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Modeling climate feedbacks to electricity demand: The case of China

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Abstract

This paper is an empirical investigation of the effects of climate on the use of electricity by consumers and producers in urban and rural areas within China. It takes advantage of an unusual combination of temporal and regional data sets in order to estimate temperature, as well as price and income elasticities of electricity demand. The estimated positive temperature/electric power feedback implies a continually increasing use of energy to produce electric power which, in China, is primarily based on coal. In the absence of countervailing measures, this will contribute to increased emissions, increased atmospheric concentrations of greenhouse gases, and increases in greenhouse warming.

JEL classification: C33; Q4; Q54

Keywords: Climate and energy; China; Panel econometric

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1. Introduction

This paper investigates the effects of climate on the use of electricity by consumers and producers, using an unusual data set assembled for urban and rural areas across China. The primary question is the direction in which the net adjustments to climate change will proceed: greater or lesser use of electricity and, therefore, greater or lesser use of greenhouse gas emitting fuels? If the feedbacks are negative, their neglect leads to overestimates of future emissions. However, if the feedbacks are positive, their neglect leads to underestimates of emissions and future global warming.

The analysis of the potential effects of climate change has received considerable attention, although not as much as the consequences of mitigating greenhouse gas emissions levels (Metz et al., 2001). This is unfortunate for two reasons. First, we have already experienced globally averaged warming and there will be continued changes in the future (Forest et al., 2000). Secondly, there may be effects of climate change that increase or decrease the difficulties of future climate mitigation through positive or negative feedbacks (Prinn et al., 1999).

We estimate the demand for electricity-using climate indicators, as well as structural and the conventional price and income variables. We do this for Chinese provinces over a six year period so that we can capture both spatial and temporal climatic differences on urban and rural consumers and industry. For residential consumers, we employ two-stage regressions. The first stage estimates the localized effect of climate and other variables on the purchase of electricity-using residential appliances; the second stage then estimates the localized effect of climate and other variables on the intensity of both appliance and non-appliance uses of electricity. Non-residential electricity demands for electricity are estimated separately as a one-stage regression.

The Third Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) identifies energy sectors as being the most vulnerable to climate change (McCarthy et al., 2001). Despite this, there are relatively few empirical studies dealing with the feedbacks of climate on energy demand. To date, numerous economic assessments of climate feedbacks on energy demand have been mainly qualitative case studies, surveys, overviews, or subjective evaluations. (Crocker and Ferrar, 1976; Linder et al., 1989; Smith and Tirpak, 1989; Nordhaus, 1991; Cline, 1992; McKibbin and Wilcoxen, 2002).

There is, however, a modest set of econometric investigations on related issues. These include models utilizing a single stage sector-disaggregated energy demand framework originating with Fisher and Kaysen (1962) and expanded upon more recently by Considine (2000). Dubin and McFadden (1984) developed a two-stage discrete-continuous methodology, used also by Vaage (2000). In most of these instances, weather data is utilized, represented by the number of heating- and cooling-degree days. One exception is Mansur et al. (2005) in which they employ National Climate Data Center data on average monthly temperature and precipitation. Like Dubin and McFadden (1984), the first stage of the Mansur et al. (2005) regressions explains fuel choice, as if energy sources other than electricity are possible in the important consumer applications.

This study is unique in that, besides its “stand-alone” value, the econometric specification is designed such that climate change researchers may be able to subsequently utilize the empirical estimates within an integrated global systems framework (e.g., Sokolov et al., 2005).

The remainder of the paper is organized as follows. Section 2 details the empirical models and data. Next, Section 3 reports and analyzes empirical results. Section 4 provides discussion of estimated elasticities. Lastly, Section 5 provides a summary and conclusions.

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2. Empirical models and data

In formulating our econometric model of electricity demand with the inclusion of climate variables, the availability of data at relatively low levels of disaggregation is essentially the "horse that pulls the carriage". We have detailed provincial economic and climate data over several years for urban and rural areas in China, covering a wide range of climate zones, forming a substantial panel data set (Fridley and Sinton, 2004; Ngo-Duc et al., 2005; State Statistical Bureau of the People's Republic of China, 1995, 1996, 1997, 1998, 1999, 2000, 2001).

The data distinguish urban and rural residential use of electricity. In addition, our data permit us to control for individual ownership of air conditioners, refrigerators, and television sets. We use proxy variables as well to capture electricity demand for lighting/illumination[1]. In estimating residential electricity demands separately for urban and rural residents, we follow the spirit of the two-stage approach initially developed by Dubin and McFadden (1984), except that we estimate a first set of individual demands for air conditioners (ACs), refrigerators and television sets (TVs), rather than a choice of fuel types. The second stage equation is residential electricity demand conditional on these first stage choices. More formally,

$$W_{it}^{\mathrm{U}} = X_{it}^{\mathrm{U}} \delta^{\mathrm{U}} + v_i^{\mathrm{U}} \tag{1}$$

$$Y_{it}^{\mathrm{U}} = Z_{it}^{\mathrm{U}} \beta^{\mathrm{U}} + \varepsilon_{it}^{\mathrm{U}} \tag{2}$$

$$W_{it}^{\mathrm{R}} = X_{it}^{\mathrm{R}} \delta^{\mathrm{R}} + v_i^{\mathrm{R}} \tag{3}$$

$$Y_{it}^{\mathrm{R}} = Z_{it}^{\mathrm{R}} \beta^{\mathrm{R}} + \varepsilon_{it}^{\mathrm{R}} \tag{4}$$

Where:

W_{it}^{U} Vector of dependent variables consisting of natural logarithm of the urban stocks of ACs, refrigerators, and TVs estimated individually and respectively.

W_{it}^{R} Vector of dependent variables consisting of natural logarithm of the rural stocks of ACs, refrigerators, and TVs estimated individually and respectively.

Y_{it}^{U} Natural logarithm of urban residential electricity demand.

Y_{it}^{R} Natural logarithm of rural residential electricity demand.

X_{it}^{U} Natural logarithm of: urban residential electricity price, urban income per capita, and mean temperature variable(s); a binary variable for differences associated with coastal provinces; for the AC equation, the natural logarithm AC price and fan price are added; for the refrigerator equation, the natural logarithm of refrigerator price is added; for the TV equation, the natural logarithm of the TV price is added.

X_{it}^{R} Natural logarithm of: rural residential electricity price, rural income per capita, and mean temperature variable(s); a binary variable for differences associated with coastal provinces; for the AC equation, the natural logarithm AC price and fan price are added;

[1] Brockett et al. (2002) indicate that the top four electricity-consuming appliances for China are (in descending order): refrigerators, air conditioners, and lighting/illumination, and televisions.

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for the refrigerator equation, the natural logarithm of refrigerator price is added; for the TV equation, the natural logarithm of the TV price is added.

Z_{it}^{U} All the same variables included in X_{it}^{U}, excluding all durable good prices; additional variables are the predicted new urban stocks of ACs, refrigerators, and TVs from the estimated Eq. (1); also included are the natural logarithm of total urban residential living space, and the natural logarithm of monthly night time (i.e. non-daylight) hours stratified by four seasons.

Z_{it}^{R} All the same variables included in X_{it}^{R}, excluding all durable good prices; additional variables are the predicted new rural stocks of ACs, refrigerators, and TVs from the estimated Eq. (3); also included are the natural logarithm of total rural residential living space, and the natural logarithm of monthly night time hours stratified by four seasons.

$\beta^{\mathrm{U}},\beta^{\mathrm{R}},\delta^{\mathrm{U}},\delta^{\mathrm{R}}$ Parameter vectors to be estimated.

$\varepsilon_{it}^{\mathrm{U}},\varepsilon_{it}^{\mathrm{R}},v_{it}^{\mathrm{U}},v_{it}^{\mathrm{R}}$ Stochastic error terms with the usual properties.

The mean near-surface air temperature varies substantially across both time and space in China. For example, the lowest mean monthly temperatures are found in the north-most provinces (e.g. Inner Mongolia) whereas, in contrast, the highest mean monthly temperatures are found in the south-central provinces (e.g. Guangdong). In order to investigate the possible effects of seasonal differences in climate and examine the sensitivity of the estimation to various formulations, we estimate separately all equations in this study using monthly, seasonal, and annual mean temperature variables as regressors. More specifically, we individually estimate three regressions each for Eqs. (1)–(4); Case A utilizes monthly mean temperatures; Case B uses second seasonal mean temperatures: summer, fall, winter, and spring; and Case C uses annual mean temperatures[2]. The specific grouping of months into the four seasonal categories may be somewhat arbitrary, which is an additional reason why we also estimate the equations using individual monthly mean temperature variables.

Unlike the information on the use of electricity for appliances, detailed data on amount of electricity consumed for lighting/illumination is not directly available. Therefore, we have constructed proxy variables to represent this use. These are the mean monthly night time hours, stratified by the same four seasons, and the total amount of residential living space. While the mean number of monthly night time hours are the only variables used that do not change from year-to-year, there is, of course, variation across provinces with latitude[3]. Significant collinearity prohibited the interaction of the mean monthly night time hours variables with residential living space. Lastly, since in China, there exist differences in taxes and other economic policies in coastal versus non-coastal provinces, these differences are controlled for via a binary variable distinguishing coastal and non-coastal provinces (Zhang and Martinez-Vazquez, 2003).

In contrast to the residential models, detailed data on the electricity-using equipment of non-residential consumers (e.g. industry sectors) are not readily available. In addition, non-residential

[2] Initially, we intended to include relative humidity as an additional climate measure, which also possesses a relatively large degree of variability across time and space in China. However, high collinearity between temperature and relative humidity variables necessitated dropping one of the measures. Temperature is most important for linkages within Global System Models (Sokolov et al., 2005).

[3] See Ngo-Duc et al. (2005) for more details.

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data does not distinguish between urban and rural areas. Thus, non-residential electricity demand is formally expressed as,

$$Y_{it}^{\mathrm{N}} = Z_{it}^{\mathrm{N}}\gamma + \mu_{it} \tag{5}$$

Where:

Y_{it}^{N} Natural logarithm of non-residential electricity demand.
Z_{it}^{N} Natural logarithm of: non-residential electricity price; gross domestic product separately for the primary, net-secondary, and tertiary industries; total non-residential floor space; mean temperature(s); and monthly night time hours stratified by four seasons; in addition, a binary variable for differences associated with coastal provinces.
γ Parameter vector to be estimated.
μ_{it} Stochastic error terms with the usual properties.

With regard to mean temperature, three versions of Eq. (5) are estimated for Cases A through C, as stipulated for the residential regressions. Another problem arises because secondary industry gross output includes the gross output of electricity; therefore, we remove gross electricity output from total secondary industry output.

The necessary spatially explicit climate data are taken from a re-processed version of the National Centers for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) reanalysis product, designed specifically for land-climate analysis and applications. The NCEP/NCAR data set is a 1°×1° spatial climate data set which "…is based on the National Centers for Environmental Prediction/National Center for Atmospheric Research reanalysis project and a number of in situ observations…These observations are obtained from surface station observations, radiosonde, aircraft and, in recent decades, satellite retrievals" (Ngo-Duc et al., 2005, p. 1–2). This quality-controlled spatially explicit data was recently developed for use mostly with global land surface models within an integrated global systems framework as well as various applications, including climate change (Ngo-Duc et al., 2005). In its initial form, the data lacked China country or provincial codes. Thus, provinces were coded utilizing a provincial boundary Geographical Information System (GIS) spatial data layer available through the Center for International Earth Science Information Network (CIESIN) at Columbia University (CIESIN, 2004). Following the same approach of Deschenes and Greenstone (2006), multiple grid cells within provinces were averaged to generate monthly mean temperatures for each province in a given year for the time period 1995 to 2000.

The time period of years 1995 to 2000, as well as the provinces chosen, were based on data availability for all economic and climate variables. The province of Chongqing was promoted from a municipality in year 1997, separate from its former position as part of the Sichuan province. For this study, Chongqing data from 1997 to 2000 was aggregated with Sichuan for consistency purposes only. Moreover, the province of Tibet was eliminated due to lack of data. Lastly, after examining scatter plots as well as systematic testing for outliers (at the 5% level) using the method developed by Hadi (1992) and further refined in Hadi (1994), we decided to exclude the provinces of Hainan, Xinjiang, and Qinghai. Using the same method for the rural residential regressions, the provinces of Beijing, Shanghai, and Tianjin were additionally excluded as extreme outliers. Although there are rural areas within these provinces, they are overwhelmingly dominated by the large cities.

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Table 1
First stage urban residential regression results

Dependent variables:	LN(UAC_STOCK)	LN(UAC_STOCK)	LN(UAC_STOCK)	LN(UREFRIG_STOCK)	LN(UREFRIG_STOCK)	LN(UREFRIG_STOCK)	LN(UTV_STOCK)	LN(UTV_STOCK)	LN(UTV_STOCK)
# Observation:	153	153	153	153	153	153	153	153	153
Estimator:	PCSE	PCSE	PCSE	PCSE	PCSE	PCSE	PCSE	PCSE	PCSE
Equation #:	1A	1B	1C	1A	1B	1C	1A	1B	1C
INTERCEPT	25.669	−20.261	2.607	5.450	5.330	5.999	9.142	10.195	9.574
	(1.99)*	(2.02)*	(0.14)	(3.14)*	(2.96)*	(3.50)*	(13.02)*	(11.45)*	(10.17)*
LN(URES_ELECPRICE)	−0.311	−0.309	0.638	0.036	0.051	0.065	−0.036	−0.035	−0.040
	(0.86)	(1.00)	(1.49)	(1.07)	(1.90)	(2.10)*	(1.90)	(1.67)	(1.53)
LN(UINCPC)	0.546	0.872	0.795	0.434	0.428	0.416	0.363	0.350	0.356
	(5.79)*	(8.04)*	(5.33)*	(6.34)*	(6.27)*	(6.54)*	(18.05)*	(12.95)*	(12.18)*
LN(AC_PRICE)	−9.816	−8.167	−3.201	–	–	–	–	–	–
	(3.07)*	(3.07)*	(2.70)*						
LN(FAN_PRICE)	7.562	6.473	1.079	–	–	–	–	–	–
	(2.24)*	(1.98)*	(1.24)						
LN(REFRIG_PRICE)	–	–	–	−0.279	−0.350	−0.395	–	–	–
				(1.38)	(1.74)	(2.10)*			
LN(TV_PRICE)	–	–	–	–	–	–	−0.720	−0.785	−0.770
							(6.86)*	(6.02)*	(5.23)*
COAST	−0.047	−0.150	0.209	0.030	0.025	0.026	0.013	0.012	0.004
	(1.52)	(0.65)	(0.59)	(2.46)*	(2.15)*	(2.33)*	(2.06)*	(1.18)	(0.04)
LN(JAN_TEMP)	−0.019	–	–	−0.003	–	–	0.000	–	–
	(0.59)			(1.01)			(0.04)		
LN(FEB_TEMP)	0.088	–	–	0.008	–	–	0.004	–	–
	(1.56)			(1.76)			(1.29)		
LN(MAR_TEMP)	0.068	–	–	0.005	–	–	0.004	–	–
	(2.57)*			(1.49)			(2.13)*		
LN(APR_TEMP)	−0.085	–	–	−0.007	–	–	0.000	–	–
	(1.79)			(0.16)			(0.27)		
LN(MAY_TEMP)	−0.090	–	–	−0.006	–	–	−0.009	–	–
	(1.37)			(1.04)			(2.47)		
LN(JUN_TEMP)	0.089	–	–	−0.005	–	–	0.006	–	–
	(1.90)			(0.74)			(1.84)		
LN(JUL_TEMP)	0.096	–	–	0.003	–	–	0.005	–	–

	(1.90)			(0.57)			(1.24)		
LN(AUG_TEMP)	0.100	–	–	0.013	–	–	−0.001	–	–
	(1.55)			(2.04)*			(0.27)		
LN(SEP_TEMP)	0.036	–	–	0.004	–	–	−0.006	–	–
	(1.00)			(1.06)			(2.58)*		
LN(OCT_TEMP)	−0.053	–	–	−0.010	–	–	−0.001	–	–
	(1.02)			(1.76)			(0.33)		
LN(NOV_TEMP)	−0.102	–	–	−0.006	–	–	−0.008	–	–
	(2.16)*			(1.10)			(2.90)*		
LN(DEC_TEMP)	0.047	–	–	0.004	–	–	0.003	–	–
	(1.52)			(0.76)			(1.60)		
LN(WINTER_TEMP)	–	1.324	–	–	0.087	–	–	0.036	–
		(2.91)*			(2.29)*			(2.22)*	–
LN(SPRING_TEMP)	–	−2.557	–	–	0.109	–	–	0.126	
		(1.01)			(0.67)			(1.30)	–
LN(SUMMER_TEMP)	–	16.555	–	–	0.398	–	–	−0.076	
		(4.23)*			(1.79)			(0.67)	–
LN(FALL_TEMP)	–	−3.767	–	–	−0.335	–	–	−0.291	
		(2.23)*			(1.81)			(2.50)*	–
LN(ANNUAL_TEMP)	–	–	3.937	–	–	0.203	–	–	−0.091
			(5.16)*			(2.74)*			(1.52)
R^2	0.615	0.616	0.341	0.986	0.989	0.992	0.991	0.996	0.996

Notes:
* = Significance at the 5% level.
Absolute *t*-statistics in parentheses.

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Table 2
Second stage urban residential regression results

Dependent variables:	LN(URES_ELECD)	LN(URES_ELECD)	LN(URES_ELECD)
# Observation:	150	150	150
Estimator:	PCSE	PCSE	PCSE
Equation #:	2A	2B	2C
INTERCEPT	−10.676	26.695	−1.394
	(0.81)	(1.43)	(0.15)
LN(URES_ELECPRICE)	−0.204	−0.132	−0.190
	(2.43)*	(2.79)*	(2.44)*
LN(UINCPC)	0.716	0.564	0.797
	(2.20)*	(2.90)*	(3.60)*
LN(WINTER_NIGHT)	−1.649	−2.004	−2.424
	(2.05)*	(2.87)*	(3.88)*
LN(SPRING_NIGHT)	−3.446	−4.099	−1.654
	(0.90)	(0.83)	(0.66)
LN(SUMMER_NIGHT)	−2.665	−4.410	0.248
	(1.18)	(1.76)	(0.17)
LN(FALL_NIGHT)	3.549	6.522	4.533
	(1.76)	(2.91)*	(2.12)*
LN(ULIVINGSPACE)	0.717	0.557	0.485
	(6.73)*	(12.04)*	(4.70)*
LN(UAC_SÎOCK)	0.039	0.078	0.096
	(2.34)*	(3.02)*	(4.98)*
LN(UREFRIG_SÎOCK)	−0.835	−0.561	−0.712
	(2.71)*	(2.03)*	(2.75)*
LN(UTV_SÎOCK)	−1.305	−1.112	−1.242
	(2.44)*	(3.29)*	(2.77)*
COAST	0.316	0.408	0.556
	(2.01)*	(1.98)*	(9.60)*
LN(JAN_TEMP)	0.207	–	–
	(3.35)*		
LN(FEB_TEMP)	−0.632	–	–
	(2.03)*		
LN(MAR_TEMP)	0.420	–	–
	(0.81)		
LN(APR_TEMP)	−1.385	–	–
	(1.90)		
LN(MAY_TEMP)	−0.419	–	–
	(0.48)		
LN(JUN_TEMP)	1.873	–	–
	(1.98)*		
LN(JUL_TEMP)	−0.743	–	–
	(0.65)		
LN(AUG_TEMP)	0.918	–	–
	(0.69)		
LN(SEP_TEMP)	−1.617	–	–
	(1.86)		
LN(OCT_TEMP)	0.647	–	–
	(0.60)		
LN(NOV_TEMP)	−0.064	–	–
	(0.11)		
LN(DEC_TEMP)	0.447	–	–

Table 2 (*continued*)

Dependent variables:	LN(URES_ELECD)	LN(URES_ELECD)	LN(URES_ELECD)
# Observation:	150	150	150
Estimator:	PCSE	PCSE	PCSE
Equation #:	2A	2B	2C
	(1.67)		
LN(WINTER_TEMP)	–	0.215	–
		(1.87)	
LN(SPRING_TEMP)	–	−0.323	–
		(0.67)	
LN(SUMMER_TEMP)	–	2.054	–
		(2.43)*	
LN(FALL_TEMP)	–	−1.928	–
		(3.55)*	
LN(ANNUAL_TEMP)		–	0.590
			(2.03)*
R^2	0.802	0.810	0.899

Notes:
* = Significance at the 5% level.
Absolute *t*-statistics in parentheses.

Table 1A in the Appendix provides a comprehensive description of all variables for Eqs. (1)–(5) with the variable names used in estimation, their definition, unit of measure, construction, and data source(s); Table 2A of the Appendix provides sample statistics.

3. Empirical results and analysis

A likelihood ratio test as prescribed by Wooldridge (2002) indicated heteroskedasticity across panels for all equations, likely due to the geographic-scale differences across provinces. In addition, following Wooldridge (2002), a test of first-order (panel-specific and common) autocorrelation lead us to reject the null hypothesis of no autocorrelation for each of Eqs. (1)–(5), finding the existence of common, not panel-specific, first-order autocorrelation. Consequently, for Eqs. (1)–(5), the classical fixed- or random-effects panel estimators cannot be employed. Instead, we estimated them using the Prais–Winsten panel-corrected standard error (PCSE) estimator[4]. In these cases, feasible generalized least squares (FGLS) is an alternative estimation procedure. However, FGLS produces estimates conditional on the estimates of the disturbance covariance matrix and are conditional upon any autocorrelation parameters that are estimated (Greene, 2003). In addition, Beck and Katz (1995) have demonstrated that FGLS variance–covariance estimates are typically positively biased.

Urban residential regression results are provided in Tables 1 and 2; rural residential regression results are reported in Tables 3 and 4; lastly, the non-residential results are in Table 5.

[4] In using the conventional panel estimators, random effects results are inconsistent and fixed-effect results utilizing annual mean temperature did not significantly differ from those reported here.

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Table 3
First stage rural residential regression results

Dependent variables:	LN(RAC_STOCK)	LN(RAC_STOCK)	LN(RAC_STOCK)	LN(RREFRIG_STOCK)	LN(RREFRIG_STOCK)	LN(RREFRIG_STOCK)	LN(RTV_STOCK)	LN(RTV_STOCK)	LN(RTV_STOCK)
# Observation:	59	60	61	125	129	132	125	129	132
Estimator:	PCSE	PCSE	PCSE	PCSE	PCSE	PCSE	PCSE	PCSE	PCSE
Equation #:	3A	3B	3C	3A	3B	3C	3A	3B	3C
INTERCEPT	17.560	32.814	81.805	−17.030	6.851	17.177	36.565	44.802	45.478
	(0.28)	(0.69)	(1.69)	(1.26)	(0.45)	(1.10)	(4.94)*	(5.25)*	(5.20)*
LN(RRES_ELECPRICE)	0.489	0.635	0.615	0.252	0.431	0.578	0.023	0.122	0.139
	(0.77)	(1.35)	(1.22)	(1.47)	(0.98)	(1.24)	(0.33)	(1.71)	(1.43)
LN(RINCPC)	0.615	0.752	0.556	0.952	0.794	0.593	0.790	0.556	0.516
	(1.87)	(1.26)	(1.07)	(7.00)*	(4.72)*	(4.90)*	(4.78)*	(2.87)*	(2.96)*
LN(AC_PRICE)	−0.963	−3.439	−10.599	–	–	–	–	–	–
	(0.15)	(0.61)	(2.04)*						
LN(REFRIG_PRICE)	–	–	–	0.631	−2.406	−2.949	–	–	–
				(0.42)	(1.32)	(1.64)			
LN(TV_PRICE)	–	–	–	–	–	–	−4.592	−5.819	−5.954
						–	(4.47)*	(4.61)*	(4.97)*
COAST	1.856	1.904	2.317	0.627	0.868	0.992	0.436	0.583	0.591
	(7.33)*	(4.19)*	(3.90)*	(4.19)*	(5.28)*	(5.96)*	(4.11)*	(5.08)*	(4.72)*
LN(JAN_TEMP)	0.403	–	–	0.068	–	–	0.025	–	–
	(0.35)			(0.41)			(0.31)		
LN(FEB_TEMP)	1.053	–	–	0.420	–	–	−0.368	–	–
	(0.38)			(0.84)			(1.39)		
LN(MAR_TEMP)	4.577	–	–	0.449	–	–	0.336	–	–
	(1.67)			(0.57)			(0.84)		
LN(APR_TEMP)	−2.634	–	–	−0.322	–	–	−0.048	–	–
	(0.49)			(0.23)			(0.06)		
LN(MAY_TEMP)	−2.808	–	–	−5.814	–	–	−2.191	–	–
	(0.43)			(3.22)*			(1.92)		
LN(JUN_TEMP)	0.096	–	–	3.172	–	–	1.570	–	–
	(0.01)			(1.49)			(1.45)		
LN(JUL_TEMP)	9.567	–	–	4.188	–	–	2.306	–	–
	(1.69)			(1.70)			(1.95)		

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LN(AUG_TEMP)	−8.744	–	–	−0.074	–	–	−2.768	–	–
	(1.68)			(0.03)			(2.02)*		
LN(SEP_TEMP)	−0.964	–	–	−0.470	–	–	−0.961	–	–
	(0.18)			(0.34)			(1.14)		
LN(OCT_TEMP)	−5.415	–	–	−0.728	–	–	0.505	–	–
	(0.87)			(0.45)			(0.73)		
LN(NOV_TEMP)	−1.288	–	–	−2.608	–	–	−0.929	–	–
	(0.31)			(3.61)*			(1.95)		
LN(DEC_TEMP)	0.868	–	–	1.333	–	–	0.501	–	–
	(0.49)			(2.96)*			(2.29)*		
LN(WINTER_TEMP)	–	0.455	–	–	0.390	–	–	0.023	–
		(0.83)			(2.42)*			(0.33)	
LN(SPRING_TEMP)	–	5.905	–	–	−1.212	–	–	0.309	–
		(1.59)			(1.26)			(0.52)	
LN(SUMMER_TEMP)	–	−4.874	–	–	3.073	–	–	−0.153	–
		(1.01)			(2.68)*			(0.24)	
LN(FALL_TEMP)	–	−4.986	–	–	−1.708	–	–	−1.135	–
		(1.55)			(1.54)			(1.54)	
LN(ANNUAL_TEMP)	–	–	0.444	–	–	0.539	–	–	−1.457
			(0.55)			(2.95)*		–	(5.60)*
R^2	0.694	0.650	0.644	0.769	0.667	0.606	0.697	0.736	0.698

Notes:
* = Significance at the 5% level.
Absolute *t*-statistics in parentheses.
LN(FAN_PRICE) automatically dropped due to collinearity.

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Table 4
Second stage rural residential regression results

Dependent variables:	LN(RRES_ELECD)	LN(RRES_ELECD)	LN(RRES_ELECD)
# Observation:	59	60	61
Estimator:	PCSE	PCSE	PCSE
Equation #:	4A	4B	4C
INTERCEPT	86.775	307.777	261.465
	(1.04)	(3.11)*	(2.42)*
LN(RRES_ELECPRICE)	−0.203	−0.645	−0.275
	(0.36)	(2.21)*	(2.48)*
LN(RINCPC)	0.141	0.255	0.038
	(0.29)	(2.80)*	(0.14)
LN(WINTER_NIGHT)	−2.463	−4.537	−3.060
	(2.11)*	(2.84)*	(2.07)*
LN(SPRING_NIGHT)	3.271	−9.136	−8.310
	(0.94)	(1.53)	(1.16)
LN(SUMMER_NIGHT)	1.618	−2.042	−0.278
	(0.32)	(0.41)	(0.10)
LN(FALL_NIGHT)	−16.042	−34.564	−33.718
	(1.98)*	(4.94)*	(3.23)*
LN(RLIVINGSPACE)	0.533	0.235	0.271
	(4.55)*	(1.51)	(2.25)*
LN(RAC_SŜTOCK)	0.085	0.234	0.119
	(3.01)*	(6.49)*	(2.54)*
LN(RREFRIG_STOCK)	0.000	0.204	0.100
	(0.01)	(1.67)	(1.09)
LN(RTV_SŜTOCK)	−0.014	−0.433	−0.129
	(0.09)	(2.46)*	(0.85)
COAST	0.574	0.803	0.789
	(5.94)*	(8.80)*	(9.14)*
LN(JAN_TEMP)	0.766		–
	(2.33)*		
LN(FEB_TEMP)	−2.058	–	–
	(2.23)*		
LN(MAR_TEMP)	−0.074	–	–
	(0.08)		
LN(APR_TEMP)	−2.081	–	–
	(1.43)		
LN(MAY_TEMP)	1.011	–	–
	(1.05)		
LN(JUN_TEMP)	3.024	–	–
	(1.58)		
LN(JUL_TEMP)	−2.344	–	–
	(1.23)		
LN(AUG_TEMP)	−3.416	–	–
	(1.18)		
LN(SEP_TEMP)	−2.016	–	–
	(1.19)		
LN(OCT_TEMP)	1.269	–	–
	(0.93)		
LN(NOV_TEMP)	3.237	–	–
	(2.43)*		
LN(DEC_TEMP)	−0.143	–	–

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Table 4 (*continued*)

Dependent variables:	LN(RRES_ELECD)	LN(RRES_ELECD)	LN(RRES_ELECD)
# Observation:	59	60	61
Estimator:	PCSE	PCSE	PCSE
Equation #:	4A	4B	4C
	(0.21)		
LN(WINTER_TEMP)	–	−0.082	–
		(0.45)	
LN(SPRING_TEMP)	–	−1.688	–
		(1.08)	
LN(SUMMER_TEMP)	–	1.030	–
		(0.40)	
LN(FALL_TEMP)	–	0.904	–
		(0.68)	
LN(ANNUAL_TEMP)	–	–	0.758
			(0.97)
R^2	0.800	0.761	0.777

Notes:
* = Significance at the 5% level.
Absolute *t*-statistics in parentheses.

3.1. Urban residential regressions

For the durable demands in Table 1, we consider first the demand for air conditioners. For Cases A through C, the magnitude and direction of the air conditioner price and income coefficients are all significant and consistent with *a priori* expectations. In contrast, although urban residential electricity prices yield the expected sign for Cases A and B, they do not appear to be a significant driver of urban air conditioner demand. Moreover, differences for coastal provinces are not significant. The price of fans is included to test the possible substitutability between fans and air conditioners as cooling devices. The estimated and largely significant positive coefficient supports this theory.

Another issue is the relatively large degree of collinearity among the monthly mean temperature variables (Case A). Thus, it is no surprise that most are individually statistically insignificant. From the estimation here, it appears that the month of March is predicted to generate the largest predicted increase in the stock of air conditioners along with the largest predicted decrease during the month of November. The seasonal Case B generates estimates that are more consistent with expectations, namely, that the largest predicted increase in air conditioner stock is during the summer accompanied by the largest predicted decrease during the fall. It is possible that the predicted significant increase during winter may be indicative of forward-looking behavior such that some households are making purchases of air conditioners at lower relative prices during winter in anticipation of summer. Lastly, Case C yields a positive and highly significant coefficient for annual mean temperature, though it fails to convey the temporal variability as in Case B.

For refrigerator and television demand, it appears that income is the largest driver of demand, as expected. In addition, most of the estimated coefficients of the durable good prices have the correct signs and are significant. However, the estimated sign, direction, and significance of urban residential electricity prices coefficients are counter-intuitive for refrigerators. Within the context

Table 5
Single stage non-residential regression results

Dependent variables:	LN(NONRES_ELECD)	LN(NONRES_ELECD)	LN(NONRES_ELECD)
# Observation:	82	83	83
Estimator:	PCSE	PCSE	PCSE
Equation #:	5A	5B	5C
INTERCEPT	45.486	41.421	40.692
	(5.42)*	(5.04)*	(5.19)*
LN(NONRES_ELECPRICE)	−0.224	−0.199	−0.202
	(3.98)*	(4.69)*	(3.90)*
LN(GDP_PRIMARY)	0.136	0.148	0.145
	(4.89)*	(4.54)*	(3.82)*
LN(GDP_NETSECONDARY)	0.502	0.445	0.376
	(7.81)*	(8.38)*	(6.01)*
LN(GDP_TERTIARY)	0.312	0.317	0.275
	(2.55)*	(3.86)*	(3.65)*
LN(WINTER_NIGHT)	−0.270	−0.499	−0.185
	(0.67)	(1.55)	(0.61)
LN(SPRING_NIGHT)	−11.316	−10.187	−8.715
	(5.46)*	(10.57)*	(5.38)*
LN(SUMMER_NIGHT)	5.249	5.195	4.751
	(3.55)*	(6.35)*	(5.28)*
LN(FALL_NIGHT)	−0.807	−1.957	−2.817
	(0.63)	(1.78)	(2.30)*
LN(FLOORSPACE)	0.161	0.145	0.163
	(2.82)*	(1.64)	(1.74)
COAST	0.213	0.248	0.249
	(3.20)*	(3.27)*	(2.81)*
LN(JAN_TEMP)	−0.054	–	–
	(0.45)		
LN(FEB_TEMP)	0.696	–	–
	(1.72)		
LN(MAR_TEMP)	0.238	–	–
	(0.31)		
LN(APR_TEMP)	−0.331	–	–
	(0.48)		
LN(MAY_TEMP)	−1.999	–	–
	(1.42)		
LN(JUN_TEMP)	2.478	–	–
	(1.48)		
LN(JUL_TEMP)	2.862	–	–
	(1.86)		
LN(AUG_TEMP)	−3.061	–	–
	(2.17)*		
LN(SEP_TEMP)	−0.953	–	–
	(0.86)		
LN(OCT_TEMP)	−0.349	–	–
	(0.66)		
LN(NOV_TEMP)	−0.757	–	–
	(1.16)		
LN(DEC_TEMP)	0.345	–	–
	(1.22)		
LN(WINTER_TEMP)	–	0.243	–

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Table 5 (*continued*)

Dependent variables:	LN(NONRES_ELECD)	LN(NONRES_ELECD)	LN(NONRES_ELECD)
# Observation:	82	83	83
Estimator:	PCSE	PCSE	PCSE
Equation #:	5A	5B	5C
		(3.40)*	
LN(SPRING_TEMP)	–	−0.212	–
		(0.67)	
LN(SUMMER_TEMP)	–	−0.040	–
		(0.07)	
LN(FALL_TEMP)	–	−0.441	–
		(0.64)	
LN(ANNUAL_TEMP)	–	–	0.090
			(0.48)
R^2	0.935	0.955	0.959

Notes:
* = Significance at the 5% level.
Absolute *t*-statistics in parentheses.

of the first stage estimation, we would expect that, in general, mean temperature has more of an impact on demand for air conditioning than refrigerators or televisions since it is a device to directly respond to increases in temperature. Thus, although some of the mean temperature coefficient estimates are significant, they certainly lack any plausible explanation.

The second stage urban residential electricity demand results in Table 2 are the most interesting. Both estimated income and electricity price coefficients (i.e. constant elasticities) are significant and consistent with *a priori* expectations for Cases A through C. Moreover, the predicted stock of air conditioners yields a positive and highly significant coefficient, as expected. The estimated negative coefficients on predicted refrigerator and television stocks seem to imply economies of scale such that, increases to the existing stock are characterized by "newer, larger, and energy efficient" units which consume less electricity per unit. Another possible explanation is that some saturation threshold for refrigerators and televisions has been reached.

Recall, the seasonal night time hours variables are intended to be proxies that capture electricity demand for lighting/illumination. The estimated negative coefficient on winter night time hours is counter-intuitive and may be capturing provincial differences. Rather, it is the positive and significant coefficient on the other proxy, namely residential living space, which supports and appears to capture more accurately, electricity demand for lighting/illumination. This is likely due to the fact that the night time hours are highly negatively correlated with mean temperatures for all Cases, most notably for Case A.

Although the log-linear formulation of our equations provides constant elasticities with respect to temperature (as well as prices and income), the stratification of mean temperature by season allow us to see how these temperature elasticities vary over time. As expected, from Case B, we see clearly that the most significant positive temperature elasticity occurs during summer, followed by a significant negative drop-off in the subsequent fall season.

With the relatively large degree of variation of temperature across both time and space, the usefulness of the constant elasticity for annual mean temperature (Case C) is not necessarily adequate. However, given the frequent use of annual mean temperature analysis in the context of

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climate research (Houghton et al., 2001), a constant elasticity for annual mean temperature is clearly the most applicable. For example, most climate change analyses include an annual mean temperature change prediction (Sokolov et al., 2005). We compare and contrast our predicted elasticities with the previous literature in Section 4.

3.2. Rural residential regressions

Relatively speaking, the estimation results for rural residents are less satisfying than the urban ones. This may be due to the differences in economic policies with regard to economic development of the urban versus rural areas (Jiang and O'Neill, 2004). As Pan (2002) indicates, the incomplete and/or inadequate data available for most of China's rural areas is largely due to the fact that "the focus of economic development in China has been on the urban part and industrial sectors with respect to investment and government policies, such as education, infrastructures, healthcare, and restrictions on mobility. This biased approach is well reflected in energy use in China" (p. 1). In Table 3, we consider first the demand for air conditioners. For Cases A through C, the magnitude and direction of the air conditioner price and income coefficients are all consistent with *a priori* expectations, though most are individually insignificant. However, unlike rural refrigerators and televisions, the first year data is available for rural air conditioner stocks is 2000, within our sample data time series of 1995 through 2000. This is likely due to the relatively small ownership of air conditioners among rural residents prior to year 2000. More recent editions of the *China Statistical Yearbook* (i.e. years 2002 through 2004) report rural air conditioner ownership for years 2001 through 2003 (State Statistical Bureau of the People's Republic of China, 2002, 2003, 2004). Our initial intention was to estimate rural air conditioner demand for years 2000 through 2003. However, the Ngo-Duc et al. (2005) climate data is not available beyond year 2000. Thus, we used rural air conditioner stocks for years 2000 through 2003 to compute an average annual growth rate. This fixed average rate was applied to generate a rural air conditioner stock series for years 1995 through 1999. The lack of data (as seen by the relatively small number of observations used in estimation) is likely to be the one reason why income is not a significant driver of rural air conditioner demand and why most estimated coefficients are individually insignificant. In addition, before year 2001, the rural supply of electricity was relatively limited[5].

Relatively speaking, this lack of data does not plague the refrigerator and television demand estimation, as indicated by the results. For these, in general, we find that income and durable prices are mostly significant with the expected signs. Moreover, we also find that winter and summer seasons imply the largest predicted increases for refrigerator demand, as expected. Annual mean temperatures are predicted to significantly decrease demand for televisions.

Once again, the second stage estimates of electricity demand as presented in Table 4 for rural residents are most interesting. In contrast to the urban regressions, rural electricity prices are significant with much greater magnitudes for the Cases B and C, thereby implying that they, "matter more", to rural residents than urban ones. Related to this are the estimated income elasticities for the rural residents as compared to their urban counterparts. From Table 1, we see that the relative magnitudes of the urban electricity price and income elasticities across Cases A through C are generally consistent. In contrast, the magnitude of the rural electricity price elasticity relative to the income elasticity varies across Cases A through C. In Case A, we estimate relatively small and insignificant income and price elasticities. However, the reverse is true for Case B, characterized by a significant increase in the absolute magnitude of these elasticities; the

[5] This additional explanation was provided by an anonymous Reviewer of the paper.

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estimated income elasticity in Case C is also insignificant as in Case A, though the price elasticity is significant for the former. The only difference between the Cases, of course, is the level of aggregation with respect to the mean temperature variables.

For the rural regressions, we find that in Case A, those monthly mean temperature variables that are also significant for their urban counterpart, are larger in relative magnitude. Specifically, the magnitudes of the estimated coefficients are larger for the months of January and February. There does appear to be some inconsistency for months such as November, whereby the estimated coefficient is positive and significant for the rural regression and negative, though insignificant, for the urban one. Most notably, the estimated coefficients on the mean monthly night time hours variables for all rural regressions are generally consistent with the urban ones, except for the significant negative fall season elasticities in rural Cases B and C, as compared to the positive and significant urban counterparts. Related to this perhaps, is that in rural Cases B and C, none of the mean temperature coefficients are significant.

Given the aforementioned relatively high negative collinearity between the mean temperatures and mean monthly night time hours variables, it appears that during our sample period, rural electricity demand responded more to seasonal night hours variation than mean temperatures with the largest significant predicted decreases occurring during the fall. This may be attributed, possibly, to rural residents partaking in more outdoor-based activities as opposed to more indoor ones, thereby, decreasing the predicted electricity demand for lighting/illumination. The most of important is the traditional annual cultural event known as the Mid-Autumn Festival in China. This event is not only for celebrating the harvest, but also a period in the fall season for family reunions and fellowship. It may also be that rural incomes were not high enough to generate significant appliance demand.

Focusing more on rural Cases B and C, in short, it appears that rural electricity demand is driven mostly by variation in electricity prices and seasonal night time hours, as opposed to income and seasonal mean temperature for the urban counterparts.

3.3. Non-residential regressions

Table 5 provides regression results for the non-residential electricity demand regressions. Again, the estimated coefficients (i.e. constant elasticities) for non-residential electricity prices are consistent with *a priori* expectations. The major difference between the residential and non-residential models is the manner in which income is measured. Unfortunately, it was not possible to decompose the gross value of non-residential output into individual sectors. We were able to disaggregate the total gross value of non-residential output is disaggregated into primary, net-secondary, and tertiary industries, the latter including various commercial and non-manufacturing sectors. The magnitudes of the estimated coefficients on the primary, net-secondary, and tertiary gross domestic product variables are consistent with, and corresponds to, the relative electricity-intensity of these sectors with the following (descending) rank order: secondary, tertiary, primary industry (State Statistical Bureau of the People's Republic of China, 2004).

In general, the mean temperature does not have a significant impact on non-residential electricity demand, as expected. For Case A, we predict only a significant decrease during the month of August. When compared to Case B, we find only a significant increase during the winter. Based on the aforementioned collinearity between the monthly mean temperature and mean night time hours variables, the monthly Case A should be taken with a "grain of salt". For Case B, it is likely that the predicted increase in non-residential electricity demand is attributed to

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increased demand for lighting/illumination given that winter realizes the lowest mean temperatures accompanied by the highest number of night time hours.

4. Elasticity analysis

Previous literature regarding the estimation of electricity demand has many price and income elasticity estimates. Since this study is focused exclusively on China, it is most appropriate to compare and contrast the elasticity estimates produced here to publications with a similar scope. This study is unique because it stratifies electricity demand into urban and rural residential as well as non-residential sectors.

Annual aggregate income elasticities of electricity demand/consumption are readily available via the year 2004 *China Statistical Yearbook*. Notwithstanding the aggregation differences, a simple averaging of these elasticities coinciding with the time period of our study for years 1995 to 2000, yields an income elasticity of +0.75. von Hirschhausen and Andres (2000) adopt an aggregate income elasticity of +0.70, attributing this trend "…to the decreasing energy-output ratio of the Chinese economy in the post-Mao reform period since 1979, when the energy use per unit of GDP fell by over 50%" (p. 234). Moreover, von Hirschhausen and Andres (2000) as well as Pesaran and Smith (1995) identify an acceptable range of short-run aggregate energy price elasticites for China (as well as other transitional economies) as ranging between −0.10 and −0.30.

Table 6 summarizes the income, price, and annual mean temperature elasticities from our study as well as those included in the previous literature. Empirical specifications in the previous literature do not include temperature variables as we have here. Thus, as an exercise in sensitivity

Table 6
Elasticity analysis

Model	ε_p	ε_p [a]	ε_I	ε_I [b]	ε_T
Urban residential electricity with climate variables (equation 2C)	−0.190	−0.100 to −0.200	+0.797	+0.700 to +0.750	+0.590
Urban residential electricity without climate variables [c]	−0.189	−0.100 to −0.200	+0.786	+0.700 to +0.750	–
Rural residential electricity with climate variables (equation 4C)	−0.275	−0.100 to−0.200	+0.038	+0.700 to +0.750	+0.758
Rural residential electricity without climate variables [c]	−0.210	−0.100 to−0.200	+0.014	+0.700 to +0.750	–
Non-residential electricity with climate variable (equation 5C) [d]	−0.202	−0.100 to−0.200	–	+0.700 to +0.750	+0.090
Non-residential electricity without climate variables [c, d]	−0.127	−0.100 to−0.200	–	+0.700 to +0.750	–

Where:
ε_p = Price elasticity of electricity demand.
ε_I = Income elasticity of electricity demand.
ε_T = Temperature elasticity of electricity demand.

[a] Based on short-run aggregate estimates (which correspond more closely to our time series of 1995–2000) from Pesaran and Smith (1995) as well as von Hirschhausen and Andres (2000).

[b] Based on average of 1995–2000 aggregate elasticities in 2004 *China Statistical Yearbook* Table 7–8 as well as those adopted by von Hirschhausen and Andres (2000).

[c] Models re-estimated without climate variables, specifically excluding mean temperatures as well as coastal binary variables to prevent them from capturing climate differences.

[d] Recall, non-residential regressions do not utilize same income measure as residential and, hence, is not a legitimate basis for comparison.

analysis, we also re-estimate residential and non-residential electricity demands, excluding mean temperatures.

In general, both price and income elasticities estimated for urban residents in this study are consistent with those in the cited literature, irrespective of the inclusion of mean temperature variables. For rural residents, although income elasticities differ substantially from previous estimates, they are statistically insignificant; the price elasticities are more consistent. In addition, non-residential price elasticities are consistent with the previous literature. However, since the income measures utilized here for the non-residential regressions differs substantially from the previous literature, no direct comparison is appropriate.

Most interestingly, however, is examining how the price and income elasticities react to the inclusion or exclusion of mean temperature variables for all models. From Table 6, it is apparent that both the price and income elasticities are consistently higher in absolute magnitude with the inclusion of mean temperature variables in the regressions. It is our conclusion that conventional estimates of these price and income elastiticies confound the effect of climate and other variables with price and income. We believe that the conventional econometric estimates of electricity demand that exclude climate variables underestimate the absolute magnitudes of income and price elasticities. Differences in the estimated price and income elasticities, including versus excluding, mean temperature variables are not individually significant. However, we employ Engle (1982) Lagrange multiplier (LM) and F-test approaches to test the significance of including temperature variables for each of the urban and rural residential as well as non-residential regressions. We treat the cases of excluding mean temperature variables as restricted models and reject each of these at the 5% level, thereby concluding that mean temperature variables do "matter" for the regressions as a whole.

5. Summary and conclusions

This paper investigates the effects of climate on the use of electricity by consumers and producers in urban and rural areas within China, taking advantage of an unusual combination of data sets in order to estimate price, income and, most importantly, temperature elasticities of electricity demand.

In fully integrated system models of global climate change, a general equilibrium economic model (e.g., Paltsev et al., 2005) is necessary in order to generate projections of anthropogenic emissions and utilize these emissions projections in a climate framework to subsequently produce climate projections, most notably, mean temperature change (e.g., Sokolov et al., 2005). However, relatively little attention has been given to modeling feedbacks from a climate model to an economic model in this context (McCarthy et al., 2001; Metz et al., 2001). Besides its "stand-alone" value, our results are an attempt to fill this void by producing econometric estimates for temperature elasticities of electricity demand that can be incorporated into such integrated system models[6]. This makes it possible to move from climate projections to electricity demand projections and, from there, to projections of fuel uses for electricity production, and then to greenhouse gas emissions, which are inputs into climate models.

The positive temperature/electric power feedback implies a continually increasing use of energy to produce electric power as global warming occurs. As long as energy is, to some degree, based on fossil fuels, it implies continually increasing greenhouse gas emissions. In the absence of countervailing measures, that entails increasing atmospheric concentrations of

[6] Constant elasticity estimates are particularly useful for computable general equilibrium models, which include them throughout their structure (Paltsev et al., 2005).

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greenhouse gases and greater greenhouse warming leading to higher temperatures, more electricity use, and so forth. Despite the fact that results of this study are relatively limited in terms of geographic scope, the positive temperature/electric power elasticities is another indication of the need to find means of reducing the buildup of greenhouse gases in the atmosphere.

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Appendix A

Table 1A
Description of variables

Variable name	Definition	Unit of measure	Data source(s)
Economic variables:			
?RES_ELECPRICE	Residential electricity price	Yuan/KWh	China Energy Databook v.6 for 1997 residential electricity price data; China Statistical Yearbook years 1996–2001 for consumer price index for electricity and other fuels used with 1997 data in order to generate Province-specific electricity prices for all remaining years between 1995 and 2000. ?=U for “Urban” and R for “Rural”.
NONRES_ELECPRICE	Non-residential electricity price	Yuan/KWh	China Energy Databook v.6 for 1997 small and large industry electricity price data; China Statistical Yearbook years 1996–2001 for consumer price index for electricity and other fuels used with 1997 data in order to generate Province-specific electricity prices for all remaining years between 1995 and 2000.
?RES_ELECD	Residential urban electricity demand	TWh	China Energy Databook v.6. ?=U for “Urban” and R for “Rural”.
NONRES_ELECD	Non-residential urban electricity demand	TWh	China Energy Databook v.6. Constructed by taking=Final Urban
?INCPC	Income per capita for urban areas	Yuan	China Statistical Yearbook years 1996–2001. ?=U for “Urban” and R for “Rural”.
GDP_PRIMARY	Gross value of output for primary industry	Ten thousand Yuan	China Statistical Yearbook years 1996–2001.
GDP_NETSECONDARY	Gross value of net output for secondary industry	Ten thousand Yuan	China Statistical Yearbook years 1996–2001. Total generated electricity volume for secondary industry obtained from: www.chinadataonline.com was converted to value terms using NONRES_ELECPRICE; the resulting total gross value of electricity output was subtracted from the total gross value of secondary industry output.
GDP_TERTIARY	Gross value of output for tertiary industry	Ten thousand Yuan	China Statistical Yearbook years 1996–2001.

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Table 1A (*continued*)

AC_PRICE	Average price of air conditioner	Yuan	From Nadel et al. (1995) available at: www.aceee.org. We used a single average 1995 price of 3600 Yuan for 2000—Watt window unit in conjunction with Consumer Price Index for Durable Goods to determine the Province-specific prices for all remaining years between 1995 and 2000.
?AC_STOCK	Stock of air conditioners (ACs)	Number of units owned (year-end) per 100 urban households.	China Statistical Yearbook years 1996–2004. ?=U for "Urban" and R for "Rural". For rural residents, data only available for years 2000–2003. Given the time series utilized is 1995–2000, the average annual growth rate in stock from 2000–2003 was computed and used to generate the rural stock series for years 1995–1999.
FAN_PRICE	Average price of cooling fan	Yuan	From "Market Report of Selected Electrical Home Appliances" available at: www.chinavista.com. Used a single average value of 150 Yuan for year 1996 in conjunction with in conjunction with Consumer Price Index for Durable Goods to determine the Province-specific prices for all remaining years between 1995 and 2000.
REFRIG_PRICE	Average price of refrigerator	Yuan	From "Market Report of Selected Electrical Home Appliances" available at: www.chinavista.com. Used a single average 1996 price of 2770 Yuan (across major brands) in conjunction with Consumer Price Index for Durable Goods to determine the Province-specific prices for all remaining years between 1995 and 2000.
?REFRIG_STOCK	Stock of refrigerators	Number of units owned (year-end) per 100 urban households.	China Statistical Yearbook years 1996–2001. ?=U for "Urban" and R for "Rural".
TV_PRICE	Average price of television	Yuan	From "Business in China: Home Appliance Makers Face Hard Year" available at: www.china.com. Used a single average 2003 price of 800 Yuan for a 21 in. color television unit in conjunction with Consumer Price Index for Durable Goods to determine the Province-specific prices for all remaining years between 1995 and 2000.
?TV_STOCK	Stock of color televisions (TVs)	Number of units owned (year-end) per 100 urban households.	China Statistical Yearbook years 1996–2001. ?=U for "Urban" and R for "Rural".
?LIVINGSPACE	Total living space of residential buildings (year-end)	Ten thousand square meters	China Statistical Yearbook years 1996–2001. ?=U for "Urban" and R for "Rural".
FLOORSPACE	Total floor space of non-residential buildings (year-end)	Ten thousand square meters	China Statistical Yearbook years 1996–2001.

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Table 1A (*continued*)

COAST	=1 for coastal Provinces, 0 non-coastal Provinces	Binary	None.
WINTER_NIGHT	Mean number of monthly night time (i.e. non-daylight) hours in winter	Numeric	NCC spatial data set. Initial data was for monthly daylight hours, which were converted to night time hours. Winter season consists of the months of: December, January, and February.
SPRING_NIGHT	Mean number of monthly night time (i.e. non-daylight) hours in spring	Numeric	NCC spatial data set. Initial data was for monthly daylight hours, which were converted to night time hours. Spring season consists of the months of: March, April, and May.
SUMMER_NIGHT	Mean number of monthly night time (i.e. non-daylight) hours in summer	Numeric	NCC spatial data set. Initial data was for monthly daylight hours, which were converted to night time hours. Summer season consists of the months of: June, July, and August.
FALL_NIGHT	Mean number of monthly night time (i.e. non-daylight) hours in fall	Numeric	NCC spatial data set. Initial data was for monthly daylight hours, which were converted to night time hours. Fall season consists of the months of: September, October, and November.
Climate variables:			
ANNUAL_TEMP	Mean annual temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; Initial data in unit Kelvin was converted to Fahrenheit.
JAN_TEMP	Mean January Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; Initial data in unit Kelvin was converted to Fahrenheit.
FEB_TEMP	Mean February Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; Initial data in unit Kelvin was converted to Fahrenheit.
MAR_TEMP	Mean March Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; Initial data in unit Kelvin was converted to Fahrenheit.
APR_TEMP	Mean April Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit.
MAY_TEMP	Mean May Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit.
JUN_TEMP	Mean June Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit.
JUL_TEMP	Mean July temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit.
AUG_TEMP	Mean August Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit.

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Table 1A (*continued*)

SEP_TEMP	Mean September Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit.
OCT_TEMP	Mean October Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit.
NOV_TEMP	Mean November Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit.
DEC_TEMP	Mean December Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit.
WINTER_TEMP	Mean Winter Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit. Winter season consists of the months of: December, January, and February.
SPRING_TEMP	Mean Spring Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit. Spring season consists of the months of: March, April, and May.
SUMMER_TEMP	Mean Summer Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit. Summer season consists of the months of: June, July, and August.
FALL_TEMP	Mean Fall Temperature	Fahrenheit	NCC spatial data set. Monthly variables for each province and for each year were averaged; initial data in unit Kelvin was converted to Fahrenheit. Fall season consists of the months of: September, October, and November.

Table A2
Sample Statistics

Variable	Mean	Standard deviation
URES_ELECD	2.036	2.250
RRES_ELECD	1.203	3.004
NONRES_ELECD	28.847	1.786
URES_ELECPRICE	0.308	1.230
RRES_ELECPRICE	0.246	1.330
NONRES_ELECPRICE	0.279	1.394
UINCPC	5110.232	1.323
RINCPC	1889.372	1.557
UAC_STOCK	6.360	6.626
RAC_STOCK	0.444	5.512
UTV_STOCK	102.822	1.140
RTV_STOCK	29.195	2.026
UREFRIG_STOCK	73.700	1.220
RREFRIG_STOCK	5.430	3.714
AC_PRICE	3331.621	172.073
TV_PRICE	862.378	46.279
REFRIG_PRICE	2663.616	135.849

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RLIVINGSPACE	7203.005	4.900
ULIVINGSPACE	3681.222	2.635
FLOORSPACE	3415.230	2.512
WINTER_NIGHT	395.403	39.464
SPRING_NIGHT	349.916	6.227
SUMMER_NIGHT	299.561	17.737
FALL_NIGHT	367.999	8.389
GDP_PRIMARY	332.953	2.657
GDP_NETSECONDARY	739.519	2.869
GDP_TERTIARY	672.499	2.482
JAN_TEMP	28.783	16.214
FEB_TEMP	34.011	13.782
MAR_TEMP	42.766	11.702
APR_TEMP	54.132	9.404
MAY_TEMP	63.749	7.913
JUN_TEMP	70.609	7.389
JUL_TEMP	75.117	7.431
AUG_TEMP	73.772	7.855
SEP_TEMP	66.635	8.888
OCT_TEMP	56.740	11.196
NOV_TEMP	43.304	13.878
DEC_TEMP	33.248	15.693
WINTER_TEMP	32.014	15.135
SPRING_TEMP	53.549	9.472
SUMMER_TEMP	73.166	7.465
FALL_TEMP	55.560	11.109
ANNUAL_TEMP	52.457	1.235

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