permanent period ($h=15$) are listed in Table 5.

Table 5

Change measures of GDP and CO_2 emissions to a shock in each type of fuel demand (Unit: %).

Change measure	VAR for coal		VAR for oil		VAR for gas		VAR for electricity	
	$h=0$	$h=15$	$h=0$	$h=15$	$h=0$	$h=15$	$h=0$	$h=15$
$R_{Ph}(P)$	4.64	0.03	3.63	0.00	8.37	0.00	2.65	0.00
$R_{Yh}(P)$	0.63	0.01	0.22	0.00	-0.02	0.00	1.26	-0.01
$R_{FCh}(P)$	2.24	0.02	1.21	0.00	1.99	0.00	2.35	-0.01
$d_{Ph}(P)$	4.64	11.01	3.63	3.80	8.37	7.39	2.65	4.84
$d_{Yh}(P)$	0.63	2.71	0.22	0.56	-0.02	-0.54	1.26	2.65
$d_{FCh}(P)$	2.24	5.77	1.21	2.05	1.99	1.03	2.35	4.85
$\delta_{Ph}(P)$	4.75	11.64	3.70	3.88	8.73	7.67	2.69	4.96
$\delta_{Yh}(P)$	0.63	2.75	0.22	0.56	-0.01	-0.54	1.26	2.69
$\delta_{FCh}(P)$	2.26	5.94	1.22	2.07	2.01	1.04	2.38	4.97

4.2. Impact measurements of fuel-switching for electrification

Given the substitution rate, r_P ($P \in \{C, O, G\}$), we can then calculate the current and permanent impacts of switching from non-electric fuels to electricity on GDP and CO_2 emissions according to (8). Fig. 5 compares the impacts on GDP and CO_2 emissions in various ranges of r_P for different displaced fuels.

Clearly, apart from the growth rate of GDP induced by the gas-electricity switching, there is a tendency for the growth rates of both GDP and CO_2 emissions to slow down as the substitution rate increases. This is mainly because more displaced fuel will be reduced with the increasing substitution rate, while there is no change in the increase of electricity demand. Then, the growths of GDP and CO_2 emissions caused by the electricity increase are not changed, while the reductions of GDP and CO_2 emissions induced by the displaced fuel decrease become greater. In particular, the above-mentioned exception for gas-electricity switching is due to the slightly negative impact of the gas shock on GDP.

Since the growth rates of GDP are higher than those of CO_2 emissions, switching from coal to electricity could decrease the carbon intensities if the substitution rate r_C is larger than 1.21 and 1.26 for $h=0$ and $h=15$, respectively. However, to avoid negative impacts on economic development, the substitution rates for $h=0$ and $h=15$ should not be larger than 3.54 and 1.73, respectively. Thus, even though certain coal-electricity switching activities have short-term advantages when $1.73 < r_C < 3.54$, there are negative impacts on the economy due to the shrinking of coal-related industries. In the long-run, the substitution rate of the best coal-electricity switching activities ranges from 1.48 to 1.73, where economic development is promoted, while CO_2 emissions are reduced in the permanent period.

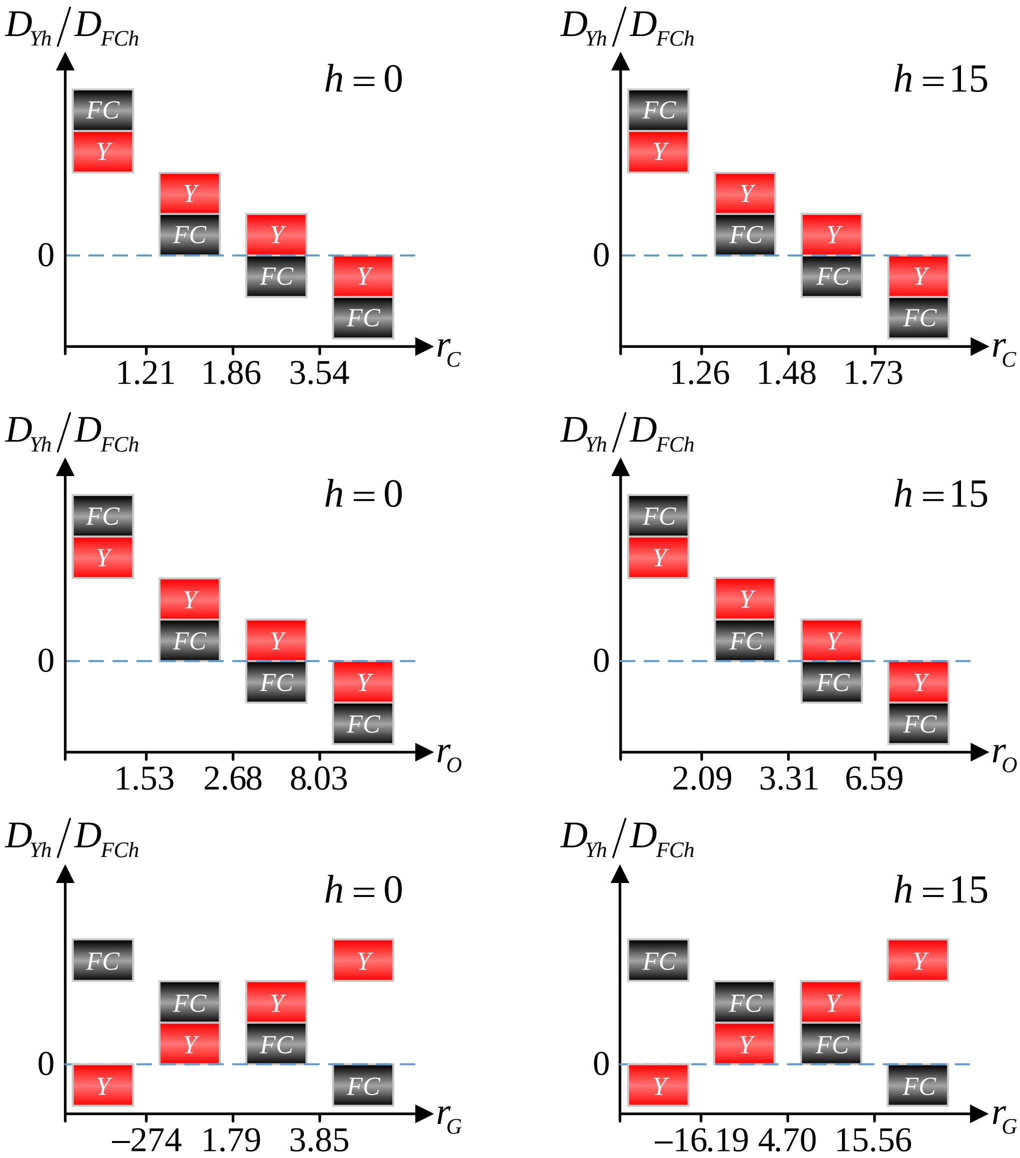


Fig. 5. Sketch of the percentage changes of GDP and CO_2 emissions at the 1st and 15th period. Notes: The boxes marked with "Y" and "FC" represent the percentage changes of GDP and CO_2 emissions respectively; that the Y box is on the top of the FC box in vertical means the growth rate of GDP is larger than the growth rate of CO_2 emissions, and vice versa.

The impacts of switching from oil to electricity are similar to the case of coal-electricity switching. In the current and the permanent periods, the carbon intensities are decreased, while the economic development is not harmed if the substitution rate

r_O ranges from 1.53 to 8.03 and from 2.09 to 6.59, respectively. Even though certain oil-electricity switching activities have short-term advantages when $6.59 < r_O < 8.03$, there are negative impacts on the economy due to the shrinking of oil-related industries. Clearly, the substitution rate of the best oil-electricity switching activities ranges from 3.31 to 6.59, where economic development is promoted, while CO_2 emissions are reduced in both current and permanent periods.

The impacts of switching from gas to electricity on GDP are unusual due to the above-mentioned negative response of economic output to the gas shock. It should be noted that it does not make sense if the substitution rate r_G is either less than 0 or very large, since these two cases are not realistic in practice (see the following subsection). Thus, we only discuss the case where the substitution rate ranges from 0 to 10. From this figure, we can see that the carbon intensities are decreased when $r_G > 1.79$, and the CO_2 emissions are even reduced with increased economic output when $r_G > 3.85$ in the current period. However, this is not a stable state, and the growth rate of CO_2 emissions is always greater than 0 in the permanent period, which means that switching from gas to electricity cannot contribute to reducing the absolute amount of CO_2 emissions, unless it is coordinated with a cleaner power structure.

4.3. Impact measurements of the current electrification policies in China

As mentioned in Section 1, the Chinese government has provided a very comprehensive policy support for electrification since 2016, with the main supported fields including residential and industrial electric heating, electric vehicles, electricity supply for shore power in ports, and agricultural irrigation and drainage. Since the accurate substitution rates for various fuels are not available, we review the roughly equivalent fuel use between typical fossil-fueled appliances and their corresponding alternative electrical appliances from the literature (Jiang et al., 2002; Lai et al., 2016; Li et al., 2009; Liu and Luo, 2005; Min and Cheng, 2007; Niu et al., 2008; Wang et al., 2007; Xu et al., 2011).

Taking China's final energy consumption structure (average ratio in the last 5 years) into account, we roughly calculate the substitution rates of these related replacements according to such equivalent fuel use data. These substitution rates are used to define some substitution cases, a certain combination of which would be the actual substitution situation. These substitution rates and their corresponding cases are listed in Table 6, where $C(0.65) \rightarrow E$ means substituting 1% of electricity consumption for 0.65% of coal consumption.

Table 6
Substitution rates and the corresponding substitution cases.

Fuel-switching form	r_P	Case name	Representative cases	
			Displaced fossil-fueled appliances	Alternative electrical appliances
Switch from coal to electricity	0.65	$C(0.65) \rightarrow E$	Coal-fired boilers and stoves	Electric heaters and boilers, electric heating films, phase-change electric heating floors
	2.06	$C(2.06) \rightarrow E$	Coal-fired boilers and stoves	Air-source, ground-source and water-source heat pumps
Switch from oil to electricity	1.49	$O(1.49) \rightarrow E$	Oil-fired boilers	Electric boilers
	3.99	$O(3.99) \rightarrow E$	Diesel generators in ships	Shore power in ports
	4.69	$O(4.69) \rightarrow E$	Oil-fired boilers	Air-source, ground-source and water-source heat pumps
	5.32	$O(5.32) \rightarrow E$	Diesel pumps for agricultural irrigation and drainage	Motor pumps for agricultural irrigation and drainage
	7.85	$O(7.85) \rightarrow E$	Gasoline-powered vehicles	Electric vehicles
Switch from gas to electricity	1.86	$G(1.86) \rightarrow E$	Gas-fired boilers and stoves	Electric heaters and boilers, electric heating films, phase-change electric heating floors
	5.87	$G(5.87) \rightarrow E$	Gas-fired boilers and stoves	Air-source, ground-source and water-source heat pumps
	7.72	$G(7.72) \rightarrow E$	Natural gas vehicles	Electric vehicles

Then, we can measure the current and permanent impacts of these substitution cases according to their corresponding substitution rates; the results are shown in Fig. 6. From this figure, we can see that carbon intensities will increase in almost all the cases of $C(0.65) \rightarrow E$, $O(1.49) \rightarrow E$ and $G(1.86) \rightarrow E$ in both current and permanent periods, which means that replacing fossil-fueled heating appliances with conventional electric heaters (not heat pumps) is not a wise choice in view of CO_2 emission reduction. Fuel-switching induced by these kinds of appliance replacements should be avoided unless the electricity is derived mainly from renewable energy sources in the implemented areas, especially if there is a high wind or photovoltaic energy curtailment ratio.

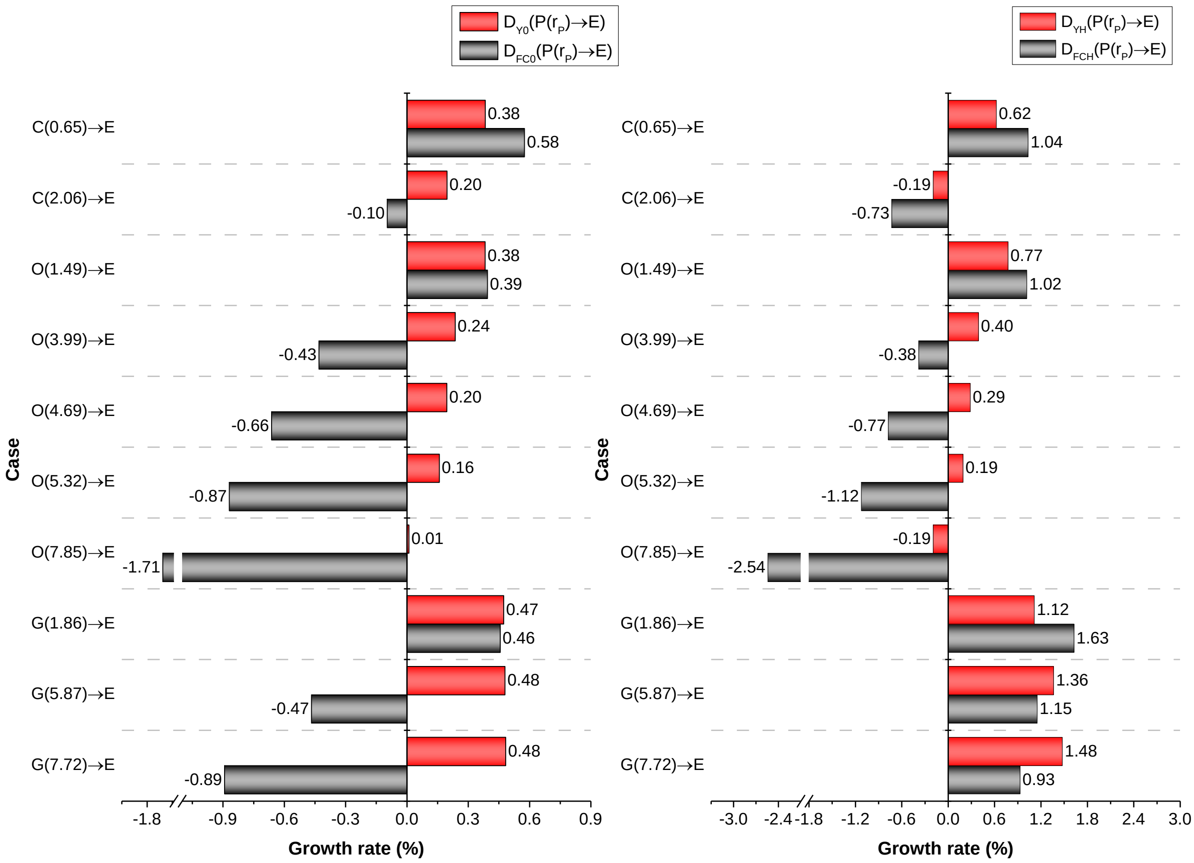


Fig. 6. The impacts of various substitution cases of electrification on GDP and CO_2 emissions.

In fact, heat pumps are a better heating choice than conventional electric heaters since the carbon intensities will decrease in the cases of $C(2.06) \to E$, $O(4.69) \to E$, and $G(5.87) \to E$ at both periods. Oil-electricity switching is the best of these cases, while coal-electricity switching may harm economic growth slightly in the permanent period. The absolute amount of CO_2 emissions is reduced in both coal-electricity and oil-electricity switching, but gas-electricity switching may increase it in the permanent period. In addition, the impacts of $O(3.99) \to E$ and $O(5.32) \to E$ are similar to the impacts of $O(4.69) \to E$, the only difference being reflected in the degree of impacts.

The substitution rates of $O(7.85) \to E$ and $G(7.72) \to E$, respectively, come from oil-electricity and gas-electricity switching, induced by the development of electric vehicles. In both cases, although CO_2 emissions are reduced while maintaining economic growth in the current period, the former case will harm the economic output while the latter will increase the absolute amount of CO_2 emissions in the permanent period. Thus, we should pay close attention to the shrinking of oil-related industries induced by developing electric vehicles, and adopt reasonable measures to offset this negative effect. Meanwhile, substituting electric vehicles for natural gas vehicles is not a good choice from the perspective of CO_2 emission reduction.

5. Conclusions and policy implications

Electrification is a sign of modern civilization. To control air pollution and promote productivity, shifting final energy consumption to electricity is advocated and encouraged by both academics and the Chinese government. However, in view of the importance of energy to the economy and the increasing concerns about climate change, the problem of how to achieve the trade-off between reducing CO_2 emissions and maintaining economic development when implementing policies to switch from various fuels to electricity remains to be solved, even though electrification helps in controlling conventional air pollutants, such as smog. Consequently, after measuring the effects of exogenous shocks in various fuel demand variables employing the impulse response functions of several VAR models, we measure the long-term impacts of fuel-switching activities for electrification on GDP and CO_2 emissions. Finally, some replacement cases from fossil-fueled appliances to their electrical counterparts, which are currently encouraged by the government, are assessed.

5.1. Conclusions

From the empirical results, we arrive at certain conclusions, as follows:

(1) All the exogenous shocks in fuel demand variables have positive and statistically significant impacts on both CO_2 emissions and fuel demands. Shocks in coal, oil, and electricity demands also have positive impacts on GDP, and the impacts of coal and electricity shocks are statistically significant. However, the gas shock has a slightly negative impact on GDP, which may be related to China’s distorted natural gas price mechanism and increasing import risks, while natural gas is the main part of the gas consumed. Nevertheless, almost all these impacts will become stable after 10 years, and even after 5 years.

(2) Carbon intensity decreases, and even CO_2 emission reductions with economic growth maintenance, are potentially achieved in both current and permanent periods for coal-electricity and oil-electricity switching. For gas-electricity

switching, although some favorable conclusions can be drawn, this is not a stable state, and the permanent impacts indicate that this kind of fuel-switching is not a wise choice from the perspective of CO_2 emission reduction (especially reducing the absolute amount of CO_2 emissions). This is most likely because China mainly uses coal to generate electricity.

(3) For heating, heat pumps are better choices than conventional electric heaters to replace the fossil-fueled heating appliances from the perspective of CO_2 emission reduction. Deployment of conventional electric heaters should only be encouraged in areas where electricity is generated mainly from renewable energy sources, especially if there is a high wind or photovoltaic energy curtailment ratio. Shore power in ports and motor pumps have similar advantages to heat pumps in reducing CO_2 emissions, and the only difference is reflected in the degree of impacts. Generalizing electric vehicles for oil-electricity switching can reduce CO_2 emissions, while maintaining economic growth in the current period, but it will harm economic development in the permanent period. Generalizing electric vehicles for gas-electricity switching can also reduce CO_2 emissions while maintaining economic growth in the current period, but it will increase the absolute amount of CO_2 emissions in the permanent period.

5.2. Policy implications

According to the conclusions drawn above, we have some implications for detailed rule-making to implement shifting final energy consumption to electricity in China:

(1) Under the present situation of a coal-based power generation structure, compared with gas-electricity switching, coal-electricity and oil-electricity switching should been given more policy support, from the perspective of CO_2 emission reduction. Furthermore, considering that the direct burning of coal is one of the most important causes of air pollution in China, coal-electricity switching is an urgent matter.

(2) The fuel-switching policies for electrification must be accompanied by cleaning the electric energy. The proportion of renewable electricity should be improved, and CCS (carbon capture and storage) technologies can be generalized under the premise of a reasonable assessment.

(3) Before implementing a fuel-switching activity, we should not only consider the immediate benefits but also adopt reasonable measures to avoid long-term negative effects. Meanwhile, even though a fuel-switching activity can control conventional air pollution, we should still take note of its impacts in other areas, such as CO_2 emissions.
(4) In a specific fuel-switching case, we should accurately assess the alternative electric appliances, since not all electric appliances are better than their fossil-fueled counterparts. We cannot say arbitrarily that electricity is superior to certain types of fossil fuels.

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