Three Essays in Energy and Environmental Economics

by

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University Program in Environmental Policy
Duke University

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Dissertation submitted in partial fulfillment of the requirements for the degree of
Doctor of Philosophy in the University Program in Environmental Policy
in the Graduate School of Duke University

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ABSTRACT

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Abstract

This dissertation is a collection of three essays in the field of environmental and energy economics. While each essay addresses different questions, they all contribute to the understanding of environment or energy economics related to energy demand using empirical analyses. The first two papers focus on domestic energy demand modeling and forecasting; one highlights the importance of appliance adoption with income growth, and the other estimates the impact of climate change on electricity consumption in China. The trend of energy demand growth applies to not only China but also the developing countries in the Southeast Asia region. To meet the rapid increase in energy demand, most countries built coal-fired power plants though cleaner options such as solar and wind technologies are getting cheaper. The involvement of Chinese finance into coal-fired power plants is controversial and often leads to concerns on environmental outcomes and carbon footprints. Hence, in the third paper, I examine the environmental impact of coal-fired power plants China financed overseas.

The first paper ("Chinese residential electricity consumption estimation and forecast using micro-data", with Jing Cao, Mun Sing Ho, Richard G. Newell, and William A. Pizer) was published in Resource and Energy Economics in 2017. Based on econometric estimation using data from the Chinese Urban Household Survey, we develop a preferred

forecast range of 85 to 143 percent growth in residential per capita electricity demand over 2009 to 2025. Our analysis suggests that per capita income growth drives a 43% increase, with the remainder due to an unexplained time trend. Roughly one-third of the income-driven demand comes from increases in the stock of specific major appliances, particularly AC units. The other two-thirds comes from non-specific sources of income-driven growth and is based on an estimated income elasticity that falls from 0.28 to 0.14 as income rises. While the stock of refrigerators is not projected to increase, we find that they contribute nearly 20 percent of household electricity demand. Alternative plausible time trend assumptions are responsible for the wide range of 85 to 143 percent. Meanwhile we estimate a price elasticity of demand of -0.7. These estimates point to carbon pricing and appliance efficiency policies that could substantially reduce demand.

The second paper turns attention from income growth to climate change. Estimating the impacts of climate change on energy use across the globe is essential for analysis of both mitigation and adaptation policies. Yet existing empirical estimates are concentrated in western countries, especially the United States. In the second paper ("Climate change and residential electricity consumption in the Yangtze River Delta, China", with William A. Pizer and Libo Wu), we use daily data on household electricity demand to estimate how electricity demand would change in Shanghai in the context of climate change. For colder days below 7°C, a 1°C increase in daily temperature reduces electricity demand by 2.8%. On warm days above 25°C, a 1°C increase in daily temperatures leads to a 14.5% increase in electricity consumption. As income increases, households' weather sensitivity remains the same for hotter days in the summer but increases during the winter.

We use this estimated behavior in conjunction with a collection of downscaled global climate models (GCMs) to construct a relationship between future annual global mean surface temperature (GMST) changes and annual residential electricity demand. We find that annual electricity demand increases by 9.3% per +1°C in annual GMST. In comparison, peak daily electricity use increases by as much as 36.3% per +1°C in annual GMST, almost four times the average electricity increase. Though most accurate for Shanghai, our findings could be most credibly extended to the urban areas in the Yangtze River Delta, covering roughly one-fifth of China's urban population and one-fourth of GDP. The second paper was published in the Proceedings of the National Academy of Sciences of the United States of America (PNAS) in 2018.

While the first two papers focus on domestic energy demand in China and use micro data sets, the third paper ("Environmental Impact of overseas coal-fired power plants financed by China") examines the infrastructure support to energy consumption, i.e. power plants, and their environmental outcomes. Using satellite measures, we first show that the SO2 increased substantially after the operation of the power plants. We further compared the performance of coal plants financed by China with the rest of coal plants in the region. Due to the small number of Chinese-financed plants that started operating during the period of 2006-2016, we have only limited results from our comparison of Chinese and

non-Chinese financed plants. We find no significant difference in SO2 impact in general, but observe higher SO2 increase after operation for the ones financed by China among the plants using subcritical technologies and lower for those using supercritical technologies, though not significantly different from the rest. Among plants larger than 500 MW, the percentage of supercritical power plants among Chinese financed coal plants is higher than the rest.

Dedication

This dissertation is dedicated to my academic advisor Billy Pizer who guided me in the process and kept me on track, to my husband, Ge Niu, who supported me along the way and traveled with me around the world, and finally to my parents, Xuede Li and Xiaohong Miao, who gave me freedom to explore different cultures.

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Acknowledgements

I have to confess that my journey to Duke University for PhD study was quite unexpected. In fact, University PhD Program in Environmental Policy is the only program I applied to in the United States. Growing up in a small town, my parents and I had limited understanding of what PhD really means. Dr. Yufeng Yang, my supervisor at the Energy Research Institute, NDRC, China, encouraged me to apply and pursue a PhD after my research-focused internship. He also made sure that all my application materials were well written, and pushed me to move forward when I encountered emotional crisis. My journey into Environmental and Energy Economics would not have begun without his mentorship and trust.

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I could not imagine getting through my PhD study without the company and support from professors and other colleagues in the UPEP program, especially my cohort: Justin Kirkpatrick, Faraz Usmani and Stephanie Stefanski. I learnt from them in and out of classrooms, including disciplinary knowledge, programming skills and professional conducts in a western culture. I am also grateful for the wisdoms shared to me from earlier graduates, including but not limited to Brian Prest, David Kaczan, Rob Fetter, Chris Paul, Jennifer Meyer and Anna Birkenbach.

My parents are always supportive of my decisions. As the only child, I left home at the age of 16 for undergraduate study at Renmin University of China. Since then, I spent very limited time with them each year but they never blamed me. With limited saving, they sponsored my exchange study at Copenhagen Business School when I was 18 and encouraged me to explore the world as I wish. My trips in Europe taught me the diversity of life and freed me mentally from the common stress to pursue success, money and fame for college graduates in China. Those trips also stimulated my curiosity about the world itself, which led to many more adventures, including the pursuit of my PhD.

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Chapter 1 Introduction

This dissertation is a collection of three essays in the field of environmental and energy economics. While each essay addresses different questions, they all contribute to the understanding of environment or energy economics related to energy demand using empirical analyses. The first two papers focus on domestic energy demand modeling and forecasting; one highlights the importance of appliance adoption with income growth, and the other estimates the impact of climate change on electricity consumption in China. The trend of energy demand growth applies to not only China but also the developing countries in the Southeast Asia region. To meet the rapid increase in energy demand, most countries built coal-fired power plants though cleaner options such as solar and wind technologies are getting cheaper. The involvement of Chinese finance into coal-fired power plants is controversial and often leads to concerns on environmental outcomes and carbon footprints. Hence, in the third paper, I examine the environmental impact of coal-fired power plants China financed overseas.

The first paper ("Chinese residential electricity consumption estimation and forecast using micro-data", with Jing Cao, Mun Sing Ho, Richard G. Newell, and William A. Pizer) was published in Resource and Energy Economics in 2017. Based on econometric estimation using data from the Chinese Urban Household Survey, we develop a preferred forecast range of 85 to 143 percent growth in residential per capita electricity demand over

2009 to 2025. Our analysis suggests that per capita income growth drives a 43% increase, with the remainder due to an unexplained time trend. Roughly one-third of the income-driven demand comes from increases in the stock of specific major appliances, particularly AC units. The other two-thirds comes from non-specific sources of income-driven growth and is based on an estimated income elasticity that falls from 0.28 to 0.14 as income rises. While the stock of refrigerators is not projected to increase, we find that they contribute nearly 20 percent of household electricity demand. Alternative plausible time trend assumptions are responsible for the wide range of 85 to 143 percent. Meanwhile we estimate a price elasticity of demand of -0.7. These estimates point to carbon pricing and appliance efficiency policies that could substantially reduce demand.

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We use this estimated behavior in conjunction with a collection of downscaled global climate models (GCMs) to construct a relationship between future annual global mean surface temperature (GMST) changes and annual residential electricity demand. We find that annual electricity demand increases by 9.3% per +1°C in annual GMST. In comparison, peak daily electricity use increases by as much as 36.3% per +1°C in annual GMST, almost four times the average electricity increase. Though most accurate for Shanghai, our findings could be most credibly extended to the urban areas in the Yangtze River Delta, covering roughly one-fifth of China's urban population and one-fourth of GDP. The second paper was published in the Proceedings of the National Academy of Sciences of the United States of America (PNAS) in 2018.

While the first two papers focus on domestic energy demand in China and use micro data sets, the third paper ("Environmental Impact of overseas coal-fired power plants financed by China") examines the infrastructure support to energy consumption, i.e. power plants, and their environmental outcomes. More importantly, the paper empirically compares the sulfur dioxide (SO2) emissions from coal-fired power plants that are financed by China with those from other coal-fired power plants in India, Indonesia, Philippines and Vietnam. Using simple difference based on the start year of power plants, we find that the operation of coal-fired power plants leads to significant increase in SO2 column amounts retrieved by the Ozone Monitoring Instrument (OMI). The magnitude of impact decreases with the radius of buffer we use to extract the SO2 levels around the power plant, and increases with the quantile we use to summarize the daily SO2 measures to the annual observation.

Due to small number of Chinese-financed plants that started operating during the period of 2006-2016, we have only limited results from our comparison of Chinese and non-Chinese financed plants. We find no significant difference in SO2 impact in general, but observe higher SO2 increase after operation for the ones financed by China among the plants using subcritical technologies and lower for those using supercritical technologies, though not significantly different from the rest. Among plants larger than 500 MW, the percentage of supercritical power plants among Chinese financed coal plants is higher than the rest.

Chapter 2 Chinese residential electricity consumption estimation and forecast using micro-data

Co-authors: Jing Cao, Mun Sing Ho, Richard G. Newell, William A. Pizer

2.1 Introduction

China's energy demand has grown rapidly in the past decade. Despite slower recent energy consumption growth as economic growth decelerates, a significant share of rising global consumption remains concentrated in China, among the other Asian countries. In 2014, China (+2.6%) and India (+7.1%) recorded the largest national increments to global energy consumption[1]. As a result of the high energy consumption and relatively heavy dependence on coal (nearly 66% of total primary energy, EIA), China overtook the United States as the world's leading emitter of greenhouse gases in 2006. The future growth path of energy consumption is relevant not only for projecting world energy market outcomes, but also for the strategies to tackle both local air pollution and global climate change.

This paper focuses on modeling and forecasting Chinese residential electricity demand using household survey data to 2025. Many previous forecasts of China's electricity demand have focused on projecting the total consumption using aggregate economic growth trends. Among sectors, the industrial sector, accounting for more than two-thirds of China's electricity consumption, attracts the most attention. In comparison,

[1] BP Statistical Review of World Energy June 2015. http://www.bp.com/content/dam/bp/pdf/energy-economics/statistical-review-2015/bp-statistical-review-of-world-energy-2015-full-report.pdf

China's demand in the commercial and residential sector has rarely been examined, though it has been projected to nearly triple between 2014 and 2040 by the International Energy Agency (IEA 2014). Moreover, this increase represents nearly half (46%) of total projected electricity growth. The U.S. Energy Information Administration (EIA) makes similar projections; however, the EIA also separates the residential and commercial sector in its International Energy Outlook (EIA 2015). There, residential consumption alone accounts for one-third of China's electricity demand growth over the next 25 years. This implies increases in both per capita residential electricity consumption and the residential share of electricity in China in the coming decades.

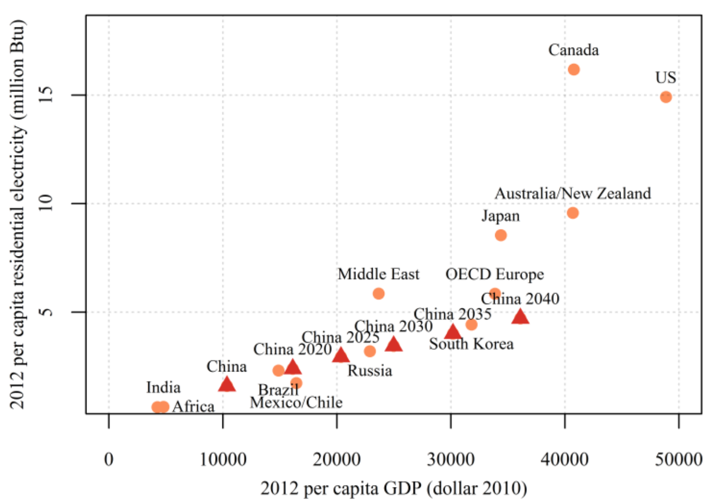

Figure 2.1: Residential Electricity Per Capita versus Per Capita GDP in 2012

Source: EIA, International Energy Outlook 2016

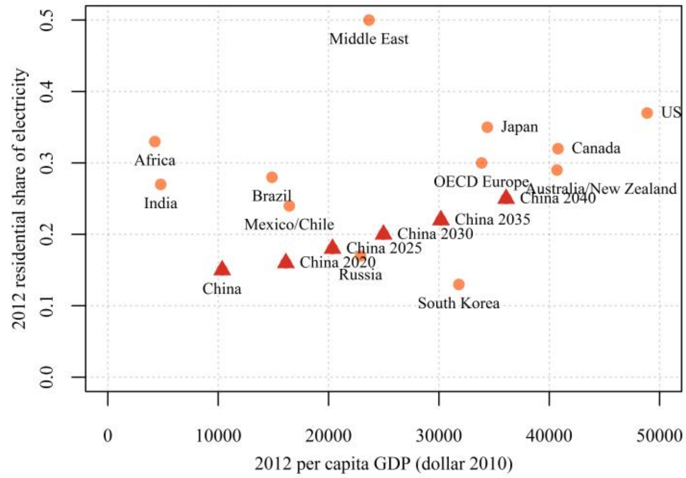

Figure 2.2: Residential Share of Electricity versus Per Capita GDP in 2012

Source: EIA, International Energy Outlook 2016

This pattern is consistent with the experience of most now-developed countries. Figure 2.1 relates per capita residential electricity consumption to GDP per capita in 2010 for several representative countries, along with the projected values for China through 2040 from EIA. EIA projects that per capita residential electricity consumption will more than double between 2010 and 2025. Figure 2.2 gives the residential share of total electricity use for the same set of countries and shows China's projected share growing from 14% to more than 20%.

With such a large portion of projected Chinese electricity demand growth being driven by households, it is important to ask what drives these forecasts. As an example of typical forecasting approaches, the residential module in World Energy Projection System Plus (US EIA), uses only GDP, energy prices, and autonomous time trends to project energy demand. Moreover, it largely uses elasticities and trends taken from EIA's domestic U.S. model. Repeated cross-sectional data, in contrast, allows us to estimate parameters directly. We can tease out the effects of income and autonomous time trends, which are otherwise highly collinear in aggregate data. We can look for non-linear income effects, as we expect elasticities to fall at higher incomes. We can also further decompose income effects into extensive margins, as households acquire larger houses and more electricity using appliances, and intensive margins related to other, non-specific income-driven demand growth including increased use of existing homes and appliances. This kind of detail is important to improve forecasts, to understand key uncertainties, and to design policies to influence future electricity demand. The latter is particularly salient as China grapples with both conventional air pollution and climate change, which would both improve with reduced household energy demand.

There are existing empirical papers on household energy demand in many countries[2], but very few studies have been conducted in China due to the lack of household-level data, at least until recently. In the United States, O'Neill and Chen (2002) focus on the role of demographic changes in aggregate US household energy demand using the Residential Energy Consumption Survey (RECS) data from 1993 to 1994. Leahy and Lyons (2010) analyze residential energy demand conditional on appliance ownership using the 2004/2005 Irish Household Budget Survey. Jones and Lomas (2015) investigate the socioeconomic and dwelling determinants of high electrical energy demand in UK

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[2] See Fell et al. (2014), Espey and Espey (2004) and Alberini et al. (2011) for more detailed review of previous studies on residential electricity demand.

households. Although some of these studies provide estimates of price and income elasticities, specifications differ and many suffer from a limited sample. This makes it difficult to credibly transfer the estimates to China given the different market and institutions. In addition, only a few studies produce forecasts using the estimated models, which is an important way to highlight the practical consequences of alternative assumptions. Our approach is to assess estimation results alongside forecast implications simultaneously.

To estimate our model and construct forecasts for China, we use a repeated cross-sectional dataset[3], the Chinese Urban Household Survey (CUHS) collected by National Bureau of Statistics of China. This is the first paper to use such data to forecast electricity use. Two other recent studies have used these data to estimate income and price elasticities. Zhou and Teng (2013) estimated income and price elasticities of electricity demand in Sichuan province. However, they did not model demand for household appliances or consider the implications for forecasts, and did not consider the other provinces. Cao, Ho and Liang (2016) estimated an energy demand system using data from all nine provinces and focused on demand choices among fuels. They similarly did not model the demand for household appliances or generate forecasts based on the results. While our parameter estimates are comparable with these studies, here our focus is building a more complete model of both appliance ownership and electricity demand.

[3] Note: The CUHS has a rotational sampling each year, that is, about one-third of samples are replaced with new households.

We then use that model (a revised version of the two-stage approach by Dubin and McFadden, 1984) to forecast electricity demand and to understand the drivers of future growth.

In particular, we explore the sensitivity of forecasts to a variety of alternative assumptions about prices, autonomous time trends, demographics, and income. Our central estimate projects an 85% increase in electricity demand from 2009 to 2025. Consistent with previous work in China and other countries we find a price elasticity of demand of about -0.7. To put this into perspective, if electricity prices in China were to rise by an additional 15%, consistent with the effect of a $10 per ton carbon dioxide price, household demand would decline by about 10%.

Assumptions about autonomous time trends are considerably more important. The difference between our high and low (absent) autonomous trend models is 143% versus 43% demand growth. Meanwhile, demographic trends (other than income) have little effect. That is, income and demographic changes aside, there still appears to be an unexplained positive trend in residential electricity consumption over time in our data. If that trend continues, it would double forecast demand growth relative to estimated income effects alone. Our central estimate is based on an assumption (suggested by the data) that this autonomous trend slows over the coming decades. Given we believe the assumption of no autonomous time trend is unrealistic, our view is that the range of 85% to 143% growth is a reasonable projection for 2009 to 2025.

We can further decompose income-driven demand growth into components related to dwelling size and appliance adoption, as well as income alone. We find that appliance adoption drives about one-third of the growth attributable to income in our data. That is, when we consider the contribution to electricity demand growth of appliance adoption (itself driven by income growth), alongside the direct effect of income growth, appliance adoption accounts for about one-third of the total. Among appliances, air conditioners (AC) units are the most important, because of both their high energy use and increasing adoption (even as other appliances become saturated). We might label this one-third the extensive margin, with a higher stock of major appliances, and the other two-thirds the intensive margin, with other, non-specific, income-driven increases in demand, including higher use of existing appliances. Dwelling size, on the other hand, has very little independent effect.

Importantly, there are clues about potential policy targets for the intensive margin. While the number of refrigerators remains relatively unchanged in our forecast, they have the highest estimated impact on energy use. Refrigerators are estimated to increase electricity use by almost 20%. Given the doubling of refrigerator efficiency in the United States over the last 20 years, this suggests such an effort in China could reduce electricity demand by nearly 10%. This points to the potential value of energy efficiency policies, which would need to be weighed relative to the costs of such policies.

Another issue of interest is whether the distribution of income growth across different segments of the income distribution has a measurable impact on expected energy growth (Auffhammer and Wolfram 2014). We do not find the income effect to be particularly sensitive to how economic growth occurs across the different income groups. We do find that the income elasticity is falling as income rises, and project that the elasticity would reach zero when income is roughly $8,200 or 57,700 RMB per capita (2010 RMB). However, ascribing more growth to richer households based on trends in the data does not substantially alter the projection.

Summarizing, our econometric analysis leaves us with a large unexplained autonomous component. While our central estimate is 85% per capita consumption growth over 2009-2025, alternative assumptions about how and whether this trend continues lower the estimate to 43% or raise it to 143%. Ruling out the possibility of no autonomous trend, our preferred range is from 85% to 143%. Despite this gap, our improved understanding of the role of appliance adoption, income, and electricity prices is helpful in thinking about future policies. Energy efficiency polices for refrigerators and modest carbon pricing, for example, might each reduce household electricity use by 10%. We owe all of these observations to our use of household level data, which allows us to separate out the effects of price, income, appliance adoption, and autonomous trends.

The remainder of the paper is organized as follows. Section 2.2 introduces the data with summary statistics. Section 2.3 explains the model framework and econometric specifications. Section 2.4 reports the estimation results and initial forecast results. Section 2.5 discusses the main forecasting results, as well as policy implications from our examination of the composition of demand growth and distribution of income growth. Section 2.6 concludes.

2.2 Data

Our objective is to explore how estimation employing microeconomic data can provide more informative projections of electricity demand for the residential sector. Forecasts based on aggregate data depend largely on extrapolating growth trends. Microeconomic data allows us to explore the relative effect of at least three distinct features observed in the cross-section: income, appliance adoption, and dwelling size. In addition, our repeated cross section over time allows us to carefully examine any remaining autonomous time trend. While these features themselves must be extrapolated, alone or jointly, their relationship with electricity demand can be estimated based on cross-sectional data.

In addition to providing greater confidence in electricity forecasts, detailed microeconomic data can provide several other benefits. First, by teasing out the relative contribution of different factors driving consumption growth, it allows us to identify the effect of key assumptions about these factors such as the persistence (or not) of autonomous time trends. Second, it can allow us to simulate the impact of alternative assumptions about the distribution of aggregate economic growth. That is, how does electricity consumption vary if growth is broad-based versus being more concentrated among the wealthy, as it has tended to be in the past. Finally, a more detailed model of residential energy use, including prices, appliances and dwelling size, allows one to assess the likely impacts of various policies, including electricity pricing and energy efficiency policies.

In this section, we describe the data sets we use and the summary statistics of variables of interest, followed by a discussion of the model and specification in the next section.

2.2.1 Chinese Urban Household Survey (CUHS)

This paper uses the cross-sectional Chinese Urban Household Survey (CUHS) data collected by the National Bureau of Statistics (NBS) from 2002 to 2009. The survey design was changed in 2007, but the change has almost no impact on the variables chosen for our analysis[4]. Households with *hukou* (registered residency status in a particular area) are included[5]; households without *hukou* would be counted if they live in the city for more than six months. The total number of households from 31 provinces surveyed is around 60,000 each year, of which about 12,000 to 16,000 households per year are from 153 cities in our 9 provinces. The 9 regions are Anhui, Beijing, Guangdong, Hubei, Liaoning, Shaanxi, Sichuan, Zhejiang, Gansu, covering all parts of the country except the sparse far west[6]. The survey employs stratified multistage random sampling to guarantee a representative sample at each level. The 9 provinces that we have access to are not

[4] Two types of refrigerators for 2002-2006 are combined into one variable for 2007-2009.
[5] Note: migrant workers from rural areas are not included.
[6] The CUHS data for these nine provinces were provided by the China Data Center, Tsinghua University.

randomly selected; they reflect a restricted sample provided by NBS. Therefore, we compare the 9-province averages to the national averages reported by the NBS to show the similarity. One measure is the number of appliances owned per 100 urban residents. The number of AC's per 100 urban residents is 68 in our sample compared to 51 for the national average in 2002. However, the difference narrowed to less than 10 by 2009. The numbers for washers, refrigerators, computers, and microwave are also slightly higher in the 9-province sample. These nine provinces are slightly more developed compared to the rest at the beginning of the sample period, but the gap diminishes over time.

The CUHS data is very comprehensive in coverage, including socioeconomic features, and detailed information on consumption expenditures. In this study, we mainly focus on electricity consumption, relevant socioeconomic variables, housing features and the stock of appliances. Data on household features (e.g., household size, dwelling size, electricity consumption) and data on household head characteristics (e.g., age and education level) are contained in two separate datasets for each of the eight years. We merged the two datasets by household identity.

Electricity prices are calculated from electricity expenditures (in RMB) and quantities (in kWh)[7]. There are ample variations in the electricity prices across provinces and across cities within provinces. The calculated prices have relatively small variations

[7] The calculated electricity price is the price averaged over the year for a household. Increasing empirical evidence has supported that consumers are more likely to respond to average prices (Fell et al., 2014). Also, with a double-log form, elasticity estimates for marginal and average rates are quite comparable (Halvorsen, 1975). Note that the tier-pricing policies have not yet been implemented during 2002-2009 hence households would not be able to influence the average prices by changing consumption.

across different districts in Beijing (the same pricing policies apply to all districts) but we observe larger variations across cities in other regions (as pricing rules usually differ from city to city). The calculated electricity prices in Guangdong are the highest, ranging from 0.6 to 1 RMB/kWh, while the prices in other eight regions are lower, with the majority falling in the 0.4 to 0.6 RMB/kWh range. Given potential endogeneity concerns about using consumption to compute the price, we also estimate our model using the average electricity price at the city level as part of our sensitivity analysis.

The sample provided by NBS includes cross-sectional sampling weights. We use these weights in our estimation to ensure that our parameters are appropriate for projecting population averages. Moreover, the weights for each year are normalized so that the total weight given to each year in the sample is the same[8]. That is, the NBS sample size varied from about 12,500 in 2002 to 16,500 in 2005-2009. The years with a smaller sample are weighted upwards to ensure that years with more observations do not have more influence on the parameters estimates. We cleaned the data through several steps (see Appendix).

Real RMB values (for income and the electricity price) are generated from the original, nominal survey data using both the provincial-level price index for a common

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[8] More specifically, if qs_{it} represents the NBS sampling weight for a given household i in year t, then the normalized weight $\widetilde{qs_{it}} = qs_{it}/\sum qs_{it} \times 10{,}000$. After normalization, the sum of the weights in each year is 10,000. Here, the arbitrary choice of "10,000" to normalize the population each year does not affect estimation.

basket calculated by Loren Brandt and Carsten Holz[9] and the official CPI data. To capture the provincial differences in price levels that is not in the official CPI, Brandt and Holz calculated the urban basket cost for different regions. We use the urban basket cost from their calculations for the base year 2002 as our price index for the first year (the price index of Beijing is normalized to 100 in 2002). The price indexes for 2003 to 2009 are then generated using the official provincial CPI inflation rate.

Finally, to examine the impact of weather on electricity consumption and better model the effect of AC units on demand, we combined the survey data with data on Heating Degree Days (HDD) and Cooling Degree Days (CDD). City-level HDD or CDD data are calculated based on the weather data from the Global Summary of the Day from the National Oceanic and Atmospheric Administration (NOAA), which has 50 weather observation points close to or in the 153 cities in our sample[10]. Temperatures are computed for each city based on the nearest observation point. To calculate HDD and CDD, we use 65°F (18°C) and 78.8°F (26°C) as the reference values for heating and cooling respectively. Although many previous studies in Europe and the United States use 71.6°F (22°C) as the reference value for cooling, we follow the recent studies (e.g., Shi et al., 2016) on China to reflect local habits, building characteristics and climate conditions in China. More specifically, HDD and CDD for city i and year t are calculated as follows:

[9] See Brandt and Holz (2006). More recent data is made available at http://ihome.ust.hk/~socholz/SpatialDeflators.html.

[10] The data is described at https://data.noaa.gov/dataset/global-surface-summary-of-the-day-gsod.

$$\begin{cases} HDD_{i,t} = \sum_{d=1}^{365}\{\max(65 - T_{i,t,d}, 0)\} \\ CDD_{i,t} = \sum_{d=1}^{365}\{\max(T_{i,t,d} - 78.8, 0)\} \end{cases} \quad (2.1)$$

where $T_{i,t,d}$ is the mean temperature on day d of year t in city i.

2.2.2 Descriptive Statistics

Table 2.1 shows the descriptive statistics for the variables used in the econometric estimation. The sample size is 122,252 households (spread across 8 years). The data used in this study and Cao et al. (2016) are, to our knowledge, the largest and most representative micro data set ever used for household energy research in China. For household real income, we use consumption expenditure instead of the reported income. There is no life-time income estimation using cohort studies as in US so we simply use consumption expenditure as a proxy for life-time income in our study.

Table 2.1 Summary Statistics of Household Data in CUHS, 2002-2009

N=122,252	variable	mean	weighted mean	sd	min	max	%change*
Electricity consumption (kWh/year)	*q*	1,430	1,484	1,047	2	24,740	7.4%
Real electricity price (RMB/kWh)	*p*	0.448	0.460	0.121	0.041	1.5	-0.9%
Real income (RMB/year)*	*y*	22,968	22,957	20,758	203	947,186	6.0%
Demeaned real income	*y_c*	1	1	0.900	0.010	41.080	6.0%
Demographic features							
Dwelling size (square meters)	*dwelling_sz*	78.545	82.215	36.085	5	300	2.2%
Rent (RMB/square meter/month)	*rent*	7.094	6.783	9.417	0	224	106%
Ownership (=1 if rent)	*ownership*	0.127	0.124	0.333	0	1	-0.9%
Household size	*household_sz*	2.915	2.961	0.817	1	13	-0.9%
Age of household head > 50 (0/1)	*age_over50*	0.410	0.396	0.492	0	1	1.0%
Education of household head (0/1)							

Primary or below	*edu_prim*	0.072	0.069	0.259	0	1	0.1%
Middle school or equivalent	*edu_mid*	0.279	0.265	0.448	0	1	-0.2%
High school or equivalent	*edu_high*	0.350	0.364	0.477	0	1	-0.7%
College level or above	*edu_coll*	0.299	0.302	0.458	0	1	0.7%
Heating type (0/1)							
Heating by air-conditioner	*heat_ac*	0.274	0.262	0.446	0	1	3.0%
Heating by gas or water	*heat_gaswater*	0.331	0.234	0.471	0	1	0.2%
Heating by other	*heat_other*	0.080	0.059	0.271	0	1	-0.5%
None	*heat_none*	0.315	0.445	0.464	0	1	-0.6%
Appliances (0/1/> =2)							
Refrigerator	*fridge*	0.962	0.962	0.364	0	2	0.0%
Computer	*comp*	0.469	0.465	0.558	0	2	14.3%
Microwave oven	*mwave*	0.488	0.488	0.507	0	2	7.6%
Waterheater for shower	*wheater*	0.784	0.812	0.479	0	2	2.7%
Washing machine	*washer*	0.953	0.960	0.316	0	2	0.2%
Air conditioner (0/1/2/3/>=4)	*ac*	0.894	0.961	0.970	0	4	8.0%
Weather							
Heating degree days	*hdd*	3,739	3,221	1,892	273	7,833	2.4%
Cooling degree days	*cdd*	285	336	224	0	919	0.7%

For continuous variables and the appliances, the '%change' is calculated as the average annual growth rate for 2002-2009. For indicators (0/1), the '%change' is calculated as the mean annual change for 2002-2009.

The first four rows include key variables—electricity use, price, and income. This is followed by demographic features, education of household head, heating type, appliances ownership and weather. In addition to the standard summary statistics (mean, standard deviation, minimum and maximum), the table includes the weighted mean estimated using the population weights in the data (column 4). We also calculate the annual percentage change of the within-year average for each variable over the 8-year period (the last column in Table 2.1 continued).

In weighted average terms, electricity consumption per household is 1,484 kWh, real income, proxied by total consumption expenditures is 23,000 RMB (roughly $3,500)[11], and dwelling size is 82 square meters. The average per capita income would be roughly one-third, given the average household size of about 3. Among appliances, the ownership rates of refrigerators and washing machines are over 95%, followed by an AC penetration rate of 89%, and computer of almost 50%. The average heating degree days and cooling degree days are 3,200 and 340 respectively.

Looking at trends over time, real income and electricity consumption increased at an average annual rate of 6.0% and 7.4%, respectively, which is consistent with the increasing per capita GDP and electricity demand at the macro level. Real electricity prices declined slightly. Among demographic features, household size decreased while dwelling size increased by 2.2% annually. Over the sample period, education levels generally rose with an increase in the number of household heads with a college education or above. Among appliances, the ownership of computers, AC's and microwave ovens grew rapidly while refrigerators and washing machines are approaching saturation.

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[11] In comparison, the average disposable income is 29,789 RMB.

2.3 Method

Electricity consumption is associated with the use of a range of household electrical devices that are operated for many years, if not decades. Hence, understanding and modeling the ownership of such appliances is critical in analyzing electricity demand in the residential sector, particularly if one's interest is ultimately related to understanding the link to income growth, to electricity prices, and to policy interventions. In addition to appliances, larger dwelling size would increase electricity consumption through higher heating or cooling demand.

Fisher and Kaysen (1962) proposed a two-stage framework that informs our modeling choice. They model consumption in the short-run as a function of income and price, given the appliance stocks. In a separate saturation model, they use population, expected income, marriages, expected energy prices and the number of wired households to explain the appliance stocks. The empirical results from their paper are constrained by the quality of the appliances data, but the two-stage framework has been found to be an improvement in results relative to a static model (Taylor et al., 1984). More recently, Leahy and Lyons (2009) use the two-stage framework to estimate a logit model investigating the determinants of household appliances and OLS models to explain household energy use conditional on appliance ownership.

Expanding on the above framework, we assume that households face a three-stage sequential and independent decision process to make each step tractable. In stage I, they choose the size of house to rent or own. In stage II, conditional on the dwelling size chosen, they choose the number of appliances for each type. In stage III, conditional on the dwelling size and the appliances chosen, households decide how much electricity to consume. Each stage is a function of income and other demographic variables, possible time trends, and previous stage(s) dependent variable(s). The last two stages include the electricity price. We adopt this three-stage framework mainly to take into account the non-linearity in the adoption of appliances and to decompose the sources of growth of electricity demand. In particular, the three-stage model allows us to compare these driving forces: dwelling size, appliance ownership, and utilization rate given dwelling size and appliances. This then allows us to both more confidently forecast demand and consider the magnitude of possible policy interventions.

Income is a main factor of interest so we tested different functional forms using linear, quadratic and cubic functions. We choose the quadratic form of income based on both economic intuition and statistical significance (particularly for the last stage). A negative quadratic term is consistent with diminishing marginal income effects. As income rises, a one percent increase in income would lead to a smaller increase in dwelling size and electricity consumption. For appliances, S-shape curves have been documented (McNeil and Letschert, 2010), where households start adopting appliances after passing an income threshold, first experiencing a speed-up in adoption and then a deceleration. Our ordered logit model imposes such behavior without a quadratic income term; however, we include it in order to provide a more flexible income-adoption relationship and for consistency with the other two stages.

As we do not have panel data at the household level, we apply the three stages to the pooled repeated cross-section of households. For each stage, we estimate a relatively simple reduced-form model. We use ordinary least squares (OLS) for dwelling size, an ordered logit (Ologit) model for appliances, and OLS for electricity consumption. This allows flexible, transparent estimation of the parameters of interest as well as projection using available income forecasts. We describe additional details below.

2.3.1 Dwelling Size Model

Housing demand is obviously not a simple choice of structure and size, but is also a location decision, where the location attributes of interest include proximity to work, schools and amenities, and environmental quality among many others. The price of a particular dwelling depends on all these characteristics. The survey data provides a per-square-meter housing price, including a rental equivalent for owner-occupied units, which we use.

Given these data constraints, in stage I, dwelling size is modeled as a continuous choice based on income, price represented by rent, household size, and other demographic features. For each household from a given year:

$$\ln(dwelling\_sz_{it}) = \alpha + \beta_1 \ln(rent_{it}) + \beta_2 \ln(y\_c_{it}) + \beta_3 [\ln(y\_c_{it})]^2 + \beta_4\, household_{sz_{it}} + \beta_5 age_{over50_{it}} + \beta_6 edu\_mid_{it} + \beta_7 edu\_high_{it} + \beta_8 edu\_coll_{it} + \beta_9 ownership_{it} + \delta_{region} + g_k\big(t,\ b_1,\ b_2,\ \delta_{year}\big) + \epsilon \qquad (2.2)$$

where the β's are parameters to be estimated; $dwelling\_sz$ is the dwelling size; $rent_{it}$ is the monthly rent for the house or the equivalent rent if the house is owned[12]; y_c is the demeaned real income represented by the real consumption expenditure[13]; $household\_sz$ is the household size (number of people); age_over50 is an indicator variable for households with a head older than 50 years old; $ownership$ is an indicator that equals 1 for rental houses; and δ_{region} are fixed effects for each of the 9 provinces. The education level of household head is captured by three indicators: middle school (edu_mid), high school(edu_high), college and above (edu_coll), all relative to primary education (which is omitted).

The general form $g_k(t,\ b_1,\ b_2,\ \delta_{year})$ represents the time trend: t is defined by $t = year - 2002;$ b_1 and b_2 are parameters; and δ_{year} are possible year indicators for 2002-2009 . We consider three different specifications of $g_k(.)$ $(k = \mathrm{A, B, C})$ to capture different possibilities for how time trends may continue into the future. In general, there is an upward trend from year to year in the data that is not explained by other demographic variables. The alternative specifications, all of which allow for this historic pattern, have little effect on the estimation of other parameters but affect future forecasts significantly. Applying different time trends allows us to examine the range of possible trajectories. Specifically, our first specification simply uses year fixed effects, which we

[12] Note: The average rent is surprisingly low in the sample, but the trend over time reflects the housing boom in 2005-2007. Assuming the variable is recorded consistently across households, we believe it is better to include it to avoid omitted variable bias.

[13] Note: we use consumption expenditure as a proxy for life-time income in our study.

then project forward based on the fixed, final year value, the second one uses a non-linear, slowing time trend, and the third specification uses a linear time trend:

$$g_A(t, b_1, b_2, \delta_{year}) = \delta_{year}$$

$$g_B(t, b_1, b_2, \delta_{year}) = -b_1\, e^{-b_2 t}$$

$$g_C(t, b_1, b_2, \delta_{year}) = b_1\, t \tag{2.3}$$

A variety of individual effects is embedded in both demographic variables and the error term. In the period before economic reform, housing was allocated by the place of employment, which complicates the dwelling choice. In the 1990s, the state-owned or enterprise-owned housing was privatized. Some organizations, especially government agencies, may still build and sell subsidized units to their staff. Employment, in turn, is likely determined in part by education and age. We should also note that urban China today is unusual, compared to developed countries, in that there is a very high ownership rate; less than 20% rent their housing. The consumption expenditures we employ to represent household income, therefore, do not include the market value of housing services for a large portion of the data; this is a potential limitation to our measure of income.

2.3.2 Appliance Stock Model

In stage II, we model each of six appliances separately. For air-conditioners (AC), the choice is categorized into owning 0, 1, 2, 3, or 4+ units (represented by 4 hereafter). For the rest, including washing machine, refrigerator, microwave, computer and water-heater, the choices are owning 0, 1 or 2+ (represented by 2 hereafter). Based on Dubin and

McFadden (1984), we model the appliance choices in a logit framework. As the possibility of the fact that multiple appliances are interrelated, the ordered logit is most suitable to capture the ordinal scale of the dependent variables. That is, someone more likely to purchase two rather than fewer devices is also more likely to purchase one or more devices rather than zero.

We illustrate the model set up for AC for each household i for a given year t; the other appliances with outcomes of up to 2 units follow similarly. We observe the outcome of AC ownership in an ordinal scale of 1, 2, 3, 4. We assume that there is an underlying variable measuring the utility from AC, denoted $\widetilde{AC}$. Whether household i owns a particular count of AC units depends on whether the underlying driver $\widetilde{AC_\imath}$ passes particular thresholds. More formally, for a household in a given year:

$$\mathrm{AC_{it}} = 0 \; if \; \widetilde{AC_{\imath t}} \le \kappa_1 ,$$

$$\mathrm{AC_{it}} = j \; if \; \kappa_j < \widetilde{AC_{\imath t}} \le \kappa_{j+1} , for \; j = 1, 2, 3 \tag{2.4}$$

$$\mathrm{AC_{it}} = 4 \; if \; \widetilde{AC_{\imath t}} > \kappa_4 ,$$

where κ represents "cuts" or thresholds to be estimated. The continuous latent variable $\widetilde{AC}$ is modeled as a linear regression on covariates:

$$\widetilde{AC}_{\mathrm{it}} = X_{it}\beta + \epsilon_i \tag{2.5}$$

where β is a vector of coefficients; X_{it} is a vector of covariates, including all the variables contained in the dwelling size regression (Eq. 2.2), demeaned dwelling size and demeaned dwelling size squared, and electricity price. We also include cooling degree days (cdd) and heating degree days (hdd) in the model for AC, but not for the other appliances. One limitation of our model is that we do not have information on the price of appliances. Through the province and year fixed effects, we implicitly control provincial-specific and year-specific price differences, but not the price differences associated with different size, brand, quality, and energy efficiency.

The random disturbance term ϵ_i is assumed to follow a standard logistic distribution. Thus, the probability for AC taking on a particular value is given as follows:

$$\mathrm{P}(\mathrm{AC_{it}} = 0) = \frac{1}{1+\exp(X_{it}\beta - \kappa_1)} \; ;$$

$$\mathrm{P}(\mathrm{AC_{it}} = \mathrm{j}) = \frac{1}{1+\exp(X_{it}\beta - \kappa_{j+1})} - \frac{1}{1+\exp\left(X_{it}\beta - \kappa_j\right)} \; , for\ j = 1,2,3$$

$$\mathrm{P}(\mathrm{AC_{it}} = 4) = 1 - \frac{1}{1+\exp(X_{it}\beta - \kappa_4)} \tag{2.6}$$

For each appliance, the parameters including both the β's and κ's can then be estimated by maximizing the log-likelihood function:

$$\log L(\beta) = \sum\{I[appliance_{it} = j] \cdot \mathrm{P}(\mathrm{appliance_{it}} = j)\},$$

$$\begin{cases} j \in \{0,1,2,3,4\} & for\ ACs \\ j \in \{0,1,2\}\ for\ other\ durables \end{cases} \tag{2.7}$$

where $I[appliance_{it} = j]$ is the indicator function that equals 1 when the number of appliances equates j for a household i in year t.

2.3.3 Electricity Consumption Model

In stage III, based on the previous studies and examination of different models, the regression model for electricity consumption conditional on appliances by household i in year t is specified as:

$$\ln(ec_{it}) = \alpha + \beta_1 \ln(y\_c_{it}) + \beta_2 [\ln(y\_c_{it})]^2 + \beta_3 \ln(p_{it}) + \beta_4 \ln(dwelling\_sz_{it}) + \beta_5\, household\_sz_{it} + \beta_6\, age\_over50_{it} + \mathrm{B}_7\, hhedu_{it} + \mathrm{B}_8\, appliances_{it} + \beta_9 hdd_{it} + \beta_{10} cdd_{it} + \mathrm{B}_{11}\, heating_{it} + \mathrm{B}_{12} hdd_{ct} \cdot heating_{it} + \beta_{13}\, cdd_{ct} \cdot AC_{it} + g_k\big(t,\ b_1,\ b_2,\ \delta_{year}\big) + \delta_{region} + \epsilon \tag{2.8}$$

Where ec is household electricity consumption (in kWh), the β's are parameters and B's are vectors of parameters. The income, price[14], dwelling size and demographic variables are the same as in the first two stages (with education indicators collapsed into the vector *hhedu*). In addition, $appliances$ represents the number of specific appliances owned, including washing machine, refrigerator, computer, microwave oven, water heater for shower and AC; hdd and cdd are heating degree days and cooling degree days respectively; $heating$ has the indicators for heating types, including heating through an air conditioning unit (*heat_ac*) heating by gas or water (*heat_gaswater*), and heating by other (*heat_other*). The category "no heating" is omitted as the reference group. We also include interactions between heating degree days and heating types ($hdd \cdot heating$), and between cooling degree days and ACs($cdd \cdot AC$). Note that hdd and cdd vary by city (using subscript c) and by year. As in the dwelling size model, the specification in Eq. 2.8 includes the term, $g_k(t,\ b_1,\ b_2,\ \delta_{year})$, for the three options for trends – year fixed effects, non-linear time trend and linear time trend.

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[14] We use the electricity price calculated at household-level for the main specification. This may cause endogeneity issue if the calculated price is correlated with other uncontrolled variables. As an alternative, we use the average price at the city level which would not be correlated with household-level unobservables. The results do not change significantly.

2.4 Estimation and Forecast Results

We now turn to estimating the model and generating forecasts based on it. We discuss each component of the three-stage approach in turn in this section, and then consider the broader observations in the next section. For each forecast, we include both the time trends and income growth. Future per capita income growth is calculated from the projections of GDP and population in the IEA's World Energy Model 2015.[15] Real GDP is assumed to grow at 9.9% per year for 2010-2013, 6.4% for 2014-2020 and 5.3% for 2021-2025 while population is assumed to grow at 0.4% until 2025 (WEM, 2015)[16]. Hence, the per capita GDP growth rate is 9.5% for 2010-2012, 6.0% for 2013-2020 and 4.9% for 2021-2025. This amounts to a 165% increase from 2009 to 2025, or a roughly one-unit increase in logged per capita income. We use the forecasted rate by IEA mainly to maintain consistency of income assumption over the whole period of 2010-2025.

To construct forecasts, we use the model to predict new values for each of the modeled variables (dwelling size, appliance ownership, and electricity consumption) for each of the households observed in 2009 based on per capita GDP growth[17] and the specified time trend. We do this in sequence so that forecast dwelling size influences appliance ownership, and dwelling size and appliance ownership in turn affect electricity consumption. The households are then averaged using the 2009 cross-sectional NBS

[15] http://www.worldenergyoutlook.org/media/weowebsite/2015/WEM_Documentation_WEO2015.pdf

[16] Note: As both the urban and rural areas are included by the WEM forecasts, we assume that the urban households follow the same GDP growth rate as the rural households.

[17] Note that the forecasts assume no change in electricity prices or degree of urbanization.

dataset weights to generate an estimated population forecast of average urban household electricity demand.

2.4.1 Dwelling Size Results

As discussed above, our model for dwelling size (Eq. 2.2) includes income, other socioeconomic variables and alternative time trends. Table 2.2 reports the estimation results for the dwelling size model using ordinary least squares (OLS). Models A-C present alternative results for different assumptions about the autonomous time trend. Model A includes indicator variables for each year; Model B includes an exponential time trend of the form $-b_1 e^{-b_2 t}$ and Model C includes a linear time trend. The coefficients for all other explanatory variables have minor differences among the three specifications, suggesting that using a non-linear trend, linear trend, or year indicators does not significantly affect the parameter estimates on the other regressors.

The impacts of the non-income variables are as follows. Higher rent reduces the dwelling size. Compared to houses that are owned, the dwelling size is 46% smaller for rental houses. An older (over 50) head of household is associated with a 6% higher dwelling size. Higher education is also associated with greater dwelling size, with as much as an 18% larger dwelling for college-educated versus primary school (the reference group). Finally, each additional household member is associated with an estimated 6% larger dwelling size. These variables are all held fixed based on their distribution in 2009 in the forecasts. We later show that our results are not particularly sensitive to alternative trends in demographic variables.

Table 2.2: OLS Estimation Results for Dwelling Size

(dependent variable = $\ln(dwewlling\_sz)$)	Model A	Model B	Model C
lnrent	-0.0598***	-0.0371***	-0.0325***
	(0.0133)	(0.00918)	(0.00858)
lny_c	0.0950***	0.0899***	0.0887***
	(0.0153)	(0.0161)	(0.0163)
lny_c^2	-0.000375	-0.00165	-0.00197
	(0.00573)	(0.00598)	(0.00610)
household_sz	0.0591***	0.0602***	0.0603***
	(0.00750)	(0.00765)	(0.00771)
age_over50	0.0480***	0.0494***	0.0501***
	(0.00957)	(0.00965)	(0.00970)
edu_mid	0.0265*	0.0263*	0.0269*
	(0.0110)	(0.0109)	(0.0109)
edu_high	0.0734***	0.0736***	0.0748***
	(0.0131)	(0.0132)	(0.0132)
edu_coll	0.178***	0.178***	0.179***
	(0.0155)	(0.0157)	(0.0157)
ownership	-0.481***	-0.464***	-0.461***
	(0.0256)	(0.0238)	(0.0235)
α	4.159***	4.157***	3.964***
	(0.0594)	(0.0775)	(0.0590)
Time trend coefficients			
b_1		0.207***	0.0223***
		(0.0485)	(0.00374)
b_2		0.235**	
		(0.0835)	
year indicators	*YES*	*NO*	*NO*
regional indicators	*YES*	*YES*	*YES*
N	110319	110319	110319
adj. R^2	0.281	0.277	0.276

Note: Clustered standard errors in parentheses, _c stands for demeaned variable

F-test suggests that b_1 and b_2 are jointly significant at 1% significant level, * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Income is the variable of greatest interest, as we use income projections (in part) to drive dwelling size forecasts. While the linear term suggests a statistically significant elasticity of 0.09—that is, a 100% increase in income raises dwelling size by about 9%—the quadratic term is not statistically significant. Moreover, the point estimate of the quadratic term suggests that dwelling size does not "peak" until income is 400 times higher than the 2009 income level; thus there is little evidence that growth in dwelling size is slowing yet as a function of rising incomes. We keep this term in the model, however, as it has the expected sign and we believe there should be some slowing in the otherwise linear relationship. Based on this estimated relationship, over the forecast horizon dwelling size will rise 10% based on forecast income growth[18].

The other item of interest is the choice among alternative time trends. The model fit is virtually identical with year indicators in Model A versus Models B and C with parameterized time trends over the eight years in the sample (adjusted R^2 of 0.28). However, for forecasting purposes, we prefer a parameterized time trend; otherwise we have to assume the year fixed effect in the last year persists forever. With the linear time trend model, dwelling size would rise 58% over the forecast horizon. Finally, the parameters b_1 and b_2 of the non-linear time trend in Model B are both significant. The point estimates suggest that, from 2009 levels, dwelling size would increase by 14% over the 2025 forecast horizon and eventually achieve a 21% increase asymptotically (holding other variables, including income, constant). Note that we have not forecast housing

[18] As mentioned in the method section, we use consumption expenditure as the proxy for lifetime income. One concern is that purchasing houses would affect consumption expenditure, causing an endogeneity issue. To address this issue, we estimate the same specification using the total household income. The income elasticity increases slightly, leading to upward-adjustment of roughly 2% in dwelling size over the forecast horizon.

prices explicitly in this projection. With an estimated price elasticity of roughly -0.05 across models A-C, this could amount to 5 percent decrease in dwelling size if housing prices doubled.

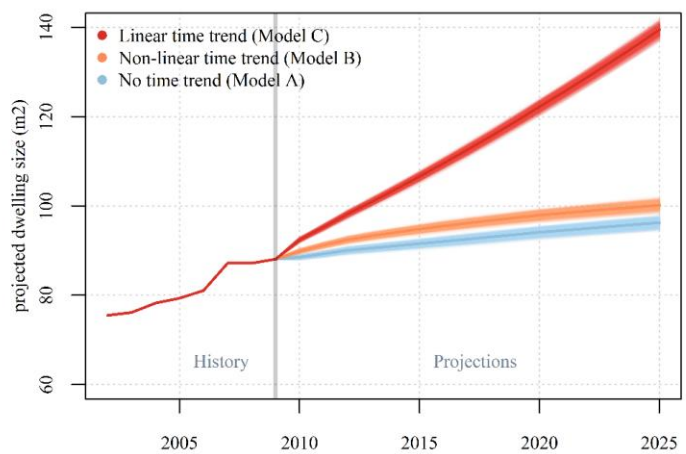

Figure 2.3: Mean Dwelling Size (in Square Meters) Projected from 2009 Using Alternative Time Trends

Notes: Shaded regions indicate variation based on uncertain demographics

Perhaps the most useful way to compare the time trends is to see how they influence the forecast. Figure 2.3 shows the three forecasts of dwelling size based on the three different time trend models and the per capita income growth projection described above. The shading in the figure represents sampling error in the demographic variables used to forecast the model.[19] This sampling error is small compared to the notable effect of alternative time trends on the trajectory over the forecast period. Model A predicts a

[19] We resample households from the 2009 cross-section data with a replacement before applying the income growth and time trend assumptions to each household, which are then averaged to produce a forecast. We then conduct this exercise 1,000 times to produce the shaded region.

9% increase; Model B predicts a 14% increase and Model C predicts a 58% increase from 2009 to 2025. That is, there is significantly higher growth in dwelling size if we extrapolate linear time trends versus keeping them fixed at 2009 levels. This is true even after controlling for income growth and rent. As we will show later, the difference in dwelling size projections, although large in and of themselves, alter the ultimate projection of electricity demand only slightly.

2.4.2 Appliance Stock Results

Table 2.3 reports the estimation results for the choice of appliances. All six appliances are modeled through the ordered logit as a function of the same variables as the dwelling size model, plus dwelling size and the electricity price. In an ordered logit, the probability of being at or above a particular count j for the indicating appliance is $\exp(X\beta - \kappa_j) / \exp(1 + X\beta - \kappa_j)$ where κ_j is the cut. The lower part of Table 2.3 shows the cuts, which are not exponentiated. The cuts are all significantly distinct from each other based on their standard errors, suggesting that assuming an underlying rank of utility level for the choices is meaningful and ordered logit models are suitable in this case.

The upper part of Table 2.3 shows the coefficients in the form of the odds ratio, i.e., the exponentiated coefficients. For example, the 0.418 estimate for *lnp* associated with refrigerators implies that the odds ratios P(fridge>=1)/P(fridge<1) and P(fridge>=2)/P(fridge<2) would both be multiplied by a factor of 0.418 (e.g., the ratio would decline) as *lnp* increases by 1 unit. Generally, all the coefficients on *lnp*, the logged electricity price, are around one-half—indicating that higher electricity prices lower the probability of higher numbers of appliances—though most are not statistically significant.

Table 2.3: Ordered Logit Estimation Results for Appliances Ownership (Odds Ratio)

	Refrigerator	Washing Machine	Computer	Microwave	Water-heater	AC
lny_c	3.099***	2.563***	4.588***	3.654***	2.670***	5.125***
	(0.269)	(0.128)	(0.235)	(0.162)	(0.133)	(0.297)
lny_c^2	0.854***	0.937*	0.854***	0.819***	0.916*	0.903*
	(0.0324)	(0.0247)	(0.0302)	(0.0291)	(0.0389)	(0.0459)
lnp	0.418*	0.637	0.434**	0.651	0.601	0.479
	(0.186)	(0.210)	(0.111)	(0.182)	(0.278)	(0.271)
lndwelling_sz_c	1.458**	1.735***	1.399***	1.298**	2.722***	2.304***
	(0.184)	(0.179)	(0.115)	(0.118)	(0.447)	(0.241)
lndwelling_sz_c^2	0.776**	0.838	0.850*	0.790***	0.742*	0.855
	(0.0707)	(0.0775)	(0.0634)	(0.0559)	(0.0972)	(0.0805)
household_sz	0.958	1.123***	0.967	0.813***	0.821***	0.815***
	(0.0365)	(0.0282)	(0.0252)	(0.0194)	(0.0214)	(0.0235)
age_over50	1.305***	1.196***	0.919	1.194***	1.059	1.275***
	(0.0803)	(0.0637)	(0.0445)	(0.0635)	(0.0472)	(0.0625)
ownership	0.617***	0.643***	0.759***	0.715***	0.559***	0.563***
	(0.0748)	(0.0513)	(0.0459)	(0.0492)	(0.0374)	(0.0581)
edu_mid	1.435***	1.626***	1.542***	1.523***	1.385***	1.437***
	(0.132)	(0.126)	(0.0960)	(0.0881)	(0.0758)	(0.0750)
edu_high	1.751***	2.087***	2.157***	2.133***	1.804***	1.864***
	(0.162)	(0.155)	(0.128)	(0.124)	(0.104)	(0.121)
edu_coll	1.830***	2.506***	3.693***	2.961***	2.185***	2.544***
	(0.176)	(0.182)	(0.240)	(0.179)	(0.160)	(0.190)
cdd (in 1,000)						6.596***
						(3.702)
hdd (in 1,000)						1.036
						(0.101)
cut1	0.293*	0.140***	4.164***	2.506	0.504	49.13***
	(0.149)	(0.0488)	(1.382)	(1.242)	(0.211)	(42.54)
cut2	138.6***	127.3***	255.3***	1502.3***	170.4***	593.0***
	(72.92)	(43.54)	(85.01)	(765.9)	(78.51)	(526.9)
cut3						3227.1***

						(2915.8)
cut4						18653.3***
						(17237.2)
year indicators	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
regional indicators	*YES*	*YES*	*YES*	*YES*	*YES*	*YES*
N	122252	122252	122252	122252	122252	122252

Exponentiated coefficients; Clustered standard errors in parentheses; cuts correspond to coefficients, not exponetiated

* $p<0.05$, ** $p<0.01$, *** $p<0.001$

Except for household size and home ownership, all other socioeconomic variables (age, education, and income) have statistically significant, positive (>1) effects. A college degree raises the odds of a higher count of computers by a factor of almost four; computers are the one item where an older head of household does not increase the odds ratio. Income initially raises the likelihood of more appliances but, with the squared income term less than one, eventually lowers the likelihood. However, by simulation, we know that this peak does not occur until average income is at least 20 times the 2009 level for microwave ovens, 30 times for refrigerator and water-heater, 60 times for computer and 30,000 times for washing machine and AC[20]. Given income rises only by a factor of 2.75 in our 2010-2025 forecast, these peaking events remain far beyond the 2025 horizon.

Dwelling size also has a statistically significantly positive impact on the adoption of appliances. Here, the quadratic terms suggest a peaking for computer, refrigerator, and microwave counts when dwelling size has roughly doubled from the current mean.

[20] The log of this multiple can also be computed based on ln(linear term) ÷ (2 ln(squared term)) as the coefficients have been exponentiated.

Given dwelling size increases by only 60% by 2025 under the most aggressive trend assumption, this also remains beyond our forecast horizon. Holding the dwelling size fixed, appliances ownership is significantly lower for the rental houses.

Only household size (aside from electricity price and home ownership) lowers the expected appliance count for microwaves, water heaters, and AC. This presumably reflects the effect, holding income and dwelling size constant, of a reduction of disposable income available for appliances when there are more household members. An example is the expenses for children. This effect does not affect refrigerator or computer expected counts and the expected washing machine count goes up, which may be viewed as a greater necessity in a larger household.

We include cooling degree days as a predictor of AC adoption. One thousand additional degree days (roughly 3 degrees C warmer every day of the year) raises the odds ratio by a factor of 6. Higher heating degree days also increases the likelihood of owning an AC, but not significantly. This is because northern China mainly uses central heating and southern China rarely needs AC for heating. Therefore, the variations in hdd within central China largely identifies the effect, based on our inclusion of region fixed effects. One limitation of the appliance models is the lack of specific equipment attributes (e.g., energy efficiency), which also play a significant role in electricity consumption.

We use these estimated adoption models to predict appliance ownership in Figure 2.4. To construct this figure, we use the projected income per capita growth described above, along with the dwelling size prediction based on Model B, to predict the probabilities of different counts for each household in the sample. We take the expected value for each household in each year based on these probabilities and construct a population average using the sample weights.

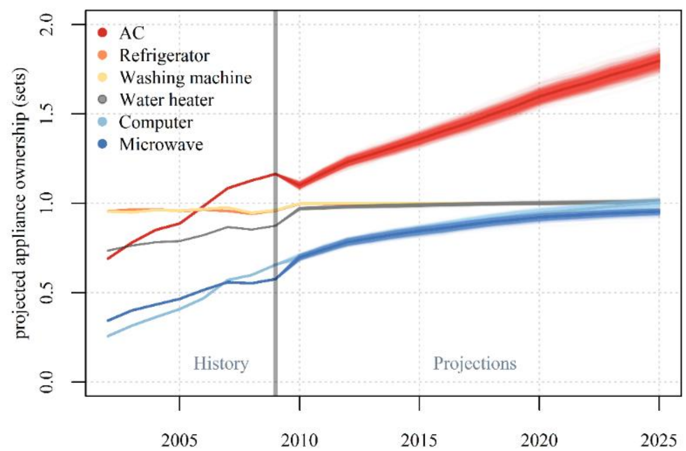

Figure 2.4: Mean Appliances Ownership (in Sets) Projected from 2009.

Notes: Shaded regions indicate variation based on uncertain demographics

It is evident that even though we allow for ownership of >=2 appliances in all cases, our model predicts an average of 1 appliance per household for all but AC units by 2025. This is true of refrigerators, and washing machines, which already near an average of 1, as well as water heaters, which were close behind. It is also true of computers and microwaves, which had only achieved about 70% penetration by 2009 but were on a clear upward trajectory. Going back to the underlying data, we note that there are very few households with more than one of these appliances in the sample, even at high-income levels, reinforcing the basis for “1” as the limiting value. Meanwhile, air conditioners remain on an upward trend and approach 1.8 ACs per household at the end of the forecast. Chinese apartments usually have separate AC units for bedrooms, not a central AC system as is typical in US homes. Central AC systems may become more popular among new buildings in the future, but this could not be analyzed in our framework as we do not observe whether a household has a central AC system in the data.

2.4.3 Electricity Consumption Results

Table 2.4 reports the OLS estimation results for the electricity consumption model. As in the earlier models, all of our electricity models include linear and quadratic income terms, allowing the income elasticity to vary with income level. Model 1 includes only the electricity price, income, year fixed effects and regional indicators as explanatory variables to serve as a "simple model" benchmark. Model 2 includes the variables in Model 1, plus dwelling size and appliance stocks, which in addition to income, are the necessary factors driving subsequent electricity forecasts. Models 3, 4 and 5 are the main specifications, additionally controlling for demographic variables, as well as heating type, weather variables, and interactions among them. Regional indicators are included in all specifications.

Another key difference is what we assume about the time trend. As with dwelling size, in Model 3 we consider year fixed effects (which provide no independent time trend), while Models 4 and 5 include non-linear and linear trends respectively. Model 6 excludes regional indicators, allowing us to examine how parameters related to weather are affected by requiring them to predict between as well as within region variations.

Table 2.4: OLS Estimation Results for Electricity Consumption

	(dependent variable = ln(electricity consumption))					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
lnp	-0.720***	-0.655***	-0.659***	-0.655***	-0.652***	-0.610***
	(0.120)	(0.136)	(0.113)	(0.113)	(0.112)	(0.0946)
lny_c	0.497***	0.330***	0.322***	0.323***	0.322***	0.337***
	(0.0173)	(0.0143)	(0.0161)	(0.0161)	(0.0161)	(0.0157)
lny_c^2	-0.0884***	-0.0877***	-0.0899***	-0.0900***	-0.0901***	-0.0917***
	(0.0102)	(0.00890)	(0.00893)	(0.00892)	(0.00893)	(0.00986)
lndwelling_sz_c		0.0739**	0.0657**	0.0657**	0.0658**	0.0652**
		(0.0265)	(0.0235)	(0.0235)	(0.0234)	(0.0210)
fridge		0.191***	0.187***	0.187***	0.187***	0.192***
		(0.0187)	(0.0194)	(0.0194)	(0.0195)	(0.0175)
comp		0.0469***	0.0589***	0.0589***	0.0589***	0.0678***
		(0.00740)	(0.00704)	(0.00707)	(0.00708)	(0.00744)
mwave		0.0729***	0.0838***	0.0839***	0.0843***	0.0902***
		(0.0132)	(0.0120)	(0.0120)	(0.0120)	(0.0123)
wheater		0.0407**	0.0506***	0.0506***	0.0506***	0.0507***
		(0.0147)	(0.0136)	(0.0136)	(0.0136)	(0.0132)
washer		0.0358**	0.0319*	0.0323*	0.0325*	0.0160
		(0.0130)	(0.0125)	(0.0126)	(0.0126)	(0.0122)
ac		0.109***	0.0744***	0.0734***	0.0733***	0.0765***
		(0.00947)	(0.0167)	(0.0164)	(0.0165)	(0.0163)
household_sz			0.0569***	0.0568***	0.0568***	0.0575***
			(0.00510)	(0.00511)	(0.00513)	(0.00490)
age_over50			0.0868***	0.0869***	0.0871***	0.0908***
			(0.00977)	(0.00973)	(0.00973)	(0.0118)
edu_mid			-0.00978	-0.00923	-0.00894	-0.00496
			(0.0137)	(0.0137)	(0.0137)	(0.0153)
edu_high			-0.0212	-0.0202	-0.0195	-0.0205
			(0.0139)	(0.0139)	(0.0139)	(0.0186)
edu_coll			-0.0565***	-0.0557***	-0.0549***	-0.0599**
			(0.0156)	(0.0156)	(0.0156)	(0.0198)
hdd (in 1,000)			0.0134	0.00981	0.0103	-0.0322
			(0.0259)	(0.0237)	(0.0235)	(0.0301)
cdd (in 1,000)			0.193	0.187	0.193	0.415**
			(0.153)	(0.137)	(0.135)	(0.156)
hdd_heat_ac			0.0449**	0.0446**	0.0444**	0.0789***
			(0.0147)	(0.0146)	(0.0146)	(0.0226)
hdd_heat_gaswater			-0.0224	-0.0219	-0.0218	0.0689
			(0.0312)	(0.0312)	(0.0311)	(0.0385)
hdd_heat_other			-0.0558	-0.0546	-0.0541	0.00296
			(0.0341)	(0.0342)	(0.0343)	(0.0359)

cdd_ac			0.0865*	0.0883*	0.0890*	0.0895*
			(0.0424)	(0.0420)	(0.0423)	(0.0439)
b_1 *(time trend)*				0.541*	0.0342***	
				(0.253)	(0.00396)	
b_2				0.0836		
				(0.0513)		
α	6.283***	5.688***	5.650***	5.966***	5.433***	5.883***
	(0.103)	(0.155)	(0.188)	(0.292)	(0.184)	(0.140)
heating types	*NO*	*NO*	*YES*	*YES*	*YES*	*YES*
year dummies	*YES*	*YES*	*YES*	*NO*	*NO*	*YES*
regional dummies	*YES*	*YES*	*YES*	*YES*	*YES*	*NO*
N	122252	122252	122252	122252	122252	122252
adj. R^2	0.342	0.385	0.397	0.397	0.397	0.387

Clustered standard errors in parentheses * $p<0.05$, ** $p<0.01$, *** $p<0.001$

2.4.3.1 Price and Income Elasticities

With the exception of Model 1, the price and income elasticities are relatively constant across all models, with a price elasticity of -0.66 and income elasticity of 0.32 at the sample average income (recall the income variable has been normalized to sample mean, so the log is zero at that point). As average income rises over the sample period and forecast horizon, however, this income elasticity falls based on the quadratic term. It is 0.28 for 2009 and falls to 0.11 by 2025. These elasticities could be viewed as “short-term” responses at the intensive margin, as dwelling size, major appliances and other demographic characteristics are controlled in the specifications. Model 1 does not control for these features, so the price elasticity of -0.72 and income elasticity of 0.50 (at the sample average) account for both higher utilization of existing appliances (intensive margin) and higher adoption rate of major appliances and larger houses (extensive margin). These might be viewed as “long-term” elasticities. As figuring out how much dwelling size and appliances adoption contribute to demand growth is critical to policy design, Models 3-5 are more informative in this sense and are therefore used in the forecast. If we use city-level average electricity price (not reported in the table) the price elasticities are slightly larger, ranging from -0.64 to -0.86.

Table 2.5 Residential Electricity Consumption Elasticities from Previous Studies

Sources	Price elasticity	Income elasticity	Income ($2010)*	Period	Country
Cao et al. (2016)	-0.55	0.65	1,115	2002-2009	China
Zhou and Teng (2013)	-0.35	0.14	1,333	2007-2009	China
Shi et al. (2012), small sample	-2.48	0.06	1,385	2008-2009	China
Our estimate for year 2009	-0.65	0.28	1,444	2009	China
Our estimate for year 2025	-0.65	0.11	3,838	2025 (E)	China
Baker et al. (1989)	-0.76	0.13	11,145	1972-1983	UK
Dubin and McFadden (1984)	-0.26	0.02	16,027	1975	US
Parti and Parti (1980)	-0.58	0.15	16,027	1975	US
Hirst et al. (1982)	-0.67	0.16	17,974	1978-1979	US
Bernard et al. (1996), IV	-0.67	0.14	18,264	1986-1989	Canada
Nesbakken (1999),short run	-0.45	0.01	23,580	1993-1995	Norway
Fell et al. (2014)	-0.48	0.01	33,600	2006-2008	US

Note: Income (in 2010 dollar) is the average of the final consumption per capita for the study period based on the World Bank data. For our estimate in 2025, the income is calculated by applying our growth rate in consumption per capita to the 2009 income level.
Link: http://data.worldbank.org/indicator/NE.CON.PRVT.PC.KD

To gain a better sense of how these estimates compare with previous work, we summarize in Table 2.5 some relevant previous studies on price and income elasticities in the residential sector from China and other countries. We restrict our selection to twelve papers that use micro-level data or papers having elasticity estimates for residential electricity in China with comparable methods. Estimates of price elasticity range from -

2.5 to -0.26; if we set aside the two lowest and two highest estimates, the range is a much tighter -0.45 to -0.67, putting our estimates at the upper end of that range.

Given the sensitivity of income elasticity to income level, we use Figure 2.5 to show the values from columns 2 and 3 of Table 2.5 in a figure alongside our estimates for 2009 and 2025. Here, the average income for the country and time period is calculated based on the final household consumption per capita data from the World Bank to make the income elasticities more comparable. Estimates of income elasticity are generally below 0.3, which is consistent with the fact that electricity consumption is typically a smaller share of richer household's expenditures. More importantly, we can see that income elasticities eventually fall to zero as income rises, usually at an income level higher than $15,000 per capita in most studies.

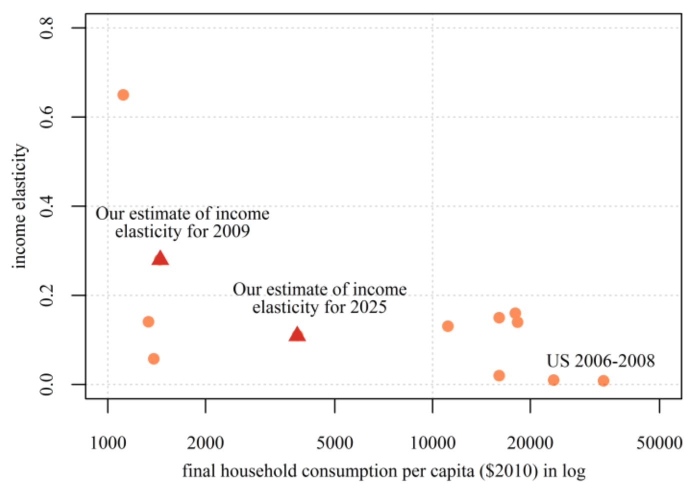

Figure 2.5: Income Elasticities versus Income Levels from Comparable Studies

Estimated future levels of income elasticity for Chinese households based on projected future income levels are consistent with the income elasticity pattern across countries of various income level. Our estimates predict that the elasticity will approach zero when income reaches $8,200 or 57,700 RMB per capita (in 2010 RMB) in urban China. Given the income growth rate we use in the forecast, this will be achieved around the year 2040. Income growth could still drive electricity growth through larger dwellings and more appliances beyond this point.[21]

Focusing on a more specific comparison, Zhou and Teng (2013) use data on 2007-2009 in Sichuan Province that is drawn from the same dataset as ours. For comparison purpose, we can apply our quadratic estimates to the mean real income for 2007-2009 (RMB 26609), yielding an income elasticity of 0.29. They find a significantly lower income elasticity, about 0.14. One reason for the discrepancy may be the absence of a quadratic income term in their specification. As they add demographic variables, their income elasticity falls. Intuitively, education indicators could be picking up what would otherwise be non-linear income effects—particularly, the higher income elasticity at middle to low-income levels. Their income elasticity, therefore, is more heavily weighted towards high-income levels (which is lower), where education does not vary. Cao et al. (2016) also draw from the same data. They report a price elasticity of -0.55 and an income elasticity of 0.65 for the middle-income group using the same data set. Their income

[21] If one employs the income elasticity from Model 1, which does not control directly for dwelling size and appliance stocks, the income elasticity reaches zero by 2050.

elasticity is roughly double ours over the historic sample; the difference may be due to their separation into income groups and use of a two-stage budgeting AIDS model which differs substantially from our reduced form model. Finally, a recent paper by Du et al. (2015) estimates the elasticities by tier pricing structure and provides an income elasticity of roughly 0.10 to 0.15, and a price elasticity of roughly -0.65 to -1.3. The set of results are comparable in scale to ours especially given that they study more recent years, although using a less representative sample.

2.4.3.2 Appliances (Except AC) and Electricity Consumption

An important advantage of our modeling effort is the ability to explicitly model the contribution of appliance adoption to electricity consumption. We find that all appliances contribute positively to electricity demand and the coefficients are all highly statistically significant except for washing machines. The coefficients are relatively constant across the three different time trend models (Models 3-5), but all appliances except refrigerators have some variation with the removal of demographic controls (Model 2) or regional controls (Model 6). This is not surprising as some appliances, like computers, are highly correlated with education.

Among the non-AC appliances, refrigerators consume the highest level of electricity, raising consumption by 19%. Given the saturation of refrigerator ownership, this will have little impact on our projections of ownership, but the saturation does point to the potential savings if the efficiency of refrigerators can be improved. For example, refrigerator efficiency doubled in the United States from 1987 to 2012 (Mauer et al., 2013).

If that same improvement occurred in China over our forecast period, it could reduce Chinese residential electricity usage by 10%; the value of these reductions would need to be compared to the costs to assess the net benefits of such efficiency improvements. Other appliances increase electricity consumption by much smaller amounts, from 3% to 8%.

2.4.3.3 AC, Weather and Heating Types and Electricity Consumption

In the preferred models (3-5), the coefficient on AC units is about 7%. However, this is not the whole story, as the interaction with heating and cooling degree days adds another 7%. That is, we find statistically significant effects of AC unit adoption interacted with cooling degree days and with heating degree days, where the latter is further interacted with whether the household uses its AC unit for heating. Here, we note that households in our sample report whether they heat with (a) their AC unit, (b) gas or hot water, (c) some other fuel, or (d) nothing, with the last serving as our reference.

To compute the effect of these interactions, we consider the estimated coefficient multiplied by the average values of the variables interacted with AC. For example, there is an average of 280 cooling degree days in the sample, so the first interaction is $0.089 \times 0.28 = 2.5\%$. Meanwhile, there are 3700 average heating degree days, and 0.27 of households use AC for heating, so the second interaction is $0.045 \times 0.27 \times 3.7 = 4.5\%$. (These numbers are also confirmed by simulation.) Of course, it is not clear whether future AC adopters will be above or below the current mean values for heating and cooling degree days of current AC owners.

In addition to the estimated effect of AC adoption being about 14%, it is important to recognize from the preceding discussion that AC units are the one appliance expected to be still growing at the end of the forecast horizon. While microwaves and computers see adoption rates increase by around 30% from 2009 to 2025, the adoption then flattens out. The adoption of AC units, in contrast, increases about 50% over the period and is projected to continue to grow at almost the same rate. Assuming the average number of units per household rises by one every 20-25 years, that would be a further 14% increase in electricity usage by 2050. Thus, AC units could be another focus for energy efficiency policies, though improvements in the US over the past 20 years have been smaller for AC than for refrigerators (Mauer et al., 2013).

Finally, it is worth noting that inclusion of demographic, weather, and regional controls matter for these estimates. The simpler model without weather and demographics suggests an AC elasticity closer to 11%, versus the 14% above. On the other hand, removing the regional controls (and introducing considerably more variation in degree days), raises the coefficient on heating-AC interaction from 0.045 to 0.079, suggesting and effect closer to 17% (the change, 0.034, × 0.27 × 3.7, from above, equals +3%). Generally, the other weather-related variables (beyond those interacted with AC) are not statistically significant. This is perhaps not surprising as it is unclear how they would relate to electricity use, independent of space conditioning.

2.4.3.4 Demographic Features

Dwelling size has a positive but small influence on electricity use. The coefficient is roughly 0.07 in all models. Given the increase in dwelling size over the forecast horizon of roughly 60% with the most optimistic trend assumption, this would contribute only 3% to electricity demand over the forecast horizon. Household size and an indicator of whether the head of household is over 50 contribute positively to electricity consumption. One more person in the household increases the electricity consumption by 5%. However, on a per person basis, larger households save energy as more appliances, for example, refrigerators and washing machines, can be shared. These results are similar to Zhou and Teng (2013).

We also see that higher education levels lead to lower electricity use—almost 6% for college-educated heads of households. This is consistent with the idea that more educated households may have increased awareness of electricity conservation methods or a preference for more efficient appliances. While this contrasts with Zhou and Teng (2013), as noted above, the absence of a quadratic income variable likely implies a bias in that study. Educational variables, which are highly correlated with income, may be picking up non-linear income effects rather than the independent effect of education holding income constant.

2.5 Forecast Electricity Consumption and Discussion

An important goal of this study is to generate forecasts of average urban household electricity demand. We also seek to understand the components of existing demand and future growth, and the potential implications of policy interventions or electricity market reforms. Figure 2.6 depicts the forecasted average urban household's electricity consumption based on Models 3-5, as well as Model 1, a recent EIA forecast (EIA 2016) and the reported data by NBS[22] (rescaled to match our data in 2009). Dwelling size is forecast using Model B (the non-linear model) described in Section 2.4.1, appliances as described in Section 2.4.2, and income based on the WEO sources as described at the beginning of Section 2.4. All other variables are assumed to maintain at the same level of those in the year 2009. Hence, income drives electricity growth both directly and indirectly through increase in dwelling size and appliances, permitting a decomposition described below.

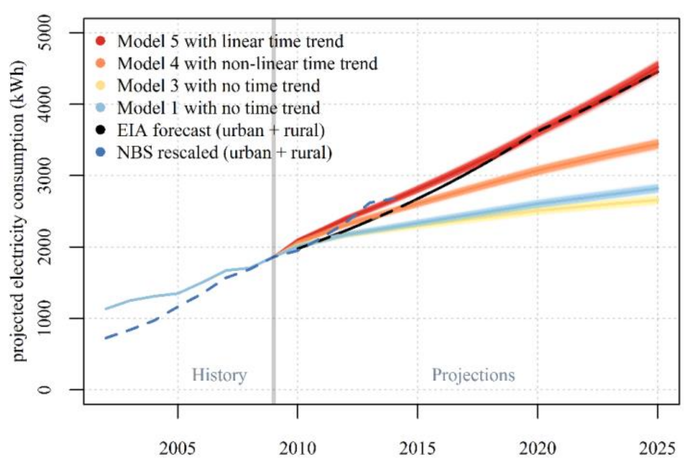

Figure 2.6: Mean Electricity Consumption (in kWh) projected from 2009 using alternative trends

Notes: Shaded regions indicate variation based on uncertain demographics

[22] The total residential electricity consumption is from the Table 4-13 Consumption of Electricity and Its Main Varieties by Sector, China Energy Statistical Yearbook 2015. The per household consumption is calculated using the population and household size from the online database on NBS website.

We first note the importance of time trend assumptions. Despite efforts to build a model that accommodates time-varying determinants of electricity demand growth—income, dwelling size, and appliance stocks—time trend assumptions still make a significant difference to the forecast results. The model with year fixed effects ignores any autonomous trend and predicts a 43% increase in household electricity consumption from 2010 to 2025[23]. The growth rate is much higher using the models that instead estimate and project such trends. Electricity consumption in 2025 increases by 143% over 2009 using a linear time trend model that simply extrapolates the average 2002-2009 trend. Given we observe a slight slowdown in growth in the historical data, we also estimate a non-linear trend model. This model projects 85% growth in electricity consumption. It is worth noting that our linear trend model produces results relatively close to the EIA projection[24]. This, of course, does not mean that the linear model is superior, but simply implies that the forecasts match. Ultimately, our best guess is somewhere between Models 4 and 5. It is unrealistic to assume the observed autonomous trend in the data stops in 2009. However, it is not clear whether we should expect the trend to slow or not over the forecast horizon.

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[23] Based on the official data from the NBS, consumption expenditures grew by 10.8% annually from 2010 to 2012 and by 9.4% annually from 2012 to 2014, compared to the 9.5% and 6% forecasted. Putting this actual growth rate would increase the forecasted growth rate (2010-2025) from 43% to 47%. Urban household disposable income grew by 12.7% annually from 2010 to 2012; using this actual growth would increase the forecasted growth rate from 43% to 45%. Per capita income grew even faster, and using it would increase the forecasted growth rate from 43% to 48%.

[24] EIA forecasts the population and residential electricity to the year 2040. We first calculate the annual growth rate implied by the calculated per capita residential electricity and then apply the annual growth rate from 2010 to our historical data in the year 2009 to make the forecasts more comparable to our results. However, it is worth noting that EIA's forecasts do not differentiate between urban and rural.

Table 2.6: Forecast Sensitivity to Non-income Changes

Variable name	Assumed change in the variable 2010-2025	Corresponding projected change in electricity consumption 2010-2025
Household size	-13%	-2.2%
Age of household head>50	16%	1.4%
Education:		
Primary or below	2%	
Middle school or equivalent	-3%	0.03%
High school or equivalent	-11%	0.22%
College or above	12%	-0.67%
Heating types:		
None	-42%	
Heating by AC	47%	1.3%
Heating by gas or water	3%	-0.4%
Heating by other	-8%	-0.1%
Heating degree days	46%	1.6%
Cooling degree days	12%	0.7%
		Total: 2.1%
Income	165%	27%

Note: Income is assumed to follow the projected per capita income growth in IEA's World Energy Model 2015. The assumed changes in other variables follow the historical trend observed in the data. We use the coefficients from Table 2.4 (Model 4) to calculate the corresponding projected change.

In Table 2.6, we summarize the forecast sensitivity to non-income time trends using coefficient estimates from electricity Model 4. Rather than fixing demographic variables at their 2009 levels, we instead consider the historical trend observed in our data from 2002 to 2009. Extrapolating those trends, we estimate the likely demographic change from 2010 to 2025, reported in the first column of Table 2.6. We then multiply by the corresponding coefficient in Model 4 to produce a projected effect on the electricity demand projection. All of these demographic trends lead to very limited changes in electricity consumption (-2.3% to 1.7%).

We considered other approaches to try to reduce uncertainty about the trend model. We compared our projections for 2010-2014 to more recently available national totals published by the NBS. However, these include both the urban and rural residents in all provinces, thus do not match perfectly to our scope. We also considered cross-validation using our sample, but the relatively short time series of 9 years makes it difficult to distinguish the linear and non-linear models.[25] Thus we ultimately prefer to highlight both the non-linear and linear time trend models as our preferred models, with projections of between 85% and 143% per capita growth from 2009 to 2025. It is feasible, through our model, to highlight the important assumptions that have to be made, including the time trend decision discussed above.

One question that motivated our work was whether creating a more detailed and disaggregated model of energy demand would improve demand forecasts. As we can see in Figure 2.6, there is little difference between using Model 1 and Model 3 as forecasting tools. Recall that the main difference is that Model 3 controls appliances and other socioeconomic characteristics while Model 1 only control price and income. This suggests that the quadratic income specification in the simple model is capable of capturing most of the total contribution of income to electricity consumption growth, directly and indirectly. In other words, controlling the dwelling size, appliances and other demographic variables in a more complicated model does not improve the forecasts substantially—so long as dwelling size and appliance adoption are similarly forecasted

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[25] We tried cross-validation by estimating the models with the 2002-2005 sample and forecast to 2009 using the same income assumption from IEA and holding other variables fixed at 2005 level. Linear-trend model performs relatively well. However, this does not give us the confidence to choose the linear-trend model as estimating a non-linear trend with four-year data is challenging. It is possible that the non-linear trend estimated from the eight-year data will perform better in the longer horizon.

using income. It is still important to separate income from time trends. The income elasticity halves from 2009 to 2025, regardless of the autonomous time trend. But as household-level data are not available for most researchers and policy makers, this result suggests that aggregated data at city-level or province-level might be sufficient. That is, such aggregate data might resolve the more singular distinction between income effects and autonomous trend and provide a basis for simple demand forecasting. However, micro-level data are still necessary to understand the relative importance of other components of growth and the potential for policy impacts, as discussed next.

2.5.1 Decomposition of Factors Driving Electricity Consumption Growth

Figure 2.7 addresses the question of how much the various components of growth contribute to the total. This figure shows the relative contribution to growth over the period 2009 to 2025 from four factors: appliance adoption, dwelling size, income effects (conditional on adoption and dwelling size), and unrelated time trends. The first two are extensive margins that increase the size of homes and the stock of major electricity-using devices, while the third includes more intensive use of the same stock. It is unclear whether autonomous time trends are extensive or intensive.

The figure suggests that appliance adoption contributes as much as 30% of the increase in energy demand, while dwelling size contributes at most 6%. Meanwhile, the contribution of an autonomous time trend ranges from zero (first column for year fixed effects) to more than equal to the combined model components of income, appliances, and dwelling size (last column). Despite the previous point that the aggregate growth projections are similar using income alone, we can now see the pathways driving the projected growth.

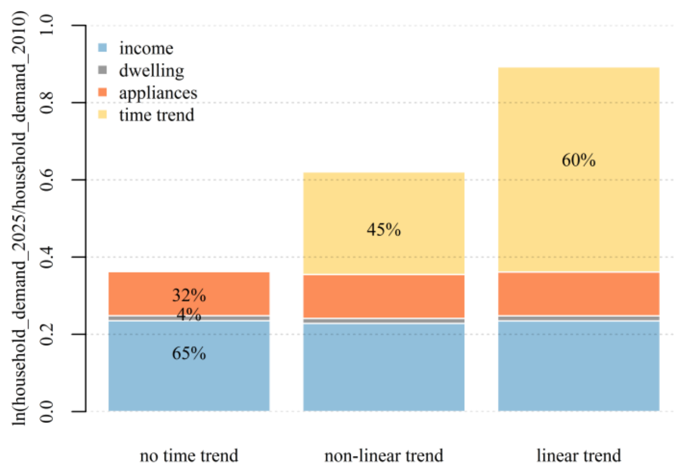

Figure 2.7: Decomposition of Projected Electricity Growth for 2010-2025 (Percentages of Each Model Total)

From earlier discussions, we know that the extensive appliance contribution is largely AC units. While refrigerators may be an obvious choice for energy efficiency policy given their larger total contribution and known potential, AC may be particularly important given the significant addition of units over the next 15 years, as well as the potential for a shift to central cooling technologies. Not only is there an intensive margin, as reflected by the parameter estimates discussed in section 2.4.3.3, the detailed projections reveal an important extensive margin.

2.5.2 Income Distribution

A final question is the possible effect of the distribution of economic growth. Auffhammer and Wolfram (2014) illustrate that different shapes of the underlying distribution of income could lead to different demand estimates, even if the mean income is the same. This would be true in our model, where we allow the income elasticity to vary with income. Given we observe changing income patterns in our data from 2002 to 2009, we have some basis for considering how income growth might vary across income levels in the forecast period.

For example, we could assume the projected 165% increase in per capita income growth over 2010-2025 applies equally to all groups, keeping the relative distribution fixed as it was in 2009. Or, we could assume a higher growth rate for wealthier households. This is consistent with recent experience in the United States (Heathcote et al., 2013), the literature on income inequality in China (Wu and Perloff, 2005) and our data. That is, over 2002 to 2009, we see 30% higher growth in the top decile of our data compared to the lower nine deciles. Consider what happens if, instead of assuming the same growth for all deciles, we assume the top decile grows 30% faster than the lower nine deciles over 2010-2025. We maintain the same aggregate growth of 165% over that time period.

Figure 2.8 shows the results. For each of the three trend assumptions, a pair of bars shows the difference in electricity demand growth between assuming (a) everyone's income grows 165%, versus (b) the top decile grows 220% while the bottom grows 145%. Each bar also indicates the contribution of the top 10% (top, labeled) versus the bottom 90% (bottom).

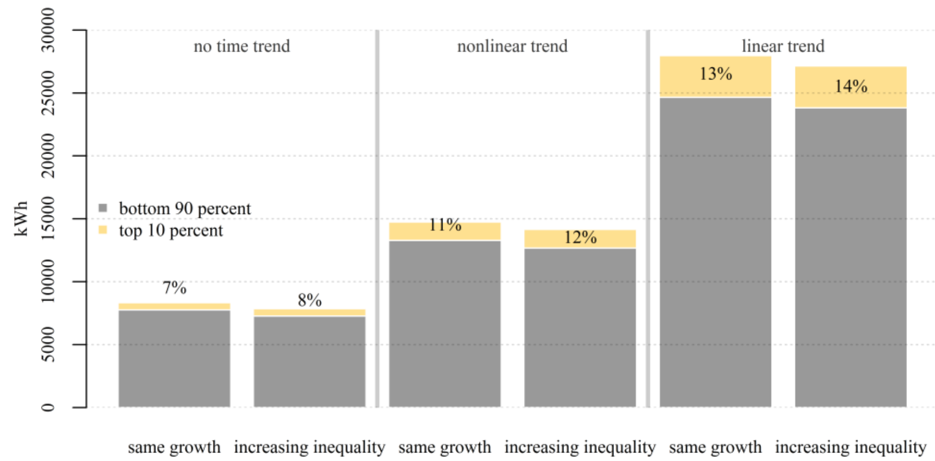

Figure 2.8: Projected Electricity Growth (in kWh) by Income Groups for 2010-2025

In general, we see a very small effect from differing growth assumptions within each pair of bars for the different trend assumptions. Assuming more growth in the top decile clearly lowers demand growth. Every dollar in income growth shifted from the poor to the rich means (a) a larger percent decrease for the poor along with a smaller percent increase for the rich, and (b) that larger percent decrease for the poor is applied to a larger energy elasticity for lower-income households. What was unclear prior to the simulation was that the effect would be small given the differential growth rates we used. Moving from left to right, the autonomous time trend is assumed to apply equally to all income groups and therefore dilutes whatever effect we see in the left two bars. Note a more extreme assumption (e.g., no income growth among the poor) would presumably show more marked effects.

2.6 Conclusions and Future Efforts

Forecasting electricity demand and the potential impact of alternative policies will be an important task as China grapples with both domestic development needs and increasing environmental concerns at home and abroad. Growth in residential electricity use is projected to contribute roughly one-third of total demand growth through 2025, yet is relatively unstudied. This paper has provided the first attempt to use household-level data to construct such forecasts. We also use that data to decompose future electricity forecasts into contributions from appliance adoption, dwelling size increases, direct income effects, and potential autonomous time trends.

Autonomous time trends—that is, growth that we cannot link to income or other observables in the data—creates considerable uncertainty, with the potential to more than double growth from estimable sources. These autonomous trends could be due to the changing relative prices of housing and appliances, changing quality of appliances—e.g., larger refrigerators and washing machines or more powerful microwave ovens—or due to adopting more energy-using habits at higher income levels. Given we think it is unrealistic to assume such autonomous trends are zero, our preferred range of projected per capita demand growth is between 85% and 143% over 2009 to 2025 using alternative linear and non-linear autonomous trends.

Consistent with other work, we find electricity price elasticities of -0.7. A price increase of 15%, consistent with a $10 per ton price on carbon dioxide emissions, would lower demand by about 10%. This would be one possible policy, along with raising consumer prices through market liberalization in the power sector, to reduce demand growth.

Perhaps most interestingly, appliance adoption—particularly a larger number of AC units—drives up to a third of future electricity growth. Efficiency policies targeted at AC units would have a high potential impact as so many new ones are expected to drive energy demand. Meanwhile, refrigerators appear to be a large source of current household energy use. Refrigerator ownership raises household electricity demand by an estimated 19%. Thus reducing energy use of these appliances in half would reduce electricity demand by 10%. However, refrigerators have also saturated the market. Nearly 100% of households have one. Few are seeking to have two or more.

These back-of-the envelope calculations of potential policy impacts could be expanded in future analysis. Such an analysis could consider more explicitly the turnover of appliances and the effect of energy and product prices, as well as electricity generation costs and environmental impacts. This would allow a better comparison of price changes, efficiency policies, or other policies to reduce electricity use. One could also focus more specifically on the role of residential energy tariffs and proposed reforms. Finally, one could consider how changing temperatures due to climate change would exacerbate the trend towards more AC adoption and higher energy use.

Looking forward, it would also be valuable to increase understanding about the residual time trend in household electricity use. Is there a difference in the income elasticity observed between households at a point in time (which we estimate) and those observed within a household over time (which would require a panel data set)? It could also be useful to understand whether and how elasticities vary through quantile regression or further sub-group analyses. These and other questions present exciting areas for future work.

Chapter 3 Climate change and residential electricity demand in the Yangtze River Delta, China

Co-authors: William A. Pizer, Libo Wu

3.1 Introduction and motivation

Climate change is a major environmental policy challenge (Tol, 2009). Understanding the magnitude of impacts is critical to improve Integrated Assessment Models (IAMs) used to estimate the social cost of carbon. Such estimates underpin policies to reduce greenhouse gas emissions and foster adaptive behaviors. Among the categories of damages,[1] incremental cooling demand in the power sector is often recognized as a top component (Rose et al., 2017). Moreover, electricity, rather than gas or other fuels, is also used for heating in the winter in the eastern and southern parts of China. Several existing studies have provided empirical evidence on the electricity–temperature response functions in the developed countries, mainly the United States (e.g. Deschênes and Greenstone, 2011; Auffhammer and Aroonruengsawat, 2011; Auffhammer et al., 2013, Auffhammer et al., 2017). In contrast, we know little about the response functions in China, where an average household's electricity consumption could double by 2040 (IEA, 2017).

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[1] Here, we follow the literature in using the term "damages" to refer to the valuation of impacts associated with climate changes, recognizing that some so-called damages are really adaptation costs. See discussion in (NASEM, 2017). There is no net benefit from this electricity use compared to a case without climate change. Rather it represents an adaptation cost to avoid even worse outcomes. We maintain this terminology for easier comparison with other studies, such as Figure 3 in (Hsiang et al., 2017).

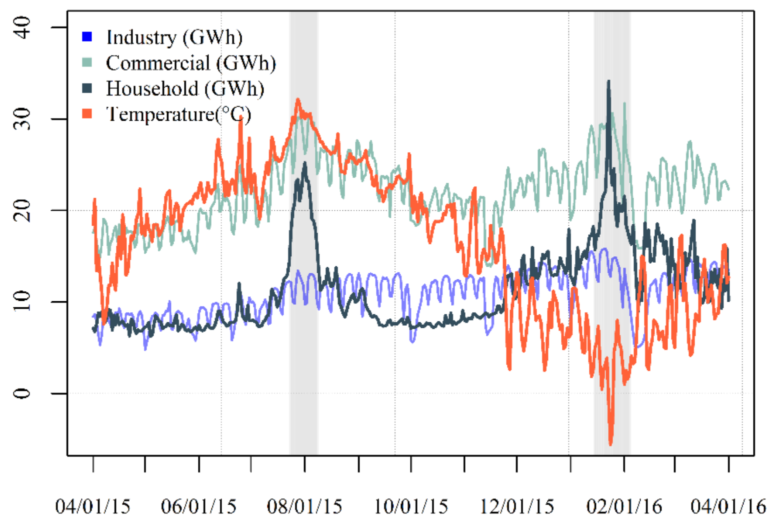

Figure 3.1 Daily Total Electricity Consumption by Sector with Daily Temperature

Notes: this covers a shorter period because the data for industry and commercial sectors are only available for this period. The gray areas highlight the periods for extreme weather, where we see the highest response in residential electricity. The electricity use in the commercial sector also responds but is not the focus of this study. Industry use relatively stable amount of electricity throughout the period.

Distinct from climate policy concerns, stakeholders in the electricity sector have a keen interest in understanding electricity demand behavior and growth. With the rapid adoption of air conditioners (that are reversible as heat pumps) in urban China over the past decade, cooling and heating have become one of the main drivers of residential electricity consumption growth. China, India, and Indonesia are projected to account for half of the total stock of air conditioners by 2050 (IEA, 2018), which has important implications for electricity consumption going forward. For utility companies, understanding the drivers of electricity demand, especially peak demand, and constructing models to obtain reliable forecasts are key components of demand side management (Peirson and Henley, 1994). Among other factors, residential electricity consumption is very responsive to temperature fluctuations. Figure 3.1 highlights this phenomenon in Shanghai, showing the contributions of residential, commercial, and industrial demand to overall usage. Although residential electricity accounts for only one-quarter of the total, it increases much more dramatically in extreme heat days (around August 1) and extreme cold days (around February 1), driving peak demand during these periods.

In this paper, we employ data on daily household-level electricity use from the State Grid Corporation of China to estimate the impact of weather on residential electricity consumption and then predict the effect of climate change. More specifically, we analyze more than 800,000 metered residential customers in Pudong, Shanghai, over the period from 2014 to 2016. With this large panel dataset, we estimate flexible non-linear response functions with individual and year-month fixed effects. We directly estimate the varying daily electricity consumption responses as the daily temperature changes. For example, for temperatures above 26°C, a 1°C increase in daily temperature leads to a 14.5% increase in daily household electricity consumption.[2] In contrast, previous studies using monthly or annual data could only estimate the increase in aggregate electricity bills due to counts of hot days per month or year (e.g. Deschênes and Greenstone, 2011; Auffhammer and Aroonruengsawat, 2011; Auffhammer et al., 2013; Davis and Gertler, 2015; Barreca, 2012).

[2] For simplicity, we use Celsius (°C) unless comparison with other studies requires conversion to Fahrenheit (°F). For reference Shanghai has relatively warm temperatures, mostly above -5°C (23°F) in the winter. Typical room temperature is around 18–21°C (64–70°F). Shanghai temperatures in summer can reach 40°C (104°F) in extreme cases.

Another aspect missing from the previous work is heterogeneity among consumers. Use of air conditioners or other heating and cooling equipment constitutes the main channel to respond to temperature changes. Ownership and use of such equipment depends on income: previous studies in Mexico (Davis and Gertler, 2015) and China (Cao et al., 2017) have emphasized the importance of air conditioner adoption as income increases in developing countries, and the marginal effect of a hotter climate has been shown to increase with income, based on a national-level panel dataset in India (Gupta, 2016). However, few studies have analyzed how electricity–temperature response functions change as income grows at the household level. Combined with an in-house survey on socioeconomic status covering 1,394 households,[3] we show that the electricity response during the winter is higher for high-income groups. However, the responses to hot summer days are very similar for all income groups in Shanghai.

We use our estimated temperature–demand model to construct an aggregate damage function using 21 downscaled global climate models (GCMs) under the Representative Concentration Pathway (RCP) RCP8.5 and RCP4.5 scenarios from the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. The regional and temporal detail of these GCMs allows us to construct a set of 42 data points (21 models x 2 scenarios) relating future global mean surface temperature (GMST) to future impacts on

[3] 30,000 residents were randomly chosen based on the IDs in the electricity data sets. The in-house surveys were conducted by a professional survey company. For comparison of summary statistics to Shanghai and China, see Appendix Table B.3.

residential electricity demand in China. Fitting a line across these data points, we find that the annual residential electricity use increases by 9.3% per 1°C increase in GMST.[4]

We also examine peak daily electricity demand because it drives future investment in grid expansion (Auffhammer, 2017). Our estimates show that the peak daily electricity use increases by 36.3% per 1°C increase in GMST, which is four times the magnitude of the annual change. Under RCP8.5, the peak daily electricity use is estimated to increase by as much as 120% on average across 21 models (and as much as 207%, according to the highest estimate), mainly in the summer period from July 1 to September 10.

Our data come from one area of Shanghai. Thus our results are most credibly extended to the remainder of Shanghai and other urban areas in the Yangtze River Delta due to relatively similar climate and economic conditions. This triangle-shaped metropolitan region comprises of Jiangsu, Zhejiang, and Anhui provinces, covering roughly one-fifth of China's urban population and one-fourth of the GDP.[5] It is less credible to extend these estimates to other regions of China. Even if income levels converge by the end of the century, cultural and climate differences remain. Nonetheless, these results are a useful benchmark in these and other emerging-country regions for which estimates are unavailable.

[4] It is important to note that this relationship is non-linear in nature. Here, we simplify the climate response in linear form, to make it easier to understand and present.

[5] Authors' calculation based on Table 2-8, 3-1, and 3-9 in China Statistical Yearbook (2017). Accessed online at http://www.stats.gov.cn/tjsj/ndsj/2017/indexeh.htm (09-07-2018).

3.2 Literature Review

Stakeholders in the electricity sector have long been aware that electricity demand is closely tied to temperature, though the relationship is complex (Peirson and Henley., 1994; Pardo et al., 2002, Valor et al., 2001). More recently, as climate change attracted increasing public attention, the relationship between weather and electricity load is no longer an issue that only matters for utility companies. Rose et al. suggest that the majority of global economic damages caused by climate change could be attributed to the electric sector (Rose et al., 2014).

Table B.1 summarizes relevant studies over the last fifteen years that examine the impact of climate change on energy demand using econometric approaches[6]. Early studies use time series of hourly load data (Crowledy and Joutz, 2003; Franco and Sanstad, 2008). Although the data frequency is high, the analysis is constrained to univariate time-series methods but touches little on the household characteristics or other determining variables. Early studies also used polynomial functions of temperature, which have been replaced by specifications that are more flexible. Some studies only report the change in electricity consumption due to a constant change in temperature over the year (e.g. 2°F warmer every day), while others use climate scenarios from existing GCM models to capture the likely pattern of climate change across the year. Calculating marginal effects of temperature change could be tricky in flexible specifications, so we use damage function

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[6] See Auffhammer and Aroonruengsawat, Auffhammer and Mansur for more complete literature reviews (11-12).

that reflects the range of potential damages under different climate models following Hsiang et al. (2017).

The last three studies in Table B.1 highlight the current state-of-the art that motivates this work. Deschenes and Greenstone (2011) use a state-level panel of annual consumption data and daily weather data over several decades to explore the flexible relationship between temperature and residential electricity demand. The results suggest that annual residential energy consumption would increase by 11 percent by the end of the century based on GCM climate projections. This paper provides the first evidence using panel data and many recent papers (noted in the table) follow their identification approach using random weather fluctuations and various measures of electricity demand.

Almost all of these studies are U.S. based and most use data from residents in California. Yet, we expect electricity consumption patterns and temperature response to differ in different contexts. For example, Davis and Gertler (2015) find little temperature response on cold days in Mexico, in contrast to the more symmetric U-shape curve estimated for the US. This has important implication on how much the demand increase due to hotter summers could be offset by a demand decrease due to warmer winters. Considering about diversities with weather conditions and many other demographic factors, country-specific studies are definitely needed. Our study is the first to examine the electricity consumption patterns of an Asian mega-city. We expect the evidence to be more relevant for China and the region more generally, though still subject to the concern that this is one small segment of the population.

Another limitation of most studies in Table B.1 is their use of monthly data that cannot capture details of peak demand. An exception is a recent study specifically addressing the frequency and intensity of peak electricity demand across the United States (Auffhammer et al., 2017). Their peak load simulations suggest significant increases in the peak load events in terms of both intensity and frequency. This is relevant for the utilities who must decide on an investment strategy to meet both average and peak load demands. But again, the estimates are solely based on the data from the United States.

Finally, existing studies generally ignore the fact that people of different socio-economic status could respond differently to weather patterns. This is particularly relevant for developing countries where socioeconomic patterns and electricity demand patterns are changing, so the average response in the future may look different from the average response today. Distinct from estimates of the average response, however, these estimates also speak to the possible distribution of non-market impacts. If poorer residents have less ability to adjust their electricity usage in response to climate change, they are presumably more uncomfortable, reflecting a non-market cost of climate change. This paper is the first to provide sub-group analysis of temperature-response function by socio-economic status based on household-level information.

3.3 Data

In order to construct our model, we make use of four data sets on household electricity use, household demographics, daily weather, and air quality data. We then make use of detailed climate change projections to relate future annual global mean temperature changes to the temporal pattern of climate change in China at the end of the century, and (with our estimate model) impacts on household electricity demand. For our main estimation, we use the cleaned daily electricity data, matched with both the average weather data from two nearest local weather stations through the National Meteorological Information Center of China and the air pollution data from the Shanghai Environmental Monitoring Center (EMC). We then use this set of estimation results in producing the end-of-century damage functions. Only for the analysis on sensitivity by income groups, we use a sub-sample merged with a survey data of 1,394 households on socioeconomic features. Below we provide details.

3.3.1 Daily electricity data

The State Grid Corporation of China (SGCC) provides the daily data sets on all the 1.8 million metered residents in Pudong, Shanghai over a two-year period from 3/1/2014 to 2/29/2016. Original data sets are stored in a confidential data center established by SGCC and is only available for academic studies under certain security agreement. We observe meter ID, a service account number and accumulated meter readings (in kWh) for all the households. As the start date of daily observations differ, to ensure that households have data for at least 2015, we drop the households with start date after 1/1/2015. This is important as we use the electricity consumption pattern over year 2015 to calculate the annual change in electricity.

We calculate the daily consumption from the accumulated meter readings. We then proceed to drop certain households that we believe would bias our estimates of future demand response. First, we drop households with average daily electricity consumption that is lower than 1 kWh or higher than 50 kWh during the sample period. These houses are very likely to be vacant or have been repurposed to uses other than regular household activities. It is important to note that some houses are vacant because of various reasons including but not restricted to long-term traveling, vacation homes and changing ownership. While some amount of vacancy or conversion to other activities is natural and could be factored into constructing aggregate estimates, it does not make sense to include them in our household-level model if we expect them respond differently. Moreover, if we are planning to use our estimates to approximate behavior in other contexts, we want a relatively clean definition of what we mean by household response.

For the same reason, we want to exclude households where it appears there were long periods of vacancy. To achieve this, we remove households that consume less than 0.3 kWh per day for more than 5% of the period (37 days). We choose 0.3 kWh as the cutoff point because it is the minimum daily electricity consumption of a relatively basic one-door refrigerator[7] and the penetration rate of refrigerator is almost 100 percent in Shanghai. The number of households left after each step is summarized in Table B.2. After these exclusions, the number of households in the electricity dataset is 841,784.

[7] Based on description of products on JD.com, one of the largest online platform for purchasing appliances.

3.3.2 Weather data

We obtain weather data from two local weather stations in Shanghai through the National Meteorological Information Center of China. The two stations report very close readings so we use the average weather data from the two stations. The raw data contain information on average, highest and lowest temperature, wind direction, wind velocity and humidity at ten minute intervals. To merge with the daily electricity datasets, we aggregate the 10-minute data to daily frequency. We use the arithmetic average across the 288 observations each day for average temperature, wind velocity, and humidity. The wind direction is recorded as a continuous variable ranging from 0°to 360°, representing the direction where the wind originates for 10-minute periods. We generate four variables: *EAST*, *SOUTH*, *WEST* and *NORTH*, each representing the total number of 10-minute periods that fall into that category[8] (the sum of the four variables always equals 144 for each day). For example, if *EAST* equals 100, it means the wind originates from the east for 1000 minutes in that day. The PM2.5 daily average are downloaded from the Shanghai Environmental Monitoring Center (EMC)[9].

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[8] East (45°~135°), south (135°~225°), west (225°~315°) and north (the rest).

[9] http://www.semc.gov.cn/aqi/home/DayData.aspx

3.3.3 Climate data

The historical and forecasted temperature data under climate scenarios are from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP dataset)[10]. The NEX-GDDP dataset provides downscaled projections across the globe for two Representative Concentration Pathways (RCPs): RCP4.5 and RCP8.5. The projections are derived from the 21 General Circulation Model (GCM) runs developed to support the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC AR5).

The projections have been downscaled to a spatial resolution of 0.25 degrees x 0.25 degrees using the Bias-Correction Spatial Disaggregation (BCSD). To match up with our electricity data in the area of Pudong, Shanghai, China (31.22°N, 121.54°E, center coordinate), we calculate the average temperature of the four closest grid points that surrounds the center coordinate from above, below, left and right. The corresponding coordinates are above (31.375°N, 121.625°E), below (30.875°N, 121.625°E), left (31.125°N, 121.375°E) and right (31.125°N, 121.875°E). The area of the selected four coordinates cover the majority of Pudong. For each of the models, we downloaded the daily maximum and minimum temperature from 1980 through 1999 (based on Retrospective Run) and from 2080 to 2099 (based on Prospective Run).

[10] Climate scenarios used were from the NEX-GDDP dataset, prepared by the Climate Analytics Group and NASA Ames Research Center using the NASA Earth Exchange, and distributed by the NASA Center for Climate Simulation (NCCS). The data can be downloaded at https://cds.nccs.nasa.gov/nex-gddp/.

3.3.4 Survey data on socioeconomic features

A key limitation of the meter data is the lack of other information about each household. Although we have detailed information about electricity consumption, we do not observe any socioeconomic information. For that reason, we conducted a survey of households that are randomly selected among the households in the electricity data set. The survey contained information on household income, age, dwelling size, household size and appliances owned. The cleaned daily electricity data and the socioeconomic data are merged successfully on 1,394 households, which is the number of households included in the following analyses.

Figure B.1 compares the pattern of electricity consumption between our matched sample (N = 1,394) and the total population (N = 841,784) in Pudong, Shanghai. The average daily electricity consumption in our matched sample closely follows the pattern in the total population. During the months with mild temperature, households consume roughly 5kWh electricity daily on average. The consumption increases dramatically during the winter and summer to more than 10kWh on average. In the summer of 2015, the highest temperature reaches 37.6°C on July 28th, causing average electricity consumption to rise over 15kWh. A similar pattern applies to the cold period in Jan 2016 when temperature falls below zero. It is worth pointing out that the majority of residents in Shanghai use heat pumps or electricity-powered space heaters for heating in the winter.

Distinct from the aggregate pattern over time, there is significant variation across and within households. Across-household variation may be driven by various factors including income, education, dwelling size and appliance ownership. Therefore, we identify the electricity-temperature ressponse function based on the within-household variations through controlling household-level fixed effects, as well as examine how the pattern varies with income.

3.4 Modelling the Temperature Response Function

Our theoretical framework follows Auffhammer and Mansur (2014), assuming that household utility is a function of electricity, appliances, and a composite good. To maximize utility, households choose the amount of electricity to consume and the number of appliances to buy subject to an income constraint. In the short run, the number of appliances remain fixed, so only the level of electricity consumption responds to exogenous weather shocks. We can therefore estimate a simple partial derivative, controlling for potential confounding factors.

3.4.1 Econometric model

Based on the theoretical framework and previous studies (Deschênes and Greenstone, 2011; Auffhammer et al., 2017; Davis and Gertler, 2015; Hsiang, 2016), we model the temperature response function using the simple log-linear equation below:

$$lnEC_{it} = \beta_0 + \sum \beta_{1_j} f_j(TEMP_t) + \beta_2 HUMIDITY_t + \beta_3 V_t + \beta_4 EAST_t + \beta_5 WEST_t + \beta_6 SOUTH_t + \beta_7 EAST_t \cdot V_t + \beta_8 WEST_t \cdot V_t + \beta_9 SOUTH_t \cdot V_t + \beta_{10} PM_{2.5} + \beta_{11} WEEKEND_t + \delta_i + \delta_{m,y} + \epsilon_{it} \quad (3.1)$$

The dependent variable $lnEC_{it}$ is the natural logarithm of daily electricity consumption, and $TEMP_t$ is the daily temperature. Note that we drop household-day observations that have daily electricity consumption equal zero (1.7%) or exceed 70 kWh (0.1%). The total number of household-day observations after cleaning is 545,768,122. The functions f_j are spline functions. The function $f_1(TEMP_t) = TEMP_t$. For $j > 1$, the function $f_j(TEMP_t)$ is equal to zero when $TEMP_t$ is less than the defined knot value k_j, and equal to $TEMP_t$ when $TEMP_t$ is greater than the knot value. Because the non-linearity of the response function has been well established in the literature, we assume that temperature response varies flexibly; i.e. β_{1_j} estimates the change in slope at each knot value k_j, $j > 1$. Existing studies typically use predetermined bins with fixed demand within each bin. Here, we use splines because they allow for slopes within bins, smoothing the response function. The smoother response also makes it easier to implement our selection criterion to determine the number of knots and produce estimates that avoid spurious detail.

The knots are located at equally spaced quantiles once the number of knots is determined, ensuring comparable numbers of observations between adjacent knots to estimate the slope. While our high-frequency data can estimate a large number of knots, we worry that using too many knots picks spurious relationships over the relatively short overall sample period of two years. We solve this problem by using a 10-fold cross-validation technique to find the number of knots where the out-of-sample prediction ceases to improve. The result is a choice of $j = 6$, or five knots (Figure B.2). Each segment of the spline covers one-sixth of the sample in this case.

By controlling individual fixed effects δ_i, we use within-household random temperature shocks to identify the β_1s. Although our identification is based on random weather shocks, controlling for other climate variables improves the estimation (Zhang et al., 2017). Thus, we control for humidity, wind velocity, and wind direction, as well as wind velocity interacted with wind direction. In addition, we control the daily PM 2.5 collected by the Shanghai Environmental Monitoring Center. Salvo (2018) recently found that higher particle pollution leads to significantly higher electricity demand in Singapore, where households adopt air conditioning to replace natural ventilation to protect health. The mechanism in Shanghai is likely to be different. Electricity consumption may increase because of fewer outdoor activities during polluted days, accompanied by the rapid adoption of air purifiers (Ito and Zhang, 2016).

Starting in July 2012, Shanghai utilities adopted both time-of-use pricing and tiered pricing for residential households. Due to the time-of-use pricing, households pay roughly half the price from 10:00 pm until 6:00 am the next morning, compared with the period from 6:00 am to 10:00 pm. This does not affect our main estimation, as households face similar time pricing from day to day, and it is not unreasonable to imagine similar pricing in the future. Tiered pricing, however, makes the electricity price experienced by each household endogenous. For the roughly 20% of households that have crossed thresholds of 3120 kWh before the end of the calendar year, the peak electricity price for the following months becomes 9% higher than the previous months, providing a small incentive to lower consumption. Only a few households cross the second threshold (4800 kWh), which would lead to another 45% increase in price. We might imagine that with future climate change, more households will cross this threshold and experience higher prices, and their future response might be more muted than we estimate. In any case, because households do not necessarily face the same price in the same month of different years, we control for year-month fixed effects $\delta_{m,y}$ instead of separately controlling for month fixed effects and year fixed effects.[11] Finally, we control for possible weekend effects, as households tend to use more electricity over the weekend.

3.4.2 Baseline Estimates

Figure 3.2 represents our main estimation results.[12] The figure uses the β_{1j} estimates to plot the projected percentage change in daily electricity consumption against temperature, relative to the least-electricity-consuming temperature. The blue shaded area represents a 95% confidence interval, with standard errors based on two-way clustering at the household and week level.[13] The effects of humidity and weekend days, though statistically significant, are small in magnitude. For example, if humidity increases from the lowest to highest level observed in the data, the daily electricity use will increase by 6%. Households consume 2% more electricity during the weekend. Other variables,

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[11] We also estimated Eq. 3.1 with year fixed effects and month fixed effects, rather than year-month fixed effects. The results are very close.

[12] Due to the large sample size and our limited computational power, we randomly assign each household to 1 of 10 subsamples (we randomly sort the households and then count them off). The results we present are the average from the 10 separate runs, which produce almost identical estimates.

[13] We thank the reviewers for correcting our original, one-way clustering method at the household level. Allowing for correlation across households as well as over time leads to larger standard errors and more accurate statistical inference.

including air pollution, are not significantly different from zero. In contrast, the temperature splines are statistically significant and high temperatures can double electricity demand. Thus, we focus on the effect of temperature.

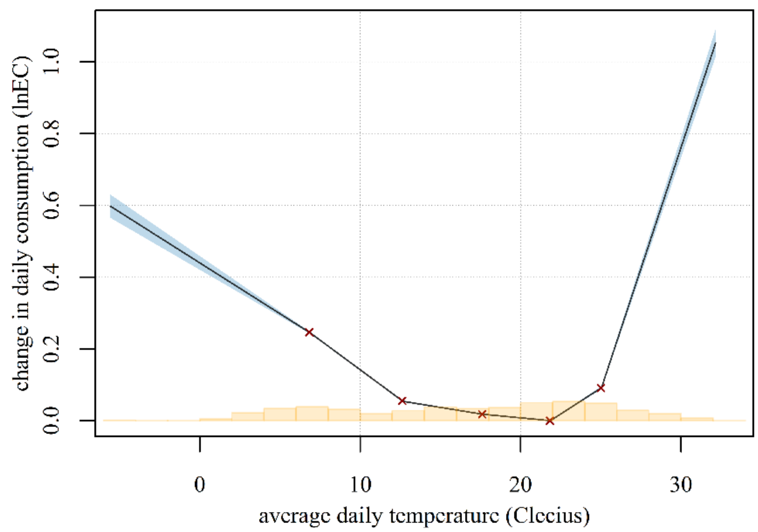

Figure 3.2 The Effect of Temperature on Daily Electricity Demand

Notes: this figure shows our main estimation results from equation (1) using the cleaned full sample of 841,784 metered residential households, where y-axis plots the predicted *lnec* (normalized to zero for lowest point). Due to the huge sample size, we randomly split the whole data into 10 subsamples. The result we present in this graph is the average from the 10 separate runs, which produce almost exactly same estimates. The degree of freedom is 6, which is chosen based on our 10-fold cross-validation, further explained in the notes of Figure B.2. The light blue shade represents the 95% confidence intervals, based on standard errors generated using two-way clustering at the household and week level. The red marks suggest the knots in the splines.

The main observation is that the temperature response function indeed follows the U-shape established in the literature, with minimal restrictions imposed on the functional form. The curve is relatively flat over 13–25°C, representing a comfortable temperature range. The curve rises steeply when temperature increases above 25°C while increasing moderately when temperature decreases below 13°C. Compared with a 20-degree day, when the electricity consumption is the lowest, a 32-degree day would lead to a 170% increase in daily electricity consumption.

Comparison with previous studies is difficult because other household level studies rely on monthly billing data. They present similarly shaped curves, but the vertical axis is the percentage increase in monthly demand for an additional day per month at the indicated temperature. If we focus on a "reference" month with average consumption and temperature in all days, we can compute a similar value using our model. Based on this approach, each additional day in the > 32°C (90°F) bin would lead to an increase of 5.7% in monthly consumption, compared to the baseline of 15–21°C (60–70°F). This is higher than the 3.2% increase estimated in the Mexico study (Davis and Gertler, 2015) but falls into the range of 2–7% increases in existing estimates for the United States (Deschênes and Greenstone, 2011).[14]

Coupled with average monthly consumption levels,[15] these percent changes associated with hot days translate into monthly electricity consumption increases of 11kWh, 5kWh, and 20–60kWh in Shanghai, Mexico, and the United States, respectively.

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[14] Note: 2–7% is calculated based on the 95% confidence interval for last bin (>90°F), according to Figure 3 in Deschênes and Greenstone (2011). To get the monthly change, we multiply the annual changes by 12, following the comparison conducted in Davis and Gertler (2015).

[15] The monthly average electricity consumption per household is 200 kWh based on our sample. Based on EIA data, US utility customers consume 10,766 kWh in 2016, equivalent to 897 kWh per month. The data are from https://www.eia.gov/tools/faqs/faq.php?id=97&t=3. We calculate the Mexico household electricity by dividing the electricity consumption (55,986 GWh in 2015) reported by the state-owned utility of Mexico (CFE) by the number of electrified dwellings. In 2015, Mexico has 31,949,709 inhabited dwellings and the access to electricity is 98.7%. The monthly electricity is hence 148 kWh. The source for Mexico electricity data is http://egob2.energia.gob.mx/portal/electricidad.html and the source for dwellings data is http://www.beta.inegi.org.mx/temas/hogares/.

The United States experiences the highest increase in kWh because its current consumption level is among the highest around the world. The gaps would be narrower in the future, however, as households in Shanghai and Mexico consume more electricity as income grows, catching up with their US counterparts. On the other hand, improvement in the efficiency of air conditioners, among other energy-saving actions, could potentially curb the growth of cooling-related demand under targeted policy incentives (IEA, 2018).

We can calculate the slope in each segment to estimate the direct impact of 1°C increases in daily temperature. For temperatures above 25°C, a 1°C increase in daily temperature would lead to 14.5% increase in daily electricity consumption. This has important implications for peak demand management as extreme temperatures rise: more investment will be necessary to meet the growth in peak demand on the hottest days. The response to lower temperatures is shallower than the response to higher temperature, but we are limited by the range of temperatures observed in Shanghai (the majority of which are above 0°C). Further research on colder areas would be valuable to see how the slope of the response function might change at low temperatures.

3.4.3 Sensitivity by Income Groups

Household-level adaption to climate change requires diverting other categories of household consumption into cooling expenditure. We therefore would expect households with differing levels of income to respond differently to the same temperature change. Our reported log-linear model assumes a particular pattern of behavior—that the adjustment is the same in percent terms but can differ by income level. As an alternative, we estimate alternate response functions for income subgroups based on a sub-sample of roughly 1,400 households for which we have collected additional demographic data. We define four groups by monthly income: <$1,600 (15% of total households in our sample), $1,600-2,700 (30%), $2,700-4,000 (34%), and >$4,000 (21%)[16].

We note that Shanghai is among the richest regions in China. In 2015, the average monthly household income in Shanghai is $2,300, more than twice the national average ($900)[17]. The average in our sample is slightly higher at $2,750, but we do observe heterogeneity in our sample, which we exploit in the sub-group analyses. Based on our own previous paper, the income elasticity of electricity usage falls to zero at a monthly income level of $2,400 per household (Davis and Gertler, 2015). Thus we would expect that the electricity consumption grows only slightly as we move from a low income group to a higher income group in our sample. Indeed, the corresponding average annual electricity consumption is 1,960 kWh, 2,260 kWh, 2,430 kWh, and 3,030 kWh, respectively, for the four income groups.

Figure 3.3 depicts the response functions by income groups (again, the lowest level of logged electricity demand for each income group is normalized to zero). The temperature response functions are almost the same for high temperature above 25°C.

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[16] Four groups are originally defined by monthly income in RMB: <10000, 10000-16667, 16667-25000 and >25000. We use 2015 average exchange rate of 6.2 RMB/USD.

[17] China Statistical Yearbook (2016).

Given the near 100% penetration rate of air conditioners in Shanghai and the hot summer, this finding suggests a convergence of cooling behaviors across income levels during hot summer for relatively developed regions. The temperature response is shallower for low-income group in the winter, however. Although air conditioners in Shanghai are universally reversible as heat pumps, behavior clearly varies. We speculate, based on anecdotes, that poorer households may endure cooler indoor temperatures by wearing more clothes, or that wealthier households may be more wasteful (e.g., opening windows more frequently to increase humidity in the air while still heating the home). Note that the absolute gap in terms of kWh will be larger than the gap in terms of percentage: higher-income groups have higher percentage responses and baseline consumption levels.

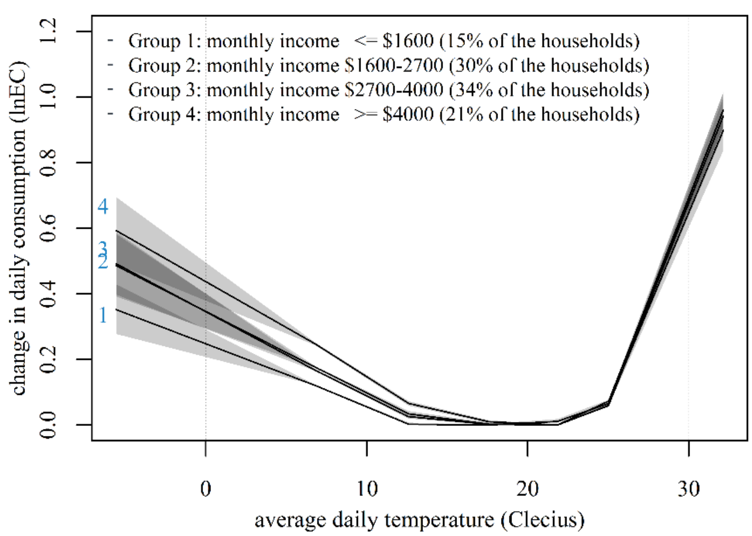

Figure 3.3 Temperature Response Functions by Income (in USD) Groups

Notes: we adopt the income categories from the survey question. Each group has at least 200 households. Each spline is estimated for the subgroup separately. The shaded area represent the 95% confidence interval. The degree of freedom is 6, which is consistent with our main specification with all households.

Taken together, this result regarding cold days suggests the increase in electricity use due to climate change could be smaller as income increases in Shanghai. Steeper slopes in cold days correspond to more energy saving as temperature gets warmer. However, this result is likely sensitive to the Shanghai context, where high incomes, a high penetration rate of air conditioners, and the significant use of electric heat all combine to drive a negative correlation between income and net climate change impacts. The situation in northern China could be very different, where incomes are lower and households use gas heating or central-station hot water. Another caveat is that our ability to identify the weather sensitivity for low- and higher-income households is limited, because households in the sample are relatively homogeneous and the sampling and data collection does not capture and identify households in the tails of income distribution.

3.5 End-of-Century Forecast

In this section, we calculate the changes in residential electricity consumption projected for the last two decades of the 21st century by applying the temperature-response curve expressed in Eq. 3.1 and presented in Figure 3.2 to two climate change scenarios: Representative Concentration Pathways 4.5 and 8.5. The RCP8.5 trajectory reflects a high climate change scenario in the face of continued high emissions growth. RCP4.5 is a more moderate scenario, in which emissions peak around 2040. We use 21 different implementations of these 2 scenarios (i.e., 42 data points) to construct a relationship between global mean surface temperature change—the typical summary measure of global climate change—and changes in annual household electricity demand over this time period. We also examine patterns of projected daily demand to give us some insight into how peak demand will change.

3.5.1 Forecasts: damage function

For each model, we first calculate the average across years of daily temperature for each of 365 calendar days in the historical period (1980–1999) and the forecast period (2080–2099) under both RCP4.5 and RCP8.5. We then calculate the difference between the future and the past average calendar day temperatures for each of the 42 model x scenario combinations. We use these changes in daily temperature to estimate the change in electricity demand using our model results in Figure 3.2. Finally, we aggregate across calendar days to estimate the change in annual electricity demand, again for each of 42 model x scenario combinations (for details, see Appendix B, Damage Function Calculation).

We note that this approach risks missing potential impacts on extensive margins (e.g., investment in better building design, etc.). Massetti and Mendelsohn (2011) emphasize the distinction between panel estimates that capture short-term weather shocks (intensive effects) with cleaner identification and cross-sectional estimates that capture long-term climate change (intensive and extensive) but risk bias from confounding variables. More recent work by Hsiang (2016) argues that panel estimates can capture unbiased long-term effects when estimated over a suitably wide range of geography and climate. However, given our limited geographic scope, we cannot appeal to Hsiang's arguments. We would hypothesize that our estimates are an upper bound for Shanghai. That is, we imagine extensive changes would lead to lower damage estimates thanks to greater long-term flexibility to save energy. In other regions, with less existing penetration of air conditioning, such flexibility might lead to larger impacts on electricity demand as households adopt such appliances in response to persistent temperature changes.

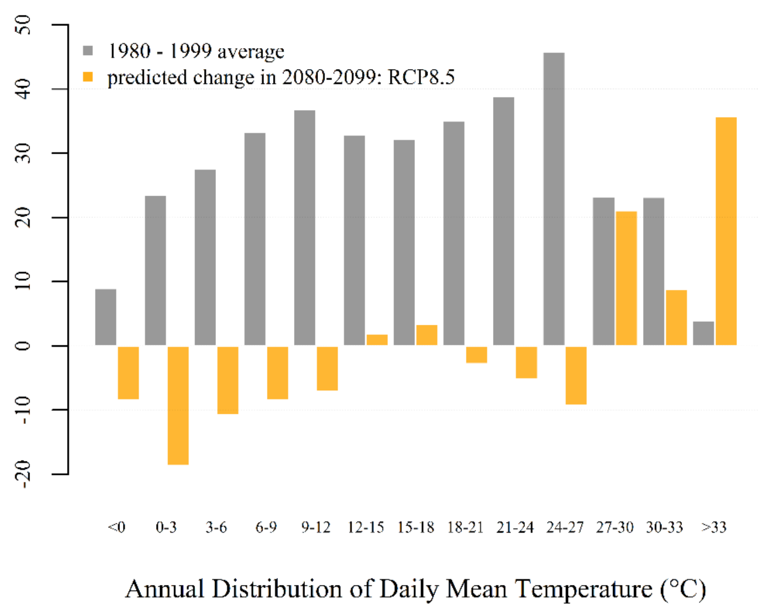

Figure 3.4 Distribution of Daily Average Temperature Change

Notes: this figure shows the historical temperature distribution and the predicted change under RCP8.5 across 13 bins. For the period of 1980-1999 and 2080-2099 respectively, we count the total number of days with temperature falling into the each bin from each model and each year. We then rescale the count within each bin such that the total count of days from all bins equals 365. Each bar for the predicted change in 2080-2099 represents the change in the number of days within each temperature bin under RCP8.5. The change under RCP4.5 is similar but roughly half in size (not shown in the graph).

Under both scenarios, the average daily temperature increase in Shanghai over the forecast period is higher than the GMST increase. Under RCP8.5, the daily temperature in

Shanghai over 2080–2099 increases by 4.5°C on average relative to 1980–1999, compared to 2.4°C under RCP4.5. By contrast, the GMST increases by 3.7°C and 1.9°C, respectively.

Figure 3.4 shows the change in temperature distribution for Shanghai under RCP8.5. Consistent with previous findings, climate change shifts the distribution of daily temperature to the right. The number of days falling within the lowest five temperature bins below 12°C decrease by more than 50 days, while the highest temperature occurs much more frequently. Compared with the reference period of 1980–1999, Shanghai would experience almost 40 more days of temperature higher than 33°C on average in 2080–2099.

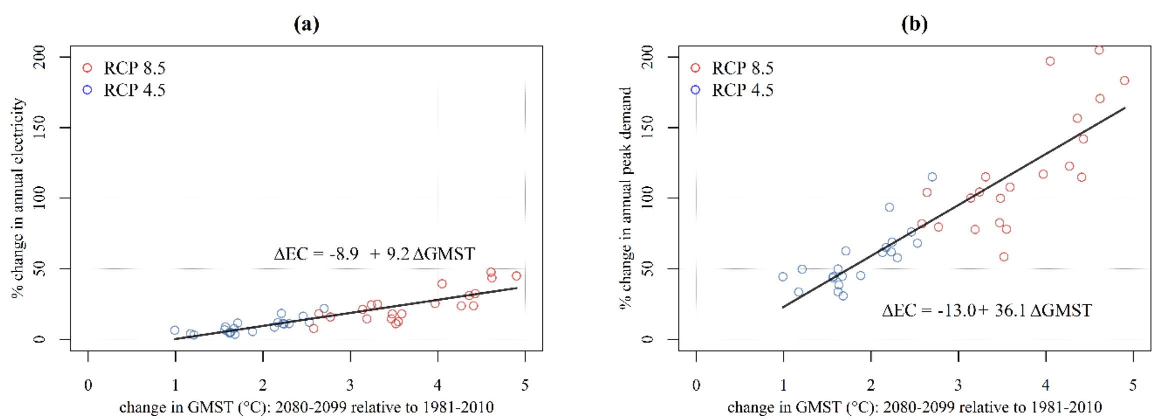

Figure 3.5 Damage Function

Notes: In (a), Y-axis shows the predicted change in ANNUAL electricity, a weighted aggregation of daily changes using electricity consumption in 2015 as the consumption pattern across a year. In (b), Y-axis shows the predicted change in PEAK annual electricity, defined as the maximum of the daily electricity change across the year. The GMST data are from Table 2 and Table 4 from Rasmussen et al. (2016), where the authors calculated the changes in GMST under 21 different climate models used in our analysis. The GMST data are matched to our calculated electricity under RCP4.5 and RCP8.5 for each of the 21 model by the model-scenario. Detailed calculation process for the change in electricity is described in SI. Damage Function Calculation.

Figure 3.5 (a) shows the relationship between the change in GMST and the corresponding annual change in electricity consumption. The GMST data are from Table 2 and Table 4 in Rasmussen et al. (2016), where the authors calculated the changes in GMST under 21 different climate models used in our analysis. Each point represents a model run. The red points and the blue points represent the RCP8.5 and RCP4.5, respectively.

Intuitively, electricity consumption increases more for higher temperature changes. Fitting a line using Ordinary Least Squares (OLS), residential electricity consumption rises by 9.3% for each 1°C at the end of the century. This is slightly higher than the slope of damage function estimated for the United States (Hsiang et al., 2017) but is reasonable because the average temperature in Shanghai is higher than the average in the United States.[18] Alternatively, if we look at the average RCP outcomes rather than the damage function, the average annual change in electricity consumption is 9.4%, corresponding to a 1.9°C change in GMST at the end of the century under RCP 4.5. Under RCP8.5, the average annual change in electricity consumption is much higher at 24.6%, corresponding to a 3.7°C change in GMST.

[18] The average temperature in United States is 12.4°C in 2015, based on Climatological Rankings data from National Centers for Environmental Information. In comparison, the average temperature in Shanghai is 17°C.

3.5.2 Forecasts: daily electricity change

Average annual changes in electricity consumption are the primary driver of annual climate damage estimates. However, peak demand changes, especially during the hot summer period, will drive future investment in grid expansion and could drive damages yet higher. Daily meter data allow us to examine and draw the daily electricity consumption change separately. Figure 3.5(b) mimics the style of Figure 3.5(a). The main difference is that here we plot on y-axis the change in annual peak demand,[19] rather than the weighted annual change. The comparison between the two figures shows significant differences in magnitude, with peak daily demand changing more dramatically than the annual average. Similar to Figure 3.5(a), we fit a line using OLS, finding an increase of 36.3% in peak demand for each 1°C at the end of the century. This is three times steeper than that of the annual damage function.

To understand this distinction, it is helpful to see the distribution of daily electricity change due to climate change across the year. To make the graph easy to read, we consolidate the 21 models and only present the average effects under the RCP4.5 and RCP8.5 in Figure 3.6. Consistent with the spline estimates, the daily electricity consumption increases dramatically in the summer and decreases only slightly in the winter. While annual electricity demand rises 9.4 and 24.6 percent under the two RCPs,

[19] In this paper, the peak is defined by the maximum daily electricity consumption across the year. It is worth noting that this differs from the definition in Auffhammer et al. (2017), where the peak is defined as the highest demand hour of the day for the whole grid system. The hourly peak at the system level could be much higher than daily peak and could differ from the peak in residential sector. Here, we provide the peak estimates mainly to draw attention to the much steeper response based on peak demand.

daily peak demand rises by as high as 57 and 120 percent. Thus, capacity investment will need to rise by more than the average increase suggests.

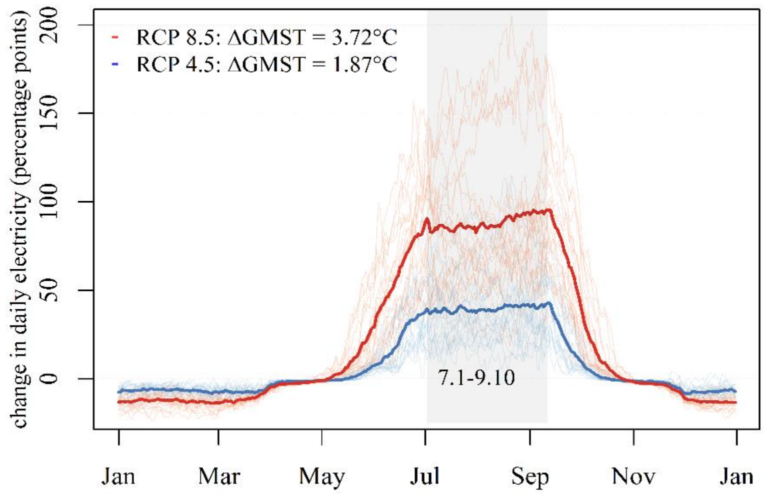

Figure 3.6 Daily Electricity Change under Climate Change

Notes: The gray area highlights the period during which the increase in daily electricity is the highest due to climate change.

3.6 Conclusion and Future Efforts

Consistent with previous studies in the United States and Mexico, we find a U-shape curve between the residential electricity consumption and temperature in Shanghai, China. The U-shape seems to hold regardless of location, while the steepness of the curve on both ends differs. Studies across diverse climate zones, such as the United States, find more symmetric U-shape curves. Our study in Shanghai is relatively steeper for hot days and flatter for cold. Mexico, in comparison, is very responsive at high temperatures even with relatively low AC penetration rate, while the response for cold days is not significantly different from zero.

These observed differences could be attributed to a combination of factors, including insulation features, appliance stock and efficiency, and usage patterns. In winter, households have a wide range of choices, including electric heaters, heat pumps, and gas-fueled furnaces, leading to different impacts on electricity consumption for a given temperature change depending on regional culture, markets, and infrastructure. Alternatively, differences in the flat portion of the U-shape curves may hint at different tolerance levels for heat and cold. Shanghai residents may have a larger comfort zone—in which they do not engage in significant space conditioning—compared to their US counterparts.[20]

Combining our estimated response curves with downscaled projections of future climate change, we estimate that each 1°C increase in GMST leads to 9.3% increase in annual electricity demand. Of equal interest, we highlight the difference between the impact on annual electricity change and the impact on peak daily electricity demand. If the global climate warms by 1°C, the peak daily electricity demand increases by 36.3%, four times the annual change. As peak demand drives investment in power plants and

[20] Though we could not rigorously examine this, households in China are observed to take actions other than heating and cooling to deal with heat and cold, e.g. changing to thinner quilts, adding bamboo beddings in summer, and wearing down jackets at home in winter. By contrast, in the United States, households seem to prefer keeping the room temperature fixed and use air conditioners together with winter quilts in the summer.

other generation sources, our result suggests that the economy-wide impact could be underestimated based on the average annual response.

Our data do not capture enough persistent weather variation to identify changes in housing characteristics and appliance ownership in response to different climates. In this way, our estimation speaks largely to the intensive margin and illustrates the relationship between household electricity usage and temperature given a fixed capital stock. On the one hand, the estimates exclude long-term adaptation, such as upgrading insulation, moving to more energy-efficient dwellings, or even migrating to cooler cities (Boustan et al., 2012). Thus, our results may overstate impacts. On the other hand, some households may adopt more space conditioning appliances as temperatures persistently change. In Shanghai, this factor is less important given the already high penetration rate of air conditioners. However, the estimates could underestimate the response in other cooler or less developed regions of China.

In contrast to developed countries, we expect climate change to occur concurrently with economic development in China and other developing countries. In this context, it is necessary to consider both climate change and income as two long-term drivers of electricity consumption in order to understand climate impacts and demand growth. Previous work by Cao et al. (including two of the authors of this paper) examined the effect of income on electricity use in the future (Cao et al., 2017). There, we found that income would lead to 85–143% growth in electricity demand in China from 2010 to 2025. As shown in our calculations in this paper, climate change will lead to about a 50%

increase in electricity demand in the most extreme scenario by the end of the century, which is important but considerably smaller than the increase due to income growth.

This paper also examined the potential interaction between income and climate by estimating the response function by income groups. We found some differences in climate sensitivity across income groups at lower temperatures, but our estimates were limited by the relatively high income levels in our sample compared to China more generally. These estimates are more relevant for our interest in the climate impacts in a richer China and less informative about impacts in poorer regions.

While our work is an important addition to the limited work on climate change impacts on energy demand in developing countries, it also points to the importance of further work in at least three dimensions.

First, we need to consider more diversity in terms of housing stock as well as heating and cooling services relative to our current sample. We would expect the effect of impact on electricity (and other energy sources) to depend on the type of residential construction and use of different heating and cooling technologies and fuels.

Second, we need to examine the relationship between income and climate impacts more closely using households with more widely varying income. We would expect more heterogeneity across a wider income range. We should also recognize that the lack of response among the lowest-income households might indicate even higher non-market costs, such as discomfort, morbidity, and even mortality.

Finally, we need to consider the longer-term, extensive margin when capital stocks adjust in ways that could both raise and lower energy impacts and when migration and public infrastructure investment emerge and interact. One approach would be to include greater regional and climate zone diversity. As highlighted by Hsiang, a panel data set across diverse climate zones can be used to capture impacts net of longer-term adjustments (Hsiang, 2016). Such research is an important input toward decisions about both energy sector planning and adaption in the future, as well as efforts to balance mitigation costs and benefits today.

Chapter 4 Environmental Impact of overseas coal-fired power plants financed by China

4.1 Introduction

About 1 billion people – roughly three times the population of the United States – still lack access to electricity (World Bank, 2017). International Energy Agency (2017) estimated that the power plants alone would require $2.7 trillion investment from 2017 to 2025. In poor countries where more sustainable electricity supply has the potential to foster higher economic growth, fossil fuel based power generation remains a necessity under many circumstances (Morris and Pizer, 2013). Meanwhile, multilateral development banks (MDBs) have 'greened' power-generation portfolios in the past decade, phasing out lending for coal-fired power plants after more than five decades (Steffen and Schmidt, 2018). The World Bank, among most other MDBs, decided to provide financial support for coal-power generation projects only in rare cases such as when countries have no feasible alternatives to meet basic energy needs (World Bank, 2013). In 2015, the Arrangement on Export Credits – a "Gentlemen's Agreement" among participants from most OECD members – restricted the official export credits[1] for the least efficient coal-fired power plants, encouraging both exporters and buyers to transit from low-efficiency to high-efficiency technologies. In contrast, public funding agencies and

[1] Offical export credits are provided by governments to support national exporters competing for overseas sales.

commercial banks in Asian countries, especially Japan, Korea and China, are becoming the lead arrangers of project finance in coal power plants overseas (Baruya, 2017).

In recent years, China, in particular, has become a major funder of energy-related infrastructure in developing countries (Dollar, 2018). Between 2000 and 2014, almost 40% of the total overseas financing from China has gone into the power sector – the highest among all sectors (Dreher et al., 2017). According to the China Global Energy Finance database, the China Development Bank (CDB) and China Export-Import Bank (CHEXIM) provided $225.75 billion in energy finance overseas between 2000 and 2017. These loans are highly concentrated in fossil-fuel based energy generation, especially coal-fired power plants. More specifically, from 2005 to 2017, more than 40% of the power generation projects financed by the CDB and the CHEXIM were coal-fired power plants (Gallagher et al., 2018).

Is there an environmental cost to China stepping into this role of financing coal-fired power plants? This paper examines one aspect of this question: is China financing coal-fired power plants that have observably higher pollution than power plants financed without China's support? If those plants are more polluting, it suggests a downside to the choice by the MDBs and some western governments to step away from financing such plants. While the goal may have been to reduce environmental impacts by stepping away, they may have inadvertently worsened pollution by encouraging China to step in. On the other hand, if they are not more polluting, it suggests that the presumed reduction in total global financing for coal-fired power plants is a net positive for the environment.

Our concern about environmental impacts follows from the significant environmental footprint for coal-fired generation. While having the potential to alleviate energy poverty and fuel economic growth, coal-fired power plants can lead to serious environmental issues and potential health problems (see Section 4.2.3). However, very few studies have examined the environmental impact of the coal-fired power plants financed by China overseas, partially due to lack of data. On the finance side, there is no official data from Chinese government on its overseas finance at the project level. On the outcome measures, unlike the US where the Environmental Protection Agency (EPA) collects detailed emission data from coal-fired power plants, the on-ground emission data in the developing countries are often missing or not comparable.

This paper fills the gap by combining the CoalSwarm Global Coal Plant Tracker and China's Global Energy Finance (CGEF) datasets along with satellite data from NASA. That is, we look at direct measures of pollution levels rather than bottom-up emission calculations. Compared to such approaches, which may or may not be consistent with observed outcomes directly related to health outcomes, our work offers important and complementary insights. Our outcome measure, the Ozone Monitoring Instrument (OMI) retrieved atmospheric SO2 column amounts, has already been used to study large point emission sources (e.g. Karplus et al., 2018; Li et al., 2010). It also offers a relatively objective view, as on-ground emission data may be susceptible to manipulation (Ghanem and Zhang, 2014). However, those existing studies mainly focus on power plants inside of

China rather than those overseas, and are not trying to compare Chinese and non-Chinese financed plants.

We examine a total number of 638 power plant units built between 2006 and 2016 in four countries in the Southeast Asia: India, Indonesia, Vietnam and Philippines, as the majority of operating coal-fired power plants financed by China are in these countries. Using a simple difference method based on the start year of power plants, we show that the operation of coal-fired power plants leads to observable increases in the SO2 column amounts. The impact of the power plants has the largest magnitude when we draw a circle of 20 km around the power plant and use 95% quantile to calculate the SO2 level: the SO2 increases almost 10% after the start-up of coal-fired power plants larger than 500 MW. The magnitude of impact decreases with the radius of buffer we use to extract the SO2 levels around the power plants, and increases when we look at a higher percentile of the SO2 over the year.

At this point, we have only limited results from our comparison of Chinese and non-Chinese financed plants. The general comparison of the plants financed by China with the rest shows no significant differences, using a difference-in-difference approach. However, when we limit the sample to plants using sub-critical technology, we observe that the coal-fired power plants financed by China leads to higher SO2 increase than the other plants (for plants larger than 300 MW), though not statistically significant. This may reflect looser SO2 controls, but we could not prove this due to lack of information. On the other hand, we observe that the coal-fired power plants using supercritical technology[2] leads to lower SO2 increase, though not statistically significant. For power plants larger than 500 MW, a larger proportion of the plants financed by China use supercritical technology. Ideally, we would want to assign randomly a project to be financed by China versus by others. In reality, the financing decision is complicated and often involve multiple stakeholders. Hence, the diff-in-diff result should be interpreted as preliminary evidence on characterizing the Chinese-financed power plants, not necessarily the casual impact of finance from China.

The rest of the paper proceeds as follows. Section 4.2 provides the background on energy finance, infrastructure gap and environmental impact. Section 4.3 describes the data, followed by Section 4.4 and 4.5 explaining the empirical strategies and findings in two steps—initially identifying the pollution from power plant start-up, generally, and then identifying the difference between Chinese and non-Chinese plants. Section 4.6 concludes.

4.2 Trends in energy finance, infrastructure gap and environmental impact

This section establishes the background on China's energy finance overseas, infrastructure gap and energy poverty, and environmental and health impacts of coal-

[2] Supercritical power plants have much higher heat efficiencies (46%) while subcritical power plants have efficiency of within 40%. The temperature and pressure in supercritical power plants are much higher, keeping the water as a supercritical fluid – neither a liquid nor a gas.

fired power plants. Section 4.2.1 describes the larger trend of Chinese overseas investment, among which energy sector is an important component. Section 4.2.2 highlights the global infrastructure gap and the need for more investment. Although this paper focuses only on the environmental impact, we have to acknowledge the development needs in the developing countries and least developed countries, which requires increasing investment to pursue economic growth. Section 4.2.3 summarizes the previous studies on the impact of coal-fired power plants.

4.2.1 China's Overseas Energy Finance

The surge of Chinese overseas investment started in early 2000s as the result of China's "going out" policy (Kong and Gallagher, 2017). Since 2013, China more formally 'branded' the overseas investment under the Belt and Road Initiative (BRI) – a multi-trillion dollar initiative. The initiative covers more than 70 countries that account for over 60% of global GDP and 70% of world population (Chen and Lin, 2018), aiming at strengthening infrastructure, trade, and investment links. The immense scale of the initiative has drawn huge public attention but the exact scope and characteristics of projects remain vague.

Though renewable choices are widely available, China continued to finance coal projects overseas. Among the pull factors, the recipient countries may prefer coal plants due to lower construction costs or ignorance of better choices. On the push-factor side, China has excessive coal capacity (Lin et al., 2016) due to historical issues along with stringent domestic policies to reduce emissions and to prioritize renewable energy (Li et al., 2019). Based on the China Global Energy Finance database, during the period of 2001-2017, among the $225.75 billion energy finance from the CDB and CHEXIM, nearly $50 billion (20%) was spent on coal projects. In terms of regional distribution of coal finance, Southeast Asia and South Asia received 70% of the total finance amount, compared to 30% for the rest of world (22% in Europe/Central Asia, 7% in Africa and 1% in LAC).

Among the power generation projects, more than 43% of the total number of projects use coal, followed by hydropower (40%). While China have funded hydropower projects across continents and especially in Africa and LAC, its current coal portfolio is much more concentrated in Southeast Asia, South Asia and Central Asia. China's leading role in coal power plants is also reflected in the trade flows. In recent years, China has become the largest exporter of equipment for coal power generation, such as boilers and steam turbines (Ueno et al., 2014).

4.3.2 Infrastructure gap

It is widely accepted that infrastructure investments are fundamental to many countries' pursuit of economic development (World Bank 2012). Under the framework of United Nations Sustainable Development Goals, infrastructure affects people's wellbeing and economic productivity through multiple channels, including "building resilient infrastructure" in Goal #9, "water" in Goal #6, and "energy" in Goal #7.

The infrastructure investment need around the world remains huge. Based on the Global Infrastructure Outlook[3], infrastructure investment will need to reach $94 trillion by 2040 to keep pace with the 25% increase in population, rural to urban migration, and economic development, globally. To achieve universal provision of clean water, sanitation and electricity under UN Sustainable Development Goals (SDGs), the total infrastructure cost adds up to $97 trillion, among which almost 20% would not be fulfilled by forecasted investments based on current trends. Mckinsey Global Institute estimated that the current trajectory of investment would lead to a shortfall of roughly $350 billion annually in infrastructure including transportation, power water and telecom systems (Woetzel et al., 2016).

Among countries, over half of global infrastructure investment needs are in Asia, requiring more than $1.5 trillion per year through 2030 ($0.4 trillion for South Asia and $0.2 trillion for Southeast Asia). The infrastructure investment gap is estimated to equal 5% of projected GDP from 2016 to 2020 factoring climate mitigation and adaptation costs for Asian countries without China[4] (ADB, 2017). Among sectors, power sector counts for half of the investment needs, followed by transportation (35%), telecommunications (10%) and water and sanitation (4%). As ensuring access to affordable, reliable, sustainable and modern energy for all is listed as the Goal 7 in the Sustainable Development Goals committed by more than 190 world leaders in 2015, designing efficient and effective

[3] https://outlook.gihub.org/

[4] With China, the gap is 2.4% of GDP.

electrification programs is crucial to achieve universal energy access, especially in developing countries. The huge infrastructure gaps call for more investments from all parties, including Multilateral Development Banks, policy banks and private actors.

From this perspective, the substantial amount of investment from China, especially under the BRI, could be potentially beneficial to fill in the global infrastructure gap and to improve economic productivity. Utilizing an original dataset of geo-located Chinese Government-financed projects during 2000-2014, Bluhm et al. (2018) finds that Chinese development projects have led to reduction in economic inequality, especially for the transportation projects connecting and facilitating economic activities. Electrification could potentially have ripple effects on the economic development, but the existing evidence is mixed. Studies have found positive impact of electrification on income, household consumption and other dimensions of human wellbeing (e.g. Van de Walle et al., 2017, Dinkelman, 2011; Chakravorty et al., 2016), while other studies do not find significant positive impacts (e.g. Burlig and Preonas, 2016).

4.3.3 Environmental and health impacts of coal-fired power plants

Along the production of power, coal-fired power plants generate numerous local externalities, including pollutants such as sulfur dioxide (SO2), nitrogen oxides, low levels of radioactive elements, ash, and other residues. In the neighborhood of power plants, households may also suffer from other local externalities, including visual dis-amenities of tall stacks and noise. SO2 emissions in less developed regions are of particular concern, as the regulatory environment to install scrubbers in those countries are generally weaker.

The potential adverse health effects from high-level SO2 exposures and acid rain are well recognized. The U.S. EPA conducted extensive evaluation of previous epidemiologic and laboratory studies and concluded that short-term exposure to SO2 would cause respiratory health effects, as summarized in the Integrated Science Assessment for Oxides of Sulfur – Health Criteria (U.S. EPA, 2008). In the Regulatory Impact Analysis of Sulfur Dioxide (SO2) Primary Standards (U.S. EPA, 2010), the monetized health effects of SO2 include respiratory hospital admissions, asthma emergency department visits, asthma exacerbation, and acute respiratory symptoms. Other effects such as premature mortality, other respiratory emergency department visits, visibility and recreation in terrestrial and aquatic ecosystems from acid rain are much harder to estimate. A recent paper estimated that the likelihoods of having a low birth weight baby and having a preterm birth increases in areas downwind of power plants (Yang and Chou, 2018). Koplitz et al. (2017) estimated roughly 20,000 excess deaths per year due to Southeast Asian coal emissions at present, which will further increase to near 70,000 by 2030.

The impact of coal plants on the neighborhood is complicated by migration patterns and sorting. Kahn (2009) shows that the population growth within 2.5 miles of the one hundred dirtiest power plants in the United States have experienced slower population growth, suggesting a migration pattern towards cleaner areas. This re-confirms that the negative impact of welfare for households closer to power plants due to environmental and health concerns. The migration dynamics could also help alleviate the negative impacts. Davis (2011) shows that the property value decreases in area near power plants. The paper also sheds light on taste-based sorting, where households with lower income, educational attainment and ownership live closer to the plants. Hence, the local impact near the power plants could disproportionately affect those with limited ability and resources to migrate. It is worth noting that both papers are conducted in the US, where the property right, ability to sell and move, awareness of environmental issues, priority of goals, among others, may differ from the situation in less developed countries.

4.3 Data and descriptive statistics

To understand the impact of overseas coal-fired power plants financed by China, we use the Global Coal Plant Tracker to provide information on existing coal plants, and the China's Global Energy Finance dataset to identify the ones financed by China. As power plants spread across countries, we use the sulfur dioxide measured by satellites as the environmental outcome to ensure comparability. Other control variables (mainly temperature and precipitation) are also from globally gridded data sets.

For the purpose of this study, we focus on four countries in the Southeast Asia: India, Indonesia, Philippines, and Vietnam. Global Coal Plant Tracker and the China's Global Energy Finance data sets are merged manually because the power plant names have small variations. The SO2 data and other gridded data are then merged to the coal plants' data by location in R. The previous atmospheric studies and environmental studies on the emissions from power plants do not offer clear guidance on the radius of buffer to be used to extract SO2 data. Therefore, we experiment with different buffer sizes in the analysis (more details are provided in Section 4.4).

4.3.1 Coal power plants: CoalSwarm Global Coal Plant Tracker (Tracker)

CoalSwarm – the global reference on coal – maintains the Global Coal Plant Tracker (referred to as the Tracker hereafter), providing information on about 12,500 existing and proposed coal-fired power plant units with a capacity of 30 MW and above across the world (CoalSwarm, 2018). Among the 12,500 units, half are operating[5]. For each power plant, the database records its capacity, start year, technology, and location, and provides estimates on the annual carbon dioxide emissions. The Tracker gathers data from public and private sources including Global Energy Observatory, national reports, Platts UDI World Energy Power Plant database, among others[6]. This is the most comprehensive power plants data across global that are publicly available, and hence is the one we use in this study.

Another comparable source, the S&P Global Platts World Electric Power Plants (WEPP) Database[7], provides data on coal-fired power plants at a cost. The Platts database is widely used in energy industry. It provides information on emission controls, in addition to name, capacity, and technology type. The major shortcoming is that it does

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[5] Among the 14,000 units, 54% are operating. Retired, cancelled and shelved plants account for 14%, 14% and 8% respectively. 4% are under construction while the rest are pre-operation (announced, pre-permit or permmitted).

[6] For methodology, see https://endcoal.org/global-coal-plant-tracker/methodology/.

[7] See https://www.spglobal.com/platts/en/products-services/electric-power/world-electric-power-plants-database

not provide latitude and longitude of the plants' location[8], making it hard to be merged with other datasets based on location.

For the 1,103 coal plant units in the four countries across all the available years and operating, we only keep the plants that are operating and started operation between 2006 and 2016 (638 units). This period experiences rapid increase in coal power plant constructions in the four countries, captures the majority of Chinese coal finance, and allows enough satellite observation on SO2 before and after. Before 2006, there were only two recorded finance flows into coal power plants in Vietnam from CHEXIM. From 2006 to 2016, new plants added roughly 180 GW capacity, with the majority built after 2010 (Figure 4.1). We do not include power plants built in 2017 because we need a full year observation after the operation start year. India leads the new operation of coal power plants in the region, while Vietnam and Indonesia experienced significant expansion from 2011 to 2016. The coal plant capacity in Philippines is limited. We do not include Pakistan in our analysis as only one power plant started operating during our study period, though it attracts lots of Chinese investment through the China-Pakistan Economic Corridor – the signature connection in the Belt and Road Initiative.

[8] See more details on the geodata in WEPP on page 21 of the database documentation. Available at: https://www.platts.com/IM.Platts.Content/downloads/udi/wepp/descmeth.pdf

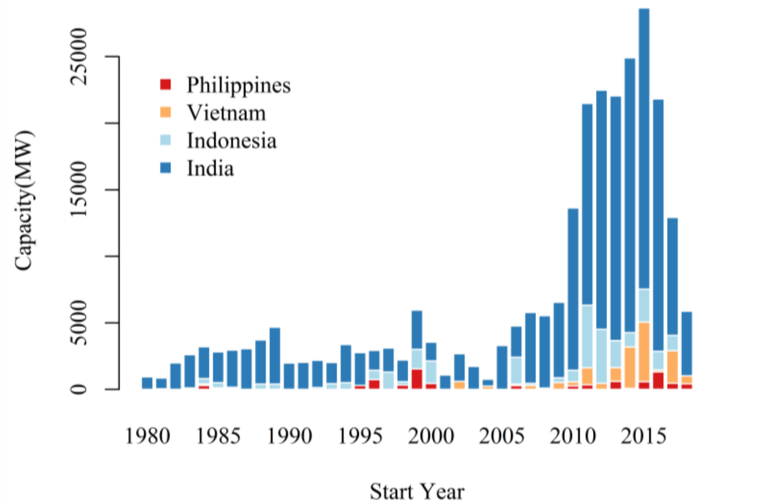

Figure 4.1 The Total Capacity of Coal-fired Power Plants by Year

4.3.2 Chinese investment: China's Global Energy Finance (CGEF)

The Tracker does not contain information on funding sources. In order to separate the coal-fired power plants financed by China with the rest, we utilize the China's Global Energy Finance database, collected by researchers at Boston University's Global Development Policy Center (Gallagher, 2017). The CGEF covers the annual flow of development finance into energy sector, including coal power plants, from the China Development Bank (CDB) and China Export-Import Bank (CHEXIM) since 2000. CDB and CHEXIM are China's two policy banks, holding more assets than the total global assets from the Western-backed multilateral development banks, including the World Bank (Gallagher et al., 2018). Given that no official data are published by Chinese agencies, the CGEF is built upon information from a wide range of sources, including official websites at the banks or host country ministries, news reports and other documents on the relevant deals[9]. Whenever possible, the records are verified by multiple sources and through interviews with Chinese stakeholders in the collection process, resulting in a relatively conservative number of coal finance flows.

We complement the CGEF with the information from AidDATA's Global Chinese Official Finance (GCOF) Dataset 2000-2014. AidDATA captures funding from Chinese government at all levels with development, commercial or representational intent (Dreher et al., 2017). The data are collected using the Tracking Underreported Financial Flows (TUFF) method, which involves extensive internet searching algorithms in initial data collection and several quality control steps to verify and refine the data[10]. The GCOF covers all sectors including Energy Generation and Supply, Transport and Storage, Industry, Mining, Construction, etc. and different stages from pledge to completion. The data do not provide sub-categories under Energy Generation and Supply, but we could identify the coal-fired power plants from the finance flow description.

Of the 638 power plant units in the four countries between 2006 and 2016, we identify 70 units that are financed by China (2 in Philippines, 18 in Vietnam, 35 in Indonesia and 15 in India). Some power plants have multiple units. If we count plants, not the units, our sample has 308 power plants in total, including 33 financed by China (1 in Philippines, 10 in Vietnam, 18 in Indonesia and 4 in India). It is clear that the power plants

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[9] For methodology description, see China's Global Development Finance: A Guidance Note for Global Development Policy Center Databases, available at: https://www.bu.edu/gdp/files/2018/08/Coding-Manual-.pdf

[10] For more detials, see AidDATA Methodology: Tracking Underreported Financial Flows (TUFF), available at: http://docs.aiddata.org/ad4/pdfs/AidDataTUFF_Methodology_1.3.pdf

China financed mainly concentrate in Vietnam and Indonesia, with only a few in India and Philippines. For Philippines, this is consistent with the general small number of power plants in the country, while for India, this may reflect geo-political factors that disfavor Chinese finance in India's power sectors. It is worth mentioning that Indonesia, Vietnam and Philippines are all covered by the Belt and Road Initiative (BRI), while India is not part of BRI.

The capacity financed by China over year fluctuates with that of the rest, and the majority of the power plants started operating from 2011 to 2015 (Figure 4.2). Of the 180 GW newly added capacity, 27 GW (roughly 15%) are financed by China. The ones financed by China are relatively larger in capacity, as smaller ones have a higher chance of receiving enough funding locally. The mean and median of Chinese-financed units are 390 MW and 330 MW, higher than 260 MW and 150 MW for the rest. In terms of technology, as shown in Figure 4.3, supercritical technology was only used for power plants larger than 500 MW, while the majority of smaller plants use subcritical technology. Among plants >500 MW, 65% of the plants financed by China use supercritical technology, higher than the 54% for the rest of plants in the region.

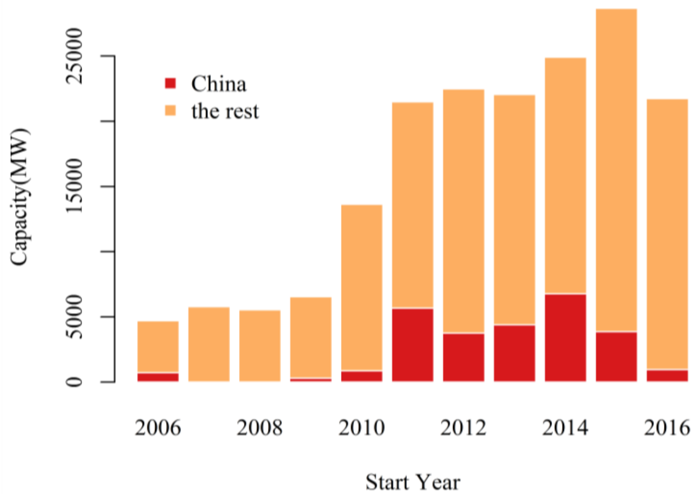

Figure 4.2 The Coal Capacity Financed by China and the Rest

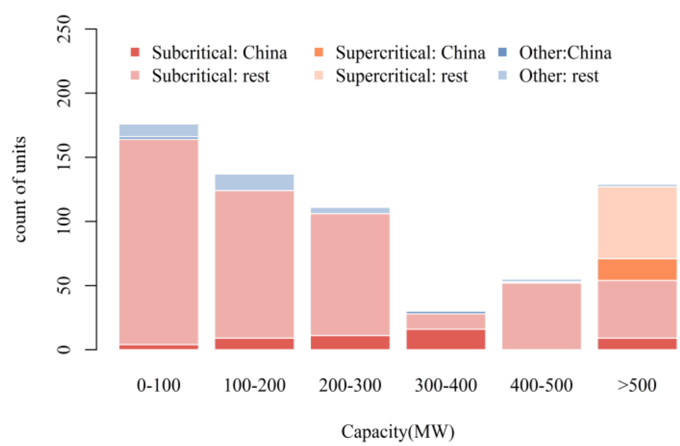

Figure 4.3 Technology Mix of Power Plants by Capacity

4.3.3 Environmental outcome (sulfur dioxide): satellite data

Our task is to estimate the levels of SO2 emissions from Chinese coal plants, relative to the rest of power plants in the region. For environmental outcomes, to ensure comparability, we use SO2 measures with broad spatial coverage based on satellite observations from OMSO$_2$e: Ozone Monitoring Instrument (OMI)/Aura Sulfur Dioxide

(SO2) Total Column L3 1d Best Pixel in 0.25°×0.25°[11] V3 (NASA, 2017). The Aura satellite was launched on 15 July 2004, and measures sunlight backscattered from the Earth over a wide range of ultraviolet and visible wavelengths. The L3 data are provided by NASA using retrieval algorithms and principal component analysis. The $OMSO_2e$ data stores the "best pixel" of original pixels collected by OMI in each grid cell. The unit of measurement is molecule per square centimeter. The OMI derived data have also been used to capture the spatial and temporal variations in SO2 (e.g. Li et al., 2010, Zhang et al., 2018), to quantify coal power plant responses to emission-control policies (e.g. Karplus et al., 2018) and to compare SO2 emissions across countries (e.g. Li et al., 2017).

Because there are no consensus on the optimal size of the circle to be used to extract SO2 around power plants, we experiment with different radiuses for a given power plant location. The size of the buffer has to be large enough to capture the SO2 traveling with wind, and has to be small enough to avoid introducing too much background noise as SO2 from the stacks gets diluted and mixed with SO2 emissions from other sources. Instead of making an arbitrary decision, we run a regression model to find the radius that gives us the strongest signal. We use SO2 data from 2005 to 2017, ensuring at least one year before and after for every plant in our sample.

[11] 0.25°×0.25° corresponds to different sizes in km×km as the earth is an oblate spheroid. Roughly, 0.25 degree corresponds to 20-30 km in the four countries we study.

4.4 Empirical analysis I: signal of power plants in satellite data

The first step in our analysis is to prove empirically that the satellite data are able to capture the effect of a new power plant. More specifically, we need to show that controlling for other variables and time trends, the SO2 measure increased significantly after the start year of a power plant. A clear signal in SO2 in this first step is fundamental to comparing the power plants financed by China with the rest.

To get the SO2 measure used as the outcome, we encounter two decisions to make. First, we need to decide the radius of the buffer we use to draw the circle around each power plant to extract the SO2 measures from the 0.25°×0.25° grids. Second, we need to decide the percentile we use to summarize the daily SO2 to an annual measure. The daily SO2 have to be aggregated to annual level, because we do not know the exact date or month of the plant operation. Due to this limitation, we are only able to compare the annual SO2 level before and after the year during with a power plant started operating. As studies examining the environmental impact of power plants using satellite data are limited, we need to determine the best radius and the best percentile by running the regression with all the combination of reasonable radiuses and percentiles.

For buffer size, Karplus et al. (2018) uses 35 km circle in their analyses, covering between 4 and 8 grids, without offering detailed justification to support this choice. Atmospheric studies studying the speed of oxidization of SO2 usually reports results for distances between 0 and 100 km (e.g. Forrest & Newman, 1977; Brock et al., 2002). Hence, we experiment with 26 different radiuses (denoted by r) in this range[12] and 21 different percentiles (denoted by p) with increments of 5% (e.g. 0, 5%, 10%).

4.4.1 Model

We estimate the impact of new power plants using a simple difference model. For each combination of radiuses and percentiles (26×21) in generating the SO2 measures, we run the following econometric model for six different capacity ranges (larger than 0, 100MW, 200MW, 300MW, 400MW, and 500MW respectively). We show results by different capacity, as we hypothesize that the signal of the power plants may only be visible in the satellite data when the capacity is larger than a certain threshold. The total number of regressions we run is 3276 ($26 \times 21 \times 6$).

$$SO2_{i,t} = \beta_0 + \beta_1 I\left(gap_{i,t} > 0\right) + \beta_2 NAcount_{i,t} + \beta_3 maxtemp_{i,t} + \beta_4 precip_{i.t} + \beta_5 trend_t + \beta_6 trend_t^2 + \delta_i + \epsilon_{i,t} \tag{4.1}$$

Where i denotes the area around a combined observation (i.e. units at the same location and with the same start year), and t denotes the year. Since not all units of the power plants started operating in the same year, we combine the units at the same location and starting in the same year to one observation in the analysis as they experience the same change in SO2 level around them. Each combined observation has a unique combination of location and start year. In other words, if two units of the same power plant (same location) were built in two different years, they would be two separate

[12] The 26 different radiuses (in km) we use are [0.1, 1, 2, 4, 5, 6, 8, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 65, 70, 75, 80, 85, 90, 95, 100].

observations. Our final sample consists of 474 observations, roughly 10% of them financed by China. $I(gap_{i,t} > 0)$ represents the indicator for treatment of 'new power plants operating', which equals 1 for each observation after the start year. As the power plant actually starts operating within the start year, this definition of the treatment corresponds to the lower bound of the impact of the power plant.

All of the control variables are extracted from gridded data covering the globe. We follow Karplus (2018) in adding climate controls, including average daily max temperature ($maxtemp$) and average precipitation($precip$), and a control for the number of missing values. The temperature and precipitation data, calculated from daily data from NASA, have lower resolution than the SO2 data at 0.5°×0.5° (around 50×50 km). We extract temperature and precipitation in a circle of 50 km, as it is the smallest circle that we have no missing value for any of the observation. $NAcount_{i,t}$ captures the total number of missing values of daily SO2 for observation i in year t, to control for the noises introduced by the way satellite operates. We also tried filling in the missing value by linear extrapolation, and the result is not very different. As using a certain method to impute the missing values could be arbitrary and the missing value pattern would be consistent for each power plant as we control for fixed effects, we do not fill in missing values in the main results we show below.

To isolate the impact of power plants from general increase in SO2, we model the time trend in quadratic form. This captures the general growth trend in SO2 without taking up too many degrees of freedom. Finally, we control fixed effects at the plant level, so essentially β_1 captures the increase in SO2 after a power plant operates. The standard errors are clustered at the plant level, using the "arellano" method (Arellano, 1978), allowing a fully general structure regarding heteroscedasticity and serial correlation. The errors are much smaller when clustered by year or without clustering.

4.4.2 Results

We run the same regression (1) for all combinations of radiuses, percentiles and capacity cutoffs ($26 \times 21 \times 6$). We first show the results using buffer of 20 km and 0.95 percentile for power plants larger than 300 MW in Table 4.1. All the model specifications control individual fixed effects at the plant level. Model 1 only controls the indicator for power plant operation and time trend. Model 2 adds the temperature, precipitation and count of missing values. Model 3 controls year fixed effects instead of time trend. One identification concern is that the increase in pollution level we observe in β_1 may capture general industrialization and economic development in the area that are not from power plant emissions. We therefore control the background SO2 level of a much larger buffer (100 km) in Model 4, and only use the difference between the SO2 in the 20 km circle and the SO2 average in the surrounding area (between 20km circle and 100 km circle) as the outcome variable (denoted 'SO2 diff') in Model 5.

In general, for plants larger than 300 MW, we observe a significant increase of around 0.03 in the column SO2, roughly 5% of the pre-operation SO2 average. For plants larger than 500 MW, the increase is around 10%. This β_1 estimate is relatively stable across specifications. When the background SO2 is controlled (as in model 4) or the difference

SO2 is used on the left-hand side (as in model 5), the estimated β_1 is slightly smaller. This reflects that there is some degree of general development around the power plant, but the SO2 increase we observe in 20 km buffer is mainly from the power plant. The effect of the number of missing value is relatively limited and become insignificant in model 4 and 5. Higher temperature would lead to higher SO2 level as cooling demand increases with the temperature, while precipitation would absorb SO2.

Table 4.1 Regression Results for First Stage

	Dependent variable (20km, 0.95, >300MW):				
	(1) SO2	(2) SO2	(3) SO2	(4) SO2	(5) SO2 diff
I(gap > 0)	**0.026*****	**0.030*****	**0.030*****	**0.027*****	**0.028*****
	(0.010)	**(0.009)**	**(0.009)**	**(0.007)**	**(0.007)**
NAcount		0.001***	0.002***	-0.00005	0.00004
		(0.0001)	(0.0002)	(0.0001)	(0.0001)
SO2_100km				1.120***	
				(0.041)	
maxtemp		0.013***	0.015***	0.012***	0.013***
		(0.003)	(0.004)	(0.003)	(0.003)
precipitation		-0.004*	-0.006**	0.001	0.001
		(0.003)	(0.003)	(0.002)	(0.002)
trend	0.016***	0.001		0.005***	0.005**
	(0.002)	(0.003)		(0.002)	(0.002)
trend2	-0.00004	0.001***		-0.0003**	-0.0002*
	(0.0002)	(0.0002)		(0.0001)	(0.0001)
Year Indicators	NO	NO	YES	NO	NO
Plant fixed effects	YES	YES	YES	YES	YES
Observations	2,587	2,587	2,587	2,587	2,587
R^2	0.307	0.331	0.356	0.574	0.067
F Statistic	351.529***	196.491***	82.081***	457.766***	28.563***
Note:			*p<0.05 **p<0.01 ***p<0.001		

Coefficient β_1 captures the signal of power plant in the satellite data so we plot the 3276 $\beta_1 s$ on the vertical axis (z-axis) in Figure 4.4. X-axis shows the 26 different buffers and the y-axis shows the 21 different quantiles. Each of the six panels shows the results for a different capacity cutoff. As we expected, the signal of power plants' emissions enhances as we focus on power plants with higher capacity.

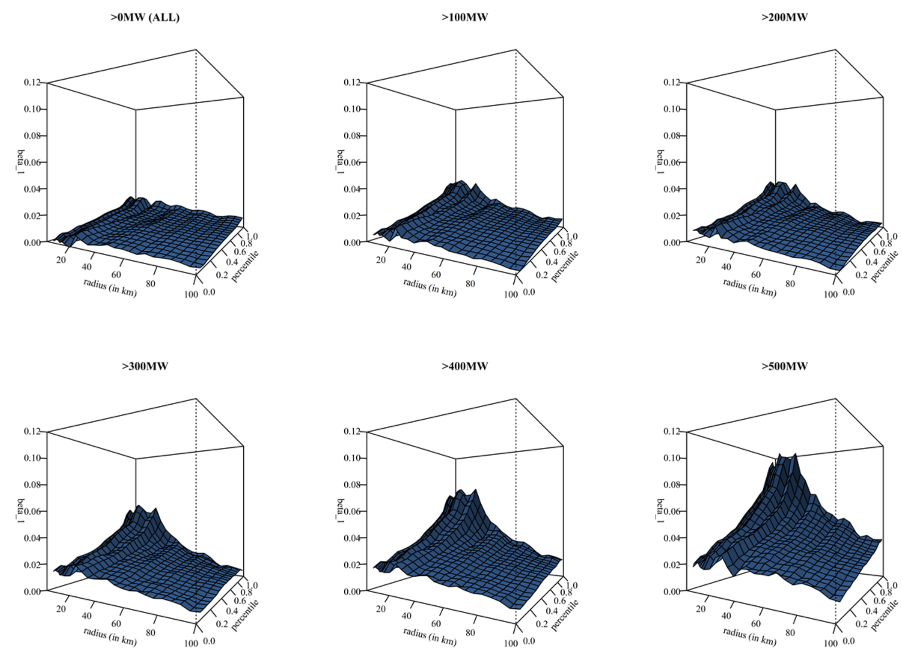

Figure 4.4 Impact of Power Plants on SO2 by Buffer, Quantile and Capacity Cutoffs

Within each panel of Figure 4.4, the β_1 increases smoothly with the percentile. Given our linear function form, this means that after a power plant starts operating, the larger daily SO2 percentile over the year will increase in larger magnitude. To avoid extremes, we use 95 percentile in the next step. This corresponds to the 15th worst day out of 365 days in a year (hereafter referred to as 'SO2 level' directly). The results with a lower percentile (e.g. median) are still significant, but with smaller magnitudes. These magnitudes are smaller than the 18% reduction of SO2 satellite measure under new emissions standards in China in Karplus et al. (2018), because the power plants covered in Karplus et al. (2018) have capacity larger than 1,000 MW. Nonetheless, they represent a substantial increase in SO2 levels.

For radius, we observe the maximum signal at around 20 km radius. The β_1 fluctuates when radius is below 20 km and steadily decreases with radius larger than 20 km. As the SO2 emission spreads with the wind, it makes sense that the highest signal appears at a certain distance rather than at the center (radius = 0). When the buffer falls smaller than the grid and the grid has missing values due to cloud coverage, the extraction method will generate missing values at the daily level. This would lead to lower annual measure at 95 percentile. Balancing the signal strength and missing values, we choose a radius of 20 km (covering 1-4 grid cells) where the signal is strongest.

A more straightforward way of showing the impact of power plants is to plot the SO2 along different years and see if we could observe the increase in SO2 at the start year (denoted year 0). This is difficult as the SO2 in the region increased in general over the period we study and the background noises prevent us from seeing a clear signal. Hence, we obtained the residuals of SO2 from a regression similar to regression (1) without the indicator for treatment (with the radius of 20 km and 95 percentile). The demeaned SO2 measures are shown in Figure 4.5. Year 0 represents the start year of a power plant. As expected, we observe much higher average SO2 after the start year of each power plant.

Similar to Figure 4.4, the signal is much stronger for larger power plants, especially above 500 MW.

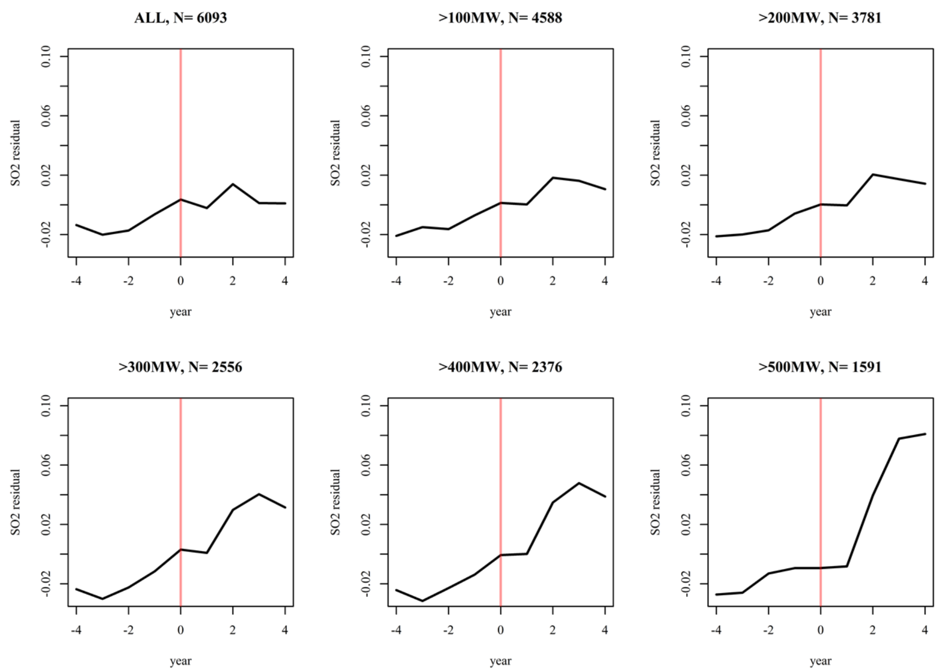

Figure 4.5 Demeaned SO2 Column Measures by Capacity Cutoffs (N: the Number of Observations, Plant by Year)

4.4.3 Falsification tests

One major concern of the identification above is that the β_1 represents the increase in general SO2 trend in the region, and has nothing to do with the operation of power plants. If this were true, then we would expect to see similar results regardless of the start year we use. To test this hypothesis, we assume a range of different start years (e.g. systematically move the start year 1 year backward or forward), and rerun the above regressions (using 20 km radius and 95 percentile).

Figure 4.6 shows the results of the falsification tests. $\beta_1 s$ are plotted with 95% confidence interval. Only the result at year 0 is the true result with the actual start year in the data. The estimate at assumed start year 1 means assuming the plants started operating one year after the actual start year. As expected, the estimates peak around year zero. For the few years before and after, the estimates are significantly larger than zero because the $\beta_1 s$ compare all the years after the start year to all the years before. For example, at the fake start year -2, the years after the fake start year capture all the real operating years and include two non-operating years, while the years before the fake start year miss two non-operating years. Hence the estimates are lower as the treatment effect is diluted, but still above zero. To conclude, the falsification results align with the timing of power plants' operation, proving that the estimate is not due to a general increase in SO2 level.

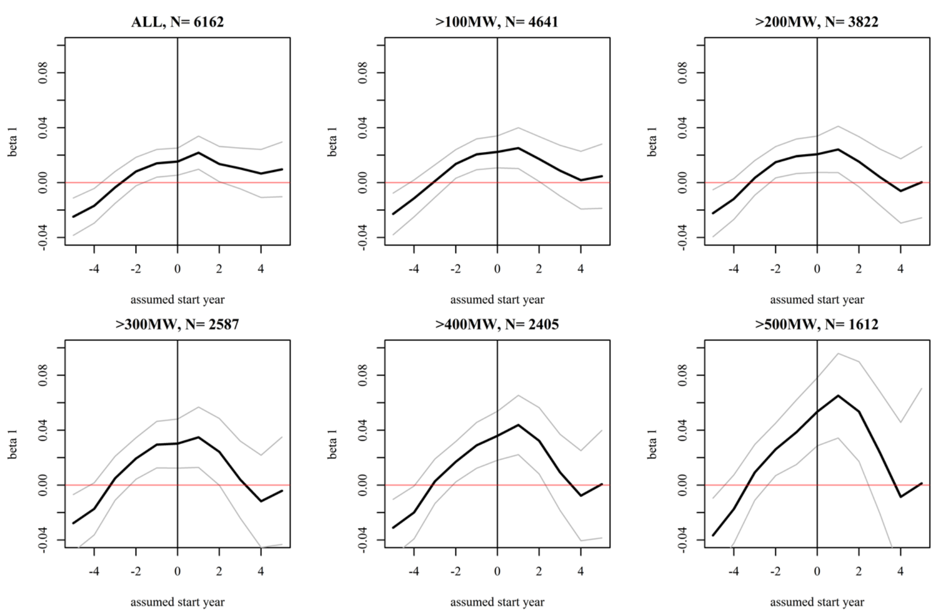

Figure 4.6 Falsification Tests of Empirical Analysis I

To sum up, we have shown in section 4.4 that SO2 measures increase significantly after the start year of power plants. The signal is strongest at the radius of 20 km and with

95 percentile. Using these two parameters, the following section explores the comparison of the power plants financed by China with the rest. Ideally, we would use power plants above 500MW in the next step, as the signal is strongest. However, the total number of power plants in the four countries we focus is limited, so we provide results for >300MW, which is a compromise between having more observations and having strong SO2 signal in the satellite data. As we increase the capacity cutoff, we are more certain that the estimate before $I(gap_{i,t} > 0)$ captures the effect of power plants, while at the same time we lose observations substantially such that we lose statistical power in comparing the Chinese-financed power plants with the rest.

4.5 Empirical analysis II: China vs. the rest

Built upon the previous section, we move on to examine whether the coal-fired power plants financed by China experience higher SO2 increases after operation.

4.5.1 Model

The model we use in this section builds upon the first difference shown in regression (4.1). Adding the comparison between the China and non-China financed plants adds another difference. Hence, we use the following diff-in-diff regression, interacting the indicator of plants financed by China ($FinanceChina_i$) with the treatment. As the plants financed by China may have different location features, we also model two different time trends. The key parameter of interest is θ_1, which shows China-financed plants are emitting more SO2 if θ_1 is significantly larger than zero. As the power plants financed by China differ in capacity with the rest, we also control the capacity of observation (could be more than one unit in the same location, denoted *totalcap*) interacted with the indicator for operation.

$$SO2_{i,t} = \theta_0 + \theta_1 I(gap_{i,t} > 0) * FinanceChina_i + \theta_2 totalcap_i * I(gap_{i,t} > 0) + \theta_3 NAcount_{i,t} + \theta_4 maxtemp_{i,t} + \theta_5 precip_{i.t} + \theta_6 trend_t * FinanceChina_i + \theta_7 trend_t^2 * FinanceChina_i + \theta_8 FinanceChina_{i,t} + \theta_9 I(gap_{i,t} > 0) + \theta_{10} trend_i + \theta_{11} trend_i^2 + \delta_i + \epsilon_{i,t} \tag{4.2}$$

4.5.2 Results with falsification tests

Figure 4.7 summarizes the result. The five models follow similar specifications in Table 4.1, all controlling the interaction between indicator for operation ($I(gap_{i,t} > 0)$) and the finance by China indicator ($FinanceChina_i$). In addition to the interaction, Model 1 only controls the time trend while Model 2 adds the other controls. Model 3 uses year fixed effects instead of quadratic trend. Model 4 controls the general SO2 in the 100 km buffer and Model 5 uses the SO2diff on the left-hand side as defined in Table 4.1. Overall, as shown in panel (a) for all plants above 300 MW, we do not find China-financed plants to perform differently than their counterparts. Given the number of China-financed plants are relatively small (31 plants >300 MW), the confidence interval is large, making most estimates of θ_1 not significantly from zero. In other words, our statistical analysis do not support China-financed plants to be dirtier or cleaner in general. If we did not model a separate time trend for China, most of the estimates under model 1-3 for all plants and subcritical plants would be significantly negative. This difference in results reflects that the places where China financed power plants experienced a slower increase in SO2 absent power plants operation.

The impact of coal-fired power plants could differ by technology. We now narrow our sample to only subcritical or supercritical plants and rerun regression (2). The results are shown in panel (b) and panel (c) in Figure 4.6. Compared to the rest of power plants in the region, the subcritical power plants financed by China have higher SO2 emissions while the supercritical power plants financed by China have lower SO2 emissions, though most of the estimates are not significant. One potential explanation is that the domestic advance of more efficient technology under stricter environmental regulations in China could have spillover effect on power plants' construction overseas. A previous study comparing the coal plants in China and the ones in the US showed that China's new coal-fired power plants are cleaner than anything operating in the United States does, as a much higher percent of Chinese coal plants uses supercritical technology[13].

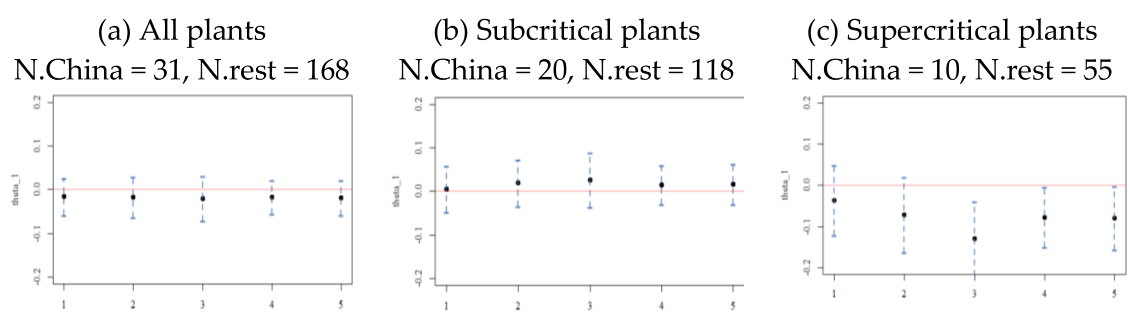

Figure 4.7 The Comparison of China-financed Plants with the Rest

[13] See Melanie Hart, Luke Bassett, Blaine Johnson, Everything you think you know about coal in China is wrong. Available at: https://www.americanprogress.org/issues/green/reports/2017/05/15/432141/everything-think-know-coal-china-wrong/

Note: the two numbers under each panel title represent the number of plants and the number of plants financed by China. The five estimates for each panel correspond to the five different model specifications following Table 4.1.

4.6 Discussion, Limitation and Future Steps

As China became a leading player in global energy finance, it is critical to understand the environmental implication of its investment. In this paper, we examine a total number of 638 coal-fired power plant units, among which 70 units were financed by China, in the Southeast Asia: India, Indonesia, Vietnam and Philippines. Our study is the first to estimate empirically the environmental impact of these coal-fired power plants using satellite data, and to compare the performance of power plants financed by China with the rest. As the power plant data and information on finance flows are not official data, our sample represents the best available sources but is not guaranteed to be 100 percent accurate and comprehensive. Better data transparency on these coal finance deals would help us gain more insights that could guide policy making to make the energy investment more sustainable and clean in the future.

Using simple difference based on the start year of power plants, we find that the operation of coal-fired power plants leads to significant increase in SO2 column amounts. The magnitude of impact decreases with the radius of buffer we use to extract the SO2 levels around the power plant, and increases with the quantile we use to summarize the daily SO2 measures to the annual observation. The signal of power plant impacts in the satellite data increases in magnitude with capacity. It is hard to observe the impact for plants under 300 MW. The impact of the power plants has the largest magnitude when we draw a circle of 20 km around the power plant and use 95% quantile. The SO2 increases almost 10% after the operation of coal-fired power plants larger than 500 MW.

While the signal of power plants in satellite-based SO2 column data is clear and survives falsification tests, it is much harder to compare the performance of plants financed by China with the rest due to relatively small sample size. When we examine all the power plants together, we find no significant differences for power plants financed by China. However, for plants larger than 300 MW, we observe that the coal-fired power plants financed by China leads to higher SO2 increase than the other plants using sub-critical technology, though not statistically significant. On the other hand, plants using supercritical technology financed by China have been shown to be cleaner, but again not statistically different from the rest.

The heterogeneous impact of Chinese-financed power plants could be conceptualized using the framework proposed by Grossman and Krueger (1993) on mechanisms through which trade and investment liberalization impact environmental outcomes. On the one hand, energy finance from China leads to an expansion of the polluting point sources, and economic activity in the region, thus increasing the local pollution ("scale effects"). As the environmental stringency in the recipient countries is generally looser than in China, the construction of subcritical power plants reflects a trend of 'race-to-the-bottom'. On the other hand, energy finance from China could be beneficial in bringing cleaner technologies to the developing countries, hinted by both the higher percentage of supercritical plants financed by China for >500 MW capacity and the cleaner outcome from supercritical power plants.

This paper focuses on the local environmental impact. It is worth noting that Chinese overseas investments in coal-fired power plants have also led to concerns on carbon emissions. The carbon consequence of the overseas fleet of power plants is significant. More than fifty coal-fired power plants has been supported by Chinese financial institutions between 2001 and 2016, which are estimated to release near 600 million metric tons of carbon dioxide annually – more than 10% of total US emissions in 2015 (Gallagher, 2016). In the long-term, if power generation, together with improvements in roads and railways, successfully spurs local businesses and economic growth, we would expect even more emission due to development investments (Zhang et al., 2017). This continuation of coal plants construction could make it very difficult or even impossible to achieve the goal of limiting temperature change to below 2° Celsius, set in Paris Agreement on Climate Change (Shearer et al., 2018).

While this study has shed light on the environmental impact of coal-fired power plants by China, in comparison with the rest, it has a few limitations. First, satellite data provides a comparable measure across different countries on environmental outcomes, but the measurements are less accurate than those captured by on-ground monitors are. Previous studies (e.g. Karplus et al., 2018) showed consistent results using the same satellite data and using the on-ground monitors in China. Nonetheless, the relationship between satellite data and on-ground measures may be complicated and different in

South Asia and Southeast Asia. Second, our analysis may be subject to selection bias, as the siting decisions of power plants financed by China may be different from the rest. We modeled different time trends for the Chinese financed plants to address this potential difference partially. A more rigorous way would be to model the siting decision directly, which would require more geo-located data on socio-economic and geo-political variables. Third, the environmental impact of small power plants (<300 MW), though not clearly captured by satellite data, could have substantial influence on the health and wellbeing of residents nearby. Fourth, many power plants are co-financed by multiple institutions. This paper focuses on the power plants that received finance from Chinese policy banks, but the performances could differ when co-financing partners are different.

Finally, our study points to a number of questions for future analysis, many of which require mixed methods, better plant-level data and deeper on-ground case studies. First, what factors could have led to the observed slightly worse environmental performance of subcritical power plants financed by China? Is it mainly because of whether the plants have installed SO2 scrubbers, the quality of coal used or the daily operational practice of the power plants (e.g. schedules)? Second, what is the underlying decision process of financing a coal power plant by the Chinese policy banks? Which player in the process decides the capacity, technology and operation details? Third, to what extent does China or the recipient country monitor the environmental performance of these power plants? Understanding these underlying mechanisms would be helpful to design policies to 'green' Chinese energy finance.

Chapter 5 Conclusion

Forecasting electricity demand and the potential impact of alternative policies will be an important task as China grapples with both domestic development needs and increasing environmental concerns at home and abroad. Growth in residential electricity use is projected to contribute roughly one-third of total demand growth through 2025, yet is relatively unstudied. The second chapter has provided the first attempt to use household-level data to construct such forecasts. We also use that data to decompose future electricity forecasts into contributions from appliance adoption, dwelling size increases, direct income effects, and potential autonomous time trends. Our preferred range of projected per capita demand growth is between 85% and 143% over 2009 to 2025 using alternative linear and non-linear autonomous trends.

Perhaps most interestingly, appliance adoption—particularly a larger number of AC units—drives up to a third of future electricity growth. Efficiency policies targeted at AC units would have a high potential impact as so many new ones are expected to drive energy demand. Meanwhile, refrigerators appear to be a large source of current household energy use. Refrigerator ownership raises household electricity demand by an estimated 19%. Thus reducing energy use of these appliances in half would reduce electricity demand by 10%. However, refrigerators have also saturated the market. Nearly 100% of households have one. Few are seeking to have two or more.

With more households using AC, we would also expect households' electricity consumption grow under a warmer climate. Estimating the impacts of climate change is essential for analysis of both mitigation and adaptation policies. Our principal finding in the third chapter, that annual electricity demand increases by 9.3% per +1°C in annual global mean surface temperature in the Yangtze River Delta, represents one of the few estimates of impacts outside western countries. This estimate can contribute to analyses of global mitigation efforts, helping to determine what level of emissions best balances costs and benefits. We note that energy demand is often one of the larger categories of monetized climate change impacts. We also estimate that peak daily electricity use increases by 36.3% per +1°C in annual GMST, assisting plans for additional capacity that will be needed in the future.

In comparison to the domestic focus of chapter 2 and chapter 3, chapter 4 analyzes the environmental impact of coal power plants financed by China. As China became a leading player in global energy finance, it is critical to understand the environmental implication of its investment. In this paper, we examine a total number of 638 coal-fired power plant units, among which 70 units were financed by China, in the Southeast Asia: India, Indonesia, Vietnam and Philippines. Our study is the first to estimate empirically the environmental impact of these coal-fired power plants using satellite data, and to compare the performance of power plants financed by China with the rest. As the power plant data and information on finance flows are not official data, our sample represents the best available sources but is not guaranteed to be 100 percent accurate and comprehensive. Better data transparency on these coal finance deals would help us gain more insights that could guide policy making to make the energy investment more sustainable and clean in the future.

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While the signal of power plants in satellite-based SO2 column data is clear and survives falsification tests, it is much harder to compare the performance of plants financed by China with the rest due to relatively small sample size. When we examine all the power plants together, we find no significant differences for power plants financed by China. However, for plants larger than 300 MW, we observe that the coal-fired power plants financed by China leads to higher SO2 increase than the other plants using sub-critical technology, though not statistically significant. On the other hand, plants using supercritical technology financed by China have been shown to be cleaner, but again not statistically different from the rest.

A. Appendix to Chapter 2

The cross-sectional Chinese Urban Household Survey (CUHS) data have two different data sets: one dataset on household features (e.g., household size, dwelling size, electricity consumption) and another dataset on household head characteristics (e.g., age and education level of household head). We first merged the two datasets by household identity generated from household code and regional code: 510420 out of 510474 observations are merged successfully. Note that it is possible that two or more people are matched to one household because multiple people are surveyed in the household. The people merged to one household would share the same household-level characteristics while differ in personal characteristics. We calculate the number of old people and the number of young people matched to each household. This information is added to the dataset as a household-level feature for each observation.

The cleaning process for the merged dataset is shown in the following table. The steps are conducted sequentially. For each step, we present the number of the observations dropped in the step and the share of the dropped observations among the total 510420 successfully merged observations. Note that we only focus on the demographic information of the household head because they are assumed to be the decision maker of the household. The observations before the cleaning process is on individual level while the unit of observations after the cleaning process is the household level.

Table A.1 Data Cleaning Process for the China Urban Household Survey (CUHS)

	Reason of dropping	Number dropped	Share(%)
Step 1.	No demographic information	125310	14.55
Step 2.	Zero electricity expenditure	11896	2.33
Step 3.	Zero household size	2569	0.50
Step 4.	Zero dwelling size	182	0.04
Step 5.	Age less than 16	50754	9.94
Step 6.	Dwelling size larger than 300 square meters	1870	0.37
Step 7.	More than 6 old people in the household	4296	0.84
Step 8.	Heat by AC but do not own AC	1093	0.21
Step 9.	Have missing values for the variables	54	0.01
Step 10.	Not household head	190144	37.24
	Total number left:	122252	23.95

B. Appendix to Chapter 3

Time-series estimation results

In the preparation of the data sample we used in the panel regression, one might worry about the relatively large drop in the whole data set after clean and the representativeness of the small sample. As the variations in regression mainly come from random shocks of temperature, we could capture the electricity-temperature relationship using the time-series regression. More specifically, we run the following regression:

$$lnEC_t = \beta_0 + \sum \beta_{1_j} f_j(TEMP_t) + \beta_2 HUMIDITY_t + \beta_3 V_t + \beta_4 EAST_t + \beta_5 WEST_t + \beta_6 SOUTH_t + \beta_7 EAST_t \cdot V_t + \beta_8 WEST_t \cdot V_t + \beta_9 SOUTH_t \cdot V_t + \beta_{10} PM_{2.5} + \beta_{11} WEEKEND_t + \delta_{m,y} + \epsilon_t \tag{S1}$$

The control variables remain the same as the main regression (Eq. 3.1). The only difference is that we no longer control the individual fixed effects and the regression is run on a single time series of the average electricity consumption. We run this regression on the whole data before cleaning, whole data after cleaning and the merged sample.

The estimated U-shape curves are similar across the samples (Figure B.3). Normally, an electricity planner is likely to care about the system response, based on the whole data before cleaning. In Shanghai, as the smart metering only started in recent years and the performance was not guaranteed in the early years, we believe that cleaning the data moves the noises. It makes sense to base our forecasts on the residents that actually frequently live in the apartments, as the vacancy rate would likely to change with the economy condition and housing prices in particular.

Damage Function Calculation

Using the relationship expressed in Eq. 3.1 and displayed in Figure 3.2, we calculate electricity change using temperature changes from 21 models and 2 RCP scenarios separately. For each model, we first calculate the average daily temperature across years for each of 365 calendar days in the historical period (1980-1999) and the forecast period (2080-2099) under both RCP4.5 and RCP8.5. We then calculate the difference between the future and the past average calendar day temperatures under RCP4.5 or RCP8.5 separately for each model. Finally, we aggregate across calendar days to estimate the change in annual electricity demand.

More precisely, let T and T' denotes the past and future average temperature for calendar day d respectively. Based on the log-linear specification, the percent change in electricity consumption (EC) change on day d is calculated as:

$$\frac{\Delta EC_d}{EC_d} = \frac{EC'_d}{EC_d} - 1 = \frac{\exp\left(\sum \beta_{1j} f_j(T'_d)\right)}{\exp\left(\sum \beta_{1j} f_j(T_d)\right)} - 1 = \exp(\beta_1(f(T'_d) - f(T_d))) - 1 \qquad \text{(S2)}$$

where $\frac{\Delta EC_d}{EC_d}$ is the percentage change in daily electricity use due to climate change through changes in temperatures from T_d to T'_d. The function $f_j(\cdot)$ represents the transformation of temperature to the spline basis. We aggregate the daily electricity consumption change using daily electricity consumption in our sample during year 2015[1]. We implicitly assume that the year-month fixed effects and other weather variables including humidity and wind remain the same for the past and future, which is a standard assumption adopted in the majority of impact literature (e.g. Deschênes and Greenstone, 2011; Davis and Gertler, 2015; Auffhammer et al., 2017).

[1] Using a weighted aggregation is important as daily electricity fluctuates from season to season. Given some households joined later than others do, more households have complete data in 2015. Therefore, we use the household pattern of 2015.

Table B.1 Recent Literature on the Impact of Climate Change on Electricity Demand

Paper	Location	Data set	Data type	Frequency	Period	Method	Climate scenario	End-of-Century increase in electricity
Crowley and Joutz (2003)	US (PJM)	hourly load data	time series	hourly	1998-2001	log-linear: quadratic terms for CDD	2°F increase in the daily temperature	3.8% of actual consumption
Franco and Sanstad (2008)	California	hourly consumption data by CA1ISO	time series	hourly	2004-2005	polynomial	Hadley3, PCM, GFDL	0.8 - 17.8% increase in average, peak increases by 1.0-19.8%
Deschenes and Greenstone (2011)	US	energy data from EIA	panel	annual	1968-2002	log-linear:10 equidistant bins	Hadley3 A1F1 (error-corrected)	11%
Auffhammer and Aroonruengsawat (2012)	California	residential billing data	panel	monthly	2003-2006	log-linear, bins based on deciles and equidistant bins	downscaled version from PCM, GFDL, CNRM	1 - 6 %
Davis and Gertler (2015)	Mexico	residential billing data and ENIGH survey data	panel	monthly	2009-2012	log-linear, predetermined bins	RCP4.5, RCP8.5	RCP4.5: 7.5%; RCP8.5: 15.4%
Auffhammer et al. (2017)	US	load balancing authorities	panel	hourly	2006-2014	linear-linear model: 3°C bins below 21°C, one bin above 21°C	RCP4.5, RCP8.5	average increase by 2.8%, peak by 7.2% under RCP4.5

Table B.2 Number of Households Left after Each Data-cleaning Step

Data cleaning steps:	N
	1,837,998
(1) drop if start-date is later than 1/1/2015	1,328,972
(2) drop if average daily consumption is lower than 1 kWh or higher than 50 kWh	1,197,082
(3) drop if the electricity consumption is less than 0.3 kWh for more than 37 days	841,784

Table B.3 Summary Statistics of Household Data in Our Sample, Compared with Shanghai, China and Urban China

	Sample	Shanghai	China	Urban China
Per capita monthly income (RMB)	5649	4798	1831	2600
Gender (% of female)	52%	50%	49%	-
Proportion of urban population	100%	88%	56%	-
Education level				
Junior middle school and below	39%	50%	70%	-
Senior high school	22%	21%	16%	-
Junior college	14%	12%	7%	-
Undergraduate and above	24%	17%	7%	-
Appliances ownership (sets)				
Air conditioners	1.93	1.81	0.82	1.15
Fridges	1.00	0.96	0.89	0.94
TVs	1.52	1.74	1.20	1.22
Washing machines	1.08	0.89	0.86	0.92
Computer	1.26	1.17	0.56	0.79
Microwave	0.83	0.84	0.37	0.54

Data source: China Statistical Yearbook (2016), available at http://www.stats.gov.cn/tjsj/ndsj/2016/indexeh.htm.

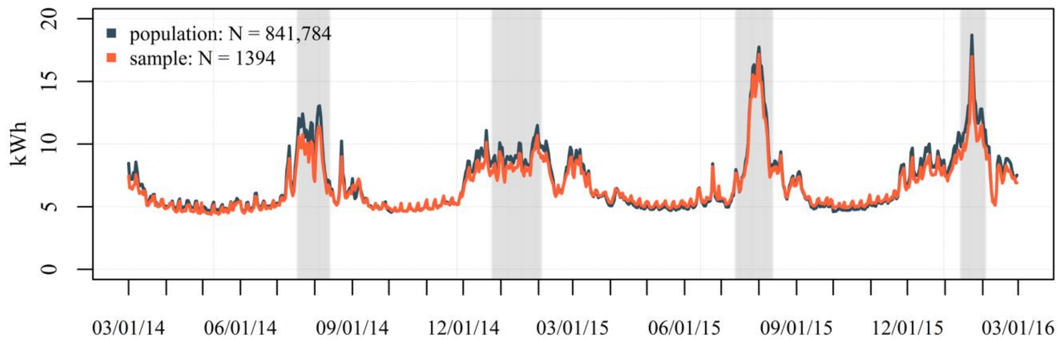

Figure B.1 Daily Average Electricity of the Sample Matches the Population

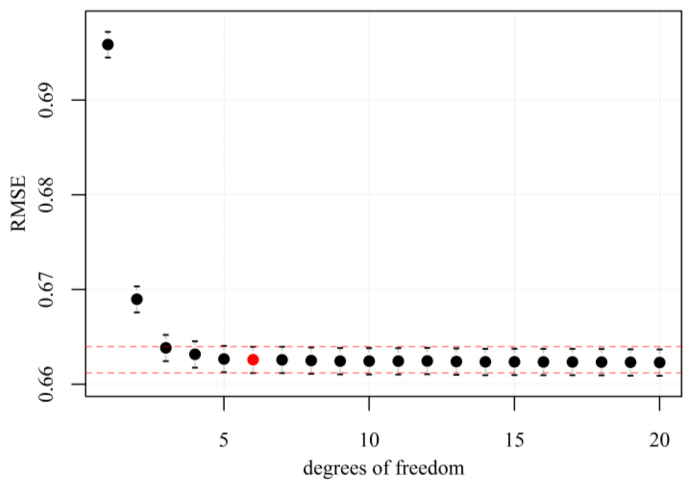

Figure B.2 Root-mean-square error (RMSE) Based on 10-fold Cross-validation

Note: the cross-validation is run on each of the 10 random subsamples and the results are the same (only one shown here). To create this figure, we first split the sample randomly into training sample (9/10 of the sample) and test sample (1/10 of the sample) based on household IDs. This would ensure that different days of a household remain in the same split sample. For each degree of freedom (df), we use the set of households in the training sample to estimate the splines and then predict using the test sample. Because out-of-sample prediction in a fixed-effect model is impossible, we first demean the data w.r.t. year-month and individual. We could then apply simple OLS regressions to the demeaned data and predict easily, which is mathematically equivalent to running the fixed-effect model. To get a sense of the distribution of RMSEs due to different initial splits, we run the above process 1000 times. The figure plots the mean of 1000 RMSEs at each df level, as well as 1 standard error (SE) above and below.

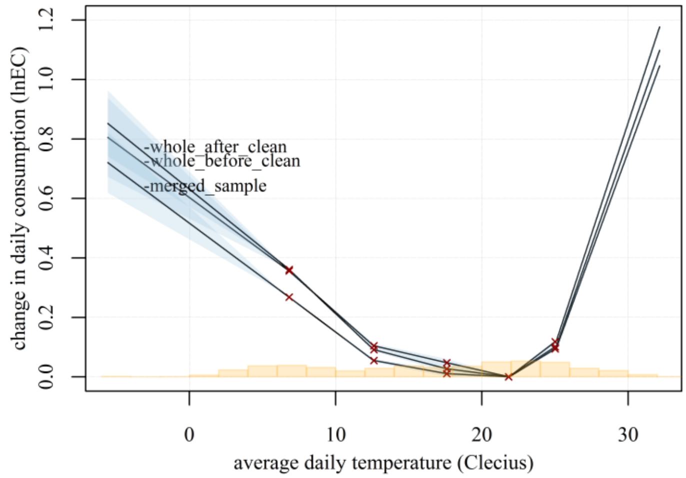

Figure B.3 The Effect of Temperature on Daily Electricity Demand Based on Time-series

Note: The graph is based on the regression results from Eq. B.1. Each curve represents a different run using a different time series of electricity on the left-hand side (whole data before cleaning, whole data after cleaning and the merged sample). The corresponding numbers of households averaged to create the time-series are: 1,837,998, 841,784 and 1,394. The light blue shade represents the 95% confidence intervals, based on standard errors generated using two-way clustering at the household and week level. The red marks suggest the knots in the splines.

References

Arellano, M. (1987). PRACTITIONERS' CORNER: Computing Robust Standard Errors for Within‐groups Estimators. Oxford bulletin of Economics and Statistics, 49(4), 431-434.

Asian Development Bank (2017). Meeting Asia's infrastructure needs.

Auffhammer M., Aroonruengsawat A. (2011) Simulating the impacts of climate change, prices and population on California's residential electricity consumption. Clim Change 109(1):191-210.

Auffhammer M., Baylis P., Hausman C. H. (2017) Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States. Proc Natl Acad Sci USA 114(8): 1886-1891.

Auffhammer M., Hsiang S. M., Schlenker W., Sobel A. (2013) Using weather data and climate model output in economic analyses of climate change. Review of Environmental Economics and Policy 7(2):181-198.

Auffhammer M., Mansur E. T. (2014) Measuring climatic impacts on energy consumption: A review of the empirical literature. Energy Economics 46: 522-530.

Auffhammer, M., & Wolfram, C. D. (2014). Powering up China: Income distributions and residential electricity consumption. The American Economic Review, 104(5), 575-580

Mauer, Joanna , Andrew deLaski, Steven Nadel, Anthony Fryer, and Rachel Young (2013). Better Appliances: An Analysis of Performance, Features, and Price as Efficiency Has Improved. ACEEE Research Report A132. Washington: ACEEE.

Barreca A. I. (2012) Climate change, humidity, and mortality in the United States. J Environ Econ Manage 63(1):19-34.

Bernard, J. T., Bolduc, D., & Belanger, D. (1996). Quebec residential electricity demand: a microeconometric approach. Canadian Journal of Economics, 92-113.Bhattacharyya, S. C., & Timilsina, G. R. (2010). Modelling energy demand of developing countries: Are the specific features adequately captured? Energy Policy, 38(4), 1979-1990. doi: 10.1016/j.enpol.2009.11.079

Bluhm, R., Dreher, A., Fuchs, A., Parks, B., Strange, A., & Tierney, M. J. (2018). Connective financing: Chinese infrastructure projects and the diffusion of economic activity in developing countries.

Bose, R. K., & Shukla, M. (1999). Elasticities of electricity demand in India.Energy Policy, 27(3), 137-146.

Boustan L. P., Kahn M. E., Rhode P. W. (2012) Moving to higher ground: Migration response to natural disasters in the early twentieth century. Am Econ Rev 102(3): 238-44.

Brandt, L., & Holz, C. A. (2006). Spatial price differences in China: Estimates and implications. Economic development and cultural change, 55(1), 43-86.

Brock, C. A., Washenfelder, R. A., Trainer, M., Ryerson, T. B., Wilson, J. C., Reeves, J. M., ... & Fehsenfeld, F. C. (2002). Particle growth in the plumes of coal‐fired power plants. Journal of Geophysical Research: Atmospheres, 107(D12).

Burlig, F., & Preonas, L. (2016). Out of the Darkness and Into the Light? Development Effects of Rural Electrification in India. Energy Institute at Haas Working Paper, 268.

Cai, J., & Jiang, Z. (2008). Changing of energy consumption patterns from rural households to urban households in China: An example from Shaanxi Province, China. Renewable and Sustainable Energy Reviews, 12(6), 1667-1680. doi: 10.1016/j.rser.2007.03.002

Cao, J., Ho, M., Liang, H. (2016). Household Energy Demand in Urban China: accounting for regional prices and rapid income change. The Energy Journal, 37. doi: http://dx.doi.org/10.5547/01956574.37.SI1.jcao

Cao J., Ho M. S., Li Y., Newell R. G., Pizer W. A. (2017) Chinese residential electricity consumption: Estimation and forecast using micro-data. Resource and Energy Economics. DOI:10.1016. Preprint, posted November 17, 2017.

Chakravorty, U., Emerick, K., & Leah-Ravago, M. (2016). Lighting up the last mile: The benefits and costs of extending electricity to the rural poor.

Chen, M. X., & Lin, C. (2018). Foreign Investment across the Belt and Road: Patterns, Determinants, and Effects. The World Bank.

CoalSwarm (2018), "Global Coal Plant Tracker", July 2018

Crowley, C., & Joutz, F. (2003, October). Hourly electricity loads: Temperature elasticities and climate change. In 23rd US Association of Energy Economics North American Conference.

Davis, L. W. (2011). The effect of power plants on local housing values and rents. Review of Economics and Statistics, 93(4), 1391-1402.

Davis L. W., Gertler P. J. (2015) Contribution of air conditioning adoption to future energy use under global warming. Proc Natl Acad Sci USA 112(19):5962-5967.

Deschênes, O., Greenstone M. (2011) Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the US. Am Econ J Appl Econ 3(4):152-185.

Dinkelman, T. (2011). The effects of rural electrification on employment: New evidence from South Africa. The American Economic Review, 101(7), 3078-3108.

Dollar, D. (2018). Is China's Development Finance a Challenge to the International Order?. Asian Economic Policy Review, 13(2), 283-298.

Dreher, A., Fuchs, A., Parks, B.C., Strange, A. M., & Tierney, M. J. (2017). Aid, China, and Growth: Evidence from a New Global Development Finance Dataset. AidData Working Paper #46. Williamsburg, VA: AidData.

Du, G., Lin, W., Sun, C., & Zhang, D. (2015). Residential electricity consumption after the reform of tiered pricing for household electricity in China. Applied Energy, 157, 276-283.

Dubin, J. A., & McFadden, D. L. (1984). An econometric analysis of residential electric appliance holdings and consumption. Econometrica: Journal of the Econometric Society, 345-362.

Energy Information Administration (EIA), International energy and data analysis (China) 2015, http://www.eia.gov/beta/international/analysis_includes/countries_long/China/china.pdf

Eric Hirst, R. G. a. J. C. (1982). Residential energy use: analysis of disaggregate data.

Fell, H., Li, S., & Paul, A. (2014). A new look at residential electricity demand using household expenditure data. International Journal of Industrial Organization, 33, 37-47.

Firth, S., Lomas, K., Wright, A., & Wall, R. (2008). Identifying trends in the use of domestic appliances from household electricity consumption measurements. Energy and Buildings, 40(5), 926-936. doi: 10.1016/j.enbuild.2007.07.005

Fischer, C. (2008). Feedback on household electricity consumption: a tool for saving energy? Energy Efficiency, 1(1), 79-104. doi: 10.1007/s12053-008-9009-7

Fisher, F.M. & Kaysen, C. (1962). A Study in Econometrics: The Demand for Electricity in the United States. North-Holland Publishing Co, Amsterdam.

Forrest, J., & Newman, L. (1977). Further studies on the oxidation of sulfur dioxide in coal-fired power plant plumes. Atmospheric Environment (1967), 11(5), 465-474.

Franco, G., & Sanstad, A. H. (2008). Climate change and electricity demand in California. Climatic Change, 87(1), 139-151.

Gallagher, KellySims. (2016). The Carbon Consequences of China’s Overseas Investments in Coal, The Center for International Environment and Resource Policy (CIERP), CIERP Policy Brief, Fletcher School of Law and Diplomacy, Tufts University.

Gallagher, K. P., Kamal, R., Wang, Y., & Chen, Y. (2016). Fueling Growth and Financing Risk. Boston University Global Economic Governance Initiative.

Gallagher, Kevin P (2017). “China’s Global Energy Finance”, Global Economic Governance Initiative, Boston University.

Gallagher, K. P., Kamal, R., Jin, J., Chen, Y., & Ma, X. (2018). Energizing development finance? The benefits and risks of China's development finance in the global energy sector. Energy policy, 122, 313-321.

Ghanem, D., & Zhang, J. (2014). ‘Effortless Perfection:’Do Chinese cities manipulate air pollution data?. Journal of Environmental Economics and Management, 68(2), 203-225.

Gillingham, R. A. a. R. (1980). An Analysis of the Short-Run Consumer Demand for Gasoline Using Household Survey Data. The Review of Economics and Statistics, 62(1), 622-628.

Grossman, G. M., & Krueger, A. B. (1991). Environmental impacts of a North American free trade agreement (No. w3914). National Bureau of Economic Research.

Gupta E. (2016) The Effect of development on the climate sensitivity of electricity demand in India. Climate Change Economics 7(02): 1650003.

Halvorsen, R. (1975). Residential demand for electric energy. The Review of Economics and Statistics, 12-18.

Hausman, J. A. (1979). Individual discount rates and the purchase and utilization of energy-using durables. The Bell Journal of Economics, 10(1), 33-54.

Heathcote, J., Perri, F., & Violante, G. L. (2010). Unequal we stand: An empirical analysis of economic inequality in the United States, 1967–2006. Review of Economic dynamics, 13(1), 15-51.

Holtedahl, P., & Joutz, F. L. (2004). Residential electricity demand in Taiwan.Energy economics, 26(2), 201-224.

Hsiang, S. (2016). Climate econometrics. Annual Review of Resource Economics, 8, 43-75.

Hsiang, S., Kopp, R., Jina, A., Rising, J., Delgado, M., Mohan, S., ... & Larsen, K. (2017). Estimating economic damage from climate change in the United States. Science, 356(6345), 1362-1369.International Energy Agency (IEA). World Energy Outlook 2014.

International Energy Agency (IEA). World Energy Outlook 2017.

International Energy Agency (IEA). The Future of Cooling: Opportunities for Energy-Efficient Air-Conditioning.

Ito K., Zhang S. (2016) Willingness to pay for clean air: Evidence from air purifier markets in China. National Bureau of Economic Research working paper no. w22367.

Jones, R. V., & Lomas, K. J. (2015). Determinants of high electrical energy demand in UK homes: Socio-economic and dwelling characteristics. Energy and Buildings, 101, 24-34.

Kahn, M. E. (2009). Regional growth and exposure to nearby coal fired power plant emissions. Regional Science and Urban Economics, 39(1), 15-22.

Karplus, V. J., Zhang, S., & Almond, D. (2018). Quantifying coal power plant responses to tighter SO2 emissions standards in China. Proceedings of the National Academy of Sciences, 201800605.

Kaza, N. (2010). Understanding the spectrum of residential energy consumption: A quantile regression approach. Energy Policy, 38(11), 6574-6585. doi: 10.1016/j.enpol.2010.06.028

Kong, B., & Gallagher, K. P. (2017). Globalizing Chinese Energy Finance: The Role of Policy Banks. Journal of Contemporary China, 26(108), 834-851.

Koplitz, S. N., Jacob, D. J., Sulprizio, M. P., Myllyvirta, L., & Reid, C. (2017). Burden of disease from rising coal-fired power plant emissions in Southeast Asia. Environmental science & technology, 51(3), 1467-1476.

Larsen, B. M., & Nesbakken, R. (2004). Household electricity end-use consumption: results from econometric and engineering models. Energy Economics, 26(2), 179-200. doi: 10.1016/j.eneco.2004.02.001

Leahy, E., & Lyons, S. (2010). Energy use and appliance ownership in Ireland. Energy Policy, 38(8), 4265-4279.

Lenzen, M., Wier, M., Cohen, C., Hayami, H., Pachauri, S., & Schaeffer, R. (2006). A comparative multivariate analysis of household energy requirements in Australia, Brazil, Denmark, India and Japan. Energy, 31(2-3), 181-207. doi: 10.1016/j.energy.2005.01.009

Li, C., Zhang, Q., Krotkov, N. A., Streets, D. G., He, K., Tsay, S. C., & Gleason, J. F. (2010). Recent large reduction in sulfur dioxide emissions from Chinese power plants observed by the Ozone Monitoring Instrument. Geophysical Research Letters, 37(8).

Li, C., McLinden, C., Fioletov, V., Krotkov, N., Carn, S., Joiner, J., ... & Dickerson, R. R. (2017). India is overtaking China as the world’s largest emitter of anthropogenic sulfur dioxide. Scientific reports, 7(1), 14304.

Li, M., Patiño-Echeverri, D., & Zhang, J. J. (2019). Policies to promote energy efficiency and air emissions reductions in China's electric power generation sector during the 11th and 12th five-year plan periods: Achievements, remaining challenges, and opportunities. Energy Policy, 125, 429-444.

Lin, J., Liu, X., & Karl, F. (2016). Excess Capacity in China’s Power Systems: A Regional Analysis. Lawrence Berkeley National Laboratory (LBNL), Berkeley.

Massetti, E., & Mendelsohn, R. (2011). Estimating Ricardian models with panel data. Climate Change Economics, 2(04), 301-319.

McNeil, M. A., & Letschert, V. E. (2010). Modeling diffusion of electrical appliances in the residential sector. Energy and Buildings, 42(6), 783-790.

Morris, S., & Pizer, B. (2013). Thinking Through When the World Bank Should Fund Coal Projects. Center for Global Development.

Murata, A., Kondou, Y., Hailin, M., & Weisheng, Z. (2008). Electricity demand in the Chinese urban household-sector. Applied Energy, 85(12), 1113-1125. doi: 10.1016/j.apenergy.2007.05.008

National Academies of Sciences, Engineering, and Medicine. 2017. Valuing Climate Damages: Updating Estimation of the Social Cost of Carbon Dioxide. Washington, DC: The National Academies Press. https://doi.org/10.17226/24651.

Nesbakken, R. (1999). Price sensitivity of residential energy consumption in Norway. Energy Economics, 21, 493-515.

O'neill, B. C., & Chen, B. S. (2002). Demographic determinants of household energy use in the United States. Population and development review, 28, 53-88.

Pachauri, S. (2004). An analysis of cross-sectional variations in total household energy requirements in India using micro survey data. Energy Policy, 32(15), 1723-1735. doi: 10.1016/s0301-4215(03)00162-9

Pachauri, S., & Jiang, L. (2008). The household energy transition in India and China. Energy Policy, 36(11), 4022-4035. doi: 10.1016/j.enpol.2008.06.016

Pardo, A., Meneu, V., & Valor, E. (2002). Temperature and seasonality influences on Spanish electricity load. Energy Economics, 24(1), 55-70.

Parti, M., & Parti, C. (1980). The total and appliance-specific conditional demand for electricity in the household sector. The Bell Journal of Economics, 309-321.

Paul Baker, R. B., John Micklewright. (1989). Modelling household energy expenditures using Micro-data. The Economic Journal, 99(397), 720-738.

Paul Baruya. (2017). International finance for coal-fired power plants. IEA Clean Coal Centre.

Peirson J., Henley A. (1994) Electricity load and temperature: Issues in dynamic specification. Energy Economics 16(4): 235-243.

Peng, R., Chang, L., & Liwen, Z. (2017). China's involvement in coal-fired power projects along the belt and road. Global Environmental Institute.

Rasmussen D. J., Meinshausen M., Kopp R. E. (2016) Probability-weighted ensembles of US county-level climate projections for climate risk analysis. Journal of Applied Meteorology and Climatology 55(10): 2301-2322.

Reiss, P. C. (2005). Household electricity demand revisited. Review of Economic Studies, 72, 853-883.

Richard Bluhm, Axel Dreher, Andreas Fuchs, Bradley Parks, Austin Strange, and Michael Tierney. (2018). Connective Financing: Chinese Infrastructure Projects and the Diffusion of Economic Activity in Developing Countries. AidData Working Paper #64. Williamsburg, VA: AidData at William & Mary.

Rose S., Turner D., Blanford G., Bistline J., de la Chesnaye F., Wilson T. (2014) Understanding the Social Cost of Carbon: A Technical Assessment. EPRI report 3002004657.

Salvo, A. (2018). Electrical appliances moderate households' water demand response to heat. Nature communications, 9(1), 5408.

Shearer, C., Ghio, N., Myllyvirta, L., Yu, A., & Nace, T. (2018). Boom and bust 2018: tracking the global coal plant pipeline. Retrieved from CoalSwarm, Greenpeace, and Sierra Club: https://endcoal.org/wp-content/uploads/2018/03/BoomAndBust_2018_r4.pdf

Shi, G., Zheng, X., & Song, F. (2012). Estimating elasticity for residential electricity demand in China. The Scientific World Journal, 2012.

Shi, Y., Gao, X., Xu, Y., Giorgi, F., & Chen, D. (2016). Effects of climate change on heating and cooling degree days and potential energy demand in the household sector of China. Climate Research, 67(2), 135-149.

Steffen, B., & Schmidt, T. S. (2018). A quantitative analysis of 10 multilateral development banks' investment in conventional and renewable power-generation technologies from 2006 to 2015. Nature Energy.

Swan, L. G., & Ugursal, V. I. (2009). Modeling of end-use energy consumption in the residential sector: A review of modeling techniques. Renewable and Sustainable Energy Reviews, 13(8), 1819-1835. doi: 10.1016/j.rser.2008.09.033

Taylor, L. D. (1975). The demand for electricity: a survey. The Bell Journal of Economics, 74-110.

Taylor, L., Blattenberg, G.R. & Rennhack, R. (1984). Residential demand for energy in the United States: empirical results for electricity. In: Moroney, J.R. (Ed.), Advances in the Economics of Energy and Resources, vol 5. JAI Press, Greenwich, CT, pp. 85–102.

Tol R. S. (2009) The economic effects of climate change. J of Econ Perspect 23(2):29-51.

Ueno, T., Yanagi, M., & Nakano, J. (2014). Quantifying Chinese Public Financing for Foreign Coal Power Plants. The University of Tokyok GraSPP Working Paper Series, 1-29.

US EPA. (2008). Integrated Science Assessment for Sulfur Oxides–Health Criteria. EPA/600/R-08/047F, National Center for Environmental Assessment, Office of Research and Development.

US EPA. (2010). Sulfur Dioxide (SO2) Primary Standards – Documents from Review Completed in 2010 – Regulatory Impact Analysis, available at https://www3.epa.gov/ttn/ecas/docs/ria/naaqs-so2_ria_proposal_2009-11.pdf (accessed on 02/06/2019)

Vaage, K. (2000). Heating technology and energy use: a discrete continuous choice approach. Energy Economics, 22, 649-666.

Valor, E., Meneu, V., & Caselles, V. (2001). Daily air temperature and electricity load in Spain. Journal of applied Meteorology, 40(8), 1413-1421.

Van de Walle, D., Ravallion, M., Mendiratta, V., & Koolwal, G. (2017). Long-term gains from electrification in rural India. The World Bank Economic Review, 31(2), 385-411.

Woetzel, J., Garemo, N., Mischke, J., Hjerpe, M., & Palter, R. (2016). Bridging global infrastructure gaps. San Francisco, CA: McKinsey Global Institute.

World Bank. (2012). Transformation through Infrastructure.

World Bank. (2013). Toward a sustainable energy future for all: directions for the World Bank Groups energy sector. Washington, DC: World Bank.

World Bank (2015). Progress Toward Sustainable Energy 2017: Global Tracking Framework Report. Washington, USA, World Bank Publications.

Wu, X., & Perloff, J. M. (2005). China's income distribution, 1985–2001. Review of Economics and Statistics, 87(4), 763-775.

Zhang P., Zhang J., Chen M. (2017) Economic impacts of climate change on agriculture: The importance of additional climatic variables other than temperature and precipitation. J Environ Econ Manage 83: 8-31.

Zhang, X. Y., Chuai, X. W., Liu, L., Zhang, W. T., Lu, X. H., Zhao, L. M., & Chen, D. M. (2018). Decadal trends in wet sulfur deposition in China estimated from OMI SO2 columns. Journal of Geophysical Research: Atmospheres, 123(18), 10-796.

Zhou, S., & Teng, F. (2013). Estimation of urban residential electricity demand in China using household survey data. Energy Policy, 61, 394-402. doi: 10.1016/j.enpol.2013.06.092

Zimmerman, D. R. B. a. M. B. (1984). An update on econometric studies of energy demand behavior. Ann. Rev. Energy, 9, 105-154.

Biography

Yating Li obtained her degrees in Bachelor of Sciences in 2012 and Master in International Economics in 2014 from Renmin University of China, and Doctor of Philosophy in May 2019 from Duke University, focusing on environmental and energy economics. She is an Energy Doctoral Fellow at Duke University Energy Initiative and a China Fellow at the Global Development Policy Center at Boston University. In her ongoing work, she examines electricity consumption in China using micro-level data sets, including the response to income growth, demographic factors, air pollution and climate change.

Yating Li is interested in understanding the footprints of Chinese overseas investment, especially on environmental, energy and development outcomes. With a grant from Duke Support for Interdisciplinary Graduate Networks, she brought together graduate students from different disciplines and different countries to work together on issues related to the Belt and Road Initiative. With an interest in the development outcomes of energy access and in energy finance, she co-led the Global Energy Access Network (GLEAN) of over 100 graduate students from five different departments to help position Duke as a central contributor to issues around energy access. She also actively contributed to several energy-related on-campus research groups including Sustainable Energy Transitions Initiative (SETI) at Duke University.