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Climatic impact on China's residential electricity consumption: Does the income level matter?

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ABSTRACT

It is widely accepted that energy use contributes to climate change. However, climate change can also affect energy demand. There is ample proof in the literature that a feedback phenomenon exists. However, empirical evidence of its mechanism and operation in different contexts is missing. As China is the largest consumer of electricity worldwide, a detailed study of its energy consumption patterns would be insightful. Moreover, how the increasing income of Chinese residents affects the climate sensitivity of electricity demand is particularly relevant. Using data from 278 cities in China over the period 2005 to 2015, this study applies a newly developed technique, partially linear functional-coefficient panel data model, which enables disclosure of the role of income levels. The results indicate that climate change significantly stimulates residential electricity consumption in hot weather rather than in cold weather. Additionally, the level of income affects climate sensitivity. Specifically, an increase in income initially increases the marginal effect of cooling degree days (days on which building cooling is desired) on electricity consumption, but the curve of the marginal increment becomes flat as income growth increases further.

1. Introduction

The energy sector is especially sensitive to climate change and climate variability. Wenz, Levermann, and Auffhammer (2017) highlight the vital role of temperature in electricity consumption. To cope with varying outside temperatures, people tend to use heating or cooling systems for their comfort, directly affecting electricity demand (Auffhammer, 2018; Li, Yang, & Long, 2018). The feedback mechanism in the residential sector is often discussed, because residential electricity consumption is directly affected by individuals' decisions (Auffhammer, 2014); therefore, the climate sensitivity of electricity demand can be easily demonstrated in this sector (Salari & Javid, 2016).

Although China's per capita residential electricity consumption is not high, its total residential electricity consumption is the highest in the world. As shown in Fig. 1, China's residential electricity consumption increased from 22.25 billion kWh in 1985 to 969.2 billion kWh in 2018, indicating an annual growth rate of 12%. Additionally, as a developing country with relatively rapid economic growth, it would be interesting to explore the effect of economic development on the climatic sensitivity of China's residential electricity demand. Moreover, the uneven development of China's cities encourages investigation on how income levels

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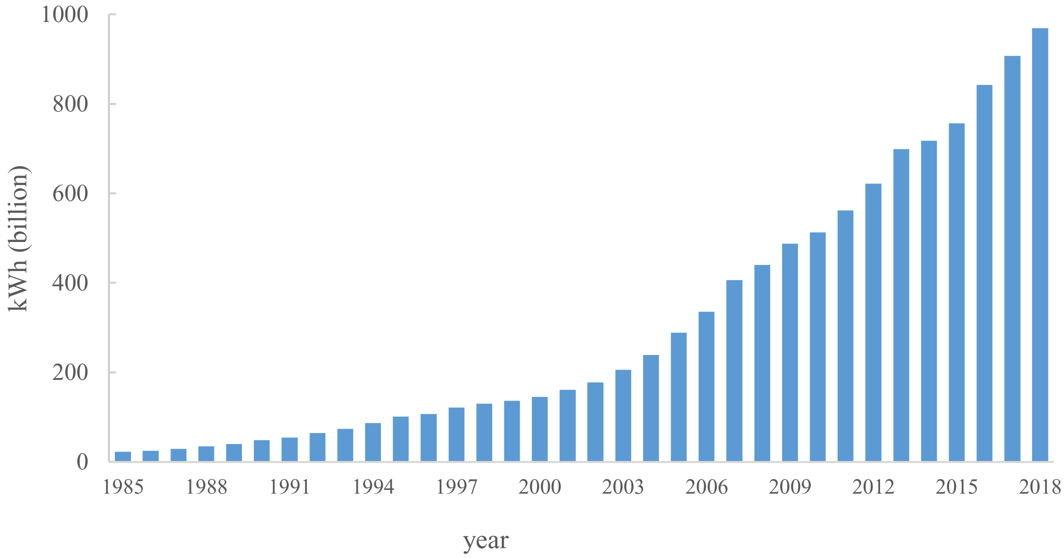

Fig. 1. Residential electricity consumption in China.
Source: China Premium Database.

affect the response of residential electricity consumption to climate variation.

This study models the role of income in the climatic sensitivity of China's residential sector. It augments existing literature from the following aspects. It employs a new empirical strategy to explore the heterogeneous effects of climate change on residential electricity demand at different income levels. Previous studies impose a specific functional form on the link between the marginal impact of climatic variations and income (Gupta, 2016; Li et al., 2018) or separately estimate the temperature-electricity curve for subgroups with different income levels (Li, Pizer, & Wu, 2019). This study applies partially linear functional-coefficient panel data models in which the marginal effects of temperature variations are considered as an unknown function of income. This strategy helps to reduce the risk of model misspecification and enables identification of how income shapes the relationship between temperature variations and residential electricity consumption in detail. The study provides new evidence on the link between climatic variation and residential electricity consumption at the city level in China. By contrast, Li et al. (2019) focus on a typical area (Shanghai). Li et al. (2018) use China's provincial data, neglecting the remarkable variations among cities even within the same province. To address this gap, this study compiles a city-level panel dataset to examine the effect of climatic variations on residential electricity consumption from comprehensive perspective; the data cover 278 cities in China over a period of 11 years. These data can take into account dynamic changes in temperature and different geographic locations in China, including different terrains and climate zones.

The rest of this paper is as follows. Section 2 reviews previous literature regarding climatic impacts on electricity consumption. Section 3 introduces the detailed methodology. Section 4 reports and discusses the empirical results. Section 5 concludes the paper.

2. Literature review

It is well documented that energy consumption can affect climate, but recent studies show that, vice versa, there is a feedback mechanism between climate change and energy demand. The effect of climate variations can be observed from electricity consumption (Mansur, Mendelsohn, & Morrison, 2008). For instance, hot weather may stimulate the need for using cooling equipment, increasing the electricity demand of households; contrarily, cold days increase electricity consumption through the use of heating appliances (Auffhammer & Mansur, 2014; Eskeland & Mideksa, 2009; Mideksa & Kallbekken, 2010). Previous research shows that there is a non-linear relationship between climate change and electricity demand (Ahmed, Muttaqi, & Agalgaonkar, 2012; Bessec & Fouquau, 2008; Moral-Carcedo & Vicéns-Otero, 2005). Auffhammer and Mansur (2014) and Hsiang (2016) provide detailed discussions and systematic reviews on existing literature. Generally, relevant studies are classified into two categories: directly estimating the response function of electricity demand (i.e., the temperature–electricity curve) to climate change and exploring the climatic sensitivity of electricity consumption based on certain constructed indicators of temperature variation.

Various econometric models have been employed to estimate the temperature–electricity curve. Theoretically, when the temperature excesses a threshold point, electricity demand for a cooling process increases; contrarily, when the temperature is below a certain level, residents might use electricity for heating, and its demand increases. Thus, there is a U-shaped relationship between electricity demand and temperature (Gupta, 2012). Methodologically, the three main types of econometric models for estimating the temperature–electricity curve are: parametric models, nonparametric models, and semiparametric models. Regarding parametric models, the simplest way to describe the U-shaped curve is by using a quadratic function of temperature. However, this approach imposes a symmetric assumption that electricity demand responds equally to upward and downward changes in temperature. For the asymmetric response of electricity demand, some studies (e.g., Bessec & Fouquau, 2008; Moral-Carcedo & Vicéns-Otero, 2005) employ smooth transition regression (STR) models to explore the relationship between temperature and electricity demand.

Although STR models improve the fitness of observations on electricity demand and temperature, they assume specific forms of the transitional function, and are thereby likely to suffer from model misspecification. Therefore, recent studies tend to adopt nonparametric and semiparametric models, which assume that the response function of electricity to temperature is unknown and do not impose any functional form. For instance, Gupta (2012) employs a semi-parametric variable coefficient approach to estimate the temperature–electricity curve in Delhi, India, which represents the temperature response function as a linear combination of the base functions of regression splines. Davis and Gertler (2015) construct a flexible semiparametric model that describes the temperature response function as a linear combination of the number of days in different temperature bins to explore the relationship between temperature and electricity consumption in Mexico. Auffhammer (2018) employs an approach similar to that of Davis and Gertler (2015) to analyze the response of residential electricity and natural gas demand to temperature variations in California, USA.

This strand of literature generally demonstrates that there is a U-shaped relationship between electricity demand and temperature, and the response of electricity demand to upward and downward changes in temperature is asymmetric. Owing to these features of the temperature-electricity curve, another strand of literature proposes the degree day approach to measure temperature variation. Contextually, heating degree days (HDD) and cooling degree days (CDD) are two widely used indicators, defined as $HDD = -\min(0, temperature - \underline{c})$ and $CDD = \max(0, temperature - \bar{c})$, respectively, where temperature denotes the daily mean temperature; $\underline{c}$ and $\bar{c}$ are two thresholds. The climatic sensitivity of electricity demand can be investigated through regressing electricity consumption on these indicators of temperature variations. Representative literature in this context includes Al-Zayer and Al-Ibrahim (1996), Considine (2000), Pardo, Meneu, and Valor (2002), and Ahmed et al. (2012).

Previous studies have expended great effort in developing state-of-the-art techniques for investigating the temperature response function or climatic sensitivity of electricity consumption. Recent studies emphasize that the relationship between energy consumption and the temperature is greatly affected by the income level. Income is thought to be related to decisions to install air conditioners (Auffhammer, 2014; Davis & Gertler, 2015). For example, in torrid summers, wealthy households use air conditioners for a longer period or purchase additional air conditioners for their comfort. Similarly, to increase indoor temperature, they are likely to use heating facilities in winter. Therefore, adaptation adjustment drives residents to use or buy more cooling or heating facilities as income increases. Therefore, income may have an impact on climate sensitivity through straightforward and backhanded approaches. Petrick, Rehdanz, and Tol (2010) include the product of temperature and income variables in their linear regression models; based on an unbalanced panel dataset of 157 countries between 1970 and 2002, they find that the marginal effect of temperature variations on energy consumption is affected by the level of income. Similarly, Gupta (2016) adds an interaction term of temperature and income variable into the baseline model to explore the role of income in the climatic sensitivity of electricity demand in India, finding that the estimated marginal effect of temperature variations increases with growing income levels.

Research on climate sensitivity has been prolific globally and has contributed rich findings. Thus far, there is considerable evidence in China's case. Li et al. (2018) use China's 30 provinces to explore the linear relationship between temperature deviation and residential electricity consumption. They find that a 1 °C deviation from the comfortable zone (18–27 °C) increases residential electricity demand by about 0.4%. For further discussion, they add an interaction term of temperature deviation and the logarithm of income into their baseline models, showing that the effect of temperature deviation decreases with growing income, which is disproportionate with the theoretical expectation. Including an interaction term essentially assumes that the effect of temperature deviation is a linear function of the logarithm of income. Thus, it might suffer from model misspecification. Additionally, it is worth highlighting that Li et al. (2018) use monthly average temperatures at the provincial level to calculate the temperature deviation indicator. The monthly data would smoothen the variations in temperature, consequently being likely to underestimate the climatic sensitivity.

Li et al. (2019) compile panel data of daily household-level electricity use in Shanghai, China, and employ semiparametric panel data models to estimate the temperature–electricity response function. They find a U-shaped relationship between household electricity use and temperature, and the comfort zone is 13–25 °C (the curve rises moderately when temperature goes below 13 °C while increasing steeply when temperature exceeds 25 °C). Moreover, to show household income affects climatic sensitivity, they classify the households into four subgroups and separately estimate the temperature–electricity curve for each. The results indicate climatic sensitivity significantly increases with growing household income in winter. Li et al. (2019) highlighted that despite Shanghai being the most developed region in China, their data lack information on income distribution, thereby limiting their ability to identify the income effect. China is a large country with considerable regional heterogeneities. Even within its provinces, there are variations across different cities. Thus, it is critical to consider the whole nation in more detail, to draw a universal conclusion. This study, therefore, proposes to fill these gaps in the existing literature by exploring the link between climate variations and residential electricity consumption in China's cities.

3. Methodology

As there is a non-linear link between temperature and energy demand (Bessec & Fouquau, 2008), the first objective is to find a suitable measurement for temperature variations. Previous studies prove that the relationship between climate change and electricity consumption is a U-shaped curve. Li et al. (2019) show that the response curve of residential electricity consumption to temperature is quite flat when the temperature range is 13 °C to 25 °C, and the electricity consumptions increase when the temperature departs from this comfortable zone.[1] Thus, this study regards 13 °C and 25 °C as the temperature thresholds, and constructs the indicators of heating degree days (HDD) and cooling degree days (CDD) as follows:

$$HDD_{it} = -\sum_{\tau=1}^{365} \min(0, Temp_{it\tau} - 13) \tag{1}$$

$$CDD_{it} = \sum_{\tau=1}^{365} \max(0, Temp_{it\tau} - 25) \tag{2}$$

where the subscripts i, t, and τ denote city, year, and day, respectively. $Temp_{i\tau}$ represents the actual temperature recorded every day in degrees Celsius. The HDD or CDD indicators capture the demand for electricity needed to heat or cool buildings. The impacts of HDD and CDD are generally found to be asymmetrical (Amato, Ruth, Kirshen, & Horwitz, 2005). The study also follows Li et al. (2018) to construct a temperature deviation (TDEV) indicator, which is the sum of HDD and CDD.

$$TDEV_{it} = HDD_{it} + CDD_{it} \tag{3}$$

The empirical study is conducted as follows. It estimates how residential electricity consumption would be affected by temperature variation. Here baseline models for residential electricity consumption are:

Model I:

$$\ln(E_{it}) = \alpha + \beta \ln(TDEV_{it}^{*}) + \gamma X_{it} + \mu_i + \varepsilon_{it} \tag{4}$$

Model II:

$$\ln(E_{it}) = \alpha + \beta_1 \ln(HDD_{it}^{*}) + \gamma X_{it} + \mu_i + \varepsilon_{it} \tag{5}$$

Model III:

$$\ln(E_{it}) = \alpha + \beta_2 \ln(CDD_{it}^{*}) + \gamma X_{it} + \mu_i + \varepsilon_{it} \tag{6}$$

Model IV:

$$\ln(E_{it}) = \alpha + \beta_1 \ln(HDD_{it}^{*}) + \beta_2 \ln(CDD_{it}^{*}) + \gamma X_{it} + \mu_i + \varepsilon_{it} \tag{7}$$

Here E_{it} is the residential electricity consumption in city i and year t.$TDEV_{it}^{*} = TDEV_{it} + 1$, $\mathrm{HDD}_{it}^{*} = HDD_{it} + 1$, $\mathrm{CDD}_{it}^{*} = CDD_{it} + 1$.[2] X_{it} is the vector of control variables introduced to account for other possible influences. All these variables are in the natural logarithm. Additionally, μ_i denotes unobserved individual effects and ε_{it} is a random error. The coefficient of β(β_1 andβ_2) measures the magnitude of the impact of climate change on electricity consumption.[3]

The influence of climate variations on residential electricity consumption may be affected by different income levels (Li et al., 2018; Li et al., 2019). Therefore, to examine the heterogeneous effects of climate change at different income levels, a simple empirical strategy that adds interaction terms into the baseline models is considered. These interaction terms can help analyze the effect of income, using two different methods as follows.

Model V:

$$\ln(E_{it}) = \alpha + \beta \ln(TDEV_{it}^{*}) + \varphi[DumRI \times \ln(TDEV_{it}^{*})] + \gamma X_{it} + \mu_i + \varepsilon_{it} \tag{8}$$

Model VI:

$$\begin{aligned} \ln(E_{it}) = \alpha &+ \beta_1 \ln(HDD_{it}^{*}) + \beta_2 \ln(CDD_{it}^{*}) + \varphi_1 [DumRI \times \ln(HDD_{it}^{*})] \\ &+ \varphi_2 [DumRI \times \ln(CDD_{it}^{*})] + \gamma X_{it} + \mu_i + \varepsilon_{it} \end{aligned} \tag{9}$$

Eqs. (8) and (9) include $DumRI \times \ln(TDEV_{it}^{*})$, where $DumRI$is a dummy variable which is set to 1 if the city is at the high-income level (above the median income). Model V indicates that the impacts of temperature deviation are β and $\beta + \varphi$ for cities at the low-income level and high-income level, respectively. Similarly, for low-income and high-income cities, Model VI implies that the impacts of heating degree days (cooling degree days) are $\beta_1(\beta_2)$ and $\beta_1 + \varphi_1(\beta_2 + \varphi_2)$, respectively.

Alternatively, the study can consider adding the product of income and climate variables, as shown in Eqs. (10) and (11).

Model VII:

[1] It should be duly noted that Li et al. (2019) do not set up any threshold temperature. These threshold parameters 13 °C and 25 °C are inferred from the estimated temperature–electricity curves in Li et al. (2019). They also divide the sample into subgroups with different income levels to estimate the temperature–electricity curves which show that the threshold parameters are quite similar, but the slopes vary greatly across subgroups.

[2] The transformation is applied to avoid taking the logarithm of zero values.

[3] One particular concern on our regression models is that there might exist bidirectional causality. Generally, residents respond to climatic shocks contemporarily by electricity consumption while energy use contributes to climate change in a relatively long run. In other words, energy use does not cause climatic change immediately so that the reverse influence would not threaten the study's estimates. Li et al. (2018) also argue that weather variables are generally regarded as exogeneity in economics which enables researchers to identify the causal effect of weather variable on residential energy consumption in statistics.

$$\ln(E_{it}) = \alpha + \beta\ln(TDEV_{it}^{*}) + \varphi[\ln(RI_{it}^{*}) \times \ln(TDEV_{it}^{*})] + \gamma X_{it} + \mu_i + \varepsilon_{it} \tag{10}$$

Model VIII:

$$\begin{aligned}\ln(E_{it}) = \alpha &+ \beta_1\ln(HDD_{it}^{*}) + \beta_2\ln(CDD_{it}^{*}) + \varphi_1[\ln(RI_{it}) \times \ln(HDD_{it}^{*})] \\ &+ \varphi_2[\ln(RI_{it}) \times \ln(CDD_{it}^{*})] + \gamma X_{it} + \mu_i + \varepsilon_{it}\end{aligned} \tag{11}$$

Model VII shows that the impact of temperature deviation is characterized as a linear function of the logarithm of the income level, that is,$\beta + \varphi\ln(RI_{it})$. As shown in Model VIII, the effects of heating degree days and cooling degree days are characterized in similar ways.

Although the above strategies describe how the impact of climate change depends on income level, some limitations are notable. For instance, Model V and Model VI simply split the sample according to the median income level. This might lead to biased estimates, and to an abrupt change in the temperature response of residential electricity consumption for the observations near the splitting point, which is difficult to interpret in economic theory. Model VII and Model VIII impose strict assumptions about the functional form, which are likely to induce model misspecification. To avoid weaknesses, the study further introduces a partially linear functional-coefficient panel model into its estimation. This can overcome biased estimates and verify the income heterogeneity. Specifically, the study assumes that the response of residential electricity consumption is a function of the income level represented by the logarithm of GDP per capita, that is, $\beta = G(\ln RI_{it})$. Substitute $\beta = G(\ln RI_{it})$ into Model I. This leads to Model IX:

$$\ln(E_{it}) = \alpha + G(lnRI_{it})\ln(TDEV_{it}^{*}) + \gamma X_{it} + \mu_i + \varepsilon_{it} \tag{12}$$

Additionally, the study replaces β_1 and β_2 with $G_1(\ln RI_{it})$ and $G_2(\ln RI_{it})$ to change Model IV. Then Model X is as follows:

$$\ln(E_{it}) = \alpha + G_1(lnRI_{it})\ln(HDD_{it}^{*}) + G_2(lnRI_{it})\ln(CDD_{it}^{*}) + \gamma X_{it} + \mu_i + \varepsilon_{it} \tag{13}$$

Methodologically, the partially linear functional-coefficient panel data model is semiparametric. The kernel regression method is widely employed to estimate the nonparametric or semiparametric models. But in this context, the fixed effects are included. Evaluating such models with the kernel regression method is complicated. Conversely, the series regression method enables the study to remove the fixed effects by taking the difference. Thus, the estimation procedure is quite convenient. Additionally, the convergent rate of the series estimator is faster than the kernel estimator in this context.

Taking Model IX as an example, to estimate the partially linear functional-coefficient panel model, the study can use the series estimation method (An, Cheng, & Li, 2016). The procedure can be seen as follows.[4]

Using a linear combination of sieve base functions to approximate the varying coefficient function$G(\ln RI_{it})$:

$$h(lnRI_{it})'\eta = [h_1(lnRI_{it}),\dots,h_{\mathrm{p}}(lnRI_{it})]\begin{bmatrix}\eta_1\\ \vdots\\ \eta_p\end{bmatrix} \tag{14}$$

Here $h(\ln RI_{it}) = [h_1(\ln RI_{it}),\dots,h_{\mathrm{p}}(\ln RI_{it})]'$ is a $p \times 1$ vector of base functions and $\eta = [\eta_1,\dots,\eta_{\mathrm{p}}]'$ is a $p \times 1$ vector of unknown parameters. Then Eq. (12) can be re-written as:

$$\ln(E_{it}) = \alpha + h(lnRI_{it})'\eta\ln(TDEV_{it}^{*}) + \gamma X_{it} + \mu_i + \nu_{it} \tag{15}$$

Here$\nu_{it} = \varepsilon_{it} + \kappa_{it}$;$\kappa_{it} = G(\ln RI_{it}) - h(\ln RI_{it})'\eta$, which denotes the sieve approximation error.

After taking the first difference of Eq. (15) to eliminate fixed effects, the following model is obtained:

$$\Delta\ln(E_{it}) = \Delta(\ln(TDEV_{it}^{*})h(lnRI_{it})')\eta + \gamma\Delta X_{it} + \Delta\nu_{it} \tag{16}$$

If all the explanatory variables are exogenous, Eq. (16) can be estimated by the least square (LS) estimator, which defines

$$(\hat{\gamma},\hat{\eta}) = [\Delta\widetilde{X}'\Delta\widetilde{X}]^{-1}\Delta\widetilde{X}'\Delta\widetilde{Y} \tag{17}$$

where $\Delta Y = \begin{bmatrix}\Delta\ln(E_{12})\\ \vdots\\ \Delta\ln(E_{NT})\end{bmatrix}$ and

$$\Delta\widetilde{X} = \begin{bmatrix}\Delta X_{12}', \ln(TDEV_{12}^{*})h(lnRI_{12}) - \ln(TDEV_{11}^{*})h(lnRI_{11})\\ \vdots\\ \Delta X_{NT}', \ln(TDEV_{NT}^{*})h(lnRI_{NT}) - \ln(TDEV_{N(T-1)}^{*})h(lnRI_{N(T-1)})\end{bmatrix}.$$

Thus, the functional coefficients $G(RI_{it})$ can be estimated as

$$\hat{G}(RI_{it}) = h(lnRI_{it})'\hat{\eta} \tag{18}$$

[4] The technical details of the approximation function are presented in Appendix A. The statistical properties of the partially linear functional-coefficient panel model can be seen in An et al. (2016) and Zhang & Zhou, 2020. Du, Zhang, and Zhou (2020) provide a Stata module for estimating the partially functional-coefficient panel data models which is available at https://github.com/kerrydu/xtplfc_Stata

4. Empirical study

4.1. Data

This paper assembles a panel dataset, including 278 cities of Mainland China, over the period 2005 to 2015. In this model, the explained variable, which is city-level residential electricity consumption (denoted as *E*), is expected to be correlated with the key explanatory variables such as TDEV, HDD, and CDD. Raw data on the daily temperature employed in this paper is acquired from the National Meteorological Information Center of China. With these data, the study calculates city-level TDEV, HDD, and CDD, respectively, through Eqs. (1) and (2).

The control variables (*X*) are selected and constructed as follows.

(1) Income (denoted as *RI*). The study introduces income, represented by real GDP per capita in the 2005 price level, into our models. As GDP indicates living standards, the city-level real GDP per capita is included to control the possible effect of income.
(2) Electricity Price (denoted as *EP*). The electricity price is controlled because its influence on electricity consumption is well-accepted (Gupta, 2016). Raw data is obtained from Li et al. (2018) and the Wind Economic Database. Due to the lack of city-level data, the provincial average electricity selling price, assuming uniform pricing for cities within each province, is collected.
(3) Fuel Price (denoted as *FP*). As other energy sources can be substituted, their prices are also likely to affect residential electricity consumption (Shen, 2014). In this paper, because neither city-level nor provincial fuel prices are available, provincial panel data of the fuel price index is used, following Wu (2012) and Lin and Du (2015). The fuel price index can only reflect changes in the fuel prices over time within each province, as with electricity price data.
(4) Equipment Price (denoted as *EQP*). Shen (2014) highlights that household equipment prices can influence purchase of appliances and finds that electricity demand is negatively correlated with its price. Therefore, an equipment price variable is introduced, represented by a household equipment price index, as one of the control variables. Here, again, provincial index is used owing to the lack of city-level data.
(5) Time trend (denoted as *Trend*). To capture common trends in cities, a time trend is included.

All data except temperature and electricity prices are acquired from the China Premium Database. The nominal variables have been deflated to 2005 constant prices, and the electricity price, fuel price, and household equipment price are all deflated by the consumer price index. Table 1 illustrates the statistical description of these variables.

4.2. Estimation results of the baseline models

Table 2 represents the estimation results of linear models I-IV. The study focuses on the coefficients of climate variables to understand how climate variation affects residential electricity consumption.

Specifically, the coefficient of ln*TDEV*is estimated as 0.1043 and is significant at the 5% level, indicating that a 1% increase in TDEV can increase residential electricity consumption by 0.1%. To analyze different effects of temperatures above and below the comfortable zone, HDD and CDD are introduced into regressions. Model II and Model III estimate impacts of HDD and CDD, respectively. The coefficient of ln*HDD* is 0.0115 but not significant. This is because cities with high HDD are concentrated in the northern areas where most regions are provided with central (district) heating services, primarily powered by coal (Li, Cao, Guo, Niu, & Xiong, 2016). Intuitively, the cost of using electricity for heating is relatively high, driving residents to use other fuels instead. Consequently, it is found that HDD does not impact residential electricity consumption significantly. However, in hot weather (the temperature is higher than 25 °C), more electrical equipment such as air conditioners will be used for cooling. Thus, a significant increase in residential electricity consumption is expected with rising temperatures during the summer. This assumption is verified by the estimation results of Model III, which shows that the coefficient of ln*CDD* is 0.0548 and significant at 1% level. This indicates that a 1% increase in CDD increases electricity consumption by 0.05%. In Model IV, both HDD and CDD are added into the baseline model simultaneously, and the results stay unchanged. These findings are similar to Davis and Gertler (2015), who find that the climate sensitivity of residential electricity consumption is extremely high on hot days, with no difference on cold days.

The study found that income may significantly stimulate residential electricity consumption, consistent with expectations. As

Table 1
Descriptive statistics of variables.

Variable	Description	Unit	N	Mean	SD	Min	Max
E	Residential electricity consumption per capita	KWH	3010	235.71	373.89	5.69	4335.66
TDEV	Temperature deviation	°C·d	3058	1630.75	1045.96	12.40	6180.20
HDD	Heating Degree Day	°C·d	3058	1426.45	1160.07	0.00	6176.10
CDD	Cooling Degree Day	°C·d	3058	203.61	171.30	0.00	912.00
RI	GDP per capita	RMB	3058	28,701.59	21,895.75	2396.00	180,174.50
EP	Electricity price	RMB/KWH	3058	0.62	0.08	0.35	0.86
FP	Fuel price index	%	3058	90.83	14.95	58.06	123.50
EQP	Household equipment price	%	3058	83.54	8.06	63.43	98.40

Table 2
Estimation results of the linear panel model.

	Model I	Model II	Model III	Model IV
ln*TDEV*	0.1043**			
	(0.0439)			
ln*HDD*		0.0115		0.0116
		(0.0154)		(0.0156)
ln*CDD*			0.0548***	0.0548***
			(0.0151)	(0.0151)
ln*RI*	0.4919***	0.4996***	0.4773***	0.4813***
	(0.1011)	(0.1001)	(0.1009)	(0.1007)
ln*EP*	0.1162	0.1105	0.0857	0.0886
	(0.0943)	(0.0934)	(0.0936)	(0.0940)
ln*FP*	0.2468***	0.2529***	0.2265***	0.2229***
	(0.0802)	(0.0811)	(0.0791)	(0.0786)
ln*EQP*	−0.4720	−0.5404*	−0.6131**	−0.5942**
	(0.3030)	(0.2988)	(0.2955)	(0.2983)
Trend	0.0474***	0.0449***	0.0448***	0.0446***
	(0.0138)	(0.0137)	(0.0137)	(0.0137)
Constant	−0.0356	0.8473	1.3282	1.1448
	(1.9517)	(1.8182)	(1.7773)	(1.8067)
City fixed effect	Yes	Yes	Yes	Yes
N	3010	3010	3010	3010

Note: Robust standard errors in parentheses; *** $p < .01$, ** $p < .05$, * $p < .1$.

shown in Model I, a 1% increase in income would lead to a 0.492% increase in residential electricity consumption. Similarly, the coefficient of ln*RI* in Model III is 0.477 and significant at the 1% level, indicating that a 1% increase in income increases residential electricity consumption by 0.477%. These estimates are smaller than those in Li et al. (2018).

The coefficient of ln*EP* is positive but insignificant even at 10% level. This may be because, in China, electricity price is regulated by the government and less determined by the market.[5] Equipment price has a significantly negative influence on residential electricity consumption in Model II-IV. This is consistent with the expectations of the study. The high price of household appliances would discourage residents from buying new equipment, given that their income is unchanged, which in turn would prevent an increase in electricity consumption. The coefficient of ln*FP* is also positive and insignificant at the 1% level. It means that the increase in the fuel price would encourage residents to use electricity instead. However, provincial data on price is employed in this paper, leading to minimal variation in the data on prices, thereby reducing the preciseness of estimation of price elasticity. Finally, the coefficient of time trend is significantly positive in all models at the 1% level.

4.3. Estimation results of linear panel models with interaction terms

The above analysis assumes the homogeneous impact of climate change on residential electricity consumption at different income levels. It explores the potential heterogeneity of climatic sensitivity next.

Table 3 reports the estimation results. It is observed that the coefficient of *DumRI* × ln *TDEV* is quite small and not significant even at the 10% level, indicating that the difference in climatic sensitivity between high-income and low-income cities is not statistically significant when climate change is measured by temperature deviation. Conversely, it can be observed that the coefficient of *DumRI* × ln *CDD* is positive and significant at the 10% level in Model VI, implying that the response of residential electricity consumption to high temperatures is stronger in the high-income cities than in the low-income cities. Since the coefficients of ln*HDD* and *DumRI* × ln *HDD* are not significant even at the 10% level, they are excluded in Model VI', which shows similar results as those in Model VI.

Similarly, Model VII-VIII' also assume that the response function is linear. The coefficient of ln*RI* × ln *TDEV* is estimated as −0.0428 and insignificant, indicating that the impact of temperature deviation on residential electricity consumption may be negative but not statistically salient. The study then considers the asymmetrical response between CDD and HDD (Model VIII). The results show that the response to HDD and CDD is still insignificant at the 10% level, which is different from that of Model VI. As in Model VI', the study excludes ln*HDD* and ln*RI* × ln *HDD* in Model VIII' and finds that the coefficient of ln*RI* × ln *CDD* is 0.0243 and significant at the 10% level. The inconsistency between the results of different interaction terms indicates possible limitations of linear model specifications, and thus assumptions on function forms need to be relaxed.

[5] For instance, the electricity price is directly determined by National Development and Reform Commission of China and only changes occasionally. As discussed in Cho, Nam, and Pagán (2004), both the administrative control on energy prices and market imperfections prevent energy prices from fluctuating as they would within a market system.

Table 3
Estimation results of linear panel models with interaction terms.

	Model V	Model VI	Model VI'	Model VII	Model VIII	Model VIII'
ln*TDEV*	0.1034**			0.5156*		
	(0.0433)			(0.3088)		
ln*HDD*		0.0099			0.1195	
		(0.0156)			(0.1775)	
ln*CDD*		0.0473***	0.0508***		−0.1539	−0.1849
		(0.0151)	(0.0150)		(0.1296)	(0.1233)
ln*RI*	0.4685***	0.4491***	0.4367***	0.8040***	0.4733***	0.3792***
	(0.1002)	(0.0997)	(0.1010)	(0.2359)	(0.1689)	(0.1189)
ln*EP*	0.1172	0.0779	0.0814	0.1043	0.0581	0.0594
	(0.0945)	(0.0931)	(0.0940)	(0.0937)	(0.0925)	(0.0923)
ln*FP*	0.2447***	0.2064**	0.2154***	0.2332***	0.2036**	0.2094***
	(0.0800)	(0.0798)	(0.0790)	(0.0827)	(0.0800)	(0.0785)
ln*EQP*	−0.4897	−0.6788**	−0.6743**	−0.5217*	−0.6783**	−0.6788**
	(0.3043)	(0.2936)	(0.2953)	(0.2941)	(0.2858)	(0.2867)
Dum*RI* × ln*TDEV*	0.0039					
	(0.0044)					
Dum*RI* × ln*HDD*		−0.0073				
		(0.0073)				
Dum*RI* × ln*CDD*		0.0190*	0.0107*			
		(0.0102)	(0.0064)			
ln*RI* × ln*TDEV*				−0.0428		
				(0.0322)		
ln*RI* × ln*HDD*					−0.0117	
					(0.0174)	
ln*RI* × ln*CDD*					0.0211	0.0243*
					(0.0135)	(0.0128)
Trend	0.0475***	0.0427***	0.0438***	0.0448***	0.0407***	0.0410***
	(0.0138)	(0.0135)	(0.0137)	(0.0135)	(0.0133)	(0.0133)
Constant	0.2789	1.9485	2.0523	−2.7459	1.7375	2.6678
	(1.9508)	(1.7988)	(1.7766)	(2.7912)	(2.2327)	(1.8055)
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
N	3010	3010	3010	3010	3010	3010

Note: Robust standard errors in parentheses; ***$p < .01$, **$p < .05$, *$p < .1$.

4.4. Estimation results of partially linear functional-coefficient panel models

Evidence that income level affects the climatic sensitivity of residential electricity demand under some restrictive assumptions was found in the above subsection. The study relaxes these assumptions using partially linear functional-coefficient models. The estimation results are reported in Figs. 2–4 and Table 4.

Fig. 2 illustrates the response function of residential electricity consumption to temperature deviation (TDEV) in Model IX. It is

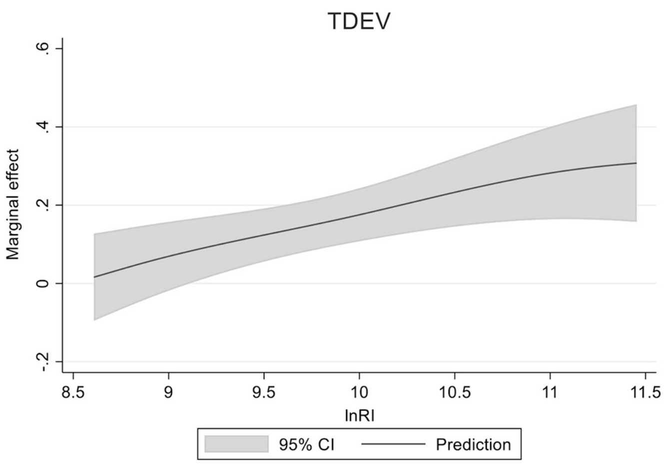

Fig. 2. Functional coefficient estimates of lnTDEV in Model IX. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Note: The figure displays the estimated coefficients for values of lnRI ranging from the 2nd to 98th sample percentile, with 95% confidence intervals shaded in grey.

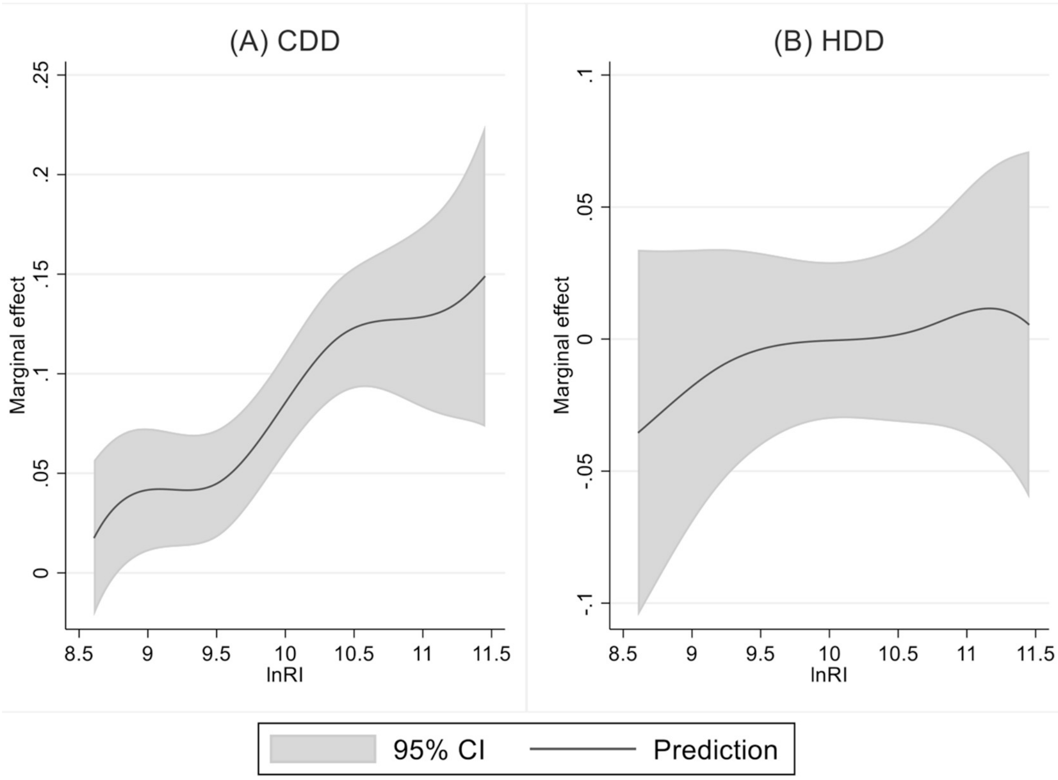

Fig. 3. Functional coefficient estimates of lnHDD and lnCDD in Model X. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Note: The figures display the estimated coefficients for values of lnRI ranging from the 2nd to 98th sample percentile, with 95% confidence intervals shaded in grey.

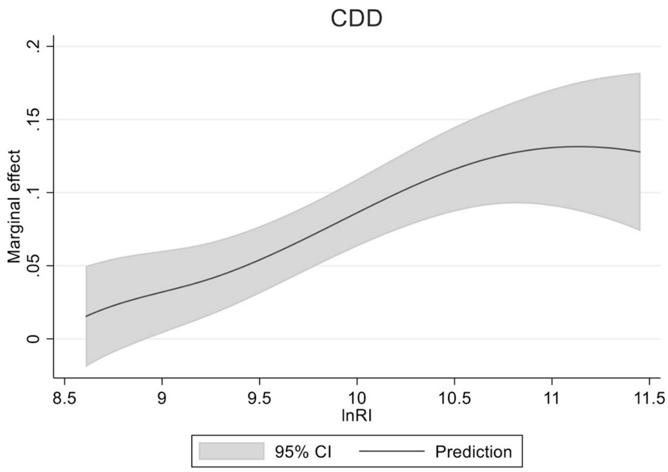

Fig. 4. Functional coefficient estimates of lnCDD in Model X'. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Note: The figure displays the estimated coefficients for values of lnRI ranging from the 2nd to 98th sample percentile, with 95% confidence intervals shaded in grey.

depicted as an upward curve. The study also finds that the 95% confidence interval includes 0 when the value of the natural logarithm of GDP per capita is less than 9.1 (equivalently, GDP per capita is less than 8955.293 Yuan at the 2005 price level). It indicates that poor residents might not significantly respond to temperature deviation from the comfort zone. When the income level exceeds 8955.293 Yuan, the 95% confidence interval stays above 0, indicating the climatic sensitivity is significant at the 5% level. Specifically, the effect of temperature deviation from the comfort zone on residential electricity consumption increases with income

Table 4
The parametric part of the partially linear functional-coefficient models.

	Model IX	Model X	Model X'
ln*RI*	−0.5859*	−0.19193	−0.07660
	(0.3007)	(0.1844)	(0.1079)
ln*EP*	0.1835**	0.1286	0.13819*
	(0.0803)	(0.8000)	(0.0765)
ln*FP*	0.1202*	0.0695	0.0649
	(0.0703)	(0.0697)	(0.0695)
ln*EQP*	−0.1353	−0.5895**	−0.5686**
	(0.2461)	(0.2510)	(0.2470)
Trend	0.0807***	0.0730***	0.0714***
	(0.0117)	(0.0124)	(0.0118)
N	2730	2730	2730

Note: Bootstrapped standard errors in parentheses; the number of replications is 1000; *** $p < .01$, ** $p < .05$, * $p < .1$. Model X' excludes HDD terms in Model X.

growth. This result is different from the linear panel model with the interaction term (shown in Model VII of Table 3), which shows that the climatic sensitivity may decrease with income growth.

The asymmetrical response to HDD and CDD, as in the previous analysis, is also considered. Fig. 3 shows the functional-coefficient estimates of ln*HDD* and ln*CDD*in Model X, respectively. It is observed that the curve of the marginal effect of HDD fluctuates around 0, and the 95% confidence interval includes 0, indicating that the effect of HDD on residential electricity consumption is insignificant. This finding is in line with our previous results. Conversely, the effect of CDD is very significant. Generally, the marginal effect of ln*CDD* shows a remarkable increasing trend with various speeds in different stages.

Since the effect of HDD was found to be insignificant, it was excluded, and the impact of CDD was re-estimated. Fig. 4 presents the estimated functional coefficients. It was found that when the natural logarithm of GDP per capita is less than 8.9 (i.e., GDP per capita is less than 7331.974 Yuan), climatic sensitivity is not only quite low but is insignificant at the 5% level. This is because the poor residents might respond to CDD increase by using low power appliances (e.g., electric fans) or even physical cooling without electricity consumption. When GDP per capita exceeds 7331.974 Yuan, climatic sensitivity becomes significant at the 5% level and rises significantly. The growth speeds up when the natural logarithm of GDP per capita exceeds 9.4 (i.e., GDP per capita exceeds 12,088.381 Yuan). After it reaches 11 (i.e., GDP per capita is 59,874.142 Yuan), the curve becomes quite flat. This result is consistent with the intuition of this study. When the residential income level is relatively low, an increase in income will encourage people to purchase and use more household equipment to improve their comfort level in response to temperature changes, resulting in more electricity consumption. However, when the income level is high enough, residents generally possess and use enough household equipment such that the additional electricity use in response to temperature changes would be relatively small. Thus, climate change would contribute less to increased purchase and use of household equipment for wealthy residents than for the relatively poor. Alternatively, the adjustment in the extensive margin tends to be small for residents with high-income levels.

As in the results of control variables (reported in Table 4), the signs and significance for most variables are consistent with previous results except for ln*RI*. The coefficient of ln*RI* becomes negative in Models IX, X, and X', and it is significant at 10% level in Model IX. Nevertheless, it should be noted that ln*RI* also enters the function of the coefficient of ln*TDEV*, ln*HDD,* and ln*CDD* so that the negative value of the coefficient of ln*RI* does not indicate that the income growth contributes negatively to residential electricity consumption.

4.5. Robustness check for temperature thresholds

The above analysis, based on the assumption that the residents' electricity consumption resists responding to temperature changes during the interval [13, 25] °C derived from Li et al. (2019), concerns whether the previous findings are sensitive to the temperature thresholds. In this subsection, the study conducts robustness analysis with these two alternative threshold combinations: {12 °C, 24 °C} (labeled as “R1”) and {14 °C, 26 °C} (labeled as “R2”).

The apparent temperature that people perceive depends not only on the air temperature but also directly links to the humidity. As humidity generally varies across different cities, the temperature thresholds for HDD and CDD should be different. But due to data availability, no studies estimating the temperature thresholds for HDD and CDD in the 278 cities of the sample exist. Thus, an alternative strategy (labeled as “R3”) based on the heat index method[6] is considered. Notably, the thresholds of the heat index for HDD and CDD are first calculated based on the original thresholds (13 °C and 25 °C) and the relative humidity of Shanghai in winter and summer during 2014–2016, i.e., the research period of Li et al. (2019). By this mean, the thresholds of heat index for HDD and CDD are 12.2 °C and 25.6 °C, respectively. Then, the daily HI by cities is calculated, based on air temperature and relative humidity. The HDD and CDD can be calculated as follows:

[6] More details can be found at NOAA (https://www.wpc.ncep.noaa.gov/html/heatindex_equation.shtml).

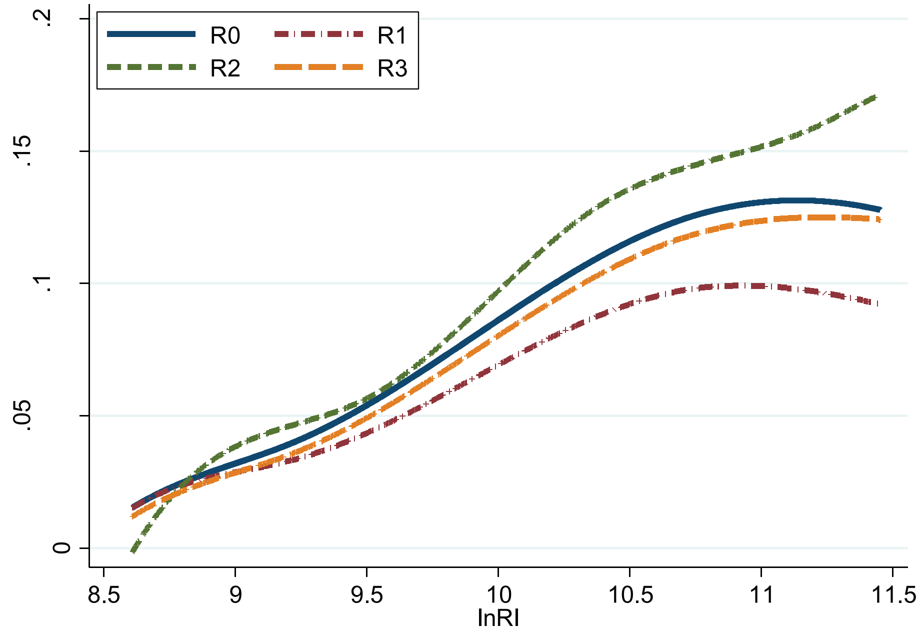

Fig. 5. Robustness check of the response curves of lnCDD.
Note: *R0*, *R1*, *R2*, and *R3* refer to the estimates with the temperature thresholds {13 °C, 25 °C}, {12 °C, 24 °C}, and {14 °C, 26 °C}, and the heat index method, respectively.

$$HDD_{it} = -\sum_{\tau=1}^{365} \min(0, HI_{it\tau} - 12.2) \tag{19}$$

$$CDD_{it} = \sum_{\tau=1}^{365} \max(0, HI_{it\tau} - 25.6) \tag{20}$$

The study re-estimates all previous models with these three different settings. The results are reported in the supplemental materials of Appendix B, from which it can be concluded that the main findings remain unchanged. Fig. 5 presents the functional-coefficient estimates of ln*CDD* in all threshold combinations together for comparison.

5. Concluding remarks

This study employs city-level panel data to investigate the potential impact of climate change on residential electricity consumption in China. Furthermore, it uses several different empirical strategies to explore how economic development affects the climatic sensitivity of residential electricity demand. The empirical evidence attests to the assumptions, leading to the following conclusions: (1) Using temperature deviation as a measure of climate change might lead to misleading conclusions since there is a remarkable asymmetry in residents' response to hot and cold weather. (2) Residential electricity consumption is positively responsive to hot days rather than cold days. (3) Different income levels have different impacts on the process through which climate change stimulates electricity consumption. Specifically, the higher the income, the greater the climate sensitivity; however, when the income exceeds a certain value, the stimulation effect remains unchanged. This is evident from the slope variations of the marginal effect of CDD: the curve initially rises sharply, and then gradually becomes gentle, with only slight fluctuations when income increases, indicating that climate change contributes less to residential electricity consumption for wealthy residents. Although high-income groups can purchase more cooling equipment, electricity consumption has already peaked due to the saturation of cooling devices in their houses; therefore, the demand will not be highly responsive to climate change again.

There are some limitations to this study. In this paper, the aggregate city-level electricity consumption of the residential sector is used. Ideally, household-level data should be used to provide more detailed information about electricity consumption behavior. Such data help to distinguish the intensive and extensive margin effects.[7] Moreover, the study employs certain province-level data, such as electricity price, fuel price, and household equipment price, due to limitations in data availability. This implies that there are no variations in the prices within different cities in the same province, which might result in poor estimation of price elasticities. Lastly, an alternative income variable, such as per capita disposable income or per capita wage, may be better proxies. However, these city-level data are not available before 2013, and prevent robust analyses by using income variables with different definitions.

[7] Li et al. (2018) is a pioneering work in China's context.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chieco.2020.101520.

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