Three Essays on the Impact of Global Warming in India

by

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B.A.(University of Delhi at Hansraj College) 2003
M.A. (Delhi School Of Economics) 2005

A dissertation submitted in partial satisfaction of the
requirements for the degree of
Doctor of Philosophy

in

Economics

in the

INDIAN STATISTICAL INSTITUTE

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2014

Three Essays on the Impact of Global Warming in India

Dedicated To Lord Krishna

Contents

[1]This chapter has been published in the journal of Energy Economics.

[2]This chapter is joint with Prof. E. Somanathan and Prof. Bharat Ramaswami

List of Figures

List of Tables

Acknowledgments

It gives me great pleasure that I have an opportunity to place on record, the contributions of several people, who have been instrumental in crystallizing this thesis. First and foremost, I sincerely thank my thesis supervisor, Prof. E. Somanathan, for his guidance, help and motivation, which made this journey a success. Apart from the subject of my research, I learnt a lot from him, which I am sure, will be useful in different stages of my life. He gave me the freedom to explore different ideas and dimensions and was supportive in his approach. He stood by me, and was always patient to listen to me. I treasure his confidence, his insight and his endurance. I also thank Prof. Bharat Ramaswami, my coadviser in the thesis for his important contribution. His wisdom and sense of judgement is amazing. I am extremely thankful for his suggestions all through. I consider myself quite fortunate to have had such an understanding and caring advisers, throughout the course of my stay at the Institute. It is indeed due to their constant encouragement that this work has materialized.

During the course of this thesis, I have benefited from discussions with several people, whose suggestions have gone a long way in developing the thesis. I am quite grateful to Dr. Abhiroop Mukhopadhyay, with whom I have had several stimulating discussions at different stages of the thesis. Thanks for his support. I thank Professors Probal Chaudhuri and Trevor Hastie and Drs. Swagata Nandi and Deepayan Sarkar for help with developing the research; and Dr. Simon Woods for his assistance with understanding the issues surrounding Generalized Additive Models (GAMs) estimation in R software with mgcv package. I also acknowledge useful comments from Drs. Indira Rajaraman, Nityananda Sarkar and Rohini Somanathan. Lastly, I must also thank the reviewers of the manuscript that have been published in Energy Economics for extremely useful comments on the first chapter.

The data for the research came from many sources. I thank Messrs. SK Sonee, Ashok Rajput, Harish Rathore, Hemant Jain and AK Kaul for their support in procuring electricity data and Mr. Shyam Kumar and Mr. Rakesh Sinha for assistance with data operations. The funding for the paper has been provided by the Planning & Policy Research Unit (PPRU) at ISI.

Finally, I thank my family members who patiently supported me and persevered with my rolling deadline of thesis submission. I must specially mention my husband Parag, who obviously had to endure a lot more of my own pressures, and my parents, to whom I owe everything in life.

Chapter 1

Introduction

This dissertation consists of three chapters. The first chapter studies the impact of climate change on electricity demand in Delhi using daily data on electricity demand and apparent temperature for the period 2000-09. It estimates a semi-parametric variable coefficient model that allows for a non-linear relationship between temperature and electricity to shift over time, a feature that is necessary to incorporate given the rapid economic growth in India. As evident from previous studies, electricity demand is a U-shaped function of temperature. Three results from our analysis have important implications for electricity-climate policy: Firstly, the rising part of the temperature-electricity curve is becoming more pronounced over time implying an increase in cooling demand per unit increase in summer temperatures. A 1^0C increase in temperature at 30 ^{0}C increased the electricity demand by over 3 MkWh in 2009 as compared to only over 1 MkWh in 2000. On the other hand, a 1^0C increase in temperature at 15 ^{0}C decreased the electricity demand by only 0.8 MkWh in 2009 as compared to 0.7 MkWh in 2000. Secondly, the increasing temperature dependence of the cooling demand shifts the temperature-electricity curve of Delhi leftwards. In particular, the minimum temperature threshold (TT) shifts from about 20-22 ^{0}C in the first half (2000-05) to about 18.5-20.5 ^{0}C in the second half (2006-09) of the period. Thirdly, while higher temperatures would increase electricity demand in all seasons except winters, the maximum impact is likely to be felt in the hot month of April, with average apparent temperatures of 30 ^{0}C, followed by October and May. Thus, the results suggest that the adverse effects of climate change on electricity demand to be asymmetrically distributed in different seasons in the future, resulting in a serious disequilibrium in the hot months.

The second chapter extends the analysis to all-India level, enabling the use of the large climatic and income variation across states to assess the dependence of the temperature-electricity demand relation on the level of income and climate. This chapter aims to understand how India's electricity demand will be affected by changes in its climate, weather and income. To what extent does the weather sensitivity of electricity demand depend on climate and the level of income? Due to growth, the impact of climate change in India will be time-varying. The climate sensitivity of electricity demand in India is likely to be highly sensitive to growth in income. Thus, both intensive and extensive adjustments in cooling and heating will play an important role in determining future climate change impacts on electricity demand. This chapter utilizes a national level panel dataset of 28 Indian states for the period 2005-2009 to show that (1) electricity demand is positively related to temperatures in summers and negatively related to temperatures in winters; (2) the effect of temperature increase on demand in summers is higher in a hotter climate as people adapt with the use of higher cooling equipment whereas there is a higher negative response to temperature increase in winters in colder climates as people adapt using higher heating equipment; (3) the effects of both the hotter and the colder climates on electricity demand are expected to be more pronounced at the higher income levels. The preferred estimates indicate that climate change will increase electricity demand by 6.9 percent with 4 percent p.a. GDP growth and 8.6 percent with 6 percent p.a. GDP growth in 2030 over the reference scenario of no climate change. This reflects the fact that the estimated marginal effect of a hotter climate is greater when income is higher. The results suggest that over 50 percent of the climate change impacts will be due to extensive adjustments and that electricity demand models that do not account for extensive adjustments are likely to underestimate the climate change impacts on electricity demand especially in developing countries like India where the current penetration of air- conditioning equipment is very low.

The third chapter studies climate change impacts on food prices and poverty in India. In this chapter, we develop a stylized two-sector (food and non-food) general equilibrium framework inspired by [Eswaran & Kotwal, 1993] for studying the impact of climate change on food prices and household welfare in India. The demand side is modelled by a preference structure rooted in Engel's law, according to which there is an inverse relationship between a household's income and its share devoted to food. The analysis is conducted separately under closed and open economy assumptions in order to judge the impact of trade. The simplicity of the model allows us to transparently assess the factors driving the results. The framework indicates how the initial conditions in terms of the level and distribution of wealth and land results in heterogeneity in a household's vulnerability to climate change in an economy.

The model is first calibrated to data from 2009. We estimate the impact of historic climate change and pollution trends over a 30-year period (1980-2009) on food prices and the welfare of the poor in 2009. We find that food prices were 4 to 8 percent higher and the real income of the landless poor was 2.4 to 4.8 percent lower in 2009 relative to a counterfactual without climate change and pollution (over the past three decades). In 2030, agricultural productivity is 7% lower compared to a scenario without further climate impacts, then food prices will be 3.6 to 10.8 percent higher and real income of the landless 1.6 to 5.6% lower. The lower numbers are obtained in open economy scenarios and the higher in closed economy scenarios, showing that trade helps to protect the poor. If the economy is closed, then improving the productivity of the agricultural sector has the greatest impact on the welfare of the poor. In contrast, if the economy is open and there are no barriers to labor movement out of agriculture, then the non-agricultural sector plays a bigger role in driving the welfare of the poor than mitigation of climate change.

Chapter 2

Global Warming and Electricity Demand in the Rapidly Growing City of Delhi: A Semi-Parametric Variable Coefficient Approach[1]

2.1 Introduction

There is growing consensus among scholars on the plausibility of increases in the Earth's mean temperature. It has stimulated attempts to assess the impact of such changes on different sectors. In light of this interest, the present paper attempts to quantify how climate change will affect electricity demand in the continental climate of Delhi ($28^0 30^{\prime}$N),

[1]This chapter has been published in the journal of Energy Economics.

which is one of the most populous cities in India. For this purpose, we use a semi-parametric variable coefficient approach to estimate the effects of apparent temperature[2] on daily electricity demand over a 10-year period (2000-09). We use the estimated model to simulate the impact of 1^0C, 2^0C and 3^0C increases in apparent temperature on the electricity demand of Delhi up to 2030.

Existing literature highlights a U-shaped non-linear temperature-electricity curve (TEC) where, starting from low levels, rising temperatures first decrease electricity demand due to lower heating requirements in cold weather but where the demand begins to increase due to the higher cooling demand in hot weather once, the level of temperature exceeds the minimum electricity demand threshold. The expected net effect of global warming on electricity demand is therefore ambiguous prima facie. Previous studies have shown that the heating effect dominates the cooling effect in cold countries such as Sweden, which means that global warming would result in a decline in electricity demand in these countries. However, scholars have predicted the reverse for Germany with the cooling effect dominating the heating effect (See [Bessec & Fouquau, 2008]). This suggests that much warmer countries such as India are also likely to experience a net increase in their electricity demand due to climate warming. No studies exist yet of the nature and extent of the climate warming effects on electricity demand in case of India. The present paper attempts such a quantification.

This is the first study to estimate a temperature-electricity curve for India, the key contribution of this paper being that it recognizes and addresses two special problems

[2]'Apparent temperature' refers to what various combinations of temperature, humidity and windspeed feel like based on human physiology and clothing science and the need for the body to maintain a thermal equilibrium.

in the estimation of temperature-electricity curves for developing countries. Firstly, with rapid changes in the economic structure of such countries in future, the relation is likely to shift over time. In this paper, we address this issue by estimating a semi-parametric variable coefficient model that allows the temperature-electricity relation to vary over time. As in [Engle et al., 1986], we model the temperature-electricity relation non-parametrically using cubic regression splines, so that weather extremes can have relatively larger impacts on electricity demand, while the other predictor variables enter the regression linearly. The innovation of this paper is to allow the non-parametric temperature-electricity relation to vary across years by interacting the non-parametric component with year. Secondly, blackouts or power-outages are common in many developing countries. This means that observed electricity use is typically less than the notional electricity demand (which is the object of interest in this study). We adjust daily electricity consumption using daily shortage data in order to obtain the unrestricted electricity demand in Delhi.

One important limitation of this study is that it takes a broad perspective, estimating the average temperature-electricity curve for the aggregate electricity demand of Delhi whereas the temperature-electricity sensitivities may differ across sectors significantly. For instance, while a large chunk of this demand is due to space conditioning and water heating in the residential and commercial sectors, which is highly sensitive to temperature, in agriculture and industrial sectors, electricity demand is determined by the level of economic activity, which is thus largely temperature insensitive. Since, given the data limitations, it is not possible to obtain the daily electricity demand data for different sectors, we have adopted an aggregated approach in this study. In the case of Delhi where 97.5%

of the population is urban, the residential and commercial sectors taken together account for approximately 80% of the total electricity demand.

A second limitation is that while electricity demand can be modeled structurally, where electricity consumption is chosen to maximize the expected utility of the households and profits of the firms, we have not adopted this model because a) the data on prices, utilization and efficiency of electricity using equipment at the household and firm level over time is not available and b) a structural model is hard to implement. Thus, as is the case with much of the literature, our study too works with a reduced form model.

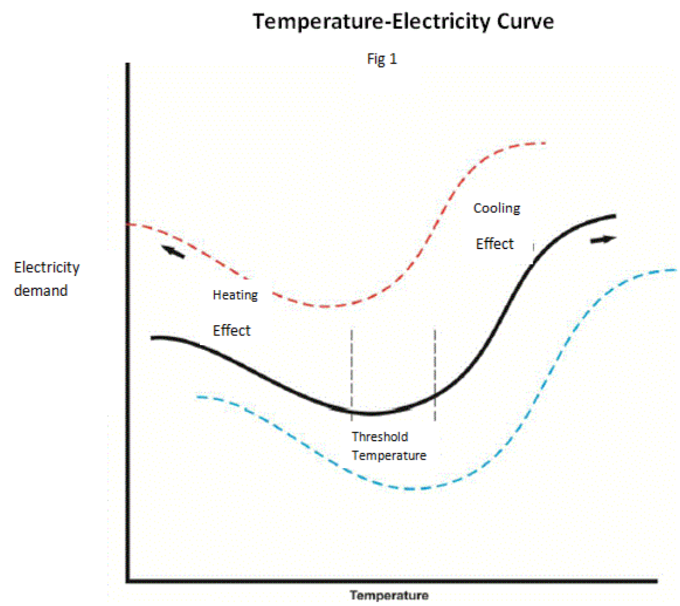
Three results from our analysis have important implications for electricity-climate policy: Firstly, we observe that the rising part of the temperature-electricity curve is becoming more pronounced over time, implying an increase in the cooling demand per unit increase in summer temperatures. For instance, a 1^0C increase in temperature at 30 ^{0}C increased the electricity demand by over 3 MkWh in 2009 as compared to only over 1 MkWh in 2000. On the other hand, a 1^0C increase in temperature at 15 ^{0}C decreased the electricity demand by only 0.8 MkWh in 2009 as compared to 0.7 MkWh in 2000. Secondly, the increasing temperature dependence of the cooling demand shifts the temperature-electricity curve of Delhi leftwards. In particular, the minimum temperature threshold (TT) shifts from about 20-22 ^{0}C in the first half (2000-05) to about 18.5-20.5 ^{0}C in the second half (2006-09) of the period. Thirdly, the results suggest that the adverse effects of global warming will be asymmetrically distributed in the different seasons. While higher temperatures would increase electricity demand in all seasons except winters, the maximum impact is likely to be felt in the hot month of April, with average apparent temperatures of 30 ^{0}C, followed by October and May. Given the dominance of summer electricity demand in the Indian electricity consumption pattern, increasing temperature dependence in the summer months with extreme temperature events may lead to capacity problems.

The rest of the paper is organized as follows. Section 2 explains time-varying temperature-electricity curves. Section 3 reviews existing studies and models that assess the impact of temperature on electricity demand. Section 4 discusses the estimation strategy while section 5 describes the data sources. In section 6, we discuss summary statistics and results of the empirical model and in section 7 we simulate future electricity demand impacts under three different climate scenarios. Section 8 concludes the paper.

2.2 Understanding the time-varying temperature-electricity curve

Let us consider a hypothetical temperature-electricity curve as represented in Figure (2.1). In this U-shaped curve, the minimum point is the threshold. A large number of socio-economic and physical factors such as the growth in incomes, extent of electrification, energy efficiency improvements, cultural habits, and prevailing climatic conditions influence the temperature-electricity curve. [Hekkenberg et al., 2009] argue that over time temporal dynamics could influence the slopes as well as the threshold temperature of the temperature-electricity curve. For instance, increased internal heat gains in commercial buildings from an increase in use of computers, or even a decrease in tolerance for heat with higher income levels, lead to a general shift towards a lower heating demand and a higher cooling demand. Thus, neglecting a downward shifting threshold temperature results in the

Figure 2.1:



underestimation of the electricity demand that arises from a temperature increase. On the other hand, ignoring an upward shifting threshold temperature results in the overestimation of the electricity demand.

The number of households owning temperature control devices (such as air conditioners and air coolers) is increasing very rapidly in India with increasing electricity access and income. According to the National Sample Survey Organization (NSSO) surveys (50th, 61st and 66th), the number of households owning an air cooler[3] or an air conditioner doubled from 32.9% in 1993 to 60% in 2009 in urban Delhi (which represents 97.5% of the total Delhi population as per the Census 2011) while it increased from 20.6% to 26% in rural Delhi. In the case of refrigerators, the upward trend was even more impressive, with pene-

[3]Air coolers based on a fan for cooling consumes much less power than air conditioners that operate on the principle of gas compression.

tration increasing from 29% in 1993 to 61.3% in 2009 in urban Delhi and from 17.7% to 38% in rural areas. In the 2004-05 NSSO survey (which provides data on the ownership of air coolers and air conditioners separately unlike in the previous rounds) only 9% have access to air conditioners and only 58% to air coolers in Urban Delhi. However, with increasing incomes, there is a very high probability that the total air conditioning electricity demand could increase substantially. Further, with increased purchasing power, the sensitivity of households to higher temperatures is likely to increase, which may further shift the location of the minimum point of the temperature-electricity curve. For instance, higher income households may want to switch on their air conditioners when the average temperature is just 19^0C in 2015 as compared to 22^0C in 2000.

According to [Kothawale et al., 2010] temperatures (mean, maximum and minimum) increased by about 0.2 ^{0}C per decade for the period 1971–2007, with a much steeper increase in minimum temperature than maximum temperature. On a seasonal scale, they observed significant warming trends in mean temperature in two seasons characterized by high humidity: i.e., monsoon and post-monsoon periods. Moreover, increasing night temperatures in these humid seasons could have significant implications for the use of air conditioners and thus for electricity demand. Since the market saturation of air conditioners is currently quite low, the response of its diffusion (along with the rising standard of living) to a long-term increase in the number of hot days and extreme temperature events may play an important role in determining how electricity consumption on the whole would respond to global warming.

2.3 The temperature-electricity curve: 'The studies so far'

The simplest way to estimate a U-shaped temperature-electricity curve is to use a regression model that is quadratic in temperature. However, such a model assumes a symmetric relationship because, at any point in the curve, upward and downward changes in temperature of equal magnitude would lead to identical changes in electricity demand. This is an extremely strong assumption and many past studies have shown that the sensitivity of electricity demand to temperature changes depends on initial temperature levels (Valor et al., 2001; Mirasgedis et al., 2004). Nonetheless, a linear parametric model can still be used to estimate a non-linear relation by using the degree day approach ([Al-Zayer & Al-Ibrahim, 1996]; [Valor et al., 2001]; [Sailor, 2001]; [Pardo et al., 2002]; [Mirasgedis et al., 2007]). This approach defines heating degree days (HDD) and cooling degree days (CDD). CDD and HDD quantify the difference between the daily mean temperatures above or below a threshold temperature (where 18^0C is used as a common threshold temperature), respectively. The HDD index is calculated on the basis of the relation: HDD=max (0,18 -T_d), where Td is the average daily air temperature on day d. The CDD index is calculated on the basis of the relation: CDD=max (0,T_d-18). These studies estimated the temperature-electricity curve with the ordinary least squares regression model using annual, monthly or daily data in the following manner:

$$
\begin{aligned}
e_d = {} & \beta_0 + \beta_1 TREND_d + \beta_2 CDD_d + \beta_3 HDD_d + \beta_4 CDD_d + \beta_5 HDD_d + \\
& \sum_{k=1}^{11} \phi_k MONTH_{kd} + \sum_{b=1}^{6} \varphi_b WD_d^b + \beta_6 HOLIDAY_d + \beta_7 X_d + \varepsilon_d
\end{aligned}
$$

where e is the demand for electricity on day d, WD is a set of week data dummies, $MONTH$ is a set of month dummies, $HOLIDAY$ is dummy for holidays, X includes socio-economic factors such as income and population, and ε is the residual term. Although this approach estimates separate linear relationships of electricity demand due to the heating and cooling demand, it relies on an arbitrary choice of threshold value (18^0C in most cases).

However, more recent studies such as those of [Moral-Carcedo & Vicens-Otero, 2005] and [Bessec & Fouquau, 2008] have estimated the above non-linear relationship by obtaining these thresholds endogenously rather than choosing it a priori using different types of non-linear threshold regression models. These studies estimated the above relationship in the following manner:

$$e_d = \beta_0 + \beta_1 TREND_d + \beta_2 (TREND_d)^2 + \beta_3 (TREND_d)^3 + \sum_{b=1}^{6} \varphi_b WD_{bd}$$

$$+ \beta_4 HOLIDAY_d + \beta_5 X_d + \beta_6 g(T_d; \gamma, c) + \varepsilon_d$$

where $g(T_d; \gamma, c)$ is a function of the temperature T_d that allows a transition from a cold to a warm regime. In the literature, the transition function has been specified in different ways as piece-wise linear or as a smooth function (exponential or logistic). The assumption of particular functional forms for the transition function is a limitation of such models.

Other researchers have attempted to address this limitation by using non-parametric methods, also known as smoothing models, to achieve greater flexibility in the functional form. To estimate the functional form from data, such models replace global estimates of the electricity-temperature function with local estimates. Local methods estimate a regression between electricity demand (E) and temperature (T) for some restricted range of E

and T. This local estimate of the dependency is repeated across the range of E and T and the series of local estimates is then aggregated to summarize the relationship between the two variables. The resulting non-parametric estimate does not impose a particular functional form on the relationship between E and T, and thus minimizes specification errors ([Powell, 1993]; [Keele, 2008]; [Ruppert et al., 2003]). The estimates are also consistent under more general conditions than are parametric estimates ([Wadud et al., 2010]; [Yatchew, 2003]). Both loess and splines are common non-parametric regression models that rely on local estimates to estimate functional forms from data. [Engle et al., 1986] estimated the impact of weather on the electricity sales of four US utilities with smoothing splines using monthly data for 7-8 years. The semi-parametric partial linear regression model estimated by them is given by

$$\mathbf{E} = \mathbf{Z}\boldsymbol{\gamma} + \mathbf{f}(T) + \boldsymbol{\varepsilon}$$

In the above regression, temperature (T) is assumed to affect electricity sales non-linearly by an unknown cubic smoothing spline function f. However, other important variables (Z) such as income and prices enter linearly in the model. The semi-parametric model consists of a conventional parametric and a non-parametric part at the same time. A fully non-parametric model is computationally complex in the presence of numerous predictors. [Hyndman & Fan, 2009], [Harvey & Koopman, 1993], and [Henley & Peirson, 1997] are some studies that use semi-parametric regressions in order to model the temperature-electricity relationship.

[Ramesh et al., 1988] is the only study that estimates the temperature-electricity relation for Delhi, assessing the impact of weather variables on the peak electricity load separately for summers and winters, separately during the period 1980-85, using the ordinary least squares parametric regression. However, as mentioned earlier, electricity demand has increased greatly since then. Moreover, while this study investigates the relationship between electricity demand and climatic conditions in Delhi in the past for the purpose of peak demand forecasting, ours is the first study that derives the non-linear dynamic temperature-electricity curve of Delhi and focuses on the time-varying impact of global warming on electricity demand using a semi-parametric variable coefficient model. Not only did the previous study not control for important climatic factors such as rainfall and windspeed, it also did not make any adjustment for the unmet electricity demand.

2.4 Estimation strategy: 'The reduced-form model'

We estimate four models in the study. While the first model is based on simple linear regression, the second specifies a semi-parametric additive model using unpenalized splines. The third estimates a semi-parametric additive model with penalized splines while the fourth model is a variable coefficient model where a smooth function of the temperature index is interacted with year to capture the time-varying impact of temperature on electricity demand.

Model 1 estimates the non-linear relationship between electricity demand (E) and apparent temperature (AT) by including a global cubic polynomial in AT in the regression equation. This model takes the following form:

$$e_{td} = \beta_0 + \beta_1 MAJH_{td} + \beta_2 MINH_{td} + \beta_3 RAIN_{td} + \sum_{t=1}^{9} \phi_t y_t$$
$$+ \sum_{b=1}^{6} \varphi_b WD_{td}^{b} + \beta_4 AT_{td} + \beta_5 AT_{td}^{2} + \beta_6 AT_{td}^{3} + \varepsilon_{td} \quad (2.1)$$

where e is electricity demand on day d of year t, $MAJH$ is a dummy variable that takes the value one for the major holiday, and zero otherwise, $MINH$ is a dummy variable that takes value one for the minor holiday, and zero otherwise,[4] $RAIN$ represents daily rainfall in millimeters (mm). WD is the set of six day dummies to describe the weekly periodicity of electricity demand where Wednesday is taken as the reference day. $\mathbf{y}$ is a set of nine-year dummies with 2000 as the base year to identify the deterministic long-term trend connected with the impact of demographic, technological, and socio-economic factors such as prices, urbanization, and the increasing number of air conditioners and air coolers on electricity demand. The inclusion of year-fixed effects accounts for any fixed differences across years that may be correlated with all unobservable factors. In matrix notation eq (1) can be rewritten in the following form

$$\mathbf{E} = \mathbf{Z}\boldsymbol{\gamma} + \mathbf{T}\boldsymbol{\eta} + \boldsymbol{\varepsilon} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \quad (2.2)$$

where, E is an $n \times 1$ vector of electricity demands, ε is an $n \times 1$ vector of errors, and $\mathbf{Z}$ is an $n \times p_1$ matrix of p_1 non-temperature predictors, γ is an $p_1 \times 1$ vector of coefficients of predictors in $\mathbf{Z}$, $\mathbf{T}$ is an $n \times p_2$ matrix of AT temperature predictors, η is an $p_2 \times 1$ vector of coefficients of predictors in $\mathbf{T}$, X is an $n \times p$ $(= p_1 + p_2)$ matrix of all predictors

[4] A major holiday is one that is declared to be a holiday for all government employees (on account of national events or religious events). Minor holidays are the 2 additional days of holidays that government employees are entitled to select for minor religious festivals from a list of scheduled holidays.

and β is an $p \times 1$ vector of coefficients of X predictors. The least squares and maximum likelihood estimator of β is $\widehat{\beta}= (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{E}$ and **Hat matrix** H is a $n \times n$ matrix, such that $\widehat{E} = HE$. We can obtain $H = X(X^TX)^{-1}X^T$ and show that $trace(H) = trace(\mathbf{X}(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T) = tr(I_p) = p =$ estimated degrees of freedom (EDF) as measured by the number of parameters in the model. This model assumes that the relationship between E and AT is strictly cubic regardless of whether this is true or not. When it is not , the power transformations often cannot adequately capture the nonlinear relationship in the data.

Model 2 estimates a semi-parametric model given by

$$\mathbf{E} = \mathbf{Z}\gamma + \mathbf{f}(AT) + \boldsymbol{\varepsilon} \tag{2.3}$$

Here, $\mathbf{f}(AT) = (f(AT_1), ...f(AT_n))'$ is a $n \times 1$ vector, where $f(AT)$ is an unknown smooth function, i.e., continuous and sufficiently differentiable function of AT. In this paper, we estimate $f(AT)$ by cubic regression splines[5] using cardinal basis functions[6]. Wood (2006) and Lancaster and Salkauskas (1986) gives full details of cardinal basis functions. Such basis functions parameterize the spline in terms of its values at the knots and thus have advantages in terms of the interpretability of the parameters along with good mathematical properties and numerical stability. $f(AT)$ can be represented as a linear combination of the

[5]Suppose there is a knot sequence $K, AT_{\min} = k_1 < .. \; k_N = AT_{\max}$, where $k_2...k_{N-1}$ are interior knots, and k_1, k_N are two knots at the boundaries of the data $[AT_{\min}, AT_{\max}]$, dividing the data into $N-1$ subintervals $[k_1, k_2]$ ...$[k_{N-1}, k_N]$. A spline is a piecewise-polynomial real function:$f : [AT_{\min}, AT_{\max}] \longrightarrow \mathbb{R}$ on an interval $[AT_{\min}, AT_{\max}]$ composed of $N-1$ ordered disjoint subintervals $[k_1, k_2]$ ...$[k_{N-1}, k_N]$. The restriction of f to an interval i is a polynomial P_i

$$P_i : [k_{i-1}, k_i] \longrightarrow \mathbb{R}$$

[6]For full details of cardinal basis functions, see Wood (2006) and Lancaster and Salkauskas (1986).

basis functions of regression splines. For instance,

$$f(AT_i) = \sum_{j=1}^{N} b_j(AT_i)\eta_j \;\; = \mathbf{B}(AT_i)\boldsymbol{\eta} \tag{2.4}$$

where $b_j(AT)$ is the basis at the jth point (commonly known as a knot), $\mathbf{B}(AT)$ is the model matrix containing N cubic spline basis for $f(AT)$ and $\boldsymbol{\eta}$ is the corresponding regression parameter vector. Thus (3) becomes

$$\mathbf{E} = \mathbf{Z}\boldsymbol{\gamma} + \mathbf{B}(AT)\boldsymbol{\eta} + \boldsymbol{\varepsilon} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}. \tag{2.5}$$

where $\mathbf{X}$ is a $n \times (p_1 + (N-1))$ model matrix. One degree of freedom is lost due to the identification constraint on $f(AT)$ i.e$\sum_{i=1}^{n} f(AT_i) = 0$. Using the Akaike Information Criterion[7], we select twelve knots ($N = 12$) or eleven basis functions. Given knots, this model becomes a fully parametric model with an expanded model matrix. We estimate predictor variable coefficients by minimizing $\| \mathbf{E} - \mathbf{X}\boldsymbol{\beta} \|^2$. The key limitation of this model, however, is that it requires the analyst to select the number and location of the knots. The number of knots directly controls the degrees of freedom of a smooth term. In order to deal with the knot selection problem, we adopt the penalized cubic spline approach. These models construct a penalty on $f()$ which will be large if f is very wiggly and small if it is nearly flat.

Model 3 adds a quadratic penalty as $\lambda\boldsymbol{\beta}^T\mathbf{P}\boldsymbol{\beta}$ and solves the following minimization problem:

$$\| \mathbf{E} - \mathbf{X}\boldsymbol{\beta} \|^2 + \lambda\boldsymbol{\beta}^T\mathbf{P}\boldsymbol{\beta} \tag{2.6}$$

[7] The Akaike Information Criterion is a measure of the relative goodness of fit of a statistical model: AIC $= 2k - 2\ln(L)$, where k is the number of parameters in the model, and L is the maximized value of the likelihood function.

In practice, it is customary to use the Akaike Information Criterion in order to select the optimal number of knots. Researchers prefer a model with a lower value of the Akaike Information Criterion.

where $\mathbf{P}$ is the penalty matrix whose coefficients depend on the second derivatives of f, a measure used commonly to represent the roughness of the smooth terms.[8] λ is the smoothing parameter that controls the trade-off between model fit and model smoothness. For $\lambda \rightarrow 0$ the minimization gives a wiggly function whereas letting $\lambda \rightarrow \infty$ gives a linear fit. The optimal λ is selected by cross validation where It works as follows: for a given value of λ , we omit the ith observation from data and fit the penalized spline to this slightly truncated data set. We denote this prediction of e_i as $\widehat{e}_{i-1}$. The model prediction errors are calculated, and this is repeated as each observation is dropped in turn. The cross-validation score is calculated as the average of the individual model prediction errors. One should choose the value of λ with the smallest cross-validation score. In practical applications one replaces the cross validation (CV) criteria by the generalized cross validation (GCV) as the CV is computationally very intensive and has other problems (Woods, 2006). Like the adjusted R-square, the GCV adjusts the average model prediction errors with the degrees of freedom (the number of parameters estimated in the model). For penalized spline models, the GCV score is

$$GCV(\lambda) = \frac{\sum_{i=1}^{n} \left[e_i - \widehat{e}_i\right]^2 n}{\left[n - tr(H_\lambda)\right]^2}. \tag{2.7}$$

Minimizing $GCV(\lambda)$ with respect to λ gives an estimate $\widehat{\lambda}$. Given λ (2.6) is minimized with respect to $\boldsymbol{\beta}$. We get $\widehat{\boldsymbol{\beta}} = \left[\mathbf{X}^T\mathbf{X} + \lambda\mathbf{P}\right]^{-1}\mathbf{X}^T\mathbf{E}$ and the hat matrix $\mathbf{H}_\lambda = \mathbf{X}\left[\mathbf{X}^T\mathbf{X} + \lambda\mathbf{P}\right]^{-1}\mathbf{X}^T$.The

[8] Wood and Augustine (2002) derive the following wiggliness measure

$$j(f) = \int \left[f''(AT)\right]^2 dAT$$

$$f''(AT) = \sum_{j=1}^{N} b''_j(AT)\eta_j \ = \mathbf{B}''(AT)\ \boldsymbol{\eta}$$

trace of H_λ , as in the linear regression, represents the degrees of freedom in the spline model and is nearly equivalent to the number of parameters in the spline fit. Due to shrinkage from the penalty term, the degrees of freedom for a penalized spline model will not be an integer. With penalized splines the exact choice of the basis dimension is not generally critical as actual effective degrees of freedom are controlled by λ. It is necessary to select the number of knots to be large enough to have enough degrees of freedom to represent the underlying true structure of the data reasonably well but small enough to maintain reasonable computational efficiency (Woods, 2006).

Model 4 extends Model 3 to a variable coefficient model to capture the time-varying impact of climate on electricity demand. Model 4a estimates the least constrained factor variable coefficient model by interacting $f(AT)$ by ten year dummies. It estimates a different smooth function of temperature for each year. Model 4b estimates a simple numeric variable coefficient model by adding an additional term in Model 3 that interacts $f(AT)$ with the year number. It assumes that the coefficients of the smooth function of temperature change linearly with the year. One can capture the time-varying effect by estimating a separate model (like Model 3) for each year. However, by pooling data for all 10 years we get more robust estimates that are preferable for the purpose of analyzing the long-term impact of climate on electricity demand.

Model 4a: We first select the number of knots for each year (N_t) and corresponding basis functions $\mathbf{B}_t(AT)$ -

$$f_t(AT) = \sum_{j_t=1}^{N_t} b_{j_t}(AT)\eta_{j_t} = \mathbf{B}_t(AT)\boldsymbol{\eta}_t. \tag{2.8}$$

In general, knots are placed at evenly spaced quantiles of the unique data. We select the

same 10 knots every year. The selected knots are $[k_0 = 6.17, 14.39, 18.47, 22.67, 26.84, 30.98, 33.87, 35.78, 37.$
$k_{10}]\ \forall\ t$. $\mathbf{B}_t(AT)$ is a row vector of basis functions for year t. $\boldsymbol{\eta}_t$ is the coefficient vector of the basis functions of year t. The model becomes:

$$\mathbf{E} = \mathbf{Z}\gamma + \mathbf{f}(\mathbf{AT})\mathbf{Y} + \varepsilon = \mathbf{Z}\gamma + \sum_{t=1}^{10} \mathbf{f}(\mathbf{AT})\mathbf{y}_t + \varepsilon = \mathbf{Z}\gamma + \sum_{t=1}^{10} \mathbf{f}_t(\mathbf{AT}) + \varepsilon \tag{2.9}$$

where, $\mathbf{f}_t(\mathbf{AT})$ is a vector of the smooth function of the temperature index of year t with dimension $n \times 1$. Here, t indexes the year with $t = 1$ for year 2000 and $t = 10$ for year 2009. $\mathbf{Y}$ is an $n \times 10$ matrix of year dummies. $\mathbf{y}_t$ is the t^{th} column of $\mathbf{Y}$. The $\mathbf{y}_t$ represents the year dummy for year t. The degrees of freedom for $\mathbf{f}_t(\mathbf{AT})$ will be determined by the choice of λ_t. Note that the same λ_t is chosen for all years resulting in the same degrees of freedom for each year. Thus, the fitting problem becomes similar to any other generalized additive models:

$$\min \quad \| \mathbf{E} - \mathbf{X}\boldsymbol{\beta} \|^2 + \sum_t \lambda_t \boldsymbol{\beta}^T \mathbf{P}_t \boldsymbol{\beta} \tag{2.10}$$

where X is a $n \times (p_1 + ((N-1) \times 10))$ model matrix. Given λ_t, eq(2.10) can be minimized with respect to $\boldsymbol{\beta}$. We get $\widehat{\boldsymbol{\beta}} = \left[\mathbf{X}^T\mathbf{X} + \sum_t \lambda_t \mathbf{P}_t\right]^{-1} \mathbf{X}^T\mathbf{E} = \left[\mathbf{X}^T\mathbf{X} + \mathbf{K}\right]^{-1} \mathbf{X}^T\mathbf{E}$,with $\sum_t \lambda_t \mathbf{P}_t = \mathbf{K}$. A smoother matrix for penalized splines with interaction can be derived as $\mathbf{H}_\lambda = \mathbf{X}\left[\mathbf{X}^T\mathbf{X} + \sum_t \lambda_t \mathbf{P}_t\right]^{-1} \mathbf{X}^T = \mathbf{X}\left[\mathbf{X}^T\mathbf{X} + \mathbf{K}\right]^{-1} \mathbf{X}^T$. As discussed previously, one degree of freedom is lost due to the identification constraint on $f_t(AT)$, which requires $\sum_{i=1}^{N_t} f_t(AT_i) = 0$ $\forall\ t$. From the above, we obtain the electricity demand on a particular day

$$e_{td} = \mathbf{z}'_{td}\boldsymbol{\gamma} + f_t(AT_{td}) + \varepsilon_{td} \tag{2.11}$$

where e_{td} is electricity demand on day d of year t. z'_{td} is a row vector of parametric predictors for day d of year t. We can write the full form of eq(2.11) therefore as

$$e_{td} = \beta_0 + \beta_1 MAJH_{td} + \beta_2 MINH_{td} + \sum_{t=1}^{9} \phi_t y_t + \sum_{b=1}^{6} \varphi_b WD_{td}^{b} + \beta_3 RAIN_{td} + f_t(AT_{td}) + \varepsilon_{td} \tag{2.12}$$

As the errors from eq(2.12) are likely to be serially correlated, we carry out the following adjustment given in Li and Racine (2007)[9]. By dropping year dummies and estimating eq(2.12) separately for each year, we obtain $\widehat{\boldsymbol{\varepsilon}_d}$ for each t. For each year t, a first order stationary auto-regressive model is defined as

$$\boldsymbol{\varepsilon}_d = \rho_t \boldsymbol{\varepsilon}_{(d-1)} + \nu_d \tag{2.13}$$

where ν_d is white noise, is estimated . By regressing $\widehat{\varepsilon}_d$ on $\widehat{\varepsilon}_{d-1}$ of year t, we obtain an estimate of ρ_t ($\widehat{\rho}_t$). The model is then transformed in order to have serially uncorrelated disturbances by subtracting estimated previous day errors $\widehat{\varepsilon}_{_{d-1}}$ from the electricity demand on a given day e_d in the following manner:

$$e_d^* = e_d - \widehat{\rho}_t \widehat{\varepsilon}_{_{d-1}} \tag{2.14}$$

By pooling estimated transformed electricity demand e_d^* for each t, the final model becomes

$$e_{td}^* = \beta_0 + \beta_1 MAJH_{td} + \beta_2 MINH_{td} + \beta_3 RAIN_{td} + \sum_{t=1}^{9} \phi_t y_t + \sum_{b=1}^{6} \varphi_b WD_{td}^{b} + f_t(AT_{td}) + u_{td} \tag{2.15}$$

[9] For more details, refer Li and Racine (2007) in chapter 18, section 18.2.2.

where u_{td} are serially uncorrelated disturbances and we get consistent estimates of the coefficients.[10]

Model 4b on the other hand interacts $f(AT)$ with year as a numeric rather than as a factor variable (as was the case in Model 4a) and thus assumes that the coefficients of the smooth of temperature change linearly with year. The model becomes:

$$\mathbf{E} = \mathbf{Z}\gamma + \mathbf{f}(AT) + \mathbf{Y}_0\mathbf{f}(AT) + \boldsymbol{\varepsilon} \tag{2.16}$$

Here, $\mathbf{Y}_0$ is a $n \times n$ diagonal matrix with year numbers $y_0 = (1, 2, 3...10)$ on its leading diagonal. In this model each row of the model matrix of $f(AT)$ is multiplied by the corresponding value of the year number. The fitting problem as in any other generalized additive model is

$$\min \parallel \mathbf{E} - \mathbf{X}\boldsymbol{\beta} \parallel^2 + \lambda_1\boldsymbol{\beta}^T\mathbf{P}_1\boldsymbol{\beta} + \lambda_2\boldsymbol{\beta}^T\mathbf{P}_2\boldsymbol{\beta} \tag{2.17}$$

where λ_1 and $\mathbf{P}_1$ correspond to $\mathbf{f}(AT)$ and λ_2 and $\mathbf{P}_2$ correspond to $\mathbf{Y}_o\mathbf{f}(AT)$. Thus this model is also estimated as a generalized additive model as discussed in detail above. The selected knots for this model are the same as in Model 4a [$k_0 = 6.17, 14.39, 18.47, 22.67, 26.84, 30.98, 33.87, 35.7$ k_{10}]. Electricity demand on a particular day is obtained as

$$\begin{aligned} e_d^* = {} & \beta_0 + \beta_1 TREND_y + \beta_2 MAJH_d + \beta_3 MINH_d \\ & + \beta_4 RAIN_d + \sum_{b=1}^{6} \varphi_b WD_d^b + f(AT_d) + f(AT_d) \times y_o + u_d \end{aligned} \tag{2.18}$$

In this model, we replace the year dummies with linear year trend $TREND_y$, which ranges from 1 for the year 2000 to 10 for 2009. Further, instead of correcting for

[10] In this process we lose one observation per year and thus the total number of observations falls to 3643 from 3653.

within year first order autocorrelation as was the case in Model 4a, we correct for the first order autocorrelation after pooling all the years for Model 4b.

2.5 Data

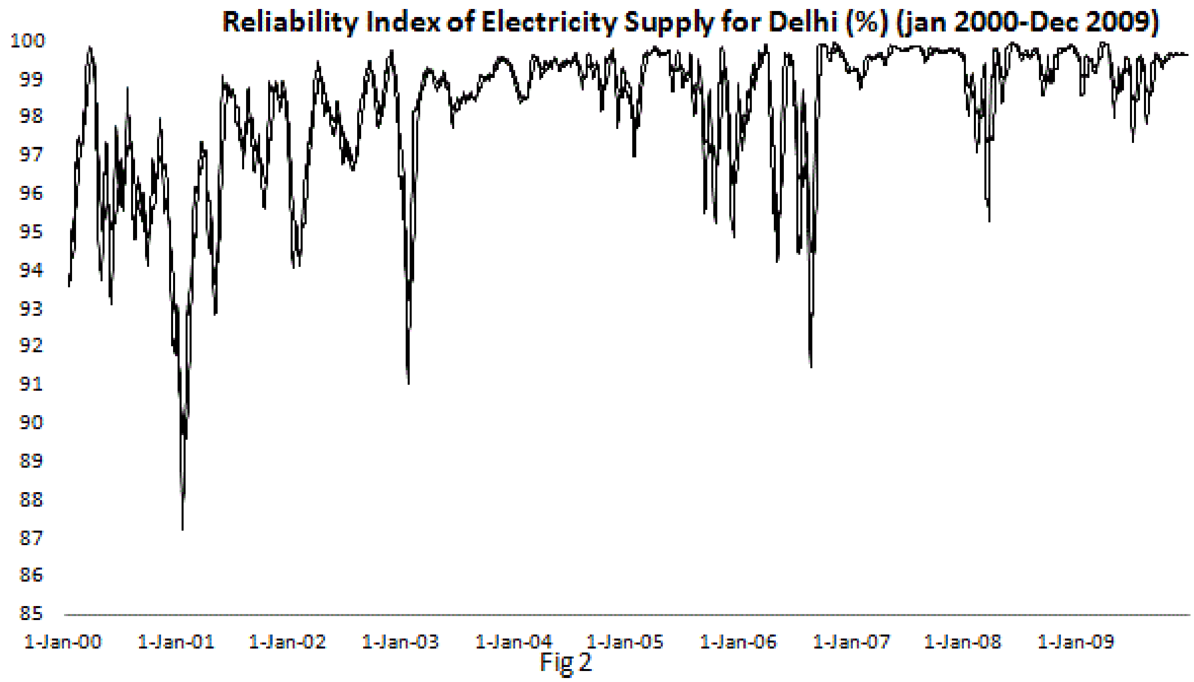
2.5.1 *Electricity Consumption and Shortage*

We obtained the data on daily electricity consumption in Delhi for 2000-09 from the operator of the national electricity grid, the National Load Dispatch Centre (NLDC). In order to estimate the impact of global warming on electricity demand, we need to recognize that the electricity systems in India are continually inhibited with power shortages, which result in rationing and disrupted electricity usage patterns. When there are regular power failures, consumers are not able to consume the quantity they need forcing them thereby to either substitute electricity with alternative energy sources such as diesel and kerosene, or resort to independent generation. As a result, the electricity consumption reported by the NLDC is constrained electricity demand, which is equal to the electricity supplied by the utilities. In order to obtain the unrestricted electricity demand for Delhi, we adjust the daily total electricity consumption of Delhi with the observed daily shortage[11] using daily electricity supply shortage data obtained directly from the Delhi Transco Ltd. This gives us

$$e_d = c_d + s_d$$

[11]The daily shortage data comprises five components: shedding due to transmission and distribution constraints; shedding by discoms in theft-prone areas; shedding in order to restrict over drawal; shedding due to grid constraints; and shedding in order to restrict under-frequency operations.

Figure 2.2:



where e_d denotes electricity demand on day d, c_d denotes electricity consumption on a given day d and s_d is the shortage (or the unmet demand) on day d. Figure (2.2) plots the reliability index of electricity (i.e., the total electricity demand met as a percentage of the total demand including the shortage). The graph shows that there has been a significant reduction in shortages in the post-2005 period.

2.5.2 *Apparent temperature and rainfall*

We obtained data on all the climatic factors from the website www.tutiempo.net/en/climate/India, which gives station-wise data for all the major weather stations in India. We first constructed the apparent temperature index (AT) for Delhi (Safdarjung station) using Steadman's (1994) formula by adjusting dry bulb temperature with humidity and wind speed, which is given below:

$$AT_{td}\left({}^{0}C\right) = T_{td} + 0.33v_{td} - 0.07w_{td} - 4$$

$$v_{td} = \frac{h_{td}}{100} \times 6.105 + e^{\left(\frac{17.27T}{237.7+T}\right)}$$

where T denotes average temperature in degree Celsius (^{0}C), v denotes evaporation, w denotes wind speed (m/s), and h denotes relative humidity (%).

2.6 Results: 'The effect of apparent temperature on electricity demand'

2.6.1 *Summary Statistics*

Table (2.1) displays the basic summary statistics that will be used to analyze the salient characteristics of the distribution of electricity demand and apparent temperature in the city of Delhi. Over the period, the average daily electricity demand (ED) increased from 50 MkWh in 2000 to 65 MkWh in 2009, with the highest daily demand increasing from 65 MkWh in 2000 to 94 MkWh in 2009. At the same time, the standard deviation of the daily electricity demand increased from 6 MkWh in 2000 to 15 MkWh in 2009. During this period, the average daily apparent temperature ranged from 26.5 and 27.7, with the peak occurring in 2009 and 2002 and the trough occurring in 2005. Figure (2.3) presents the box plot of daily electricity demand and daily apparent temperature by months. It shows that the greatest consumption occurs during the summer (led by May) and monsoon months (led by July) and the lowest consumption occurs in the post-monsoon (led by November) and

Table 2.1:

Table 1-Summary Statistics for Elecricity Demand (E) and Apparent temperature(AT) 2000-2009

Year	Variable	NO Of Days	Mean	Standard Deviation	Min	Max
2000	E	366	49.77	6.16	32.52	64.64
	AT		27.23	9.45	7.62	42.53
2001	E	365	51.57	6.90	36.20	64.34
	AT		27.24	9.05	9.06	40.82
2002	E	365	54.47	8.02	39.47	70.47
	AT		27.70	9.25	9.33	42.53
2003	E	365	55.06	7.59	38.58	72.21
	AT		27.07	9.04	8.71	40.90
2004	E	366	57.73	8.50	39.80	74.66
	AT		27.37	8.79	7.67	39.91
2005	E	365	58.78	8.94	40.55	77.88
	AT		26.45	9.08	8.61	43.45
2006	E	365	61.44	10.61	40.01	83.26
	AT		27.30	8.42	6.17	40.27
2007	E	365	61.35	11.26	39.72	85.30
	AT		27.27	9.35	7.15	43.83
2008	E	366	62.05	11.16	41.75	84.62
	AT		27.28	8.89	6.97	40.53
2009	E	365	65.31	14.70	38.41	94.31
	AT		27.69	8.81	11.06	42.54

winter months. Figure (2.4) presents a box plot of daily electricity demand by week days in order to examine the variation in electricity demand according to week days.. According to the chart, non-working days–Sundays and Saturdays—record lower consumption than working days.

2.6.2 *Main Results*

Tables (2.2,2.3,2.4) summarizes the results of the estimated models. We estimate all models by the likelihood maximization approach or the penalized likelihood maximization (for Models 3 and 4) using the mgcv package in R. For Models I and 2, we use the usual frequentist approach in order to calculate standard errors and p-values for model coefficients.

Figure 2.3:

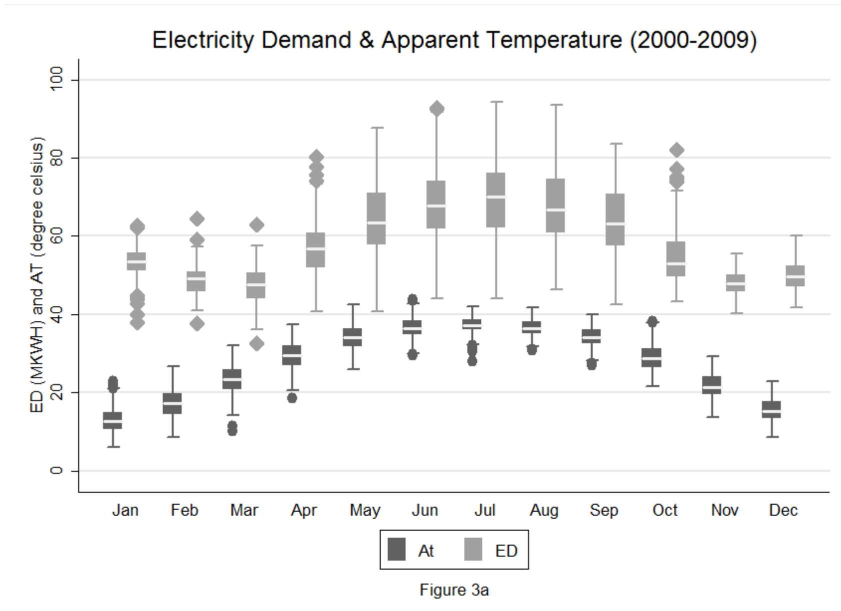


Figure 2.4:

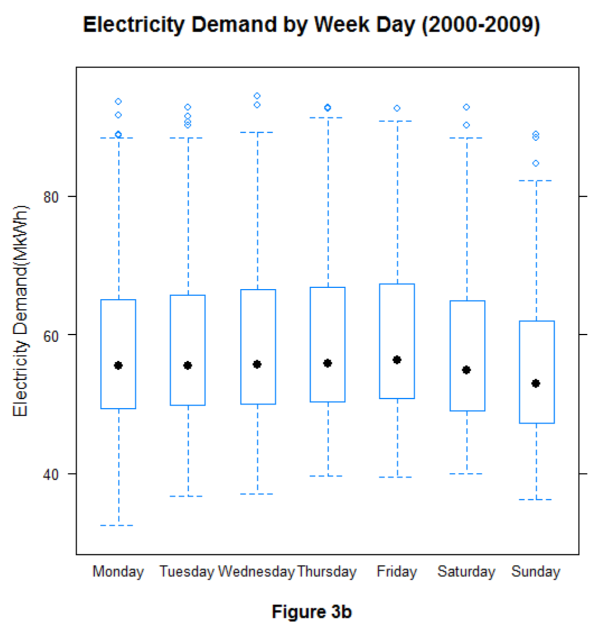


Table 2.2:

Table-2a Parameter results					
Models	**1**	**2**	**3**	**4a**	**4b**
Constant	88.11 ** (1.45)	49.96** (.24)	49.96** (.24)	50.15** (.17)	49.35** (.14)
2001	2.22** (.28)	2.29** (.27)	2.29** (.27)	2.08** (.20)	
2002	4.7** (.281)	4.8** (.27)	4.8** (.27)	4.7** (.20)	
2003	5.9** (.28)	6.2** (.27)	6.2** (.27)	5.88** (.20)	
2004	8.5** (.281)	8.64** (.27)	8.64** (.27)	8.45** (.20)	
2005	10.11** (.28)	10.27** (.27)	10.27** (.27)	10.09** (.20)	
2006	12.58** (.28)	12.86** (.27)	12.84** (.27)	12.57** (.20)	
2007	11.75** (.28)	12.07** (.27)	12.05** (.27)	11.82** (.20)	
2008	12.69** (.28)	13.09** (.27)	13.06** (.27)	12.82** (.20)	
2009	16.14** (.28)	16.30** (.27)	16.30** (.27)	16.03** (.20)	
Friday	0.96** (0.23)	0.93** (0.22)	0.93** (0.22)	0.95** (0.16)	.98** (.16)
Monday	−0.58* (0.23)	−0.54* (0.22)	−0.54* (0.22)	−0.54* (0.16)	−0.54* (0.16)

In case of Models 3 and 4, we report the Bayesian p-values and standard errors. We perform the Wald tests of significance for each parametric and smooth term.

Model 2 estimates the non-linear relationship by unpenalized splines using 12 knots selected by the Akaike's Information Criterion. The goodness of fit diagnostics and Table (2.5) show that Model 2 is a significant improvement on Model I at 99% confidence levels. An F-test based on the residual values of the semi-parametric model 2 and the parametric

Saturday	−0.99**	−0.98**	−0.98**	−0.95**	−0.95**
	(0.23)	(0.22)	(0.22)	(0.16)	(0.16)
Sunday	−3.62**	−3.55**	−3.55**	−3.56**	−3.56**
	(0.23)	(0.22)	(0.22)	(0.16)	(0.16)
Thursday	.28	.24	.25	.32	.31
	(0.23)	(0.22)	(0.22)	(0.16)	(.16)
Tuesday	−.11	−.08	−.08	−.06	−.08
	(0.24)	(0.22)	(0.22)	(0.16)	(0.16)
Major	−3.5**	−3.4***	−3.4***	−3.3**	−3.4**
	(0.32)	(0.31)	(0.31)	(0.22)	(0.22)
Minor	−.38	−.27	−.27	−.42 *	−.47 *
	(0.26)	(0.25)	(0.25)	(0.18)	(0.18)
Rainfall	−.043**	−.052**	−.052**	−.053**	−.053**
	(.01)	(.01)	(.01)	(.01)	(.01)
AT	−5.91**				
	(0.19)				
AT^2	.21**				
	(0.01)				
AT^3	−.002**				
	(0.0001)				
Trend (year)					1.56**
					(.02)

Notes:

** significant at 99% significance level

* Significant at 95% significance level

Dependent variable for all models is electricity demand

Table 2.3:

Table 2b. Approximate significance of smooth terms in Semiparametric Models

	EDF	F	p-value
Model 2			
f(AT)	11	1856	0.000
Model 3			
f(AT)	8.73	1899	0.000
Model 4a			
f(at):2000	6.4	218.6	0.000
f(at):2001	6.2	279.3	0.000
f(at):2002	6.3	369	0.000
f(at):2003	6.3	314.1	0.000
f(at):2004	6.2	448.9	0.000
f(at):2005	6.5	460.4	0.000
f(at):2006	6.3	712.5	0.000
f(at):2007	6.5	764.5	0.000
f(at):2008	6.2	767.3	0.000
f(at):2009	6.1	1417.6	0.000
Model 4b			
f(at)	5.8		0.000
f(at):yearno	8.9		0.000

Table 2.4:

Table 2c. Goodness of Fit Diagnostics

Model	**1**	**2**	**3**	**4a**	**4b**
Adjusted R^2	0.873	0.884	0.884	0.94	0.93
AIC	20031.87	19709	19709	17474.5	17638
GCV	14.301	13.09	13.091	7.09	7.3
No Obs	3643	3643	3643	3643	3652
Model DF (degrees of freedom)	22	30	26.67585	81.918	25.7
Residual DF (N-DF)	3621	3613	3616.33	3561.08	3626.3

Table 2.5:

Table 3a Comparing Model I and Model 2 (F-test)						
	Residuals(1)	Res.DF(2)	Diff.df(3)	Diff.res(4)	F=$\frac{(4)/(3)}{ModelII(1)/(2)}$	P-value
Model I	51472	3621				
Model 2	46904	3613	8	4568	43.984	000

model I yields an F-statistic of 43.984, which has a p-value of .0. This implies that a local fit captures the non-linearity between electricity demand and temperature much more accurately than the global fit of the parametric model.

Model 3 estimates penalized splines with 20 knots as compared to the 12 knots used for the unpenalized spline Model 2. The goodness of fit diagnostics and Table (2.6) show that the results from Model 3 are not statistically different from Model 2. The F-test based on residual values of Models 2 and 3 yields an F statistic of 2.04 and a p-value of 0.12.[12] The advantage of using penalized splines is that the results are not influenced by the number of knots when a fairly large number of knots is selected.

Model 4a, in comparison with Model 3 in Table (2.7), shows a significant improvement at the 99% confidence level (with F-statistic=59.31 and P-value=0). Both the generalized cross-validation (GCV) and Akaike Information Criterion (AIC) are much lower for Model 4. It has a high adjusted R square of .94 implying that it has the ability to explain 94% variation in the electricity demand. The Durbin-Watson statistic (2.01) shows that the estimated model has no autocorrelation.

Model 4a performs only marginally better than Model 4b in respect of adjusted

[12] The test statistic is defined as:

$$F = \frac{(RSS_{\text{smaller}} - RSS_{\text{larger}})/[df_{\text{res,larger}} - df_{\text{res,smaller}}]}{(RSS_{\text{larger}})/[df_{\text{res,larger}}}$$

Table 2.6:

Table 3b Comparing Model 2 and Model 3 (F- test)						
	Residuals(1)	Res.DF(2)	Diff.DF(3)	Diff.Res(4)	F=$\frac{(4)/(3)}{ModelIII(1)/(2)}$	P-value
Model 2	46904	3613				
Model 3	46964	3615	-2.26	-60.177	2.0436	0.1229

Table 2.7:

Table 3c Comparing Model 3 and Model 4a (F-test)						
	Residuals(1)	Res.Df(2)	Diff.Df(3)	Diff.res(4)	F=$\frac{(4)/(3)}{ModelIV(1)/(2)}$	P-value
Model 3	46964	3615.3				
Model 4	24684	3561.1	54.2	22277	59.31	000

R and other goodness of fit diagnostics. The Durbin-Watson statistic (2.1) shows that the estimated model has no autocorrelation. Moreover, Model 4a has the limitation that we cannot forecast for the future from this model. Figure (2.5) plots year-fixed effects from Model 4a which shows that the yearly trend is nearly linear. Similarly, the basis coefficients of Model 4a seem to change linearly over 2000-09 in Figure (2.6). We therefore estimate the much simpler Model 4b imposing linearity assumptions on these coefficients. The advantage of using Model 4b is that we can forecast the time-varying temperature-electricity curves for the future.

Figure 2.5:

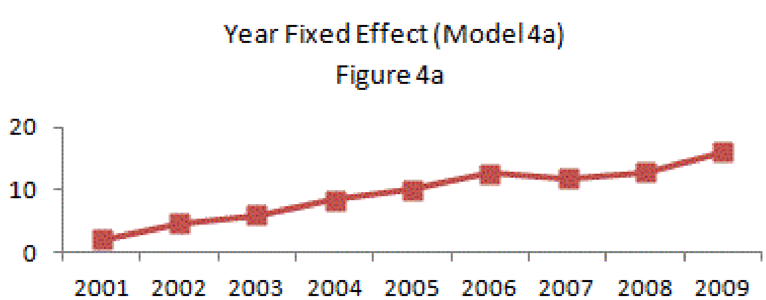
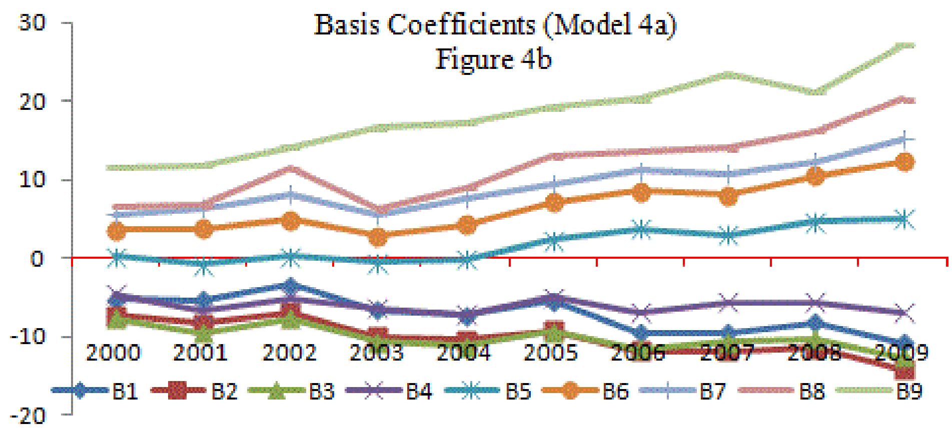


Figure 2.6:



We find Models 4a and 4b to give similar results with regard to linear predictors. We observe rainfall to have a significant negative impact on electricity demand, with a 1 millimeter increase in rainfall reducing electricity demand by 0.05 MkWh in both models. As expected, both holiday dummies turned out to be highly significant and negative. On a major holiday, electricity demand is estimated to be about 3 MkWh lower than the average demand. On a minor holiday, on the other hand, the reduction in demand was only 0.4 MkWh. The estimates of parameters which model the weekly cycle of electricity demand indicate that on Mondays, Saturdays and Sundays electricity demand tends to be lower than the average level (with Wednesday as the reference day) while it is higher on Fridays. These results are as expected since holiday and weekend loads show quite a different response to temperature than those on weekdays. Mondays show a lower demand possibly due to the holiday effect of the previous day (also called holiday inertia) while Fridays show a relatively higher demand, due possibly to the build-up of work at the end of the week. Thus, most of the parametric results are in line with previous studies done in this context.

The effect of apparent temperature on electricity demand is clearly non-linear. The estimated degrees of freedom (edf) for the temperature smooth term estimates and their p-values support the hypothesis that the coefficients are statistically significant. The same smoothing parameter λ_t is chosen for all years resulting in equal degrees of freedom (approximately 6) for each year $f_t(AT)$ in Model 4a. In the case of Model 4b, the estimated degrees of freedom are also about 6 for $f(AT)$ and about 9 for $f(AT) \times y_0$. Figures (2.7, 2.8) plots all the estimated temperature-electricity curves along with the Bayesian confidence intervals[13] (the shaded region) for both models. For Model 4a it plots $\widehat{f}_t(AT)$ for each t along with $\widehat{f}_t(AT) \pm 2 \times SE(\widehat{f}_t(AT))$. For Model 4b it plots $\widehat{f}(AT)+ \widehat{f}(AT) \times y_0$ with $(\widehat{f}(AT)+ \widehat{f}(AT) \times y_0) \pm 2 \times SE(\widehat{f}(AT) + \widehat{f}(AT) \times y_0)$.

Figures (2.9, 2.10) plots the marginal effect (first derivative) curve from both models of each temperature-electricity curve in Figures (2.7, 2.8) with 95% Bayesian confidence intervals (see shaded region). For Model 4a it plots $\widehat{f}_t'(AT)$ for each t along with $\widehat{f}_t'(AT) \pm 2 \times SE(\widehat{f}_t'(AT))$. For Model 4b it plots $\widehat{f}'(AT)+ \widehat{f}'(AT) \times y_0$ with $(\widehat{f}'(AT)+ \widehat{f}'(AT) \times y_0) \pm 2 \times SE(\widehat{f}'(AT) + \widehat{f}'(AT) \times y_0)$.

We obtain the minimum temperature threshold for the corresponding year when a marginal effect curve cuts the zero line from the y-axis. Over time, it is evident that the minimum temperature threshold is falling and the temperature dependence curves of Delhi

[13] As the penalized splines fit is a trade-off between bias and variance one should account for possible bias in the estimate of f in the determination of variability bands. Wabha(1983) and Nychka(1988) have demonstrated how the Bayesian approach take in to account possible bias in the estimate of $\widehat{f}$. Models 3 and 4, effectively impose prior beliefs about the likely characteristics of the correct model by imposing a particular penalty (Woods,2006). In this approach, we specify a prior distribution on the parameters $\boldsymbol{\beta}$ such that it reflects our belief that smooth models are more likey than wiggly models. The prior distribution on $\boldsymbol{\beta}$ is chosen to give a convenient form for the posterior distribution of $\boldsymbol{\beta}$ given the assumed normal distribution of electricity demand ($\mathbf{E}$) i.e., ($\boldsymbol{\beta}|\mathbf{E}$). For Model 4a, it is $\boldsymbol{\beta}|\mathbf{E} \backsim \mathbf{N}(\widehat{\boldsymbol{\beta}}, \left[\mathbf{X}^T\mathbf{X} + \sum_t \lambda_t \mathbf{P}_t\right]^{-1} \sigma^2)$ and for Model 4b it is $\boldsymbol{\beta}|\mathbf{E} \backsim \mathbf{N}(\widehat{\boldsymbol{\beta}}, \left[\mathbf{X}^T\mathbf{X} + \lambda_1\mathbf{P}_1 + \lambda_2\mathbf{P}_2\right]^{-1} \sigma^2)$,with $\widehat{\sigma}^2 = \frac{\|\mathbf{E}-\mathbf{X}\boldsymbol{\beta}\|^2}{[n-tr(\mathbf{H}_\lambda)]}$

Figure 2.7:

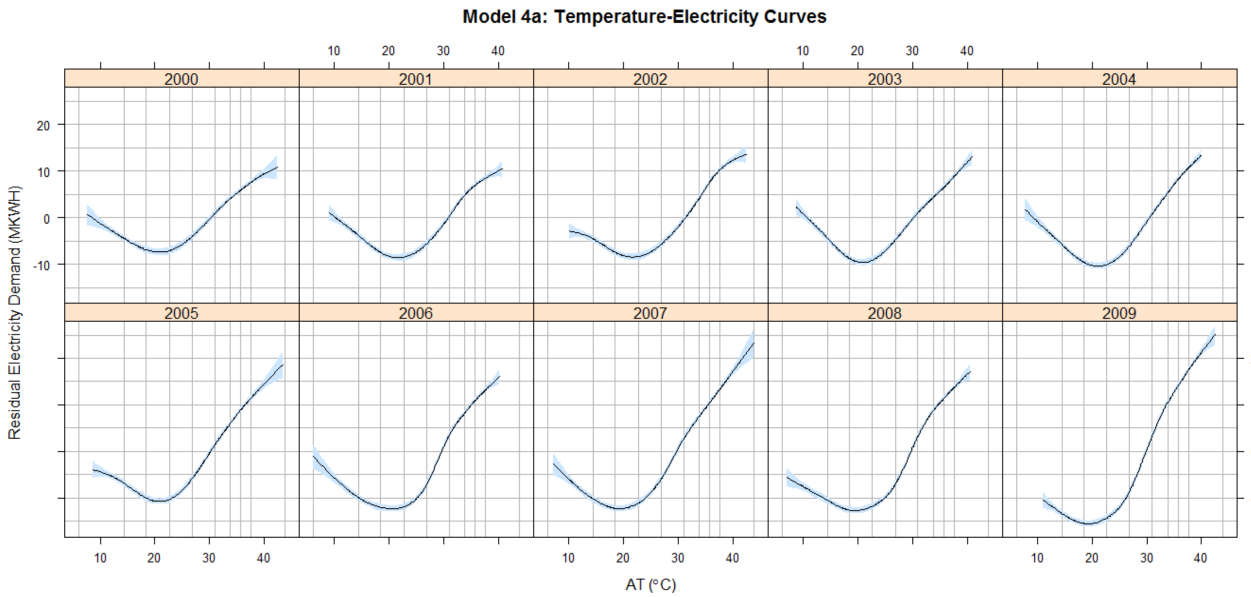


Figure 5a

Figure 2.8:

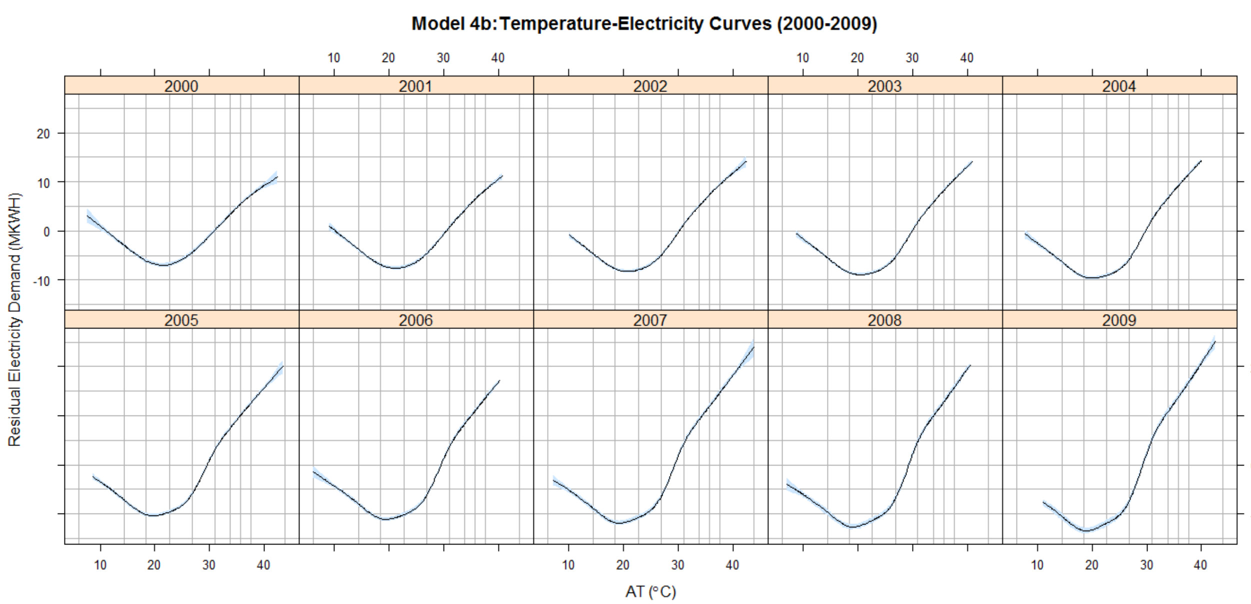


Figure 5b

Figure 2.9:

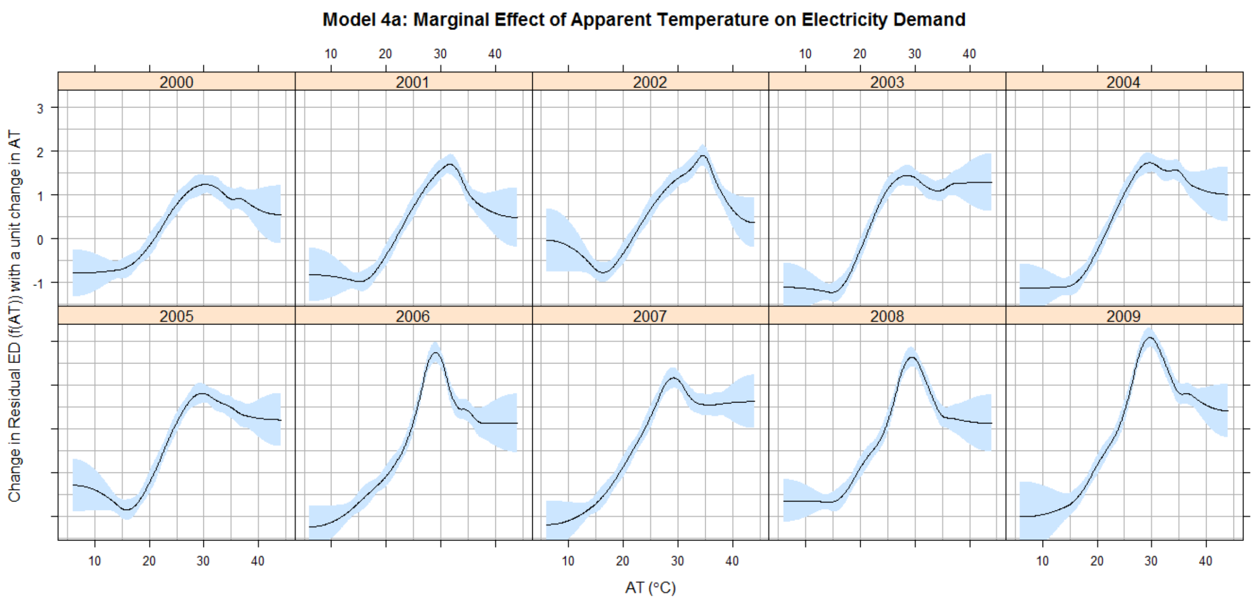


Figure 6a

Figure 2.10:

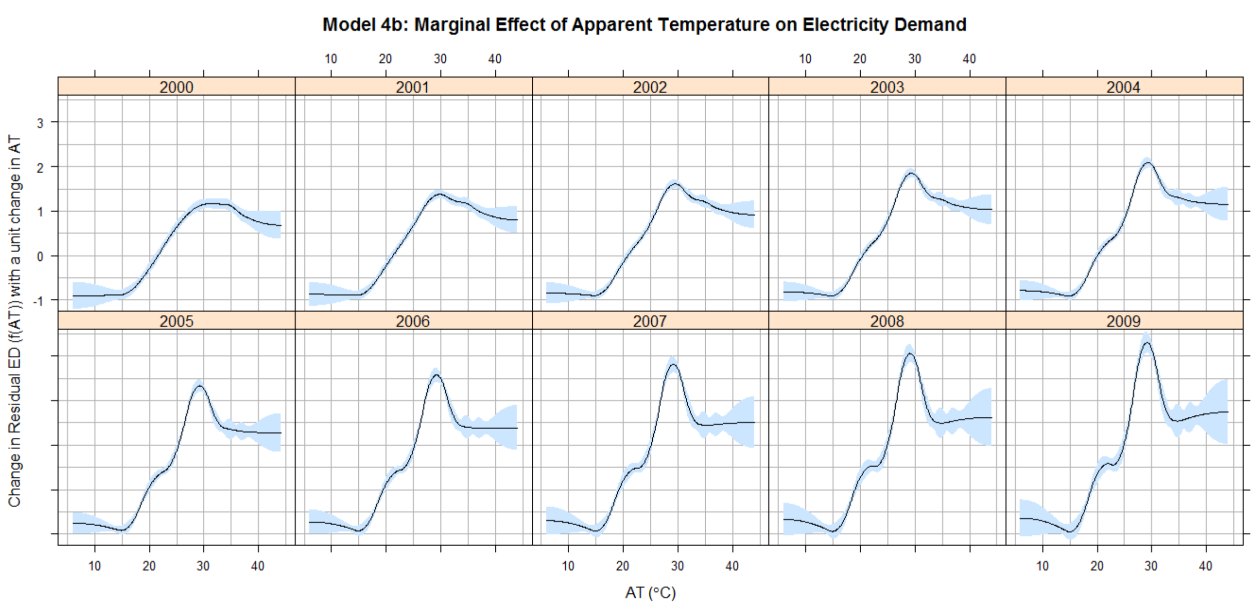


Figure 6b

are moving leftwards. Figure (2.11) plots these estimated threshold intervals represented by the shaded region (at zero line) in Figures (2.9, 2.10). It is clear that threshold intervals have shifted from approximately 20-22^{0}C in 2000-05 to about 18.5-20^{0}C in 2006-09 during the period of analysis .

	2000	2001	2002	2003	2004
Model 4a	19.6-**20.9-**22.1	20.6-**21.7-**22.6	20.4-**21.7-**22.6	20.1-**20.9-**21.6	20.1-**21.1-**21.9
Model 4b	20.7-**21.6**-22.2	20.4-**21.2**-21.9	20.1-**20.8**-21.5	19.8-**20.4**-21.1	19.5-**20.1**-20.7
	2005	2006	2007	2008	2009
Model 4a	20-**20.9**-21.8	19.1-**20.5**-21.7	18.4-**19.3**-20.5	18.6-**19.5**-20.7	18.5-**19.2**-20.3
Model 4b	19.3-**19.7**-20.4	19-**19.5**-20.1	18.8-**19.2**-19.9	18.7-**19**-19.7	18.5-**18.9**-19.5

It is possible to explain this shift through reference to the increase in the use of air conditioners and air coolers with rising incomes. In other words, people's sensitivity to hot temperatures is likely to increase with their ability to afford expensive cooling devices, which would in turn result in their switching of such devices at relatively lower temperatures.

In addition to the leftward shift of the temperature-electricity curve, we observe that the rising part of the curve is becoming steeper over time, implying an ever increasing cooling demand per unit increase in summer temperatures. As discussed previously, this may partly be attributable to the increasing penetration of energy intensive cooling devices such as air conditioners that give greater control over rising temperatures to the residents, especially in the humid summer climate of Delhi. The effect of the decline in heating demand per unit increase in winter temperatures, however, is much lower than the increase in cooling demand in summers. For instance, in both models, a 1 ^{0}C increase in temperature at 30 ^{0}C in the summer increased electricity demand by over 3 MkWh in 2009 as compared to only over 1 MkWh in 2000. On the other hand, a 1 ^{0}C increase in temperature at 15 ^{0}C in the winter decreased electricity demand by only 0.8 MkWh in 2009 as compared to 0.7

Figure 2.11:

Model 4a: Apparent Temperature Threshold Interval

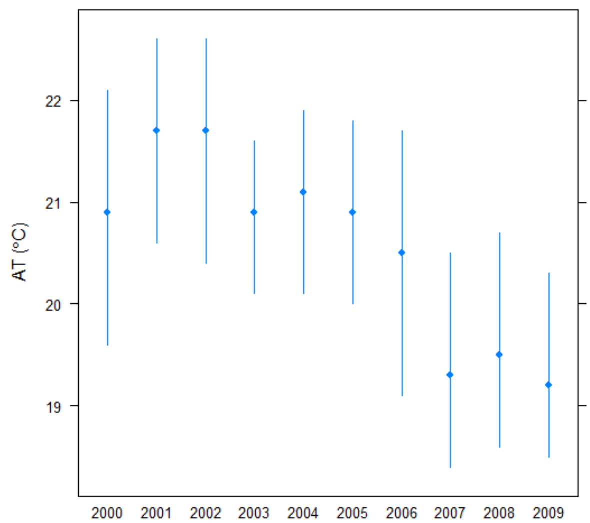


Figure 7a

Model 4b: Apparent Temperature Threshold Interval

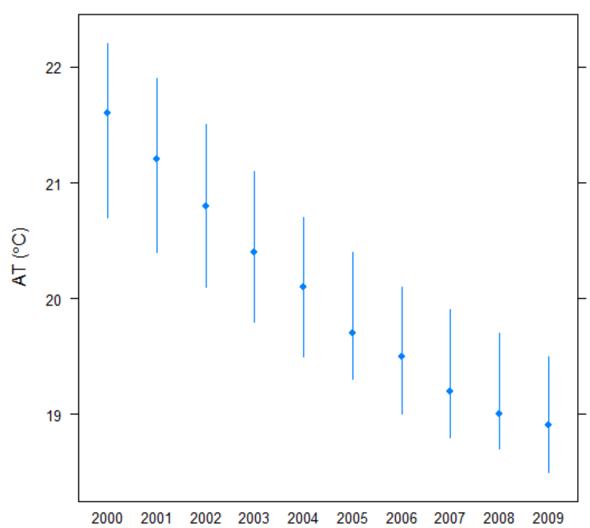


Figure 7b

MkWh in 2000.

In an earlier study which estimated a threshold transition model, Carcedo and Otero (2005) found 15.5 ^{0}C as the upper heating demand threshold and 18.4 ^{0}C as the lower cooling demand threshold for Spain. The smooth transition model obtained 15.4 ^{0}C as an optimal threshold temperature. In another study, Bessec and Fouquau (2008) found the threshold temperature to be about 16 ^{0}C for the whole sample of European countries while it was 14 ^{0}C for the sample of cold European countries and 22.4 ^{0}C for the sample of hot European countries. Although the thresholds obtained in this paper are not directly comparable with the previous studies, due to the average temperatures that those studies are based on in contrast with the apparent temperatures used in the present study, the thresholds give a fairly good idea about how threshold temperatures may vary both spatially and temporally with economic growth and that therefore they cannot be assumed to be static.

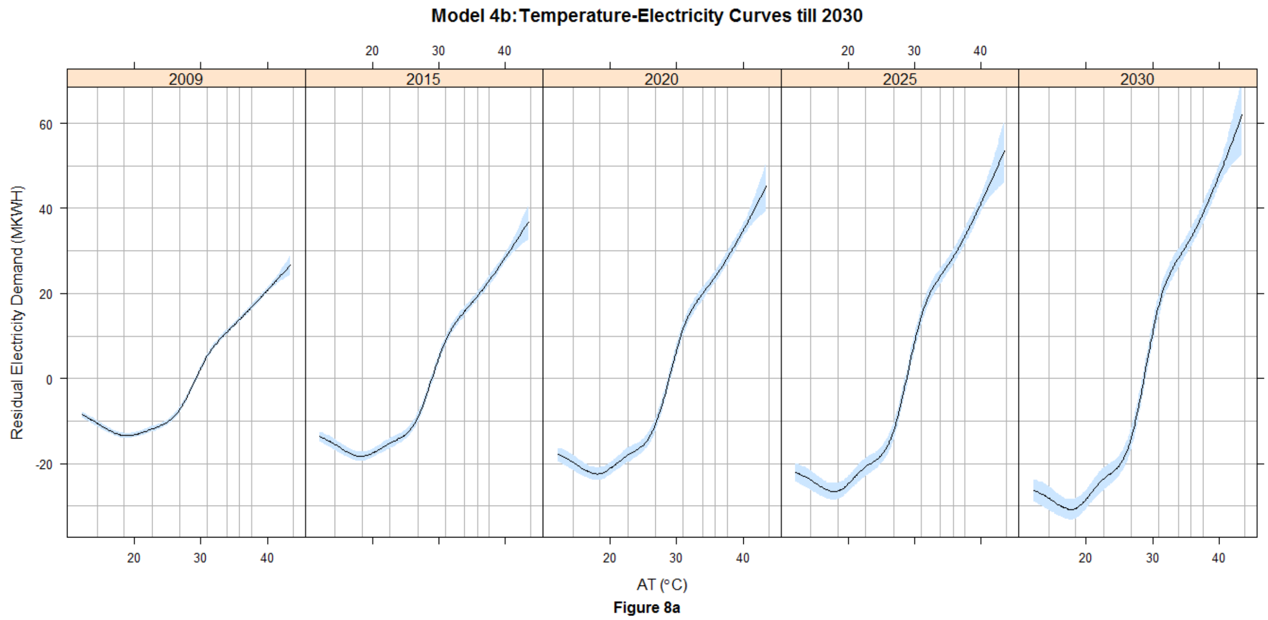
2.7 Global warming and electricity demand

The leftward shifting temperature-electricity curve and the rightward shifting temperature distribution may have significant implications for electricity demand in India in future.

2.7.1 *Key assumptions*

Based on the existing global warming projections for India by the Intergovernmental Panel on Climate Change (IPCC) and the Hadley Centre,we assume three hypothetical

Figure 2.12:



scenarios for global warming: a uniform 1 ^{0}C, 2 ^{0}C and 3 ^{0}C increase in daily apparent temperatures between 2009 and 2030 over the daily apparent temperature for 2009. Assuming that other predictor variables are the same as in the year 2009, we therefore use the estimated model to predict the impact of 1 ^{0}C, 2 ^{0}C and 3 ^{0}C increase in daily apparent temperatures on the electricity demand in Delhi till the year 2030.

2.7.2 Results: The impact of global warming

As shown in the previous section, the impact of temperature change or global warming on electricity demand is likely to be time-varying. Figures (2.12, 2.13, 2.14) therefore plots the forecasted temperature-electricity curve, the marginal effect curve and the threshold temperature up to 2030 under the baseline scenario (i.e., assuming that the temperature remains the same as in 2009) using Model 4b.

Figure 2.13:

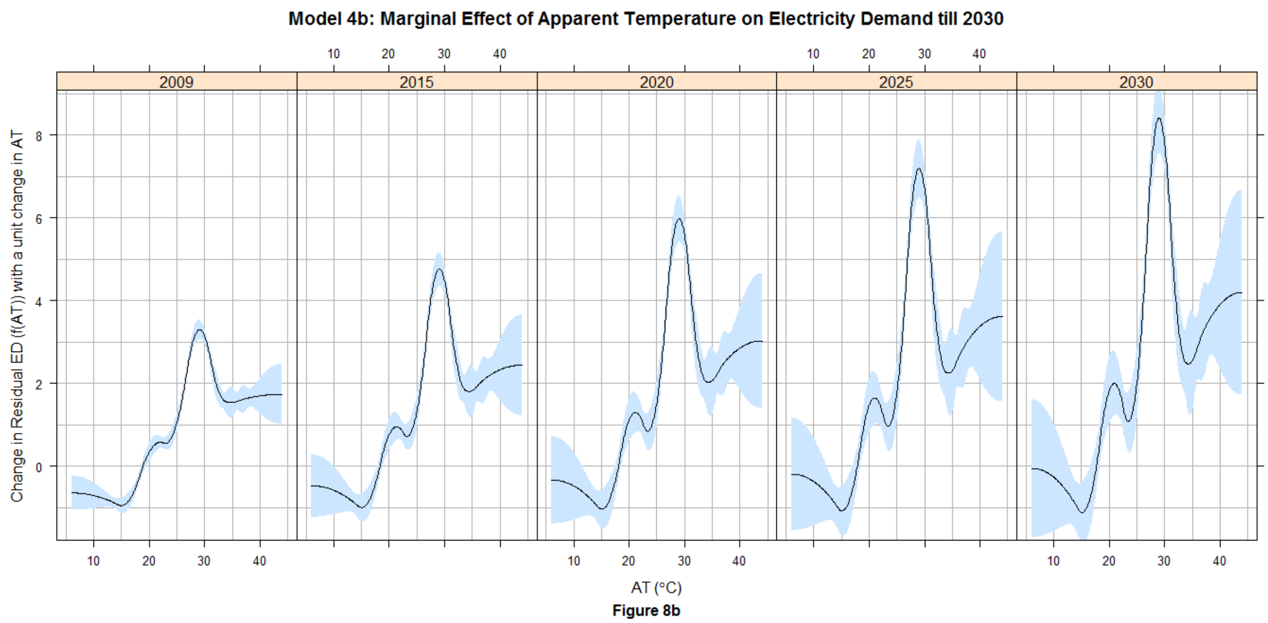
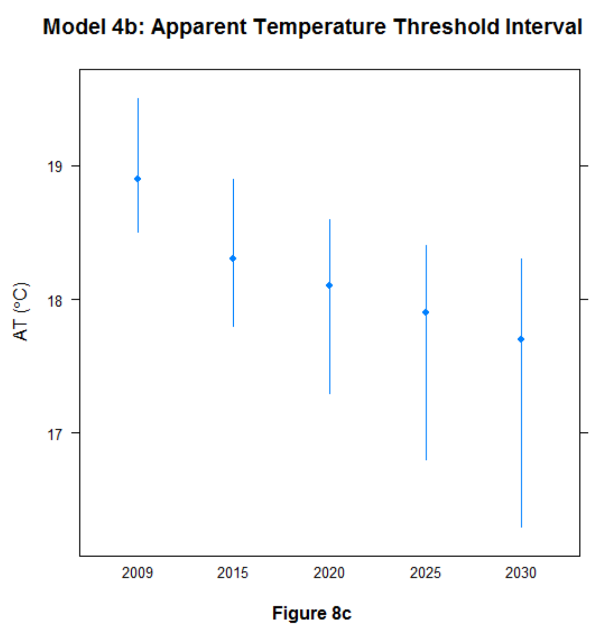


Figure 2.14:



The results show that the rising part of the curve is likely to become much steeper in future. A 1 ^{0}C increase in apparent temperature at 30 ^{0}C is expected to increase electricity demand by over 5 MkWh in 2015, 6MkWh in 2020, 7 MkWh in 2025 and about 8 MkWh in 2030. We observe that the threshold apparent temperature is likely to fall from about 19^{0}C in 2009 to 17.7^{0}C by 2030.

Figures (2.15, 2.16, 2.17) displays the results for the three global warming scenarios. A 1 ^{0}C increase in apparent temperature increases the electricity demand by about 402 MKWH (or 1.7%) in 2009 over its base electricity demand of 23827 MKWH, 564 MKWH (or 2.1%) in 2015 over its base electricity demand of 27522 MKWH, and 968 MKWH (or 2.6%) in 2030 over its base electricity demand of 36761 MKWH. A 2 ^{0}C increase in apparent temperature, on the other hand, increases net electricity demand by about 842 MKWH (or 3.5%) in 2009, 1182 MKWH (or 4.3%) in 2015 and 2032 MKWH (or 5.5%) in 2030. Similarly, A 3 ^{0}C increase in apparent temperature increases net electricity demand by about 1321 MKWH (or 5.5%) in 2009, 1856 MKWH (or 6.7%) in 2015 and 3191 MKWH (or 8.7%) in 2030.

In addition, Figures (2.15, 2.16, 2.17) also disaggregates the impacts of global warming by months. Higher temperatures increase electricity demand in the summers (led by April and May) and in the monsoon period (led by September) and post-monsoon period (led by October) while lower temperatures decrease the electricity demand in winters (led by January). It is evident that the maximum impact is likely to be felt in the hot month of April with an average apparent temperature of 30^{0}C, followed by the months of October and May. The marginal effect curve peaks at about 30^{0}C, indicating the maximum sensitivity

Figure 2.15:

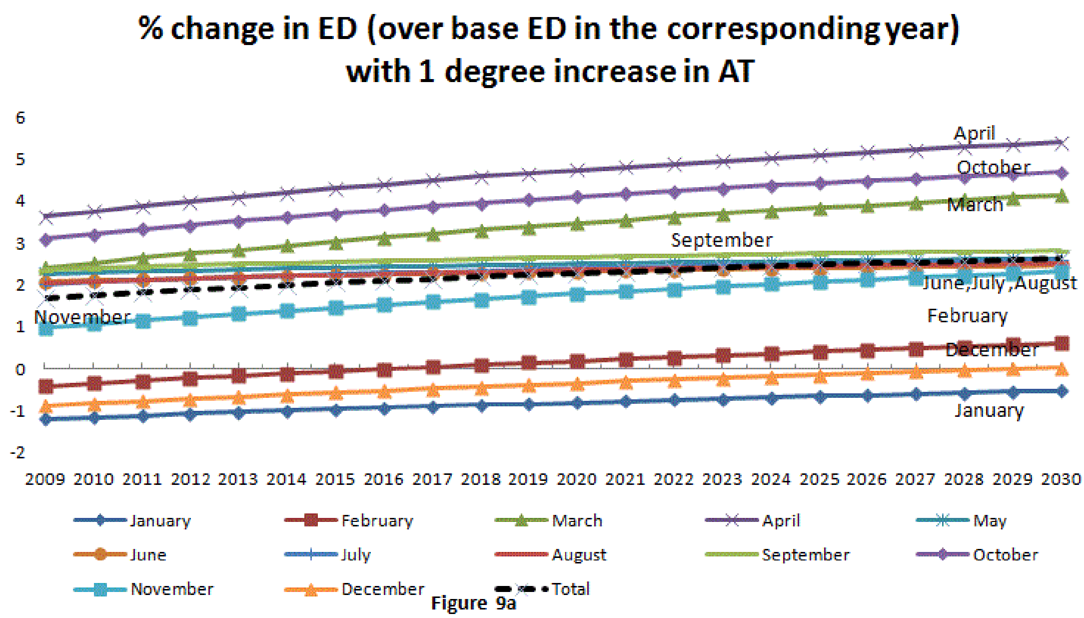


Figure 2.16:

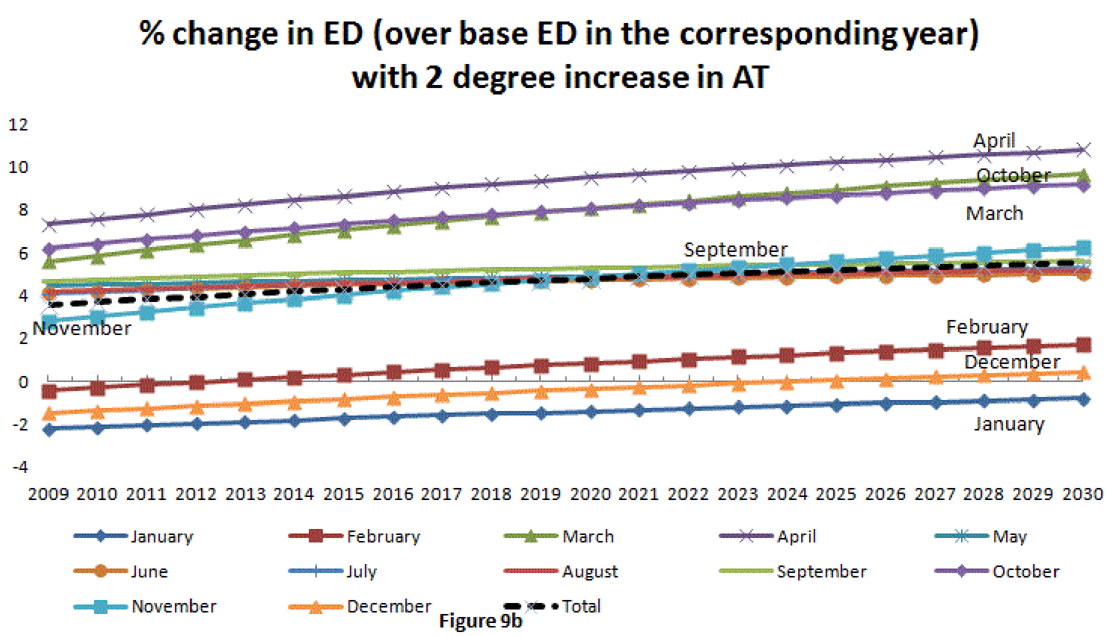


Figure 2.17:

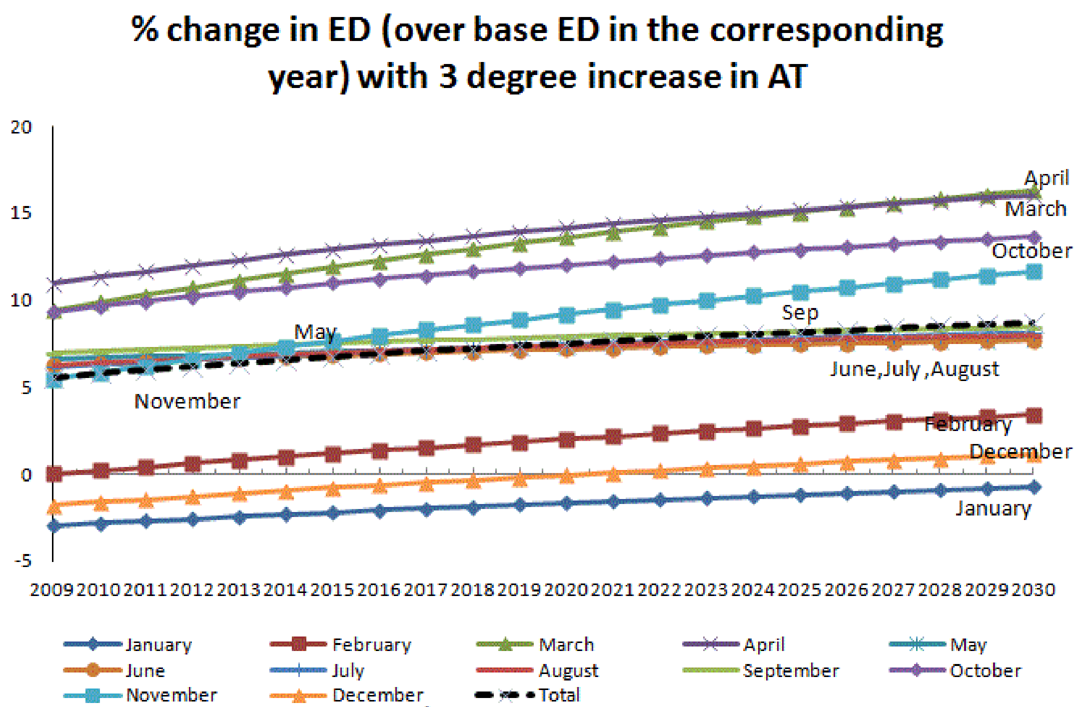


Figure 9c

of electricity demand to temperature at this level. As demand peaks during the months of June and July, the additional increments in electricity demand due to higher temperatures (over 30^0C) slow down and the marginal effect curve stabilizes.

Although a 1^0C increase in temperature increases the total electricity demand by 1.7% in 2009, the demand increases by about 3.6% in April, by 3.1% in October, and by 2.4% in September, May, and March. On the other hand, a 1^0C increase in temperature decreases electricity demand by 1.2% in January, 0.4% in February and 0.9% in December. Moreover, athough at present higher temperatures reduce electricity demand in the month of February, this trend may be reversed in future years with a leftward shift of the temperature threshold shifting the balance between the decreasing electricity demand for heating and the increasing electricity demand for cooling resulting from global warming. With a 2^0C and 3^0C increase in apparent temperature we may witness this trend much faster. Since electrical energy saved in winters cannot be easily stored for use in summers, global warming could result in a serious disequilibrium in electricity supply and demand during some months of the year in future.

In order to evaluate the prediction performance, we have compared the actual demand of two years (2008-09) with the predicted demand. In this evaluation, we have calculated the predicted demand for the two years using coefficients of the estimated model (based on 2000-07 data), known temperatures, and information on other drivers in these years. We have not used data from the forecast period for the model estimation. Figures (2.18, 2.19) illustrates the difference between observed and predicted electricity demand in 2008 and 2009. These graphs demonstrate that the model predicts demand in both years

Figure 2.18:

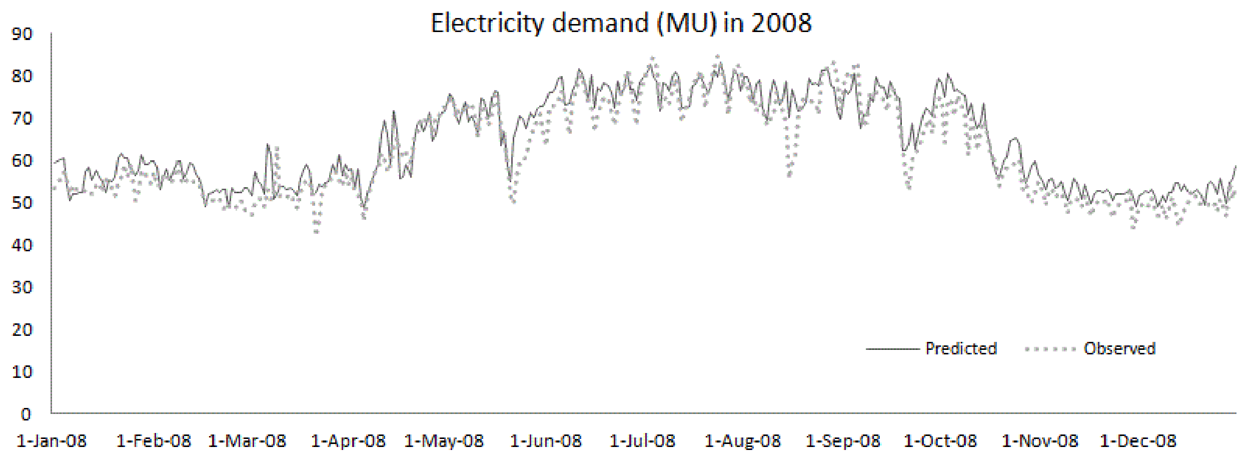
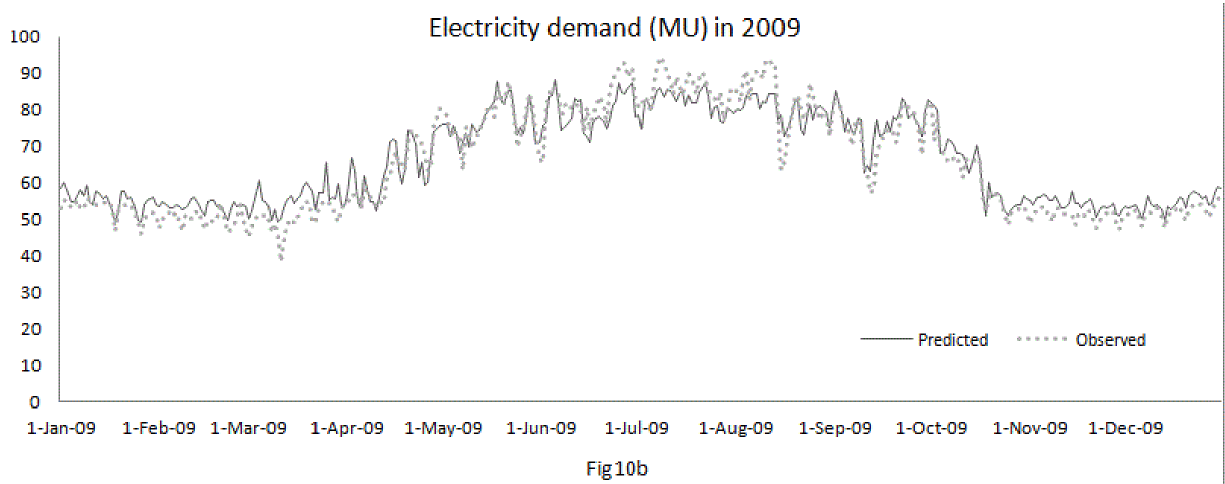


Fig10a

remarkably well. For instance, in 2008 the mean observed electricity consumption is about 62 MkWh while its standard deviation is about 11 MkWh. The root mean square error of predicted electricity consumption is 4.3 MkWh and the mean absolute error is 3.4 MkWh. Both these measures are much lower than the standard deviation of the electricity demand.

There are limitations to our research design when it comes to measuring the impacts of global warming on electricity demand in Delhi. Firstly, although the twenty-year prediction that our model offers has important implications for analyzing the impact of global warming on electricity demand, being based on available data for the past ten-years, these long-term forecasts may not carry a very high degree of precision. For instance, since in the factor variable coefficient model, the basis coefficients seem to change linearly with year over the past ten years, we impose the assumption that these coefficients change linearly with year in the numeric variable coefficient model. However, in an uncertain world, the underlying assumption may not hold true till 2030. A two year ahead prediction evalu-

Figure 2.19:



ation give some reassurance regarding the accuracy of the prediction, predicting electricity demand for two years from eight years of data is a safer proposition than predicting demand for twenty years with ten years of data. Hence, the results obtained in this study should not be interpreted as exact forecasts but as simply indicative of the direction and magnitude of the effects that might be expected from climate change. Secondly, as against the uniform global warming scenarios considered in the paper, there is a large body of evidence which suggests that temperature change has been non-homogeneous across months and seasons in the past. As discussed in Section 2, summers and post-monsoon seasons have shown the maximum shift. For instance, the average apparent temperature in April has shown a maximum increase of 2.21 ^{0}C over two decades (1990-99 and 2000-10). Rising temperatures during this season coupled with the peaked marginal effect curve during this period will intensify the disequilibrium problem. A monthly disaggregation of climate impacts will therefore enhance the policy relevance of the scenarios considered in this paper. Thirdly, this study only investigates the total electricity demand pattern for possible changes related to apparent temperature. Apart from the effect of global warming on total electricity demand, global warming will have significant impacts on future peak electricity demands and its variability. Colombo et al. (1999), using Canadian data, have shown that with climate change, the average peak demand may not increase drastically; instead, the number of high-electricity-consumption days may increase appreciably due to higher variability, placing a stress on power utility to meet this higher demand. However, due to data limitations, we have not considered peak demand, which is left for future research.

2.8 Conclusions

Both changing lifestyles and economic conditions in India have made electricity demand increasingly sensitive to temperature. This paper provides valuable insights into potential interactions between increasing cooling degree days and increasing incomes, and the impact of the resulting long-term adjustments (such as the higher penetration of air cooling devices) in the electricity sector. The results from a semi-parametric variable coefficient model indicate that the variation in the slope of the temperature-electricity curve and the threshold temperature is important for future electricity demand projections. An important contribution of the paper is the estimation of climate impacts by months. The model projects that the warming can result in significant increases in future demand, particularly during the hot months of April and May. These results can be extremely useful in managing the seasonal electricity disequilibrium situation in Delhi. For instance, demand-side management by shifting electricity loads from periods of deficit supply to surplus supply via dynamic pricing and other control mechanisms may help those in charge of energy policy-making and policy-implementation to cope with the problem. Policy makers may also consider providing various kinds of incentives on the purchase of energy efficient appliances. [Datta & Gulati, 2011] has shown the effectiveness of various incentives provided by US States and utility companies on the sales of Energy Star appliances. For instance, they found that with the average rebate for a clothes washer of $50 there is 10% increase in the share of energy-efficient clothes washers.

Policy makers will moreover need to come up with new measures to meet increased electricity demand due to global warming. They would, for instance, have to make a choice between fossil fuels and renewable energy sources for electricity generation. [Chakravorty et al., 1997] show that if the historical rates of cost reduction in the production of solar energy are maintained, more than 90 percent of world's coal would never be used. The world will move from oil and natural gas to solar energy. [Chakravorty et al., 2012b] find that nuclear power can reduce the cost of generating clean energy significantly and relatively quickly.

The results obtained in our study will be of use to electricity production and sales companies too in order to a) understand existing temperature-electricity sensitivity so as to manage risks related to unpredictable changes in energy demand under extreme weather events, for e.g., a heat wave; b) quantify the impact of projected global warming on electricity use; and c) forecast required future capacity investments in the electricity sector. The estimated threshold temperature of our study would be of use to HVAC[14] (heating, ventilation and air-conditioning) designers for the purpose of improving the efficiency of

[14]HVAC (heating, ventilation, and air conditioning) refers to technology for indoor or automotive environmental comfort. HVAC is important in the design of medium to large industrial and office buildings such as skyscrapers or marine environments such as aquariums, where safe and healthy building conditions take into consideration temperature and humidity, including "fresh air" from outdoors.

electricity use in their products. At present, the comfort standard practiced by HVAC designers is the same as that adopted in the U.S.A. for cooling buildings (i.e., air-conditioned buildings). Since a large amount of electricity is consumed by HVAC systems in buildings, designing HVAC (for comfort) as per the changing climatic conditions in India could bring down the electricity demand drastically.

Comprehensive assessment of impacts however requires not just sound empirical research but more geographical coverage, especially in areas where severe global warming is likely to occur. Hence, any future work on the topic should seek to extend the approach to other states in India in order to get an overall estimate of global warming on total electricity demand in India since the different socio-economic profiles of the states would lead to different temperature-electricity curves. It is our hope nevertheless that the present study would contribute to a better understanding of the dynamic non-linear temperature-electricity curve in a rapidly growing city.

Chapter 3

The Impact of Development on the Climate Sensitivity of Electricity Demand in India

3.1 Abstract

The climate sensitivity of electricity demand in India is likely to be highly sensitive to growth in income. Thus, both intensive and extensive adjustments in cooling and heating will play an important role in determining future climate change impacts on electricity demand. This chapter utilizes a national level panel dataset of 28 Indian states for the period 2005-2009 to show that (1) electricity demand is positively related to temperatures in summers and negatively related to temperatures in winters; (2) the effect of temperature increase on demand in summers is higher in a hotter climate as people adapt with the use

of higher cooling equipment whereas there is a higher negative response to temperature increase in winters in colder climates as people adapt using higher heating equipment; (3) the effects of both the hotter and the colder climates on electricity demand are expected to be more pronounced at the higher income levels. The preferred estimates indicate that climate change will increase electricity demand by 6.9 percent with 4 percent p.a. GDP growth and 8.6 percent with 6 percent p.a. GDP growth in 2030 over the reference scenario of no climate change. This reflects the fact that the estimated marginal effect of a hotter climate is greater when income is higher. The results suggest that over 50 percent of the climate change impacts will be due to extensive adjustments and that electricity demand models that do not account for extensive adjustments are likely to underestimate the climate change impacts on electricity demand especially in developing countries like India where the current penetration of air- conditioning equipment is very low.

3.2 Introduction

This chapter aims to understand how India's electricity demand will be affected by changes in its climate, weather and income. To what extent does the weather sensitivity of electricity demand depend on climate and the level of income? Due to growth, the impact of climate change in India will be time-varying. We saw in chapter 2 that the rising part of the U-shaped temperature-electricity curve of Delhi is becoming steeper over time implying an increase in cooling demand per unit increase in summer temperatures. In this Chapter, I extend the analysis to the all-India level, enabling the use of the large climatic and income variations across states to assess the dependence of the temperature-electricity demand relation on the level of income and climate.

I estimate the relationship between daily electricity demand, daily temperature (a key indicator of weather), climate and income across 28 spatially differentiated Indian states[1] using state-level panel data for the period 2005-2009. This is the first econometric study that estimates the impact of climate change on the electricity demand in the case of India. This research is novel in that it uses high frequency daily data to analyze the dynamics of adjustment across differentiated Indian states by modeling India's electricity demand within a panel framework using state and region fixed-effect models.

The study finds that the climate sensitivity of electricity demand in India is likely to be highly sensitive to its income growth. Between 2009 and 2030, India's GDP will double if it grows at 4 percent p.a. and treble if it grows at 6 percent p.a. According to my preferred estimates, in a reference scenario with no climate change, electricity demand in India is expected to surge by 105 percent with 4 percent p.a. GDP growth and by 224 percent with 6 percent p.a. GDP growth by 2030. If India's climate warms by 1^0C during this period, then the demand for electricity is likely to increase by 119 percent with 4 percent p.a. income growth, and by 252 percent with 6 per cent p.a. income growth by 2030. Thus, as a result of climate change, electricity demand is estimated to be 6.9 percent higher than in the reference scenario with 4 percent p.a. GDP growth and 8.6 percent higher than in the reference scenario with 6 percent p.a. GDP growth by 2030. This reflects the fact that the estimated marginal effect of a hotter climate is greater when income is higher. Over 50 percent of the climate change impacts on demand are due to extensive adjustments in cooling and heating requirements. Thus, electricity demand models that

[1] The India is made up of 27 states and one union territory, namely, Chandigarh.

do not account for extensive adjustments are likely to underestimate the climate change impacts on electricity demand, particularly in developing countries such as India where, unlike in the case of developed countries, the penetration of cooling technologies is very low at present. In 2007, for instance, approximately only 2 percent of households had access to air-conditioners as against 87 percent in the U.S. ([Sivak, 2009]). However, in a warmer and a richer future economy, there is bound to be rapid adoption of energy-using equipment ([Wolfram et al., 2012]). [Akpinar-Ferrand & Singh, 2010] for example, have shown air-conditioning to be a significant preventive mechanism in avoiding extremely hot days and that it should be considered a key climate adaptation strategy for India.

As I have shown in Chapter 2 there is a non-linear relationship between temperature and electricity demand as the electricity demand is positively related to temperatures in summer and negatively related to temperatures in winters. Therefore, climate change is expected to reduce electricity consumption in winters and increase electricity consumption in summers. Also, climate change will affect electricity demand by changing how people will respond along both extensive and intensive margins of adjustment (see review by [Auffhammer & Mansur, 2012]). For instance, in the short run, during summer, people may adapt by using existing cooling equipment more intensively on a hot day while, in the long run, they may choose to buy an air-conditioner to mitigate expected reduction in comfort due to changed climate [Sailor & Pavlova, 2003]. Thus, while the long-term climate will determine the space-conditioning equipment stock in different states, the daily external weather or temperature determines the utilization of the equipment for heating or cooling. To capture both intensive and extensive adjustments due to climate change, I estimate the impact of daily weather as well as long-term climate on electricity demand in India.

This study estimates the non-linear relationship by a piecewise linear function using two segments: one for the summer where temperature is above the predetermined reference temperature, and another one for winters where temperature is below the same reference temperature. The approach assumes a V-shaped temperature-electricity curve with the minimum electricity demand point occurring at the reference temperature. I use cooling degree days (CDD) and heating degree days (HDD) that describe the deviation of daily mean temperature from a reference temperature[2] as a measure of severity of hot and cold weather respectively. For this study, I estimate the transition point of electricity demand from heating to cooling as 20.3 from the observed data. This reference temperature fits the data best as it minimizes the residual sum of squares in the estimated piecewise regression. I determine the slope of the rising segment by relating daily electricity demand and daily CDD in summers. I determine the slope of the falling segment by relating daily electricity demand and daily HDD in winters.

Thus, I use the daily CDD and HDD to analyze weather-related electricity demand. The sums of daily CDD and HDD over a year constitute the indicators for heat and cold stress, respectively, as well as the description of a state's climate. I determine the cooling degree day index (CDDI) and heating degree day index (HDDI) of each state as the average of the annual cooling degree days and heating degree days, respectively, during 2005-2009 in order to analyze the impact of long-term climate on electricity demand. I allow the slope of the rising part of the curve to depend on the climate by interacting CDD with the

[2]The reference temperature is defined as the outdoor temperature at which the cooling (or heating) systems do not need to run in order to maintain comfort conditions. When the outdoor temperature is below/above the reference temperature, the cooling/heating systems need to operate, resulting therefore in increased energy requirements.

CDDI in summers and the slope of the falling part of the curve to depend on the climate by interacting HDD with the HDDI in winters. I have utilized this method since a higher positive response to temperature increase is expected in summers in a hotter climate as people adapt by installing more cooling equipment, while a higher negative response to temperature increase is expected in winters in a colder climate as people adapt by installing more heating equipment. I also expect the effects of both the hotter and the colder climate to be more pronounced at higher income levels. [DePaula & Mendelsohn, 2010] analyzed the interaction between income distribution and climate change impacts in Brazil using cross-sectional household level data and found that the temperature elasticity of electricity consumption varies significantly across income classes. Thus, I have included a three way interaction of CDD, CDDI and income in summers and HDD, HDDI and income in winters in the study to investigate the impact of income on the climate sensitivity of electricity demand in India.

I have conducted the climate change analysis using near-term (2030/2016-2035) and mid-term (2050/2045-2065) scenarios for South Asia developed by the Intergovernmental Panel on Climate Change and that are presentated in Working Group-1 of the Fifth Assessment Report. With the whole temperature distribution shifting rightwards with global warming, there has been an increase in the cooling degree days and reduction in the heating degree days. Consequently, the CDDI will increase while the HDDI will fall. In this Chapter, I combine the estimated electricity demand model with predicted changes in both daily degree days and long-term climate to develop estimates of the changes related to electricity demand in India. With that aim in mind, Section 2 of the Chapter describes the data sources and reports summary statistics. Section 3 presents the econometric approach while Section 4 describes the results. Section 5 assesses the magnitude of my estimates of the effect of climate change. In Section 6, I present the conclusions and policy implications of my findings.

3.3 Data and Summary Statistics

3.3.1 Data Sources

I base the empirical results of the study on daily data for the period 2005 through 2009 for the 28 states. The dependent variable is the daily electricity demand of the state, measured in million kilowatt hour (MKWh), as obtained by the operator of the national electricity grid, the National Load Dispatch Centre (NLDC). The electricity consumption reported by the NLDC is restricted electricity demand, which is equal to the electricity supplied by the utilities. To obtain the unrestricted electricity demand, I add the state electricity supply shortage to the electricity consumption data of NLDC. For Delhi and the eastern states, I have obtained the observed daily shortage respectively from the Delhi Transco Ltd. and the NLDC. For the other states, the observed daily shortage[3] data is only available from 2008 onwards; therefore, I use the monthly shortage data published by the Central Electricity Authority (CEA) of India to derive an approximate electricity supply shortage for each day for the period before 2008.

The explanatory variables fall into three categories: (1) climate and weather vari-

[3]The daily shortage data comprises five components: shedding due to transmission and distribution constraints; shedding by discoms in theft-prone areas; shedding in order to restrict overdrawal; shedding due to grid constraints; and shedding in order to restrict under-frequency operations.

ables; (2) socio-economic characteristics; and (3) seasonal factors. The first category of explanatory variables is climate and weather variables. I convert the mean daily temperature into cooling degree days (CDD) during summer (with the mean temperature above 20.3^0C) and heating degree days (HDD) during winter (when the mean temperature is below 20.3^0C). The CDD and HDD quantify the difference between the daily mean temperatures above or below a reference temperature. I calculate the HDD on day d on the basis of the relation: HDD_d=min $(0,\mathrm{T}_d$-20.3), where T_d is the mean temperature on day d. I calculate the CDD on day d on the basis of the relation: CDD=max $(0,\mathrm{T}_d$-20.3). As a measure of climate during summer, I use the average of the annual cooling degree days during 2005-2009 or the state cooling degree day index (CDDI). As a measure of climate during winter, I use the absolute value of the average of the annual heating degree days during 2005-2009 or the state heating degree day index (HDDI). I define the CDDI and HDDI as

$$\begin{aligned} CDDI_{it} &= 1/5\left(\sum_{d=1}^{d=1825} max(0, T_{id} - 20.3)\right) \\ HDDI_{it} &= 1/5\left(-\sum_{d=1}^{d=1825} \min(0, T_{id} - 20.3)\right) \end{aligned}$$

The daily rainfall is the other weather variable. I construct both state-level daily temperature and daily rainfall using the $1^0\times\ 1^0$ gridded daily dataset published by the Indian Meteorological Department[4] (IMD).

The second set of variables that the study uses are socio-economic variables: income, population and electricity prices. I use the gross domestic product per capita of a state as an indicator of income and its stage of development. I take the annual real GDP

[4]For Delhi and Chandigarh that are not identified in this gridded dataset due to their small size, I have obtained station-level data from the website www.tutiempo.net/en/climate/India.

(1999-2000 prices) of the state and population from the Ministry of Statistics and Programme Implementation. I construct the annual electricity price of the state using data from the Central Electricity Authority (CEA) of India. First, I calculate the state electricity prices for each sector - Agriculture, Commerce, Industry and Residential Use- by taking the simple average over different categories[5] (voltage and phases). I construct the average electricity price for a state by taking the weighted average of the prices in these four sectors with the share of electricity sales of each sector in total sales taken as weights.

The final category of regressors consists of variables accounting for industrial seasonality and agricultural seasonality. In the agricultural sector (that accounts for 18 percent of total electricity demand), energy requirements for water-pumping depend on a state's agricultural season and rainfall pattern. To capture agricultural seasonality, I control for agricultural pumpsets and include an interaction of pumpsets with accumulated rainfall in the past 7 days. The latter determines soil moisture and, therefore, the demand for pumping. I obtain data on annual electricity using state agricultural pumpsets from the CEA. Industrial electricity consumption (that accounts for about 45 percent of total demand) is largely temperature-insensitive. However, there can be industrial seasonality due to business cycles, dependence on agriculture for its supply of raw materials and product demand. To capture industrial seasonality, I derive a state-specific monthly index of in-

[5] Since power requirement varies among consumers in terms of voltage and phases, the CEA computes the average rates of electricity supply for various categories of consumers. For instance, in the case of industries, it computes electricity prices for three different types: three-phase small-scale 400V; three-phase large-scale 11 KV, and three-phase very large-scale 33 KV. For domestic consumers, it gives prices for 230 V single-phase or 400 V three-phase used for lighting, air-conditioning, water heating, cooking, etc. For agricultural consumers, it reports prices for 230 V single-phase and 400 V three-phase used for running tube wells and pump sets. For commercial consumers, it gives prices of 230 V single-phase and 400 V three-phase used for equipment and appliances.

dustrial production[6] (MIIP). First, I calculate the percentage deviation from the average in the MIIP at all-India level for each month and year[7]. I take the average of the five percentage deviations from the average in MIIP obtained for each month during 2005-2009 as an indicator of the industrial seasonality for that month at all-India level. I multiply this all-India indicator of industrial seasonality by the share of industrial electricity consumption in the total electricity consumption of a state and the share of the state's industrial output in the industrial output of India in order to get a measure of state-specific MIIP . I take the data on the all-India monthly index of industrial production and the share of the state's industrial output in the industrial output of India from the Ministry of Statistics and Programme Implementation. I obtain the share of industrial electricity consumption in the total electricity consumption of a state from the CEA.

3.3.2 Summary Statistics.

Table (3.1) reports state-level summary statistics of all variables. The sample comprises a balanced panel of 28 states and a total of 51,128 observations. For each state, there are 1819 daily observations during the years 2005-2009 after allowing for the necessary lags (i.e., the sum of rainfall in the past seven days). Over the period, mean state daily electricity demand increased from 60 MKWh in 2005 to 79 MKWh in 2009 while the mean state daily temperature increased from 24.3 to 25 degree Celsius[8]. About 78 percent of the sample observations represent the cooling demand with the observed mean temperature

[6] Data on state-level MIIP is not available for most states.

[7] For instance, if in January 2005, the MIIP is 120 while the average MIIP in 2005 is 100, then the percentage deviation for January in 2005 is +20%

[8] The annual mean temperature of India in 2009 was about +.91 degrees Celsius above the average temperature (recorded during the 1961-1990 period) and was the warmest year since 1902. This superseded the earlier five warmest years: 2002(0.71), 2006(0.60), 2003(0.56), 2007(0.55), and 2004(0.51) (GOI 2009).

above 20.3^0C while 22 percent represent the heating demand with the observed mean temperature below 20.3^0C. This shows an almost equal variation in temperature in summers and winters. The average CDD is 6.8, which is higher than the average absolute value of HDD at 3.8, reflecting relatively mild winters and hot summers.

Since India, given its vast size, displays a large variation in terms of its climate among states, the CDDI too varies significantly from a low of 417 to a high of 2712 degree days. Similarly, the HDDI varies between 0 and 1927 degree days. Equally important, the real gross state domestic product per capita over the period too varies significantly, from a low of INR 7500 to a high of INR 89300. At the same time, the mean state real gross state domestic product per capita increased by 30 percent from approximately INR 25,300 in 2005 to INR 33,000 in 2009.

I plot all the states in the two-dimension space of gross domestic product per capita and climate for the year 2009. Figure (3.1) presents a scatter plot of state gross domestic product per capita versus CDDI. The plot shows that most states are hot with a high value of the CDDI. While the states in the top right of the scatter plot are both hot and rich, the states in the bottom right are hot but poor. Figure (3.2) presents a scatter plot of state gross domestic product per capita versus HDDI. The plot shows that most states (except the northern states) experience mild winters with a low value of the HDDI. The northern states, on the other hand, with both high CDDI and HDDI, are characterized by strong temperature variation during the different seasons. The southern states, with the highest CDDI and zero HDDI experience only slight seasonal variations in temperature. The western and the eastern states experience mild winters and hot summers while the

Table 3.1: State-level Summary Statistics

Variables	Mean			Standard deviation		Max	Min	Obs
	2005-2009	2009	change	overall	Within			
			from 2005		state			
Daily Electricity Demand (MKWH)	69.53	79	19	78.22	16.31	431.5	0.1	51128
Climate and Weather								
Daily mean Temperature (^{o}C)	24.5	25	0.66	5.5	4.9	39	0.6	51128
Daily CDD ([Temp-20.3]*D(T>20.3))	6.5	6.8	0.4	3.3	3	18.7	.001	40034
Daily HDD ([Temp-20.3]*D(T<20.3))	-4.3	-3.8	-0.6	3.4	2.7	0.00	-19.7	11094
Cooling Degree Day Index (CDDI)	1864	1864	-	542	0	2712	417	51128
Heating Degree Day Index (HDDI)	328	328	-	408	0	1927	0	51128
Rainfall (sum of last 7 days (mm))	31.78	27.8	7	51.4	49	703	0	50932
Socio-Economic								
GDPPC (Rs)	29000	33000	7600	15315	3231	89300	7500	51128
Population (million)	40.3	41.5	2.3	42.3	1.3	195	0.94	51128
Price(Paise/KWH)	269	243	-60	67	37	458	133	51128
% Villages Electrified	83.6	84.6	2.6	19	2.3	100	30.4	51128
Agriculture Pumps (thousand)	555.8	577.5	49.6	800.6	41.6	3116.6	0	51128
State MIIP						7554	-4082	51128

Note: All entries are simple averages over all 28 states.

north-eastern states experience mild winters and mild summers.

Over the five years of the study period, relatively little variation within states is evident, for population, agricultural pumpsets, percentage of villages electrified and real electricity price that are used as control variables though they vary significantly between states.

Figure 3.1:

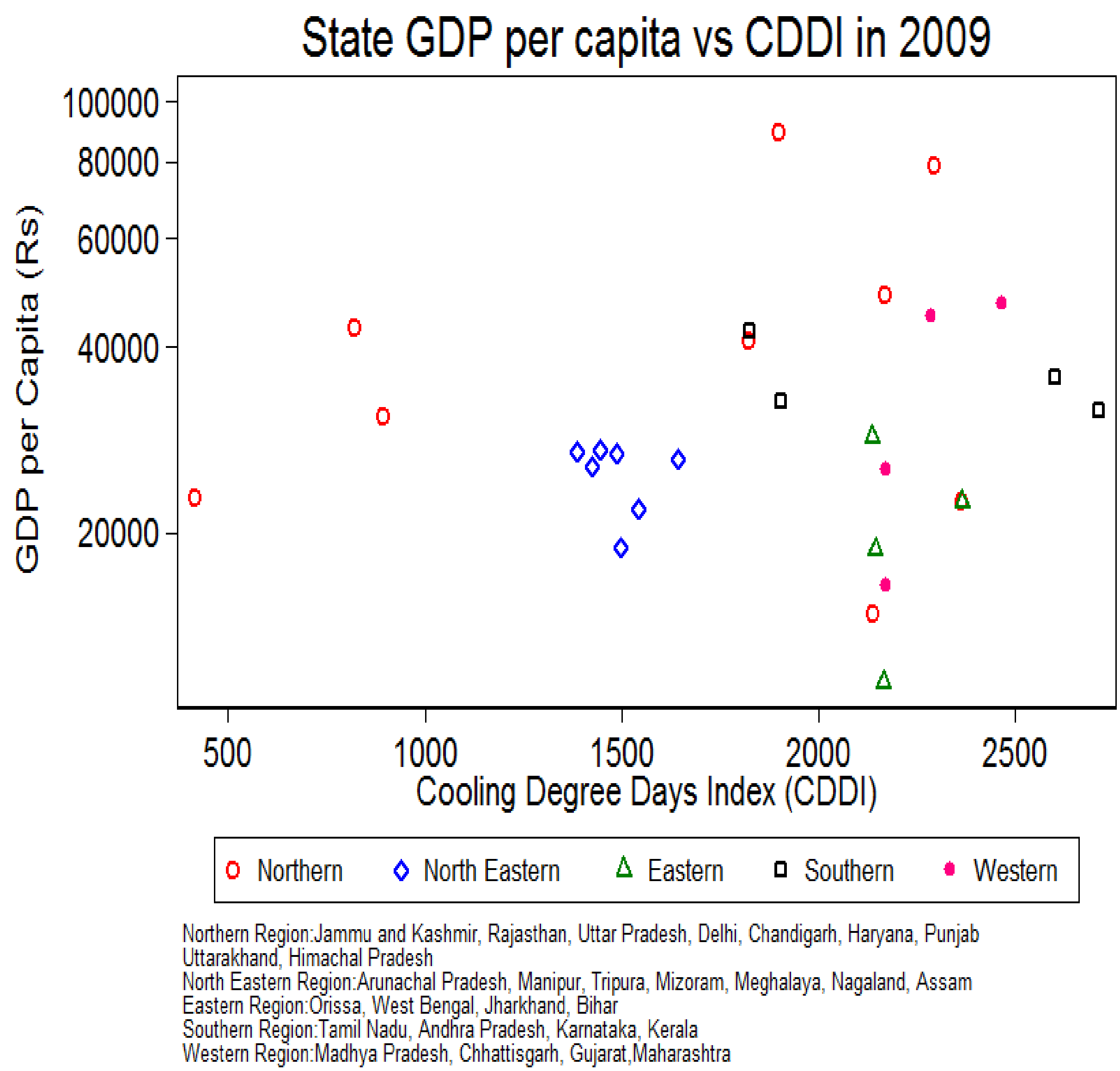
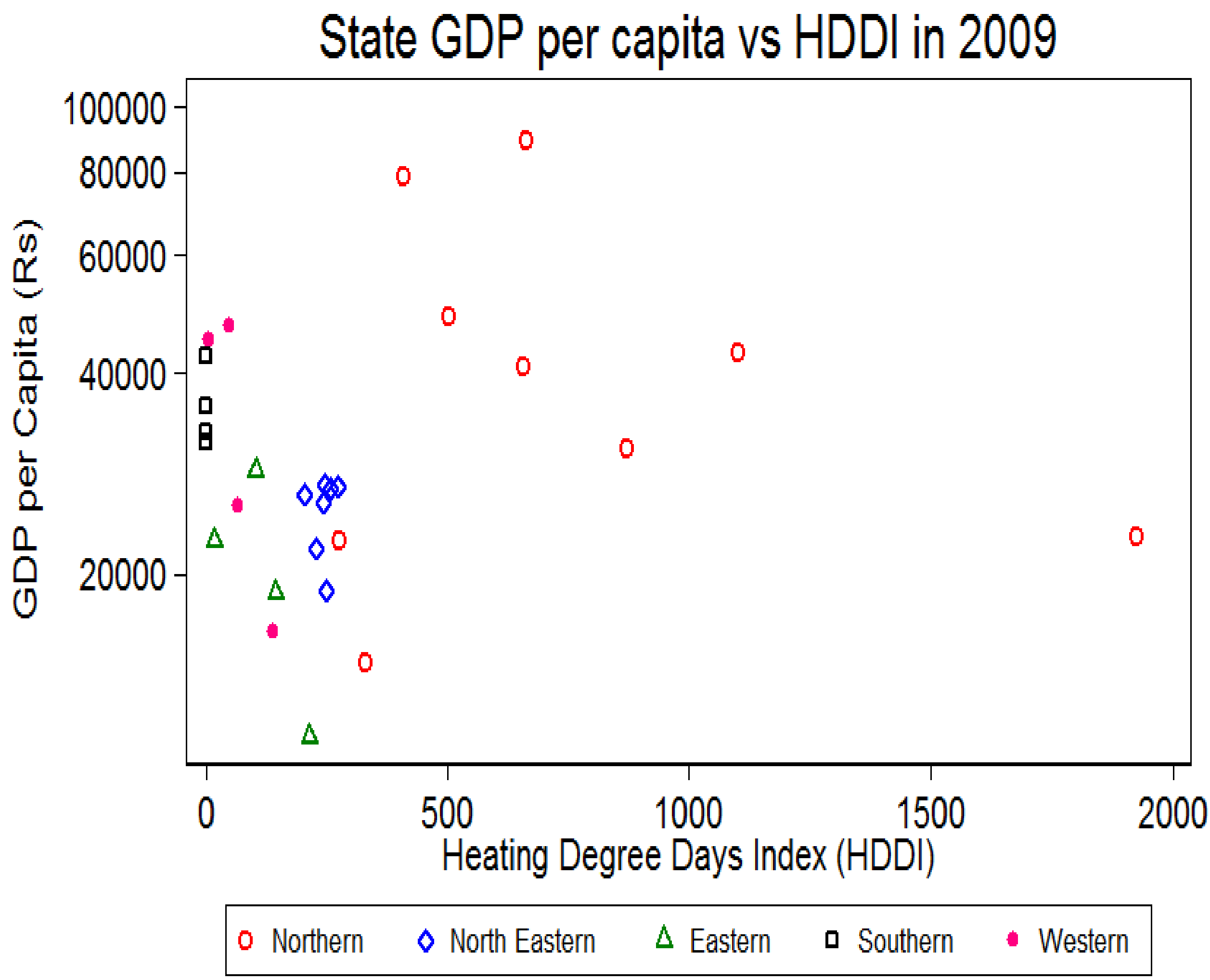

State GDP per capita vs CDDI in 2009
GDP per Capita (Rs)
100000
80000
60000
40000
20000
500
1000
1500
2000
2500
Cooling Degree Days Index (CDDI)
Northern
North Eastern
Eastern
Southern
Western
Northern Region:Jammu and Kashmir, Rajasthan, Uttar Pradesh, Delhi, Chandigarh, Haryana, Punjab
Uttarakhand, Himachal Pradesh
North Eastern Region:Arunachal Pradesh, Manipur, Tripura, Mizoram, Meghalaya, Nagaland, Assam
Eastern Region:Orissa, West Bengal, Jharkhand, Bihar
Southern Region:Tamil Nadu, Andhra Pradesh, Karnataka, Kerala
Western Region:Madhya Pradesh, Chhattisgarh, Gujarat,Maharashtra

Figure 3.2:



Northern Region:Jammu and Kashmir, Rajasthan, Uttar Pradesh, Delhi, Chandigarh, Haryana, Punjab
Uttarakhand, Himachal Pradesh
North Eastern Region:Arunachal Pradesh, Manipur, Tripura, Mizoram, Meghalaya, Nagaland, Assam
Eastern Region:Orissa, West Bengal, Jharkhand, Bihar
Southern Region:Tamil Nadu, Andhra Pradesh, Karnataka, Kerala
Western Region:Madhya Pradesh, Chhattisgarh, Gujarat,Maharashtra

3.4 Empirical Strategy

This section describes the econometric framework that I use to assess the temperature and climate sensitivity of electricity demand. In Chapter 2, I estimated the U-shaped temperature electricity curve that varies over time for Delhi using the semi-parametric variable coefficient approach. In this chapter, I estimate the observed non-linear relationship between electricity consumption and temperature using a piecewise linear regression method. As external temperatures deviate above or below the reference temperature, the electricity demand increases proportionally. The V-shaped temperature-electricity curve is estimated with the minimum electricity demand point occurring at the reference temperature. I have selected the reference temperature of 20.3 Celsius as it minimizes the residual sum of squares and fits the observed data best[9]. I determine the upward sloping segment of the curve by regressing the daily electricity demand on the daily CDD in summers. I allow the slope of this rising segment to depend on climate and income by including interactions of CDDI and GDPPC with CDD. Similarly I determine the downward sloping segment of the curve by regressing daily electricity demand on daily HDD in winters. I allow the slope of this falling segment to depend on climate and income by including interactions of HDDI and GDPPC with HDD.

The first prediction of my empirical model is that electricity demand is positively related to temperatures in summers and negatively related to temperatures in winters. I first estimate a natural log electricity demand regression, which includes weather variables (CDD

[9]The commonly used reference temperature in the literature is 18 degrees Celsius. This threshold varies from region to region. In the case of India, though I searched between 17-22^{0}C, I found the residual sum of squares to be minimum in the interval 20.3–21^{0}C. In chapter 2, I found that the minimum temperature threshold interval for Delhi has shifted from approximately 20-22^{0}C in the 2000-05 period to about 18.5-20^{0}C in the 2006-09 period.

and HDD) plus controls for socio-economic characteristics and seasonal factors without interactions, as follows:

$$\begin{aligned}
\ln(E_{id}) \quad = \quad & \theta_i + \kappa_Q + \upsilon_w + \delta \ln(GDPPC_{it}) + \eta \ln(Pop_{it}) + \gamma \ln(price_{it}) \\
& + \vartheta \ln(Pump_{it}) + \rho \ln(Pump_{it}) * (Rain\ in\ Week)_{id} + \omega (Rain\ in\ Week)_{id} \\
& + \pi (Major\ Hol)_{id} + \alpha HDD_{id} + \beta CDD_{id} + \varepsilon_{id} \qquad (3.1)
\end{aligned}$$

where $\ln(E_{id})$ is the log of total electricity demand of a state i on day d. θ_i is a state-specific fixed effect allowing an idiosyncratic daily electricity demand for each state. It accounts for factors such as climate, geography, state-specific policies and natural resource endowments, which are fixed for a state over time. The term θ_i sweeps out the variation between states with estimates based on only the variation within each state. κ_Q is a quarter fixed effect allowing for general shocks in daily electricity demand affecting all states each quarter. This captures industrial and agricultural seasonality that might influence daily electricity demand during a year. υ_w is a day of week fixed effect that captures the weekly periodicity of electricity demand. For example, there may be lower demand on weekends. $\ln(GDPPC_{it})$ is the log of gross domestic product per capita of a state in year t, $\ln(Pop_{it})$ is the log of the population of a state in year t, $\ln(price_{it})$ is the log of the electricity price of a state in year t, $Major\ Hol$ is a dummy variable that takes the value one for a major holiday, and zero otherwise [10] , $\ln(Pump_{it})$ is the log of the number of electricity using agricultural pumpsets of a state in the year t , $Rain\ in\ Week$ measures the sum of

[10] A major holiday is one that is declared to be a holiday for all government employees (on account of national or religious events). Minor holidays are the 2 additional days of holidays that government employees are entitled to select for minor religious festivals from a list of scheduled holidays.

daily rainfall in millimeters (mm) in the past 7 days and is interacted with the number of agricultural pumpsets. CDD_{id} =max (0,T$_{id}$-20.3) is the cooling degree days on day d for state i . It takes a positive value in summers when temperature is above 20.3^0C and zero in winters when temperature is below or equal to 20.3^0C. HDD_{id}=min (0,T$_{id}$-20.3) is the heating degree days on day d for state i . It takes a negative value in winters and zero in summers. The last term, ε_{id}, in equation (3.1) is the stochastic error term.

I expect $\beta > 0$ and $\alpha < 0$. This prediction is quite straightforward and is confirmed by the existing literature ([Al-Zayer & Al-Ibrahim, 1996]; [**?**]; [Valor et al., 2001]; [Sailor, 2001]; [Pardo et al., 2002]; [Mirasgedis et al., 2007]).

Prediction 2 of my model states that the effect of the temperature increase in summers is generally higher in a hotter climate as people adapt with higher cooling equipment. Similarly, a higher negative response to temperature increases in winters is to be expected in colder climates as people adapt with higher heating equipment. To evaluate this prediction, I estimate Model B that includes an interaction of CDD_{id} with $CDDI_i$ and an interaction of HDD_{id} with $HDDI_i$ .I estimate the model as

$$\begin{aligned} \ln(Ed_{id}) &= \theta_i + \kappa_Q + \upsilon_w + \upsilon\prime X_{id} \\ &\quad + \alpha_1 HDD_{id} * HDDI_i + \beta_1 CDD_{id} * CDDI_i + \varepsilon_{id} \end{aligned} \tag{3.2}$$

where X includes all controls for socio-economic characteristics and seasonal factors as in eq (3.1). It is worthy of note that, in Model B, I drop the independent terms of HDD and CDD, the reason being that the slope of the rising segment of the V-shaped curve will be zero if the $CDDI$ is zero and the slope of the falling segment will be zero if the $HDDI$ is zero. The marginal effect of daily temperature on the log of electricity demand is

$\alpha_1 * HDDI_i$ if $T_{id} \leq 20.3^0C$ and $\beta_1 * CDDI_i$ if $T_{id} > 20.3^0C$. I expect $\beta_1 > 0$ and $\alpha_1 < 0$. I base the estimates of β_1 and α_1 in this model on within-state variations in CDD and HDD and between-state variation in the $CDDI$ and $HDDI$.

According to Prediction 3 of my model, the effects of both the hotter and the colder climates are expected to be more pronounced at the higher income levels. Thus, I include a three-way interaction of CDD, $CDDI$ and ln $GDPPC$ in summers and HDD, $HDDI$ and ln $GDPPC$ in winters to study the impact of income on the climate sensitivity of electricity demand in India. In other words, income and climate will interact to determine the temperature sensitivity of the electricity demand in a given state. To evaluate this hypothesis, I estimate Model C as:

$$\begin{aligned} \ln(Ed_{id}) &= \theta_i + \kappa_Q + \upsilon_w + \upsilon\prime X_{id} \\ &\quad +\alpha_1 HDD_{id} * HDDI_i + \beta_1 CDD_{id} * CDDI_i \\ &\quad +\alpha_2 HDD_{id} * HDDI_i * \ln(GDPPC_{it}) \\ &\quad +\beta_2 CDD_{id} * CDDI_i * \ln(GDPPC_{it}) + \varepsilon_{id} \qquad (3.3) \end{aligned}$$

The marginal effect of daily temperature on the log of electricity demand is $\alpha_1 * HDDI_i + \alpha_2 HDDI_i * \ln(GDPPC_{it})$ if $T_{id} \leq 20.3^0C$ and $\eta_1 * CDDI_i + \eta_2 * CDDI_i * \ln(GDPPC_{it})$ if $T_{id} > 20.3^0C$. We expect $\alpha_2 < 0$ and $\eta_2 > 0$.

For robustness checks, I estimate a less restrictive model using region fixed-effects instead of state fixed-effects. I estimate Model D as:

$$\begin{aligned}\ln(Ed_{id}) &= R_i + \kappa_Q + \upsilon_w + \upsilon\prime Z_{id} \\ &+\alpha_1 HDD_{id} * HDDI_i + \eta_1 CDD_{id} * CDDI_i \\ &+\alpha_2 HDD_{id} * HDDI_i * \ln(GDPPC_{it}) \\ &+\eta_2 CDD_{id} * CDDI_i * \ln(GDPPC_{it}) + \varepsilon_{id} \qquad (3.4)\end{aligned}$$

where Z includes all controls in X and two additional regressors, the proportion of villages electrified, and the share of industry in the gross domestic product of a state. R_i captures unobserved region-level heterogeneity by region fixed-effects. It accounts for factors which are fixed for a region over time. This model is likely to suffer from omitted variable bias as there are factors such as state-specific policies that may also be correlated with other explanatory variables such as income which may influence electricity demand significantly though this model does not account for them. The key advantage of this model is that it estimates coefficients using variation across states within a region, and variation within states over time. This would result in more precise estimates for the variables which are observed annually such as GDPPC, population, and price as the variation within a state over time is relatively much less than variation across states.

3.5 Regression Results

Table (3.2) summarizes results from all the models. The Table shows the marginal effects and associated standard errors of all the variables at sample means. Table A1 in the appendix reports the full estimation results. I use a range of models in order to explore the sensitivity of calculated coefficients to the equation specification. All models are estimated by ordinary least squares OLS. I report Newey-West type standard errors by Driscoll and Kraay (1998) that allow for autocorrelated and cross-sectionally correlated errors of the general form.

Column (1) of Table (3.2) reports the estimates of the basic model without interactions as in eq(3.1). In column (2), I interact HDD with the HDDI and CDD with the CDDI and estimate eq(3.2). In addition to the weather and climate interaction in column (2), column (3) adds the interaction of HDD with the HDDI and GDPPC and CDD with the CDDI and GDPPC to estimate eq(3.3). Column (4) estimates a region fixed-effects model as in eq(3.4). The R^2 value in all models is essentially unity; however, this is an artifact of the inclusion of state or region dummies. I prefer the full interacted state fixed-effect Model C over other models as it has the lowest standard errors for most of the coefficients. For purposes of robustness checks, I also estimated (but do not report for brevity) models with state-by-quarter fixed-effects and state-specific trends and find the results of the study to remain substantively unchanged.

Of primary interest here is the impact of change in the weather (CDD, HDD) and climate (HDDI, CDDI) on electricity demand. The basic results remain similar across models although in the more restricted state fixed-effect models (column (1-3)), the coefficients and standard errors of weather and climate variables are smaller than those in the region fixed-effects regression (column (4)), suggesting that unobserved state differences (for e.g., state-specific policies) may have biased the parameter estimates in the column (4).

As discussed above, the impact of temperature on electricity demand is non-linear

Table 3.2: Marginal Effect of Determinants of Electricity Demand at Sample Mean

	State Fixed-Effect			Region Fixed-Effect
	(1)	(2)	(3)	(4)
	Model A	Model B	Model C	Model D
VARIABLES				
Key Variables				
HDD	-0.00586***	-0.00111***	-0.00162***	-0.0152***
	(0.000994)	(0.000246)	(0.000236)	(0.000711)
CDD	0.0196***	0.0147***	0.0145***	0.0196***
	(0.000911)	(0.000876)	(0.000839)	(0.000872)
CDDI		0.00554***	0.00544***	0.00736***
		(0.000330)	(0.000316)	(0.000328)
HDDI		0.00135***	0.00197***	0.0184***
		(0.000298)	(0.000286)	(0.000862)
Log(GDPPC)	1.130***	1.132***	1.131***	.706***
	(0.0212)	(0.0208)	(0.0192)	(.0069)
Control Variables				
Log(Population)	0.109	0.111	0.168**	0.883***
	(0.104)	(0.113)	(0.0817)	(0.00430)
Log(Price)	0.0114	0.0125	0.0104	-0.188***
	(0.0102)	(0.0109)	(0.0106)	(0.00815)
MIIP	1.51e-05***	1.80e-05***	1.88e-05***	2.01e-05***
	(2.17e-06)	(2.27e-06)	(2.34e-06)	(2.29e-06)
% Villages Elect				0.00984***
				(0.000112)
Industry Share				0.0257***
				(0.000403)
Major Holiday	0.000923		0.00223	-0.0157***
	(0.00382)		(0.00368)	(0.00542)
Log(Agr_Pumpsets)	0.0100**	0.00986**	0.0122***	0.0400***
	(0.00487)	(0.00502)	(0.00420)	(0.00272)
Rainfall_Weeksum	-0.000506***	-0.000522***	-0.000465***	-0.000387***
	(4.58e-05)	(4.63e-05)	(4.67e-05)	(8.94e-05)
Observations	50,932	50,932	50,932	50,932
R-squared	0.993	0.993	0.994	0.97
State FE	YES	YES	YES	NO
Quarter FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Region FE	NO	NO	NO	YES

Driscoll and Kraay (1998) Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

with the slope going from negative or zero at low temperatures to positive impacts with increases in temperature. This pattern is borne out clearly in Table (3.2). The impact of a 1^0C change in temperature in winters (when temperature is below 20.3^0C) is small but negative and significant across all specifications. The impact of a 1^0C change in temperature in summers (when temperature is above 20.3^0C) is large and positive and significant across all specifications.

The magnitude of the coefficient of the CDD exceeds the coefficient of the HDD in all the models. The results indicate a seasonal heterogeneity in how people will respond to climate change along intensive margins of adjustment. For example, for the preferred Model C of this study, a 1^0C increase in temperature in summer increases expected daily electricity demand by 1.5 per cent (as a result of greater usage of cooling equipment) while a 1^0C increase in temperature in winter reduces electricity demand by about 0.2 percent (due to lower usage of heating equipment) at the sample mean of income and climate.

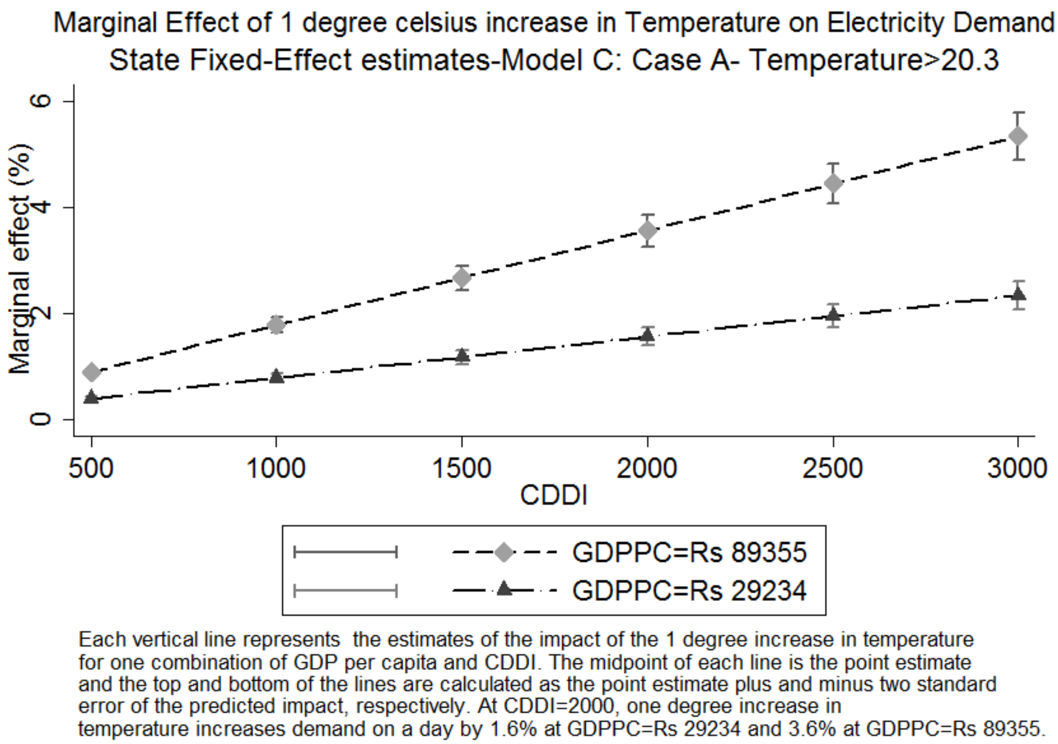
The response to the CDDI and HDDI captures the adjustment along the extensive margin due to climate change. Across specifications, the marginal impacts of CDDI and HDDI are positive and significant. For my preferred specification (Model C), I estimate an average of a 0.5 percent and 0.2 percent increase in electricity demand for a 100-degree day increase in the CDDI and HDDI, respectively. In Model D, the marginal effect is slightly higher at 0.7 percent for the CDDI (with the same standard error as in Model C) whereas it is significantly higher at 1.8 percent for the HDDI (though very noisy).

The results provide useful insights on how the intensive adjustments may depend on the extensive adjustments due to climate change. In Model B, when I include only the two-way interaction term of CDD and CDDI in summers and HDD and HDDI in winters, both the interactions are significant and have the expected signs. The interaction of CDD with CDDI is positive signifying that a hotter climate will lead to more space-cooling equipment and higher temperature sensitivity. The interaction of HDD with HDDI is negative signifying that the colder climate will lead to more space-heating equipments and higher negative temperature sensitivity.

In Models C and D, the interaction of the CDD with the gross domestic income per capita and CDDI is positive and significant at the $p<.01$ level. The sizes of the coefficients suggest that the interaction effect of the CDDI with income that I have identified is quite large. Thus, I expect the effects of hotter climate to be more pronounced at the higher income levels. The interaction of the HDD with the gross domestic income per capita and HDDI is negative and significant at the $p<.11$ level in Model C. Model D (estimated with region fixed effects), which includes both the two-way interaction of HDD and HDDI and the three-way interaction of HDD, HDDI and income, lead to a positive and significant coefficient on the three-way interaction term. This may indicate misspecification in the model as the variation in the HDDI is less (with many states having zero HDDI) and it may not be enough to estimate this effect. Thus, I drop the three-way interaction of HDD, GDPPC and HDDI in Model D to get meaningful estimates of the coefficients.

Although these results provide good insight into the magnitude and importance of each interaction effect, a visual inspection of the marginal effect of temperature at various combinations of climate and income may be more helpful in recognizing the presence of interactions. Figures (3.3) and (3.4) present the temperature sensitivity in summers and

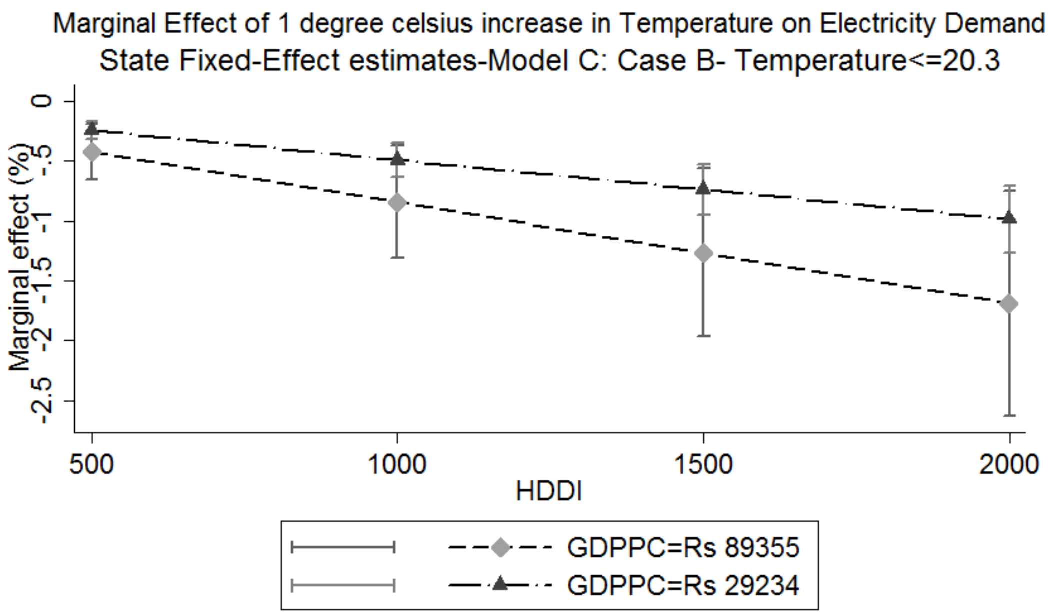
Figure 3.3:



winters, respectively, from Model C. At the mean income (INR 29,234) and CDDI of 2000, a 1 degree increase in temperature in summer increases expected daily electricity demand by about 1.6 per cent. At the highest level of income (INR 89,355) in the sample and CDDI of 2000, a 1 degree increase in temperature in summer increases expected daily electricity demand by about 3.6 per cent. At the mean income (INR 29,234) and HDDI of 500, a 1 degree increase in temperature in winter decreases expected daily electricity demand by about 0.2 per cent. At the highest level of income (INR 89,355) in the sample and HDDI of 500, a 1 degree increase in temperature in winter decreases expected daily electricity demand by about 0.4 per cent.

I draw the following conclusions based on the above results. The degree to which

Figure 3.4:



Each vertical line represents the estimates of the impact of the 1 degree increase in temperature for one combination of GDP per capita and HDDI. The midpoint of each line is the point estimate and the top and bottom of the lines are calculated as the point estimate plus and minus two standard error of the predicted impact, respectively. At HDDI=500, one degree increase in temperature decreases demand on a day by .2% at GDPPC=Rs 29234 and .4% at GDPPC=Rs 89355.

electricity demand in a given state is sensitive to changes in climate will depend both on its climate type and on the level of its economic development. As people's standard of living improves, their use of air conditioners and other temperature-controlling equipment tool will increase, thus increasing their sensitivity to climate change. As discussed earlier, the overall impact of climate change will be jointly determined by both intensive and extensive adjustments. The study finds that the interaction of income with the CDDI and CDD in summers has a much higher impact on electricity demand than the interaction of income with the HDDI and HDD in winters. As income determines how people adapt to climate change, both global warming and income growth will have asymmetric effects on electricity consumption in summers and winters. The results also indicate that an increase in temperature in summers has an impact on electricity consumption which is seven times the size of the impact of an equivalent increase in temperature on electricity consumption in winters and that an increase in net electricity demand would therefore be the likely result of climate change.

The control variables in Table (3.2) provide a rich set of results in and of themselves. The coefficients of the socio-economic variables such as GDPPC, population, price and pumpsets turn out to be more precise with much smaller standard errors in the region fixed-effects regression than the state fixed-effects regressions. The reason is the much larger variance in the socio-economic variables across states within a region than within a state over time, which results in greater residual variation and more precise estimates in the region fixed-effect model than in the state fixed-effect model.

Electricity demand is higher in the wealthier states than in the poorer states. A

1 percent increase in income per capita results in about 1-0.7 percent increase in daily electricity demand in most models. Interestingly, the elasticity of electricity demand with respect to GDPPC is higher than elasticity of electricity demand with respect to temperature and climate. As expected, price has a significant negative impact and population has a significant positive impact on electricity demand in the region fixed-effects regression. A 1 percent higher electricity price results in about 0.2 percent decrease in daily electricity demand. A 1 percent increase in population results in almost 0.9 percent increase in the daily electricity demand of a state. As expected, in the state fixed-effect models, price and population (with a small, within-state variation) turns out to be insignificant in most models. Most models suggest that higher the use of agricultural pumpsets higher the electricity demand; that rainfall has a significant negative impact on electricity demand; that the interaction of pumpsets with accumulated rainfall in the last thirty days is negative and significant; that on holidays, Saturdays and Sundays, expected electricity demand is estimated to be somewhat lower than the average level; that the index of industrial seasonality has a positive impact on electricity demand; that an increase in the proportion of villages electrified results in an increase in electricity demand; that higher industrial share in the income of a state increases electricity demand.

3.6 Impact of Climate Change on Electricity Demand

In this section, I explore the effect of predicted climate change on electricity demand. I calculate the predicted impact on electricity demand for each state as a difference between predicted electricity demand under the reference scenario of no climate change and the predicted electricity demand under the climate change scenario for two time-periods, short-term (2030) and mid-term (2050). I then sum each state's change in electricity demand to calculate the impact on India. Although these short- and mid-term predictions have important implications for analyzing the impact of global warming on electricity demand because they are based on available data for the past five-years, these long-term forecasts may not carry a very high degree of precision. In an uncertain world, the underlying assumptions of our predictions may not hold true till 2030 and 2050. Hence, the results obtained in this study should not be interpreted as exact forecasts but as roughly indicative of the direction and magnitude of the effects that might be expected from climate change on electricity demand.

According to the fifth assessment report by the Intergovernmental Panel on Climate Change (IPCC), the mean surface temperature increase in South Asia is likely be in the range of 1°C to 1.5°C (medium confidence) for the period 2016-2035 (relative to 1986-2005) and in the range of 1.5-3°C (medium confidence) for the period 2046-2065. In line with these scenarios, for the purposes of projections in this paper, I consider a uniform increase of 1°C in the mean temperature for 2030 and a uniform increase of 2°C in the mean temperature for 2050. I apply these scenarios uniformly by season and region to India in the calculations that follow. In addition to these two uniform scenarios, I also predict the future electricity demand under the reference scenario of no climate change.

I consider two different scenarios for future growth in the gross domestic product of India: a) the target average growth rate in the twelfth Five-Year Plan of 6 percent per year from 2010 to 2050; b) average annual growth rate of 4 percent per year from 2010 to 2050. I assume population to grow at an average annual rate of 1.1 percent per year (medium UNDP scenario). I assume that the individual states will grow at a rate that will enable them to maintain their share in India's GDP at the same mean share rate as during the 2005-2009 period. I assume the same for future state population projections. The percentage of villages electrified, the number of agricultural pumpsets and the share of the industry in the state's GDP in each state increase linearly between 2010 and 2050 at the rate achieved during 2005-2009. For other predictor variables such as-rainfall, prices, holiday and week day dummy, and industrial seasonality index (MIIP), I assume the same values as in 2009.

Between 2009 and 2030, India's GDP will double if it grows at the 4 percent p.a. and treble if it grows at 6 percent p.a. According to the preferred Model C of this study, in a reference scenario with no climate change, electricity demand in India is expected to double (that is, increase by 105 percent) between 2009 and 2030 with 4 percent p.a. GDP growth and more than treble (i.e., increase by 224 percent) with 6 percent p.a. GDP growth. Between 2009 and 2050, India's GDP will increase by a factor of 4 if it grows at 4 percent p.a. and by a factor of 10 if it grows at 6 percent p.a. The electricity demand is expected to become 4 times (i.e., increase by the factor of 3) with 4 percent p.a. GDP growth and 10 times (i.e., increase by the factor of 9) with 6 percent p.a. GDP growth by 2050.

Estimates of the impact of climate change: Results from the two models (C and D) are given in Table(3.3). Although climate change will happen in future, I present climate change impacts for the 2009 economy in order to compare the impacts with the richer economies of 2030 and 2050. The study finds that the climate sensitivity of electricity

Table 3.3: Predicted Impact of Climate Change on Electricity Demand

			State Fixed Effect (Model C)		Region Fixed Effect (Model D)	
			GDP growth p.a from 2009			
Year	Intensive(I) / Extensive (E)	Scenario	4%	6%	4%	6%
2009	I	1^0c	2	2	2.5	2.5
2009	I+E	1^0c	4.4	4.4	5.9	5.9
2030	I	1^0c	3	3.7	3.8	4.9
2030	I+E	1^0c	6.9	8.6	8.95	11.6
2050	I+E	1^0c	9.4	13	12.1	17.7
2050	I+E	2^0c	21.6	30.7	28.5	43

demand in India is likely to be highly sensitive to income growth. In 2009, I expect a 1 degree increase in the mean temperature to result in about 4–6 percent increase in the electricity demand over the reference scenario of no climate change. In 2030, I expect a 1 degree increase in the mean temperature to result in about 7–9 percent increase in the electricity demand over the reference scenario with a 4 percent growth in the GDP and about 9–12 percent increase in the electricity demand over the reference scenario with a 6 percent growth in the GDP. In the most likely scenario of a mean temperature increase of about 2^0C by 2050, I expect electricity demand to rise about about 22-29 percent higher with a 4 percent growth in the GDP and about 31-43 percent higher over the reference scenario with a 6 percent growth in the GDP. In 2030 and 2050, India will be a much richer economy; thus, I predict the impact of a 1 degree increase in the mean temperature to be accordingly higher in comparison with 2009.

Table(3.3) also presents the contributions of intensive and extensive adjustments separately in the event of an increase in total electricity demand due to climate change for the years 2009 and 2030. i obtain the contribution of intensive adjustments by allowing the temperature distribution to change where the CDD and HDD on each day is increased by

1^0c holding the CDDI and HDDI constant. The results suggest that the contribution of extensive adjustments is somewhat higher than that of intensive adjustments. Also the share of extensive adjustments in total climate impacts increases with the level of income. For example, according to the preferred Model C of my study, the share of extensive adjustments in total impacts is about 54 percent in 2009 and 57 percent in 2030 (in the 6 percent growth scenario). Of the total increase in electricity demand of 8.6 percent over the reference scenario in 2030 under the 6 percent GDP growth scenario, I predict a 3.7 percent increase due to intensive adjustments and 4.9 percent increase due to extensive adjustments. Thus, extensive adjustments play an important role in determining the impact of climate change on electricity demand in India. The results of the study suggest that electricity demand models that do not account for extensive adjustments are likely to underestimate the climate change impacts on electricity demand, especially in developing countries like India, where the current penetration of space conditioning equipment is very low.

The extent of climate change effects on individual states will depend on their climate type and level of income. Thus, Delhi, Chandigarh, Gujarat, Maharashtra, Haryana, Punjab, Kerala, Karnataka, Andhra Pradesh and Tamil Nadu can be categorized as relatively rich and hot states with above average gross domestic product per capita and cooling degree days. Bihar, Jharkhand, Orissa, Uttar Pradesh, Madhya Pradesh, Rajasthan, Chhattisgarh and West Bengal, on the other hand, are relatively hot but poor states with above average cooling degree days and below average gross domestic product per capita. Himachal Pradesh with above average gross domestic product per capita and above average heating degree days is a relatively rich and cold state. Uttarakhand and Jammu and Kashmir with below average gross domestic product per capita and above average heating degree days are relatively poor and cold states. Figures (3.5) and (3.6) show the predicted climate change impacts by state across India in 2030.

The five rich and hot states-Delhi, Maharashtra, Gujarat, Andhra Pradesh and Tamil Nadu-will therefore be the most affected in terms of electricity demand due to climate change with an estimated impact of 11-17 percent. The next most affected group includes Karnataka, Kerala, Haryana, Orissa and Chandigarh with the estimated impact at 8-12 percent. The third most affected group comprises poor and hot states such as Bihar, Jharkhand, Uttar Pradesh, Madhya Pradesh and all north-eastern states with the estimated impacts at 3-10 percent. The least affected states are the three cold states-Jammu and Kashmir, Himachal Pradesh, and Uttarakhand. Jammu and Kashmir turns out to be the only state the net electricity demand of which reduces by 1-5.5 percent due to climate change in 2030. In the case of Himachal Pradesh and Uttarakhand, there will be an increase in electricity demand but it would be less than 2 percent.

3.7 Conclusion

The empirical evidence from India in this study suggests that the climate sensitivity of electricity demand in a developing country is likely to be highly sensitive to income growth. I use a state-level panel dataset to estimate the effect of daily temperature (a

Figure 3.5:

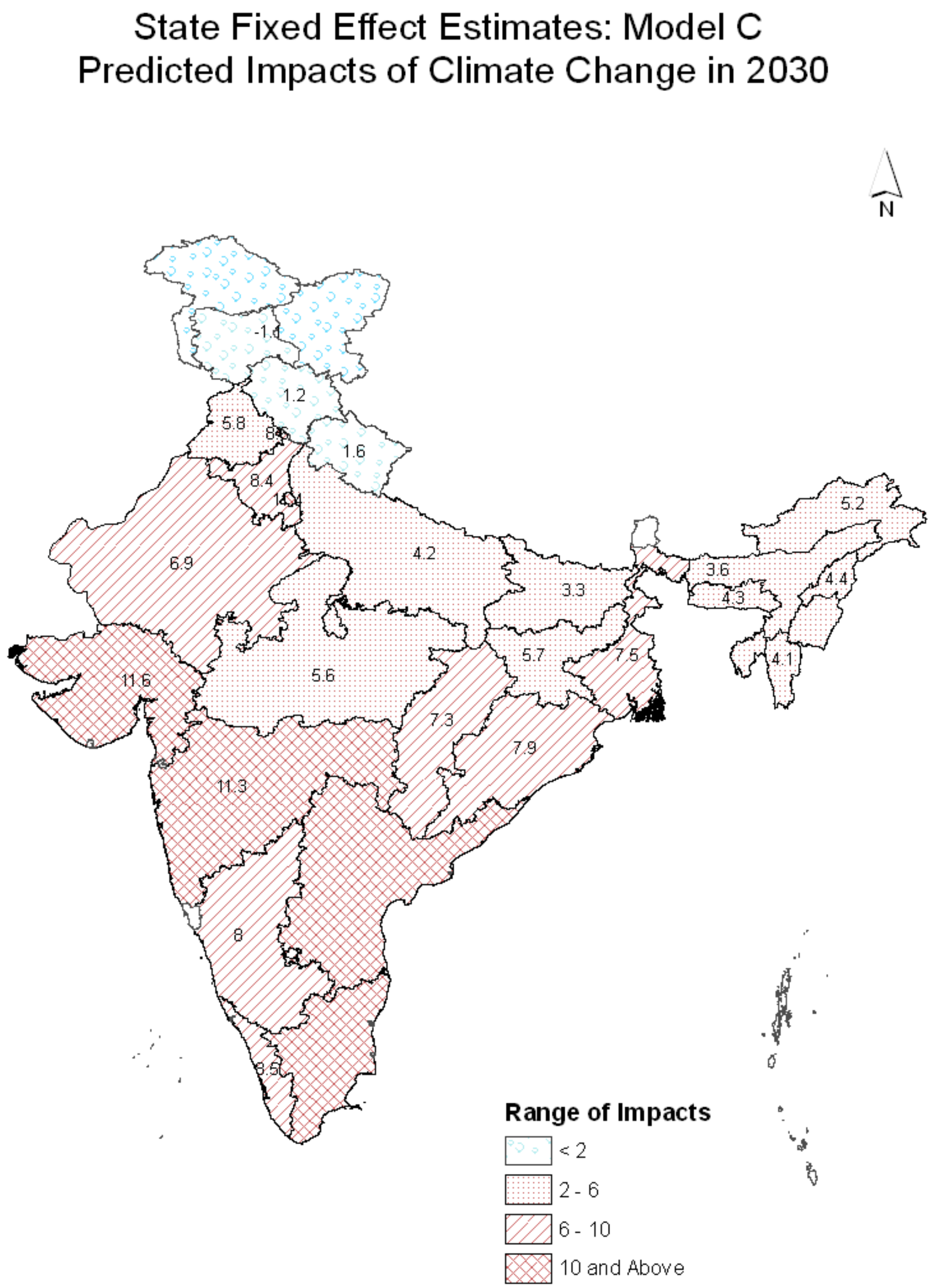
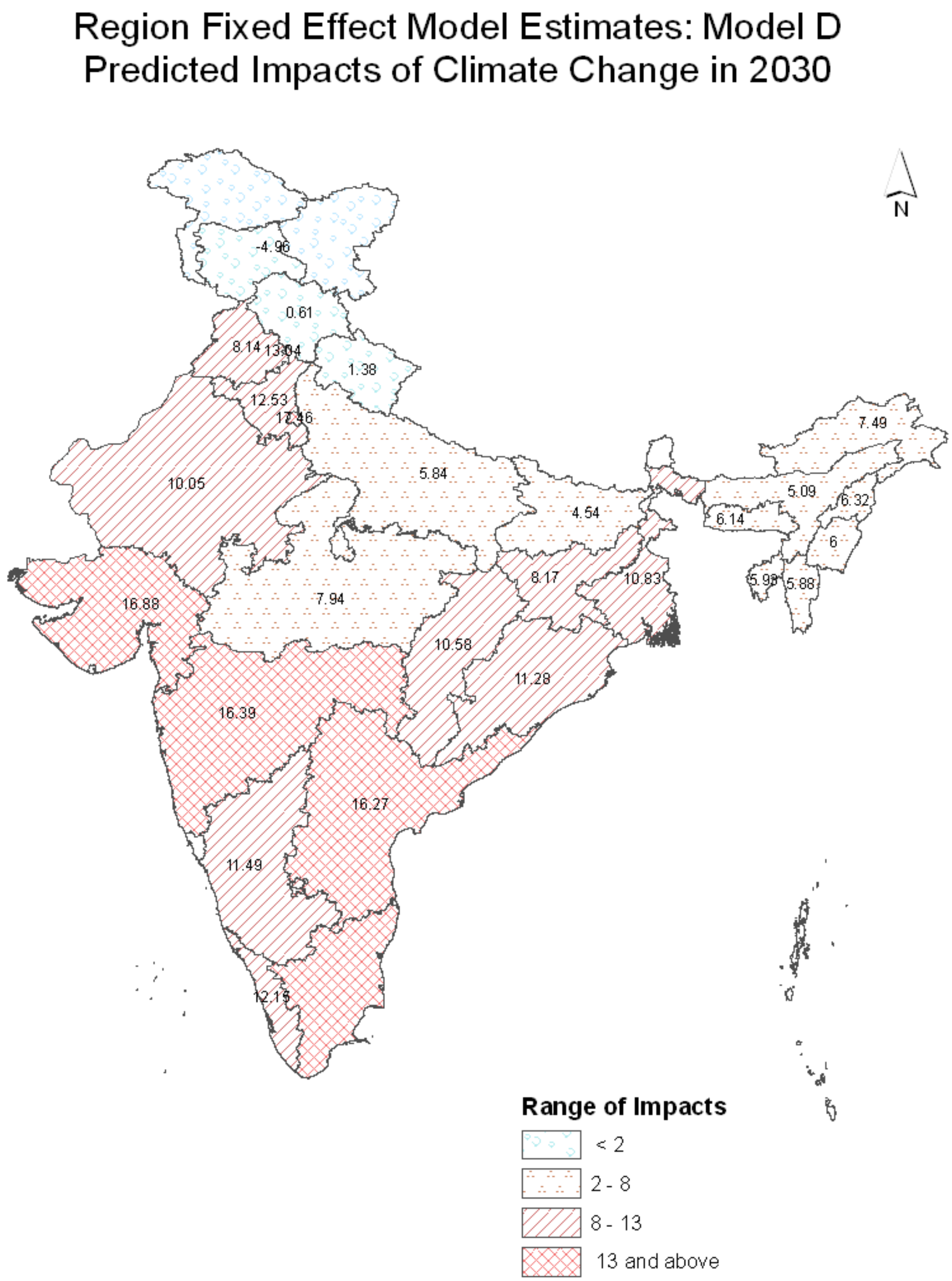

State Fixed Effect Estimates: Model C
Predicted Impacts of Climate Change in 2030
N
-1.4
1.2
5.8
1.6
8.4
5.2
6.9
4.2
3.6
4.4
3.3
4.3
5.7
7.5
4.1
11.6
5.6
7.3
7.9
11.3
8
Range of Impacts
< 2
2 - 6
6 - 10
10 and Above

Figure 3.6:


Region Fixed Effect Model Estimates: Model D
Predicted Impacts of Climate Change in 2030
N
-4.96
0.61
8.14
1.38
12.53
7.49
5.84
10.05
5.09
6.32
4.54
6.14
6
8.17
10.83
7.94
16.88
5.88
10.58
11.28
16.39
16.27
11.49
Range of Impacts
< 2
2 - 8
8 - 13
13 and above

key indicator of weather) and long-term climate on electricity demand which is conditional on state or region fixed-effects. My preferred estimates, using a 1 degree Celsius uniform climate change scenario, indicate that climate change will increase electricity demand by 6.9 percent with 4 percent p.a. GDP growth and by 8.6 percent with 6 percent p.a. GDP growth in 2030 over the reference scenario of no climate change. This reflects the fact that the estimated marginal effect of a hotter climate on electricity demand is greater when income is higher among the populace than otherwise. It points to the critical need to engage in electricity demand management and boost efficiency in use of electricity to become a low-energy consuming society in the future.

The rapid increase in electricity demand due to climate change results from both intensive and extensive adjustments in heating and cooling requirements. The findings of the study suggest that over 50 percent of the climate change impacts will be due to extensive adjustments. This highlights the importance of potential interactions between increasing cooling degree days and increasing incomes, and the impact of the resulting long-term adjustments (such as the higher penetration of air cooling devices) on the electricity sector. Electricity demand models that do not account for extensive adjustments are likely to underestimate the climate change impacts on electricity demand, especially in developing countries like India where the current penetration of space conditioning equipment is very low.

Additionally, the analysis indicates considerable heterogeneity in the predicted impacts across states. The nature and extent of the impacts will vary geographically, depending on the climate and development status of the states. Thus, the states to be most affected by climate change will be the rich and hot states. Further, research using data from other countries and sectors would prove extremely useful in helping us understand not just how climate and income changes in the future may impact electricity demand but also how historic climatic and income differences across different parts of the world may have contributed to existing differences in electricity demand between nations.

Appendix Tables

Table 3.4: Estimates of Electricity demand Models 2005-2009

	State Fixed-Effect			Region Fixed-Effect
	(1)	(2)	(3)	(4)
	Model A	Model B	Model C	Model F
VARIABLES				
Log(GDPPC)	1.130***	1.132***	1.019***	0.551***
	(0.0212)	(0.0208)	(0.0191)	(0.00882)
Log(Population)	0.109	0.111	0.168**	0.883***
	(0.104)	(0.113)	(0.0817)	(0.00430)
Log(Price)	0.0114	0.0125	0.0104	-0.188***
	(0.0102)	(0.0109)	(0.0106)	(0.00815)
Log(Agr_Pumpsets)	0.0115**	0.0118**	0.0140***	0.0454***
	(0.00484)	(0.00502)	(0.00418)	(0.00268)
MIIP	1.51e-05***	1.80e-05***	1.88e-05***	2.01e-05***
	(2.17e-06)	(2.27e-06)	(2.34e-06)	(2.29e-06)
Major Holiday	0.000923	0.00161	0.00223	-0.0157***
	(0.00382)	(0.00378)	(0.00368)	(0.00542)
lpump_rainsum7	-4.85e-05***	-6.03e-05***	-5.72e-05***	-0.000169***
	(1.11e-05)	(1.12e-05)	(1.12e-05)	(1.68e-05)
Rainfall_Weeksum	-1.34e-05	8.99e-05	0.000117	0.00133***
	(0.000113)	(0.000111)	(0.000112)	(0.000177)
HDD	-0.00586***			
	(0.000994)			
CDD	0.0196***			
	(0.000911)			
HDDI*HDD		-0.000337***	0.00250	-0.00230***
		(7.46e-05)	(0.00192)	(0.000108)
CDDI*CDD		0.000791***	-0.00772***	-0.0111***
		(4.71e-05)	(0.000433)	(0.000538)
HDDI*HDD			-0.000293+	
*Log(GDPPC)			(0.000188)	
CDDI*CDD			0.000833***	0.00120***
*Log(GDPPC)			(4.34e-05)	(5.28e-05)
% Villages elect				0.00984***
				(0.000112)
Industry share				0.0257***
				(0.000403)
Constant	-8.791***	-8.873***	-8.789***	-18.11***
	(1.770)	(1.955)	(1.429)	(0.116)
Observations	50,932	50,932	50,932	50,932
R-squared	0.993	0.993	0.994	0.97
State FE	YES	YES	YES	NO
Quarter FE	YES	YES	YES	YES
Day of Week FE	YES	YES	YES	YES
Region FE	NO	NO	NO	YES

Driscoll and Kraay (1998) standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1, +p<.11

Chapter 4

Climate Change, Food Prices, and Poverty in India[1]

4.1 Abstract

We develop a simple two-sector (food and non-food) general equilibrium model for studying the long-run impact of climate change on food prices and the distribution of welfare in India. We find that food prices were 4 to 8 percent higher and the real income of the landless poor was 2.4 to 4.8 percent lower in 2009 relative to a counterfactual without climate change and pollution (over the past three decades). In 2030, agricultural productivity is 7% lower compared to a scenario without further climate impacts, then food prices will be 3.6 to 10.8 percent higher and real income of the landless 1.6 to 5.6% lower. The lower numbers are obtained in open economy scenarios and the higher in closed economy scenarios, showing that trade helps to protect the poor. If the economy is closed,

[1] This chapter is joint with Prof. E. Somanathan and Prof. Bharat Ramaswami

then improving the productivity of the agricultural sector has the greatest impact on the welfare of the poor. In contrast, if the economy is open and there are no barriers to labor movement out of agriculture, then the non-agricultural sector plays a bigger role in driving the welfare of the poor than mitigation of climate change.

4.2 Introduction

Climate change is expected to have major impacts on agricultural productivity and poverty with South Asia being one of the most vulnerable regions of the world. One of the emerging challenges will be to understand and quantify the impacts of a changing climate on the welfare of the poor. Between 1950-51 and 2010-2011, India's per-capita gross domestic product has increased greatly by almost 500 percent, but per-capita foodgrain output has increased by just 28 percent [GOI, 2011]. About 17.5% of the population in India was undernourished in 2010-12 [von Grebmer et al., 2013]. Real food prices have risen significantly in the last two decades. An Indian population increasing from 1.2 billion in 2009 to 1.5 billion by 2030 together with higher incomes will lead to increased food demand. In this context, reduced food availability and higher food prices resulting from climate change can have large effects on poverty [Hertel & Rosch, 2010] [Datt & Ravallion, 1998] [Ravallion, 1990] [Chakravorty et al., 2012a].

Agriculture accounts for about 15% of India's GDP so that even a significant decline in agricultural output of, for example, 20%, would mean a decline of only 3% in GDP. But this assumes that food prices would not rise when food output falls. Food accounted for more than one-half of the average household's expenditure in 2009 and this share was about two-thirds for the poorest household. So a rise in food prices can be very serious and climate change can impose significant welfare losses, with the poor being affected the most. For these reasons, past studies that quantify the impact of climate change on agriculture in terms of GDP loss (either using cross-sectional or panel data) are of limited value when assessing the impacts on economic welfare. As food prices may change significantly relative to current food prices, welfare impacts have to be analyzed within a general equilibrium framework.

The main question of interest here is: How important will climate change be relative to other factors in determining the welfare of the poor? We find that a combination of trade and economic growth can help buffer the poor against climate change. If the economy is closed, then improving the productivity of the agricultural sector has the greatest impact on the welfare of the poor. In contrast, if the economy is open, then the non-agricultural sector plays a bigger role in driving the welfare of the poor. The key implication of the analysis in this paper is that changes in productivity growth will have a much larger impact on the welfare of the poor than mitigation of climate change (unless climate impacts are larger than those considered in this study).

In this paper, we develop a stylized two-sector (food and non-food) general equilibrium framework inspired by [Eswaran & Kotwal, 1993] for studying the impact of climate change on food prices and household welfare in India. The demand side is modelled by a preference structure rooted in Engel's law, according to which there is an inverse relationship between a household's income and its share devoted to food. The analysis is conducted separately under closed and open economy assumptions in order to judge the impact of trade. The simplicity of the model allows us to transparently assess the factors driving the results. Since there are only a few parameters, sensitivity analysis on them can be conducted. The framework indicates how the initial conditions in terms of the level and distribution of wealth and land results in heterogeneity in a household's vulnerability to climate change in an economy.

The model is first calibrated to data from 2009. We estimate the impact of historic climate change and pollution trends over a 30-year period (1980-2009) on food prices and the welfare of the poor in 2009. We find that food prices were 4 - 8 percent higher and the real income of the landless poor was 2.4 - 4.8 percent lower relative to counterfactuals without climate change in the open and closed economy models respectively. We then examine impacts for the economy calibrated to projections for 2030. If the economy is closed to trade, a landless poor person is made significantly worse off by climate change since the price of food rises considerably. If agricultural productivity is 7% lower in 2030 compared to a scenario without climate and pollution impacts, then food prices will be about 10.8 percent higher and the real income of the landless 5.6% lower. For nearly all farmers, landholdings are too small for the resulting higher land rent to compensate for the fall in real income. Opening the economy to trade makes the poor (who depend mainly on labor rather than land for their incomes) better off by moderating the rise in the price of food. In the open-economy case, food prices are 3.6 % higher and the real income of the landless 1.6 percent lower than the counterfactual of no further climate change and pollution. For 2030 we consider seven combinations of agricultural productivity, non-agricultural productivity and population. It should be stressed that our results are the outcomes that would obtain without frictions in consumption, trade and labor market. For instance, we assume that all foods are perfect substitutes and that there are no barriers to trade and labor market movements between agriculture and non-agriculture happens smoothly. Frictions would possibly exacerbate the climate change impacts.

The major impact of climate change in India on income is expected to come via losses in crop production.[2] [Mendelsohn et al., 2001] using a Ricardian approach, finds that climate change reduces yields by about 30-60% in the long run (2080) relative to the1990s. [Rosenzweig & Iglesias, 2006] using an agronomic crop model find that yields are expected to fall by about 14.3% in the long run (2080) relative to the 1990s due to climate change. [Guiteras, 2009] using annual panel data on yields and weather, projects that climate change over the period 2010-2039 will reduce major crop yields by 4.5 to 9 %, while in the long-run (2070-2099) yields are likely to fall by 25 % or more in the absence of adaptation relative to 1990s. [Auffhammer et al., 2012] found that during 1966-2002 the rice yield was about 5.7% lower due to climate change since the 1960s. [Gupta et al., 2013] found that wheat yields in India would have been higher in 2009 by 0.7-3.3% if climate has not changed during 1981-2009. According to a recent study, wheat and rice yields are lower by 5.2% and 2% in India and by 5.5% and 0.1% in the world respectively, compared to yield projections without climate trends during the period 1980-2008 ([Lobell et al., 2011]). In addition to climate change, higher ozone concentrations are expected to reduce yields in 2030 over 2009 by 5-7% for India and by 2-3% for the world ([Van Dingenen et al., 2009] and [Avnery et al., 2011]). Further, it is expected that CO_2 fertilization is likely to increase global yields in the next

[2]There is recent research suggesting adverse impacts of climate change on non-agricultural sectors ([Dell et al., 2013] [Hsiang et al., 2011] [Sudarshan & Tewari, 2013]) that we do not examine here.

20 years at 1.8% per decade ([Lobell & Gourdji, 2012]). The estimates of the climate change impact on crop yields vary across studies due to different models and assumptions. [Gosling et al., 2011] provides an extensive review of studies done for India. While these studies are important to quantify the output loss due to climate change, we also need to estimate the impact of climate change on food prices if we want to obtain the effect of climate change on economic welfare.

Further, climate change is likely to have a more serious impact on tropical countries like India than on temperate countries. This shift in the geographic distribution of production is expected to result in a corresponding shift in trade flows[3]. [Fischer et al., 2002] estimate that by 2080 cereal imports by developing countries would rise by 10-40%. Thus, the net economic effect of climate change on the agriculture of any country will depend as much on its role in agricultural trade as on the impacts of the changed climate on crop yields. [Reilly & Hohmann, 1993] using static world policy simulation (SWOPSIM) model found that international trade will reduce the severity of climate change impacts on world agriculture and result in relatively small impacts on individual economies.

[Nelson et al., 2010] find that climate change will increase the number of malnourished children in 2050 relative to perfect mitigation by about 9-10 percent using the Impact model. Because Impact is a partial equilibrium model it cannot estimate directly the poverty effects of agricultural productivity declines from climate change.[Jacoby et al., 2011] quantifies the distributional impacts of climate change in rural India. Using a comparative static framework, the impact of climate change on household consumption is expressed as the im-

[3][Huang et al., 2011] provides an extensive review of studies on climate change and trade in agriculture.

pact of changes in temperature on returns to land and labor. The key idea is that food prices remaining constant, a fall in agricultural productivity leads to changes in returns to land and labor. In general equilibrium, however, a change in food prices also matters to wages and rentals and their model considers this impact as well. However, the Jacoby et.al model does not solve for equilibrium food prices. The study takes price changes from the projections of [Hertel et al., 2010]. Because the price changes are taken as exogenous, their model is not appropriate to study the role of trade as an adaptation mechanism. For instance, how do welfare impacts vary between a closed and an open economy? Such a question cannot be answered within the Jacoby et.al analysis. In addition, it is not clear whether the framework allows climate change in India to affect world food prices[4].

In sum, while there are a number of studies that quantify the impact of climate change on agricultural yields there are very few studies examining the impact of climate change on the income of the poor that take general equilibrium effects into account. In this study, we examine the total welfare loss and the distribution of losses in India under two different climate change scenarios, explicitly taking into account changes in the price of food and its impact on the distribution of income.

4.3 The Model

4.3.1 Closed economy case

Consider an economy of N individuals of which N_l are in the labour force. The total land in the economy is denoted by A. Production functions in both food and non-food

[4]India accounts for about 20 percent of world rice production, 13 percent of world wheat production.

sectors exhibit constant returns to scale. The agricultural sector produces food (F) using two inputs, land (A_F) and labour (L_F). The food production function is Cobb-Douglas:

$$Y_{_F} = \theta_{_F} A_F^{1-\alpha} L_F^{\alpha}. \tag{4.1}$$

The non-food sector using only labour (L_T) produces a good that, for the sake of concreteness, we will refer to as textiles (T) . We use textiles as the numeraire good and we use P to denote the price of food. The non-food production function is

$$Y_{_T} = \theta_{_T} L_T. \tag{4.2}$$

The linear technology means that the wage in terms of textiles is fixed:

$$W = \theta_{_T} \tag{4.3}$$

Thus, market clearing conditions for land and labour are $A = A_F$ and $N_l = L_F + L_T$. We denote the wage rate by W, labor income per capita by $w = WN_l/N$ and per unit land rent by r. Using (4.3), we obtain labour demand in agriculture as

$$\theta_{_T} = P\theta_{_F} \alpha A_F^{1-\alpha} L_F^{\alpha-1}$$

So

$$L_F = A\left(\frac{\alpha P \theta_{_F}}{\theta_{_T}}\right)^{\frac{1}{1-\alpha}} \tag{4.4}$$

Labour market clearing implies

$$L_T = N_l - A\left(\frac{\alpha P \theta_{_F}}{\theta_{_T}}\right)^{\frac{1}{1-\alpha}} \tag{4.5}$$

We can write the equilibrium rent equation as

$$r = \theta_T^{\frac{\alpha}{\alpha-1}} \left(\frac{1-\alpha}{\alpha}\right) (P\theta_F)^{\frac{1}{1-\alpha}} \alpha^{\frac{1}{1-\alpha}} \tag{4.6}$$

On the consumption side, individuals have identical Stone-Geary preferences, used to capture Engel's Law in a simple way. The utility function of an individual i is

$$U_i = (f_i - \underline{f})^{\rho} (t_i - \underline{t})^{1-\rho} \tag{4.7}$$

with $0 < \rho < 1$, $(f_i - \underline{f}) > 0, (t_i - \underline{t}) > 0$.

Here, f_i and t_i represents total food consumption and non-food consumption of the ith individual, and $\underline{f}$ and $\underline{t}$ represent the subsistence food and non-food consumption. An individual maximizes utility subject to the budget constraint given by $M_i = w + ra_i$ where a_i is the amount of land possessed by individual i. We obtain the demand for F and T by individual i as

$$f_i = \underline{f} + \frac{\rho}{P}\left(w + ra_i - P\underline{f} - \underline{t}\right) \tag{4.8}$$

$$t_i = \underline{t} + (1-\rho)(w + ra_i - P\underline{f} - \underline{t}) \tag{4.9}$$

Multiplying (4.8) by P, we see that ρ is the proportion of the excess of income over subsistence consumption that is spent on food, so that expenditure on each commodity is linear in the excess of total expenditure over subsistence expenditure. We obtain total demand for F and T in this economy by adding demand functions of all the individuals. F_d represents total food demand and T_d represents total food demand.

$$F_d = \underline{f}N + \frac{\rho}{P}(wN + rA - P_{F}\underline{f}N - \underline{t}N) \;, \tag{4.10}$$

$$T_d = \underline{t}N + (1-\rho)(wN + rA - P_{F}\underline{f}N - \underline{t}N) \;, \tag{4.11}$$

In general equilibrium, all four markets clear: $A = A_F$; $N_l = L_F + L_T$; $F_d = Y_{F}$; $T_d = Y_{T}$. The market clearing condition for food can be dropped by Walras' law. We have already used the first two conditions. The general equilibrium of this closed economy is entirely determined by the solution to the remaining textile market clearing condition. Using (4.2), (4.3), (4.5), (4.6) and (4.11), we can write this equation only in P and the exogenous parameters:

$$\underline{t}N + (1-\rho)\left(\theta_{T}N_l + A\left(\theta_{T}^{\frac{\alpha}{\alpha-1}}\left(\frac{1-\alpha}{\alpha}\right)(P\theta_F)^{\frac{1}{1-\alpha}}\alpha^{\frac{1}{1-\alpha}}\right) - P\underline{f}\;N - \underline{t}N\right) \tag{4.12}$$

$$= \quad \theta_{T}\left(N_l - A\left(\frac{\theta_{T}}{\alpha P\theta_{F}}\right)^{\frac{1}{\alpha-1}}\right) \tag{4.13}$$

Totally differentiating eq(4.13) with respect to to θ_{F} and simplifying, we obtain the elasticity of the price of food with respect to the total factor productivity θ_{F}. The elasticity of the price of food with respect to temperature is then just the product of the elasticity of the elasticity of the price of food with respect to the total factor productivity θ_{F} ($\varepsilon_{P\theta_{F}}$) and the elasticity of the total factor productivity θ_{F} with respect to temperature ($\varepsilon_{\theta_{F}\tau}$) and is given by

$$-\left(\frac{dP}{d\theta_{F}}\frac{\theta_F}{P}\right) = \varepsilon_{P\theta_{F}} = \left[\frac{\left(\frac{1-\alpha}{\alpha} + \frac{1}{1-\rho}\right)Y_{F}\left(\frac{\alpha}{1-\alpha}\right)}{\left(\frac{1-\alpha}{\alpha} + \frac{1}{1-\rho}\right)Y_{F}\left(\frac{\alpha}{1-\alpha}\right) - \underline{f}\;N}\right] = \frac{1}{1 - \frac{\underline{f}\;N}{Y_{F}\left(1+\frac{\eta}{(1-\rho)}\right)}}, \tag{4.14}$$

Note that, by assumption $\frac{\underline{f}\,N}{Y_F} < 1$ and $1-\rho > 0$, so $\varepsilon_{P\theta_F} > 1$. In a closed economy, the price of food rises more than proportionally with a decline in θ_F.

$$-\left(\frac{dP}{d\tau}\frac{\tau}{P}\right) = \varepsilon_{P\tau} \tag{4.15}$$

$$= \frac{\left(\frac{d\theta_F}{d\tau}\frac{\tau}{\theta_F}\right)}{1-\frac{\underline{f}\,N}{Y_F\left(1+\frac{\eta}{(1-\rho)}\right)}} = \frac{\varepsilon_{\theta_F\tau}}{1-\frac{\underline{f}\,N}{Y_F\left(1+\frac{\eta}{(1-\rho)}\right)}}, \tag{4.16}$$

where $\eta = \frac{\alpha}{1-\alpha}$ and τ is temperature.

From eq(4.15) we have three key results: First, the higher is the share of minimum food consumption in total food supply $\left(\frac{\underline{f}\,N}{Y_F}\right)$, the greater will be the response of food prices to global warming ($\varepsilon_{P_F\tau}$). This happens because a productivity decline in agriculture reduces incomes and reduces the demand for both goods. However, when $\left(\frac{\underline{f}\,N}{Y_F}\right)$ is high, the reduction in non-food demand has to be proportionately greater. So this has to be matched with a corresponding shift of labour from the non-food sector to the food sector. So the relative price of food has to increase enough to induce this shift. As the economy grows, food prices will be less sensitive to climate impacts. When the economy is richer, the marginal product of labor in agriculture is higher and $\left(\frac{\underline{f}\,N}{Y_F}\right)$ is low. So, a smaller food price rise is sufficient to induce enough labor into agriculture to increase food supply to meet demand.

Second, if α is high, then so is η and therefore the elasticity of food prices with respect to temperature will be low. This follows from the fact that α is the output elasticity of labor. So when this is high, any fall in agricultural productivity is easily met with a small shift of labor from the non-food sector to the food sector and therefore, the required rise in the price of food is small.

Finally, the higher is ρ i.e., the proportion of excess income spent on food, the lower will be $\varepsilon_{P_F\tau}$. As noted earlier, the loss in agricultural productivity reduces incomes and demands for both goods. When ρ is high, the percentage decline in food demand is much greater than when ρ is low. Hence the sectoral shifts in labor and output are also smaller in the case when ρ is high. Therefore, the food price increase is also smaller.

4.3.2 Open economy case

We now allow India to be an open economy. There are 2 economies- India (I) and Rest of the World (R). Both the economies have the same form of the production functions and utility functions as in the closed economy case. Economies differ only in their labour shares, total factor productivities and endowments. In Appendix A, we have derived the general equilibrium equation for P in the open economy case. We obtain

$$\begin{aligned} -\left(\frac{dP}{d\tau}\frac{\tau}{P}\right) &= -\varepsilon_{P\tau} = \frac{s^I\varepsilon(\theta^I_F\tau)(\frac{\eta^I}{1-\rho}+1)+s^R\varepsilon(\theta^R_F\tau)(\frac{\eta^R}{1-\rho}+1)}{1+s^I(\frac{\eta^I}{1-\rho})+s^R(\frac{\eta^R}{1-\rho})-\frac{\underline{f}\,(N^G)}{(Y^G_F)}}. \\ &= \frac{s^I\varepsilon(\theta^I_F\tau)+s^R\varepsilon(\theta^R_F\tau)}{1-\frac{\underline{f}\,(N^G)}{(Y^G_F)\left(1+\frac{\eta}{(1-\rho)}\right)}} \text{ if } \eta^I=\eta^R. \end{aligned}$$

Here, $\varepsilon(\theta^I_F\tau)$ denotes the elasticity of agricultural productivity in India with respect to the climate change (τ), $\varepsilon(\theta^R_F\tau)$ denotes the elasticity of agricultural productivity in rest of the world with respect to the climate change (τ). N^I, N^R and N^G(which equals $N^I_F+N^R_F$) denote the supply of labour in India, the rest of the world and world respectively, Y^I, Y^R and Y^G(which equals $Y^I_F+Y^R_F$) denote the supply of food in India, the rest of the world and world respectively, α is the share of labour in food output of India and we represent the ratio $(\frac{\alpha}{1-\alpha})$ by η^I, β is the share of labour in food output of the rest of the world and we represent the ratio $(\frac{\beta}{1-\beta})$ by η^R, s^I(which equals $\frac{Y_F^I}{(Y_F^I+Y_F^R)}$) is India's share in world food supply and s^R(which equals$\frac{Y_F^R}{(Y_F^I+Y_F^R)}$) is the share of the rest of the world in world food supply, $\frac{f\ (N^G)}{(Y_F^G)}$ is the minimum food required for survival as a share of global food supply. We find that now the food price elasticity is a weighted average of productivity elasticities in both regions. India being a tropical country, we expect $\varepsilon(\theta_F^I\tau) > \varepsilon(\theta_F^R\tau)$. If climate change affects agricultural productivity less in the rest of the world, as is expected, than in India, the net increase in the food price in India will be less compared to a closed economy case. Thus, one of the key contributions of this study is to help understand how international trade can function as an adjustment mechanism.

4.3.3 Welfare analysis

We use equivalent variation as a measure of welfare change[5]. Equivalent variation (EV) is defined as the amount of money paid to an individual with base prices and income that leads to the same satisfaction as that generated by a price and income change. In other words, EV satisfies $V(P, M_i + EV) = V(P', M_i')$ where V is the indirect utility function.

$$EV_i = e(P, V_i(P', M_i')) - M_i.$$

where e is the expenditure function. Therefore, from the definition, $EV > 0$ if and only if the individual is better off with the price and income change. We are interested in the EV of a change in θ_F to θ_F' when climate changes. A change from θ_F to θ_F' results in P

[5]We have used Equivalent Variation (EV) for welfare analysis and not Compensating Variation (CV) because with EV we can measure and compare income in different scenarios in current or 2009 prices. This is not possible with CV as in case of CV income in each scenario is measured at new prices.

changing to P' as given by (4.13), and income $w+ra_i$ changing to $w+r'a_i$ s given by (4.6). From eq(4.7), eq(4.8) , eq(4.9) and expenditure minimization we can derive the expression for the equivalent variation as

$$
\begin{aligned}
EV_i &= \theta_T \times \left(\frac{N_l}{N}\right)\left[\left(\frac{P}{P'}\right)^{\rho}-1\right]+fP-\underline{f}P'\left(\frac{P}{P'}\right)^{\rho}+\left[\underline{t}-\underline{t}\left(\frac{P}{P'}\right)^{\rho}\right] \\
&\quad -a_i\left(\theta_T\right)^{\frac{\alpha}{\alpha-1}}\left(\frac{1-\alpha}{\alpha}\right)\alpha^{\frac{1}{1-\alpha}}\left[\left(\theta_{_F}P\right)^{\frac{1}{1-\alpha}}-\left(\theta'_{_F}P'\right)^{\frac{1}{1-\alpha}}\left(\frac{P}{P'}\right)^{\rho}\right]
\end{aligned}
$$

Note that if $\left(\theta_{_F}P\right)^{\frac{1}{1-\alpha}} < \left(\theta'_{_F}P'\right)^{\frac{1}{1-\alpha}}\left(\frac{P}{P'}\right)^{\rho}$for $\theta'_{_F} < \theta_{_F}$, then the second term is positive and the EV is increasing in land ownership. By putting $EV_i = 0$, we obtain the cut-off level of land $\widehat{a}$ such that individual i is indifferent to the change

$$
\widehat{a} = \frac{\theta_T \times \left(\frac{N_l}{N}\right)\left[\left(\frac{P}{P'}\right)^{\rho}-1\right]+fP-\underline{f}P'\left(\frac{P}{P'}\right)^{\rho}+\left[\underline{t}-\underline{t}\left(\frac{P}{P'}\right)^{\rho}\right]}{\left(\theta_T\right)^{\frac{\alpha}{\alpha-1}}\left(\frac{1-\alpha}{\alpha}\right)\alpha^{\frac{1}{1-\alpha}}\left[\left(\theta_{_F}P\right)^{\frac{1}{1-\alpha}}-\left(\theta'_{_F}P'\right)^{\frac{1}{1-\alpha}}\left(\frac{P}{P'}\right)^{\rho}\right]}
$$

We discuss the distribution of losses in both closed and open economy cases.

4.4 Data sources and method used for calibration

4.4.1 Production parameters in the food sector

The model is calibrated using data from 2009. Table (4.1) displays the list of production parameters, their calibrated values and the data sources used in the process. In this table, data values on gross cropped area in India, arable and permanent crops land for the rest of the world, Indian population, rest of the world population, value of labor elasticity or α measured as the share of labor income (wages) in total agricultural output for India and the rest of the world, productivity in the non-food sector for India θ_T^I measured as the annual wage income of casual workers were directly drawn from the mentioned data sources. For other variables, the data sources were used to construct the desired variable.

For both India and the world, the output of food in the production function is obtained from food balance sheets of the Food and Agriculture Organization[6] (FAO). By multiplying each food item by its calorific value and summing over all food items total food output is obtained in calories. We find that India's share in world calories is about 14%. For India data on gross cropped area (A_F) of 195 million hectares is taken from the land use statistics. For the rest of the world, Arable and permanent crops land is taken from the FAO. The total number of agricultural workers is computed as product of population, workforce participation rate and the proportion of workers employed in the agricultural sector. Given agricultural output and the factor inputs of land and labor employed in agriculture and the production function parameter α the agriculture total factor productivity (TFP) for India and rest of the world is solved from the production function specification. The non-agriculture TFP of India θ_T^I of Rs 30039 is assumed to be equal to the average annual wage of casual workers in the agriculture and non-agriculture sectors. The only production parameter that remains to be fixed is the productivity in the non-food sector in the rest of the world. As we will see later this parameter will be pinned down by the general equilibrium condition.

[6]The food items in the food balance sheets included cereals, pulses, sugarcrops, sugar and sweeteners, oilcrops, vegetable oils, vegetables, fruits, spices, stimulants (tea,coffee etc), alcoholic beverages, meat, animal fat, milk, aquatic products.

Table 4.1: Production Parameters (2009)

	Parameter	Value	Source
1	Annual Food output India (Y_F^I) trillion calories/year	1040	Computed from FAO
2	Annual Food output ROW (Y_F^R) trillion calories/year	6410	Computed from FAO
3	India's share in world calories $\left(\frac{Y_F^I}{(Y_F^I+Y_F^R)}\right)$	14%	Computed from FAO
4	Gross cropped area India (A_F^I) in million hectares	195	Land use statistics
5	Arable and permanent crops land for ROW (A_F^R)	1338.35	FAO
6	India population (N^I) in million	1207.74	FAO
7	ROW population (N^R) million	5449.14	FAO
8	Work force Participation rate, India	.3966	Intrapolation,Censuses 2001, 2011
9	Work force Participation rate, ROW	.469	[Bank, 2011]
10	% of total workers in agriculture, India	.49	[GOI, 2009]
11	% of total workers in agriculture, ROW	.3456	[Bank, 2011]
12	Agriculture workers India (L_F^I) million	234.7	Computed as 6*8*10
13	Agriculture workers ROW (L_F^R) million	883	Computed as 7*9*11
14	α, share of labor in output for India	.46	[Eswaran et al., 2007]
15	α, share of labor in output for ROW	.35	[Alston et al., 2010]
16	θ_F^I, Productivity in the non-food sector in India	4897500	Using 1,4,12,14 as explained in text
17	θ_F^R, Productivity in the non-food sector in ROW	5539400	Using 2,5,13,15 as explained in text
18	θ_T^I, Productivity in the non-food sector in India (Rs)	30039	[GOI, 2009]

4.4.2 Consumption parameters

Table (4.2) displays the list of consumption parameters. First, we calculate the calorie price P, measured as an average household price from the consumption schedue of the National Sample Survey (2009). For each food item the National Sample Survey gives expenditure and quantity consumed. We calculate total calories consumed by each household using calorific values for each food item obtained from the National Sample Survey (2009). We calculate the food price for each household by dividing food expenditure of a household by food calories consumed. The average price for all the households (with adult equivalent calorie consumption per day greater than 500 and less than 10000) is Rs .0104 per kcal.

Second, we estimate the Stone-Geary linear food expenditure function using the individual level data from National Sample consumption expenditure survey (2009) by non-linear least squares to obtain the value of three unknown parameters $\underline{f}$, $\underline{t}$ and ρ.

$$\frac{P_h\ f_h}{n_h} = P_h\ \underline{f} + \rho\left(\frac{M_h}{n_h} - P_h\underline{f}\ - \underline{t}\right) + \varepsilon_h$$

where P_h is the calorie price of the household h , f_h denotes calories consumed by houshold h, n_h is number of equivalent adults in household[7] h, M_h represents total income of household h as measured by the sum of food and non-food expenditure. $\underline{f}$ and $\underline{t}$ are constrained to be non-negative. We obtain $\underline{f}$ as 61,5216 calories adult equivalent per year or 1685 calories adult equivalent per day, $\underline{t}$ as 0 and ρ as .25.

4.4.3 General Equilibrium

Given the production and consumption parameters in Table (4.1) and (4.2), the general equilibrium equation in the open economy is used to solve for the only remaining unknown, i.e., the productivity in the non-food sector of the rest of the world. This is displayed in Table(4.3). If this economy were closed, the equilibrium price would be different and we can no longer use the price computed in table that is valid for a open economy. To consider the implications of climate change for a closed economy, we use the general equilibrium condition in eq(4.13) for a closed economy to compute the equilibrium food price. This is also shown in Table (4.3). We find that the price of food would be about 14 percent higher if the economy was closed to trade. The next section numerically simulates

[7] To determine adult equivalent reference scale we used the consumer unit (that is used as an indicator of the energy requirement of a group of persons of different sexes and ages in NSS 2009 nutrition intake report) weight 1 for male in the age group 20-39 as the norm. The average calorie requirements of males and females of other age groups are expressed as a ratio to this norm. The adult-equivalent fraction assigned to each individual varied from .43 for the new borns to 1.03 for males in the age group of 10 to12 years of age.

Table 4.2: Consumption Parameters (2009)

Parameter	Value	Source
P (Rs per Kcal) in the open economy	.0104	Computed from NSSO (2009)
ρ	.25	Estimated from Non-linear Least squares
$\underline{f}$ (calories per day) adult equivalent	1685	Estimated from Non-linear Least squares
$\underline{t}$	0	Estimated from Non-linear Least squares

Table 4.3: Calibrated Values from General Equilibrium

Parameter	Value	Source
θ_T^R, Productivity in the non-food sector (Rs) in rest of the world	37,455	Solved from General Equilibrium of Open Economy
P (Rs per Kcal) in the closed economy	.0119	Solved from General Equilibrium of Closed Economy

the open and closed economy to past climate change and pollution trends.

4.5 Impact of changes in climate and pollution during 1980-2009

In this section, we seek to understand the impact of historic climate change and pollution trends over a 30-year period (1980-2009) on food prices and welfare of the poor in the calibrated economy compared to a counterfactual economy (without climate change). In Section 5, we reconsider these impacts for an economy that is calibrated to data projected for 2030. This analysis helps us to compare the welfare impacts obtained in 2009 with the richer economy of 2030 and understand the underlying adjusting mechanism. Table (4.8) provides information on estimated impacts on crop yields of past changes in climate and pollution. Based on the existing literature on climate change impacts, we derive past loss in crop yields for India and the rest of the world by adding the estimated impacts of warming, CO_2 fertilization, and ozone pollution, on crop yields.

Table 4.4: Climate Impacts on Agricultural Productivity during 1980-2009

Parameter	India		Rest of the World	
	% change	Source	% change	Source
Global Warming	-3.5	[Lobell et al., 2011]	-3.1	[Lobell et al., 2011]
CO_2 fertilization	+3	[Lobell & Gourdji, 2012]	+3	[Lobell & Gourdji, 2012]
Ozone	-4.7	[Van Dingenen et al., 2009];	-2.4	[Van Dingenen et al., 2009]
		[Avnery et al., 2011]		[Avnery et al., 2011]
Total	-5.3		-2.5	

For India, a 5.3% fall in θ_F during 1980-2009 is obtained by adding a 3.5 percent fall in yields (as estimated by [Lobell et al., 2011]) and a 4.7 percent fall in yields due to the ozone effect (obtained by backward projection of the estimated impact of ozone during 2000-2030 by [Van Dingenen et al., 2009]) to a 3 percent positive effect of CO_2 fertilization (1.5 percent per decade as given in [Lobell & Gourdji, 2012]). Similarly, we obtain a 2.5% decline in agricultural productivity for the rest of the world during 1980-2009. In case of ozone impacts, we find that there are limited past studies available and thus we have obtained a rough estimate for crop yield loss during 1980-2000 due to ozone pollution by projecting expected future changes (during 2000-2030) backward till 1980. For instance, for India the studies by [Van Dingenen et al., 2009] and [Avnery et al., 2011] find that on average (over rice with 57% share and wheat with 43% share) crop yield losses due to ozone during 2000-2030 in India are likely to be about 2.34 percent per decade. As in the past, ozone concentrations would have been lower than in the present and future, we have assumed 4.7 % loss in yields in India due to ozone over during 1980-2009[8].

[8] We multiply 2.3 by 2 (resulting in 4.7%) and not 3 for estimating the the likely impact of ozone on crop yields in India during past 3 decades 1980-2009. This is done as in the past ozone concerteration would have been lower than in present. This is only a very rough estimate.

4.5.1 Closed Economy

The closed economy equilibrium in calibrated and counterfactual 2009 economies is described in the first three columns of Table (4.5). The calibrated equilibrium food price is about Rs .0119 per calorie and the share of the food sector is about 52%. About 33% of the total workforce is employed in the food sector. We get a high share of agriculture in total output and a lower share of agriculture in the labor force as compared to reality in India as we have not incorporated human and physical capital in the non-food sector. Since, we are interested mainly in the impact on the poor who don't have human and physical capital, this does not matter much for our purposes. The annual wage rate or θ_T is about Rs 30000 and rent per hectare is Rs 28770. The income of the landless is about Rs 14716. It is obtained by multiplying θ_T with the ratio of the number of workers to the number of adult equivalent persons in the economy. The share of food in the total expenditure of the landless is 62.5%.

We now discuss the total welfare loss and the distribution of losses relative to a counterfactual without climate change. Welfare impacts of climate change in the past three decades are presented in Figure(4.1). As productivity in the agricultural sector falls, so does the food supply. Since food demand is inelastic, P rises by more than the fall in productvity. We find that in the closed economy case food prices rise significantly as a result of an adverse productivity change or climate change. With 5.3% decline in θ_F relative to counterfactual, P increases by about 8.3%. With higher P, the marginal revenue product of labor increases in the agricultural sector and labor shifts from the non-food sector to the food sector. The labor force in the food sector (L_F) increases by about 4.8%.

Table 4.5: General Equilibrium in the Closed and Open Economies (2009)

Variable	Closed Economy		Open Economy	
	Counterfactual	Baseline	Counterfactual	Baseline
	No climate change		No climate change	
Food Demand (10^{12} kcal)	898.6	869.7	923.9	901.8
Food Demand (Kcal) adult equivalent/day	2517	2436.8	2589	2527
Non-Food Demand (10^{12} Rs)	9.8	9.6	9.6	9.4
labor in Food sector (10^6)	152	159	125	122
labor in Non-Food (10^6)	327	320	354	356
Food Price (Rs/kcal)	.0110	.0119	.0099	0.0104
Annual Wage Rate (Rs)	30039	30039	30039	30039
Rent per hectare (Rs)	27444	28770	22668	22180.5
Food sector share (%)	50	52	43.5	43.1
Share of food in expenditure of landless(%)	59.6	62.5	56	57.5
Food imports as % of food demand	-	-	11	14.4
Non-Food exports as % of Non-food output	-	-	9.5	12.6

Figure 4.1: The Impact of Past Climate Change and Pollution in Closed and Open Economies on Welfare in 2009 Relative to a Counterfactual with no Climate and Pollution Change Over 1980-2009

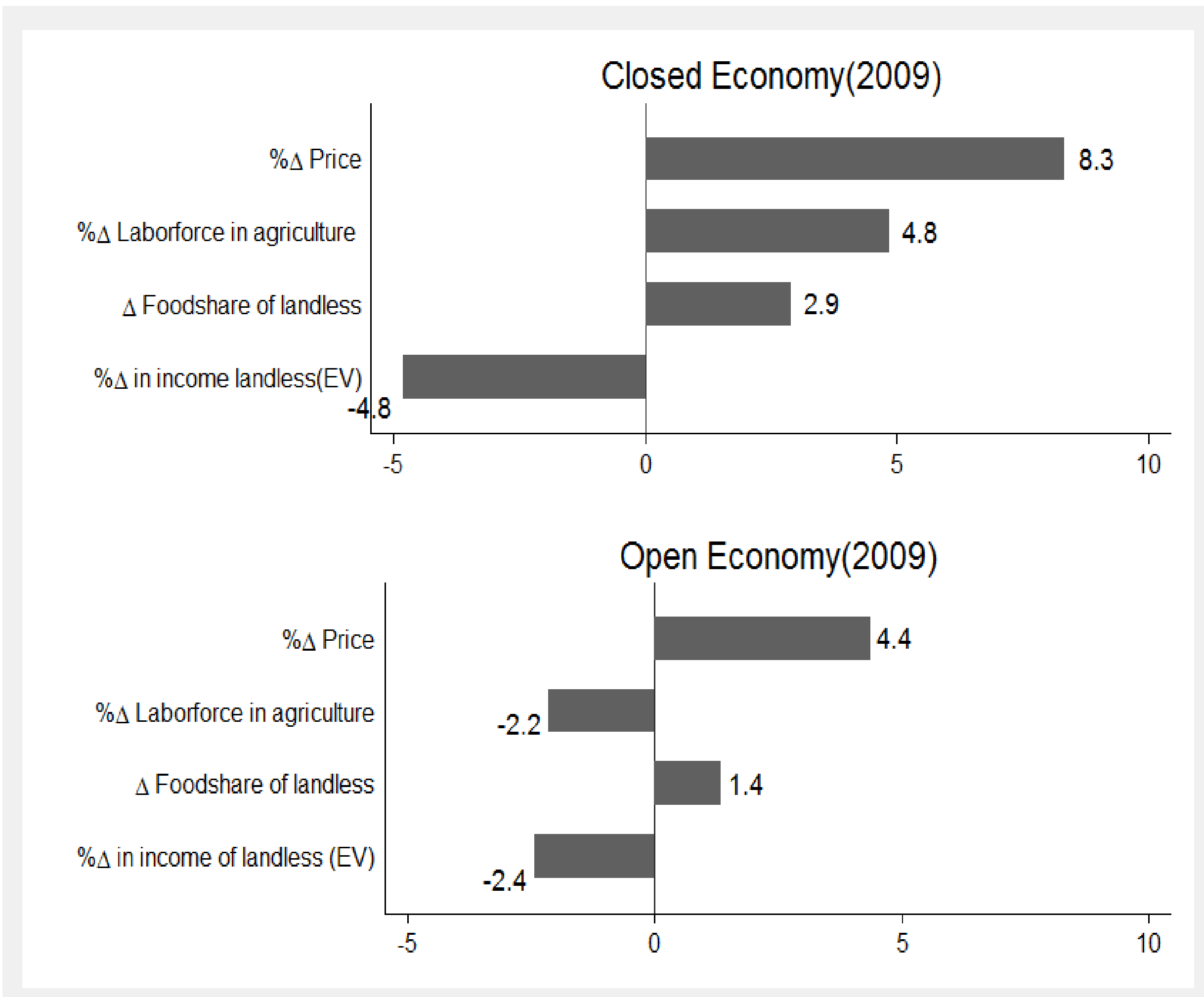
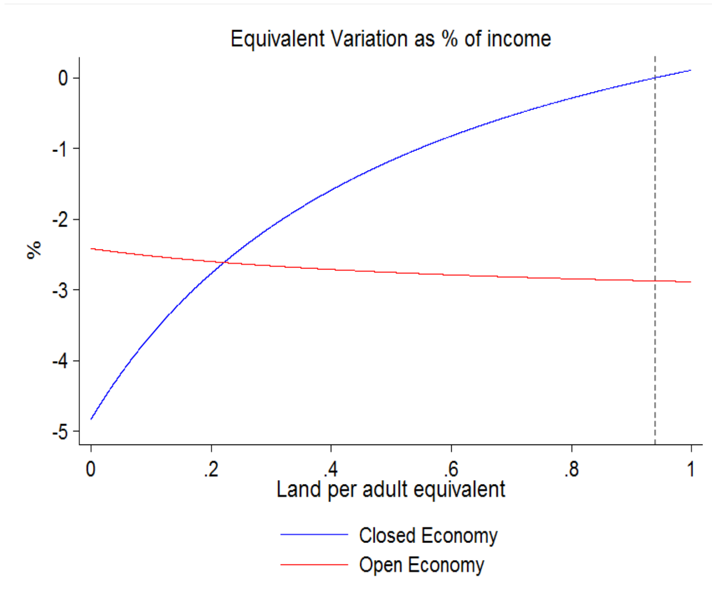


Figure 4.2: The Impact of Past Climate Change and Pollution in Closed and Open Economies by Land Ownership



As regards returns to factors of production, real wages fall with higher food prices but rents increase because of greater farm employment. The net impact of higher food prices on real wages and rental income from land will determine an individual's welfare loss or gain from climate change. Since wage and rental incomes move in opposite directions, there exists a threshold level of land such that if an individual owns land above that threshold he gains from the higher food price from climate change. Figure(4.2) plots equivalent variation as percentage of income and land owned per adult equivalent. The equivalent variation as percentage of income increases as the land per adult equivalent of an individual increases. The threshold level of land is equal to .94 hectares. In India more than 50% owns no land or only tiny amount of land (less than .009 hectares), 75% of the population owns land per adult equivalent less than .15 hectares and 90% owns land per adult equivalent less than .40 hectares (National Sample Survey 2009).

Qualitatively, the direction of outcomes can be anticipated. As the price of food increases it reduces the real wage rate received by the landless poor making them worse-off. This will adversely impact their consumption of food and non-food. As the relative price of food increases the demand for food falls due to the substitution effect. Further, as real income falls, food and non food demand both fall due to the income effect. As substitution and income effects work in the same direction for food, food consumption of the landless poor falls. For non-food demand, substitution and income effects work in opposite directions and the relative strength of the two effects determines the final consumption of non-food. The calibrated model can be used to quantify these effects. For landless workers, the fall in θ_F of 5.3% leads to a decline in non-food consumption by about 7% and a decline in food consumption by about 3%. The share of food in total expenditure increases from 59.6% to 62.5%. The landless workers are worse off and the equivalent variation is negative. It is Rs. 711 or 4.8% of the income. These numbers illustrate clearly that ignoring general equilibrium effects will greatly understate the impact of global warming on the poor. The EV for the landless falls one-for-one with declining food productivity alone even though the food sector constitutes only 52% of the economy in the baseline model.

For a landowning farmer, rent increases with higher P (given that the percentage increase in price is greater than the percentage fall in agricultural productivity). For a small landholder the fall in labor income may not be fully compensated by higher rent and thus such farmers lose from climate change . For a large land holder the fall in labor income may be more than fully compensated by higher rent and he gains from climate change. Consider a small land holder (with owned land of 0.1 hectare) and a larger landholder (with holding of 1.5 hectares). The small farmer loses from climate change and ends up with a negative EV of about Rs 635. However, the larger landowner gains enough from higher rents and ends up with a positive EV of about Rs 424.

We now examine the sensitivity of these results to changes in key parameter values. The idea is to obtain interval estimates rather than point estimates for a reasonable range of parameter values. Figure (4.3) displays results for different values of ρ, the proportion of excess income spent on food. In the baseline, $\rho =.25$. We observe that the results are not highly sensitive to ρ . As discussed in Section 2.1, higher ρ implies lower food price elasticity with respect to θ_F. We see that even if we double the value of ρ from 0.25 (when the food price rises by 8.3%) to 0.5, the food price still rises substantially by 7%. Similarly, we see that the equivalent variation as a percentage of income for a landless person does not vary much with different values of ρ.

Figure (4.4) displays results for three different values of α which is the output elasticity of labor. The baseline closed-economy case is based on $\alpha =.46$. We observe that results are quite sensitive to α . Lower value of α results in higher food price elasticity with respect to θ_F and higher equivalent variation and higher welfare losses for a landless person. As α for the world is .35, we reduce α by 23% from the baseline to see what happens if India's output elasticity of labor converges to the world average. When α is equal to .35 the food price rises by more than 9% as against 8.3% in the baseline and the equivalent variation as percentage of income also falls from -4.8% to -5.9% .

Figure (4.5) displays results for three different values of $\underline{f}$, the subsistence level of food consumption. In the baseline closed economy case $\underline{f}$=1685 calories/day. From Section

Figure 4.3: Sensitivity Analysis on the Share of Food in Excess Income

(ρ)

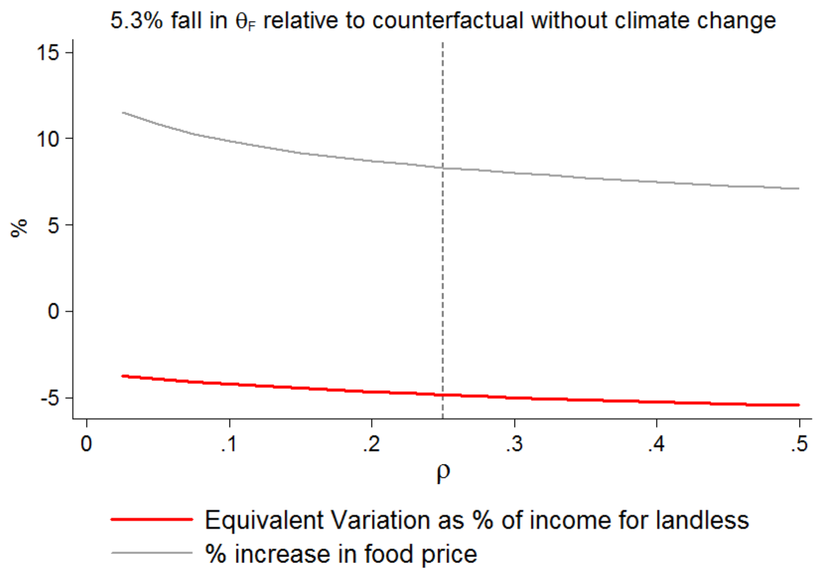


Figure 4.4: Sensitivity Analysis on the Output Elasticity of Labor in the Food Sector

(α)

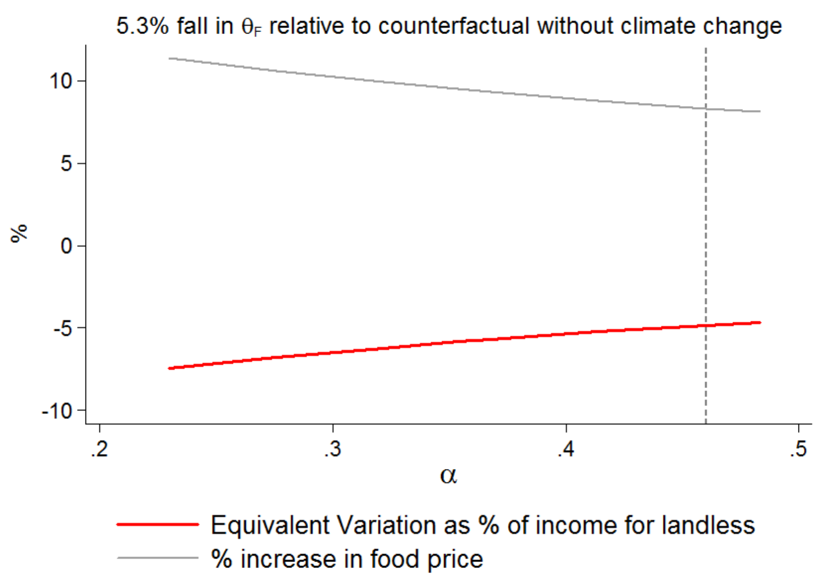
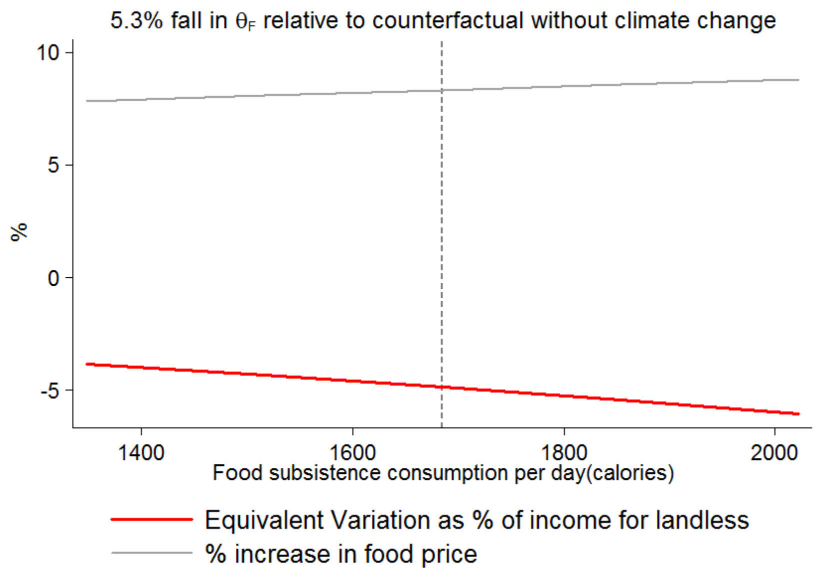


Figure 4.5: Sensitivity Analysis on Subsistence Food Consumption

($\underline{f}$)



2.1, we know that higher $\underline{f}$ implies higher food price elasticity. For doing sensitivity analysis we take lower and higher values of $\underline{f}$ as compared to the baseline value. We observe that food prices are relatively less sensitive to $\underline{f}$. If we increase $\underline{f}$ by 20%, equivalent variation as percentage of income of a landless person falls from -4.8% to almost -6% , and food prices rise by about 8.7%.

Overall, we see that the welfare impacts are more sensitive to production parameters than consumption parameters . So substitutability between labor and land, and hence the nature of agricultural technology will be one of the key determinants of the impact of climate change on the welfare of the poor.

4.5.2 Open economy

We now discuss the open economy. The baseline open economy equilibrium before climate change is described in the last two columns of Table (4.5). The equilibrium food price of about Rs .0103 per calorie is about 15% lower than in the closed economy. The share of the food sector in total output is 43% rather than 52%. India imports about 14.4% of total food demand from the rest of the world. About 25.5% of the total workforce is employed in the food sector. Relative to the closed economy the labor force employed in the non-food sector is higher and so is the output of the non-food sector. India exports about 12.5 percent of its non-food output to the rest of the world. As the non-food total factor productivity θ_T^I is the same in the closed and open economies, the annual wage rate in the open economy is also the same as in the closed economy i.e., Rs 30000. However, rent per hectare falls to Rs 22100 because of lower food sector employment. Wage rate per adult equivalent and the income of the landless is about Rs 14700 as before. The food share of the landless falls to 57.5%.

Figures (4.1) displays open economy results for the climate change scenarios. Due to θ_F^I being by 5.3% lower relative to the counterfactual in India and a fall in θ_F^R by 2.5% in the rest of the world, food prices are 4.4% higher. The food price impact is smaller for the open economy as compared to the closed economy. For a landless person, the (negative) EV is Rs 355 or 2.4% of the income. Thus a landless individual is better off in the open economy as compared to the closed economy. Thus, what happens in the rest of the world really matters to the poor in India.

As the gap between the percentage decline in agricultural productivity and the consequent percentage rise in food prices is lower in the open economy, land rents in India are lower relative to the counterfactual with no climate and ozone change. Figure(4.2) plots EV as % of income and land adult equivalent. The equivalent variation is a decreasing function of land per adult equivalent and is negative for all farmers. Thus, all farmers lose and in fact the large farmers lose more than the small farmers. The closed economy result is overturned because the increase in food prices is less than the fall in agricultural productivity and, therefore, rents fall. In this scenario (negative) EV for the small landholder of .1 hectares is Rs 428 and EV for the landholder of 1.5 hectares is even more negative at Rs 1440.

This result is similar to [Jacoby et al., 2011] which finds that in the most likely scenario of stable and falling food prices the welfare declines for the wealthiest households are marginally more severe than for the poorest. However, in the more pessimistic scenario for global food prices, wealthy households do a lot better and even gain from climate change.

It is important to note that the real economy impacts would be some where between the closed and open economy results as for some goods we observe trade is open and for some it is closed. Thus, closed and open economy results provide the higher and lower bounds of the impacts. We conclude that food prices were 4 - 8 percent higher and the real income of the landless poor was 2.4 - 4.8 percent lower relative to counterfactual without climate change and pollution (over past three decades) in 2009.

Table 4.6: Population and Total Factor Productivity Average Annual Growth Rates for the Three Scenarios During 2009-2030

Variable	Region	Low	Medium	High	Source
N	India	0.8%	1.1%	1.38%	UNDP Forecasts
θ_F	India	.75%	1.5%	2.25%	Bosworth and Collins (2007)
θ_T	India	1.52%	3.04%	4.56%	Bosworth and Collins (2007)
N	Rest of the world	.66%	.94%	1.21%	UNDP Forecasts
θ_F	Rest of the world	.92%	1.84%	2.76%	Alston etal (2010)
θ_T	Rest of the world	1.1%	2.2%	3.3%	Bosworth and Collins (2003)

Note: For all variables but population the low scenario has a growth rate that is 50% lower than in the medium scenario and the high scenario has a growth rate that is 50% higher than in the medium scenario.

4.6 Impact of changes in climate and pollution from 2009-2030

In this section, we study how changes in climate and pollution will impact welfare in an economy calibrated to data projected for 2030. The calibrated values for 2030 are same as that of 2009 except in the following ways. The 2030 economy will be different from the 2009 economy in three key respects- the state of technology[9] in the food sector and in the non-food sector, and the level of population. While the first two could reduce the impact of global warming, population growth will intensify the problem by increasing food demand. We use scenarios for total factor productivity growth in agriculture, total factor productivity growth in non-agriculture, and population growth, and consider the impact of different assumptions by comparing equivalent variation under different scenarios. Table (4.6) discusses assumptions and sources used for constructing different scenarios.

A medium or baseline 2030 scenario assumes that all three variables will be growing

[9] In our model that has no capital, technology and productivity are equivalent.

at rates projected by the sources in Table (4.6). In the high population scenario, the population in 2030 is 6 percent higher than in the medium population growth scenario, while productivity growth in agriculture and non-agriculture follow the medium scenarios. In the low population scenario, the population in 2030 is 6 percent lower than the medium population growth scenario, while growth in agricultural and non-agricultural productivity follows the medium scenario. A high productivity in agriculture scenario is one where total factor productivity (TFP) in agriculture in 2030 is 16.7 percent higher than in the medium agriculture productivity growth scenario, while non-agriculture TFP and population follow the medium scenario. A low productivity in agriculture scenario is one where TFP in agriculture in 2030 is 14.4 percent lower than in the medium productivity growth scenario, while growth in non-agriculture TFP and population follows the medium growth scenario. A high productivity in non-agriculture scenario is one where TFP in non-agriculture in 2030 is 36% higher than in the medium productivity growth scenario and growth in agriculture TFP and population follow the medium scenario. A low productivity in non-agriculture scenario is one where TFP in non-agriculture in 2030 is 26.8% lower than in the medium productivity growth scenario and growth in agriculture TFP and population follow the medium scenario. We summarize these scenarios in Table (4.7).

In the analysis changes in climate and pollution are introduced by changing total factor productivity (θ_F) in the agricultural sector. According to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the projected change in global mean surface air temperature for the period 2016–2035 (relative to 1986–2005) is likely to be in the range 0.3–0.7°C (medium confidence) (See [IPCC, 2013]). The mean

Table 4.7: Summarizing 7 Scenarios for 2030

Scenarios (2030)	Region	N^I	θ_F^I	θ_T^I
Medium or Baseline	India	Medium	Medium	Medium
High population	India	High	Medium	Medium
Low population	India	Low	Medium	Medium
High productivity in agriculture	India	Medium	High	Medium
Low productivity in agriculture	India	Medium	Low	Medium
High productivity in non-agriculture	India	Medium	Medium	High
Low productivity in non-agriculture	India	Medium	Medium	Low

Note: In the all above scenarios it is assumed that N^R, θ_F^R and θ_T^R in the rest of the world grow at the medium rate.

surface temperature increase in South Asia is likely be in the range of 1°C to 1.5°C (medium confidence) . Based on the existing literature on climate change impacts discussed in the introduction, we derive scenarios for India and the rest of the world by adding the estimated impacts of warming, CO_2 fertilization, and ozone, on crop yields. Table (4.8) shows climate impacts in moderate and severe scenarios drawn from the literature. A moderate scenario corresponds to a one-degree increase in temperature and a severe scenario corresponds to a 2-degree increase in temperature.

A moderate scenario of a 7% fall in θ_F is obtained by adding a 5.5 percent fall in yields due to 1 ^0C temperature rise (as estimated by [Lobell et al., 2011] in Fig s7) and a 5 percent fall in yields due to an increase in ozone pollution in the next two decades (which is esimated by taking average of mid range loss estimates given in two studies - [Van Dingenen et al., 2009] and [Avnery et al., 2011]) to a 3.6 percent positive effect of CO_2 fertilization expected in the next two decades (1.8 percent per decade as given in [Lobell & Gourdji, 2012]). Similarly, we obtain a severe scenario of a 13% decline in agri-

Table 4.8: Climate Impacts in Moderate and Severe Scenarios, 2009-2030

Parameter	India (% change)			Rest of the World (% change)		
	M	S	Source	M	S	Source
Global** Warming	-5.5	-11	[Lobell et al., 2011]	-3	-6	[Lobell et al., 2011]
CO_2 fertilization	+3.6	+3.6	[Lobell & Gourdji, 2012]	+3.6	+3.6	[Lobell & Gourdji, 2012]
Ozone**	-5	-6	[Van Dingenen et al., 2009]	-2.2	-3.37	[Van Dingenen et al., 2009]
			[Avnery et al., 2011]			[Avnery et al., 2011]
Total*	-7	-13		-2	6	

Note: M-Moderate scenario S-Severe scenario.

*The total impacts are rounded to the nearest integer value. ** For India we have taken weighted average of loss estimates for 2 major crops-wheat (with share 43%) and rice (with share 57%). For ROW we have taken weighted average of loss estimates for 3 major crops– wheat (with share 47%), maize (with share12.6%) and rice (with share 40%).

cultural productivity in India by adding 11% fall in yields due to 2 ^0C temperature rise (obtained by doubling the 5.5% impact in moderate scenario of 1 ^0C increase in temperature) and a 6 percent fall in yields due to an increase in ozone pollution in the next two decades (which is esimated by taking average of higher end loss estimates given in two studies -[Van Dingenen et al., 2009] and [Avnery et al., 2011]) to a 3.6 percent positive effect of CO_2 fertilization. A moderate scenario of a 2% fall in agricultural productivity for the rest of the world is obtained by adding 3% fall in yields (estimated based on past 3 decades crop losses estimated during 1980-2008) and a 2.2 percent fall in yields due to an increase in ozone pollution in the next two decades (which is esimated by taking average of mid range loss estimates given in two studies -[Van Dingenen et al., 2009] and [Avnery et al., 2011]) to a 3.6 percent positive effect of CO_2 fertilization. A severe scenario of 6% fall in agricultural productivity in the rest of the world is obtained by adding 6% fall in yields (doubling the impact estimated in moderate scenario) and a 3.37 percent fall in yields due to an increase in ozone pollution in the next two decades (which is esimated by taking average of high end loss estimates given in two studies -[Van Dingenen et al., 2009] and [Avnery et al., 2011]) to a 3.6 percent positive effect of CO_2 fertilization. We impose these scenarios on the economy when it is closed to trade and when it is open to trade.

The effect of climate change can also be described in terms of a reduction in the growth rate of θ_F^I and θ_F^R over 2009-2030. In the medium scenario, θ_F^I and θ_F^R growth is reduced by 0.36 % p.a and 0.1% p.a in the moderate scenario respectively and 0.67% p.a and 0.3% p.a in the severe scenario respectively.

4.6.1 Closed Economy

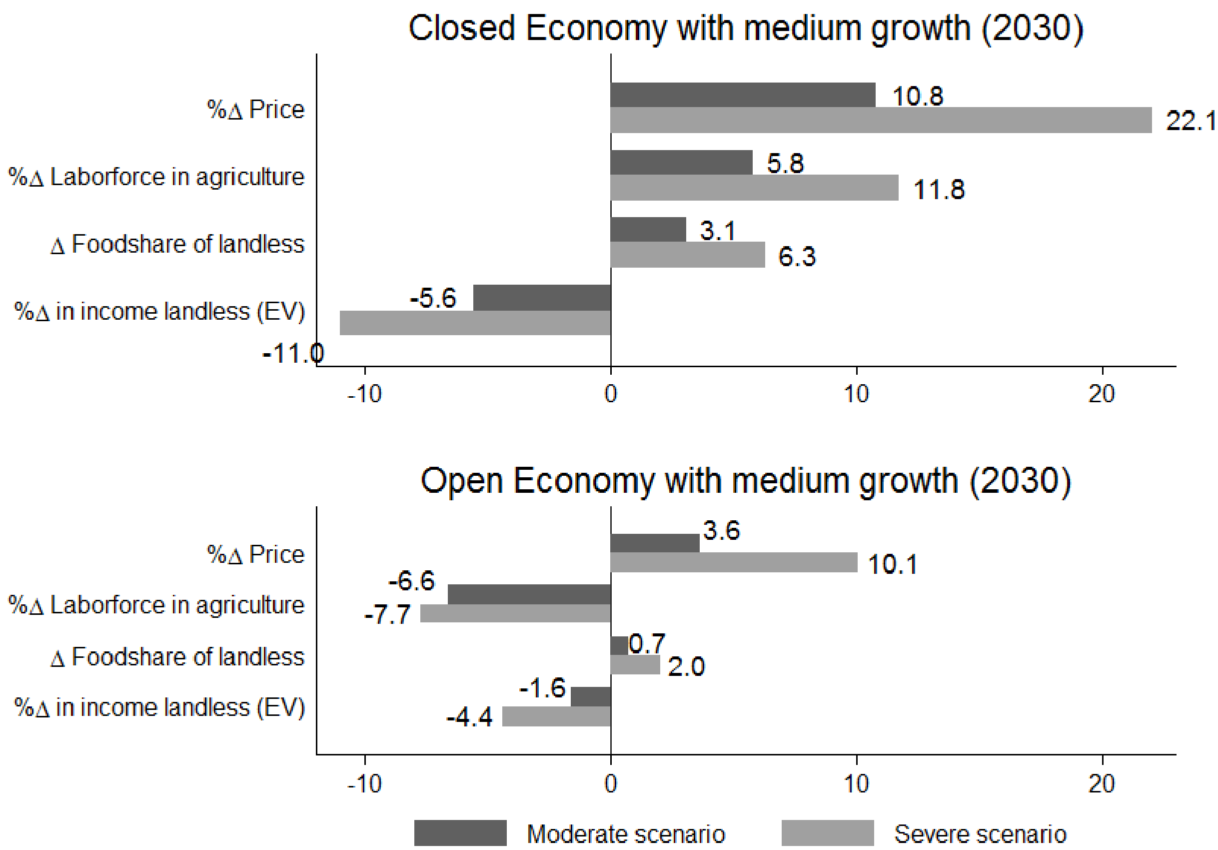
The second and third columns of Table (4.9) show values of important variables obtained in general equilibrium in 2030 under the medium scenario with no climate change. Food prices are about 43% higher than in 2009[10]. The landless poor are about 75% richer. In the richer economy, as expected the share of the food sector falls to 46.4% in 2030 from 52% in 2009. About 28.5% of the total workforce is employed in the food sector. The annual wage rate or θ_T is Rs 56340 and rent per hectare is Rs 58206. Wage rate per adult equivalent or the income of the landless is Rs 27600. The food share of the landless falls to 53.5% from 62.5% in 2009.

Figure (4.6) shows results for the medium growth scenario. In the 2030 baseline economy the share of subsistence food consumption in total food consumption $\left(\frac{\underline{f}\,N}{Y_F}\right)$ is lower than in 2009. So the elasticity of the food price with respect to θ_F is lower. However, the impact of climate change is still quite high. Even the moderate decline of 7% in θ_F increases food prices by almost 10.8% while this is 22% in case of a severe decline in θ_F of 13%. In this scenario, the landless poor are 75% richer and the equivalent variation as percentage of income is -5.6% when θ_F falls by 7% and is -11% when θ_F falls by 13%.

Figure(4.7) shows the income of the landless poor in seven different socio-economic development scenarios for 2030 economy discussed above at 2009 prices. Thus the 2030 income in 2009 prices is obtained by adding the 2009 income and the equivalent variation

[10] [Headey, 2014] finds that there is a long-run correlation between higher food prices and lower poverty. Our model suggests that the causality that [Headey, 2014] assumes is wrong. The conclusion of our model is that reduced poverty comes from higher productivity growth. If there is greater productivity growth in the non-food sector than in the food sector, then food prices rise. But, higher food prices do not cause lower poverty. If higher food prices result from lower productivity in agriculture, for example, from climate change, then they are associated with increased poverty.

Figure 4.6: Impact of Climate Change and Pollution from 2009-2030 on Welfare in Closed and Open Economies



Note: Moderate scenario of 7% fall in θ_F^I and 2% fall in θ_F^R : Growth rate of agricultural productivity (θ_F^I) in India declines by .36% p.a and in ROW (θ_F^R) declines by .1 p.a relative to no climate change medium growth scenario in 2030.

Severe scenario of 13% fall in (θ_F^I) and 6% fall in (θ_F^R): Growth rate of agricultural productivity (θ_F^I) in India declines by .67% p.a and in ROW (θ_F^R) by .3% p.a relative to no climate change medium growth scenario in 2030.

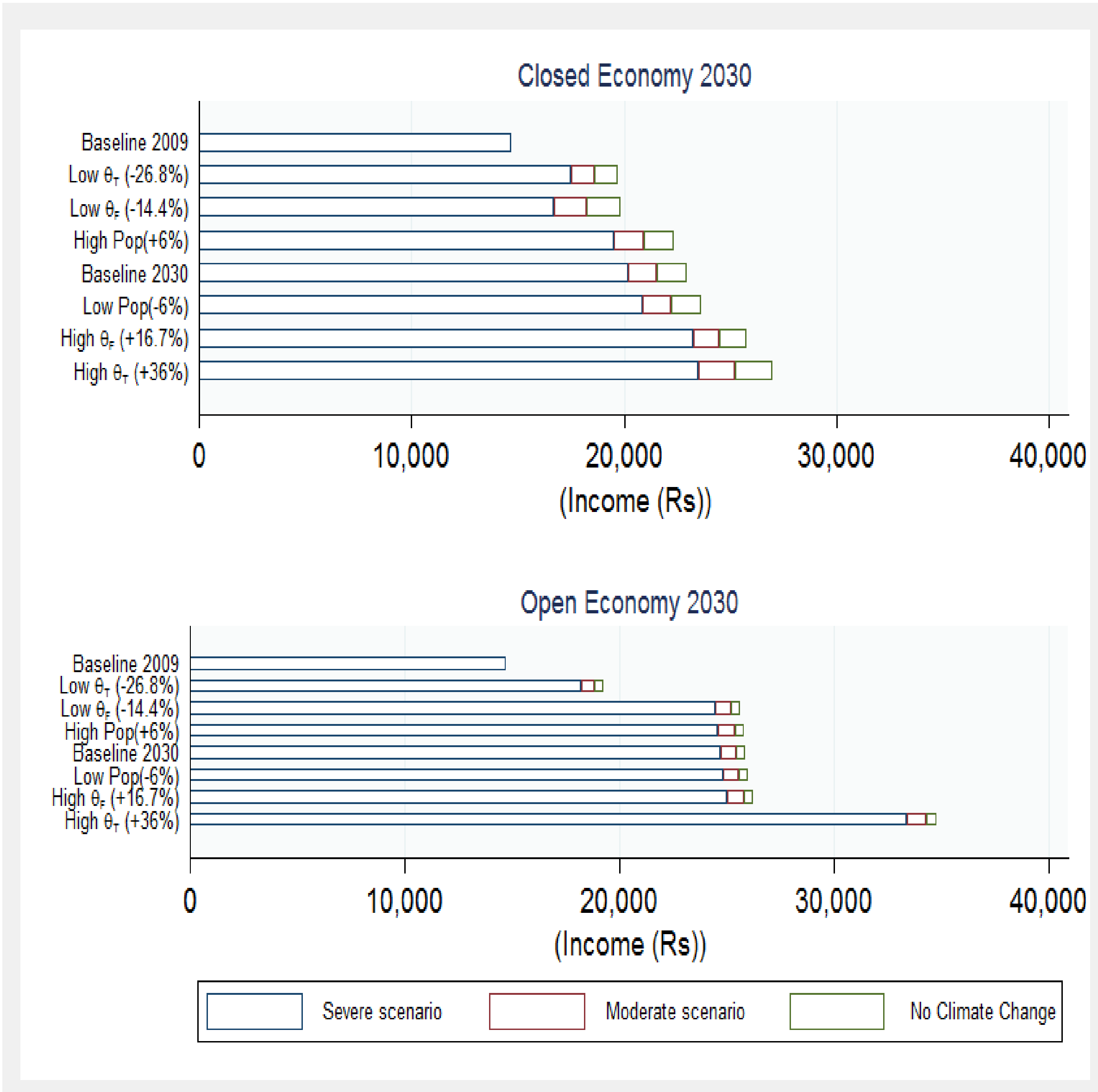
Table 4.9: General Equilibrium in Baseline Cosed and Open Economies (2030)

Variable	Closed Economy		Open Economy	
	Value 2030	Change over 2009 baseline (%)	Value 2030	Change over 2009 baseline (%)
Food Demand (10^{12} kcal)	1231	41.5	1398.5	55
Food Demand (kcal) adult equivalent/day	2741	12.5	3114.5	23
Non-Food Demand (10^{12} Rs)	24.3	153	23.1	145.7
labor in Food sector (10^6)	172	8	89.2	-26.8
labor in Non-Food (10^6)	431	34.7	513.5	44
Food Price (Rs/kcal)	0.017	42.9	0.0119	15.4
Annual Wage Rate (Rs)	56340	87.5	56340	87.5
Rent per hectare (Rs)	58206	102	30254	36.4
Food sector share (%)	46.4	-15.6	27.4	-36.4
Food share of landless(%)	53.5	-14.4	45	-21.7
Nominal income of the landless (Rs)	27600	87.5	27600	87.5
Real income of the landless in 2009 prices (Rs)	25781	75	26236	78
Food imports as % of food demand	-	-	35	143
Non-Food exports as % of Non-food output	-	-	20.2	60.3

of the change from 2009 to 2030. In each scenario, the length of the bar denotes the income of the landless poor without the climate change. The first break from the right in the bar shows what the income would be if there is moderate climate change (7% fall in θ_F) and the second break from the right shows what income would be if there is a severe climate change (13% fall in θ_F).

In 2030, the landless poor are better off than in 2009 in all scenarios even with severe climate change. Income of the poor differs in all these seven socio-economic development scenarios in 2030. It is highest in the high non-agricultural productivity scenario, followed by high agricultural productivity scenario. In both these scenarios the income of the poor with moderate climate change is higher as compared to baseline 2030 (medium growth for all variables) without climate change. Income of the poor is lowest in the low

Figure 4.7: Real Income of the Landless under Different Growth Paths in Closed and Open Economies



Note: Moderate scenario of 7% fall in θ_F^I and 2% fall in θ_F^R : Growth rate of agricultural productivity (θ_F^I) in India declines by .36% p.a and in ROW (θ_F^R) declines by .1 p.a relative to no climate change medium growth scenario in 2030.

Severe scenario of 13% fall in (θ_F^I) and 6% fall in (θ_F^R): Growth rate of agricultural productivity (θ_F^I) in India declines by .67% p.a and in ROW (θ_F^R) by .3% p.a relative to no climate change medium growth scenario in 2030.

agricultural productivity scenario, followed by low non-agricultural productivity scenario. In both these scenarios income of the poor even without climate change is lower as compared to baseline 2030 with moderate climate change. The severe climate change in baseline 2030 is nearly similar to being at the lower end of agricultural productivity or non-agricultural productivity. The implication is that plausible variation in productivity growth in both agriculture and non-agriculture can affect the welfare of the poor by as much or more than the mitigation of climate change.

Another way to understand the relative importance of factors that determine the welfare of the poor is to derive the percentage change in the income of the poor in 2030 in each of the scenarios over the baseline medium growth scenario as a result of a one percent increase in agricultural productivity over the baseline medium growth scenario, one percent increase in non-agricultural productivity over the baseline medium growth scenario and one percent reduction in the population over the baseline medium growth scenario. We find that a one percent increase in agricultural productivity is likely to increase the real income of the poor by .82 percent. On the other hand a one percent increase in productivity in the non-agriculture will increase income of the poor by .51 percent and one percent lower population is expected to increase the real income of the poor by about .45 percent. When India is closed to trade, agricultural productivity growth increases the welfare of the poor more than non-agricultural sector growth or controlling population.

Open economy

The last two columns of Table (4.9) show values of important variables obtained in general equilibrium in 2030 in the medium scenario in the open economy case. We assume that the rest of the world would be growing at the medium rate of 1.84 % (θ_F^R), 2.2 percent (θ_T^R) and .94 percent (N). In the richer economy, since agricultural productivity is projected to grow faster and non-agricultural productivity slower in the rest of the world than in India, the share of the food sector in india falls considerably to 27.4 percent in 2030 from 43.1 percent in 2009. The world equilibrium price of food increases by about 20 percent from .01 in 2009 Rs to .012 in 2030. About 14.8 percent of the total workforce is employed in the food sector. The annual wage rate or θ_T is about 56000 Rs (87% higher than in 2009) and rent per hectare is 30000 Rs. Wage rate per adult equivalent in the economy or model income for the landless poor is about 27600 Rs. The food share of the landless poor falls to 45 percent from 57.5 percent in the open economy of 2009.

Figure(4.6) shows the impacts of moderate and severe climate change on the 2030 baseline open economy, i.e. assuming medium growth scenario. The moderate decline in θ_F increases food prices by 3.6% and by 10% with severe decline in θ_F. The price increase with the moderate decline in θ_F is consistent with previous projections by [Hertel et al., 2010] that predicted 3.6 % increase in the world average price for all cereals in the most likely scenario of climate change. For a landless person, the equivalent variation as a percentage of income is -1.6% in the moderate decline in θ_F and -4.4% in the severe decline in θ_F.

As in the closed economy case, we have considered the same seven socio-economic development scenarios in this open economy as discussed above. Figure(4.7) compares the income of the landless poor in these scenarios. Clearly, in contrast to the closed economy the moderate climate change results in only a small decline in the income of the poor in all the scenarios. Income of the poor is highest in the high non-agricultural productivity scenario and even with the severe climate change, income in this scenario is higher than the income in the baseline 2030 without climate change. Similarly, the income of the poor is lowest in the low non-agricultural productivity scenario and even without climate change income in this scenario is much lower compared to the baseline 2030 income with severe climate change. The implication is that plausible changes in productivity growth in the non-agriculture sector will have a much larger impact on the welfare of the poor than the mitigation of climate change. Thus, the effect of the improvement in the non-agricultural productivity on the welfare of the poor stands out. On the other hand, improving agriculture productivity does not make much difference to the income of the poor because India is a food importer.

A 1% increase in agricultural productivity over the baseline medium growth scenario increases income of the poor by only .076% over the baseline medium growth scenario. But, a 1% increase in productivity in non-agriculture increases income of the poor by .96%. In 2030, India will account for only 18% of the total global food supply and import 35% of its food. Higher agricultural productivity impacts the poor by reducing food prices and thereby increasing the real income of the poor. However, food prices fall by only a small amount and improves the welfare of the landless only marginally. On the other hand, higher non-agricultural productivity increases the real income of the poor by increasing wages directly and thus have a much bigger impact. A 1% lower population increases the income of the poor by only .06%. Lower population impacts the poor indirectly by lowering food prices and thus has a much lower impact as in the case of agricultural productivity. If India can import its food without frictions from the rest of the world, improving non-agricultural productivity is likely to increase income and welfare of the poor much more than improving agricultural productivity to reduce climate change impacts or spending resources in controlling population.

4.7 Conclusion

Some of the key results of the study are as follows. First , the buffering effect of international trade on the welfare of the poor can be very important. In the closed economy case, the landless poor are significantly worse off with climate change as prices rise considerably. In the open economy case, the landless poor are better off because the price increase is moderated by trade. It really matters to the poor what happens in the rest of the world. If climate change results in a large decline in agricultural productivity in the the rest of the world as well, then food prices rise significantly in the open economy and affect the welfare of the poor negatively. Second, in the richer economy of 2030 the welfare impacts of climate change are less severe. Thus, climate is only one of the many factors that will shape food security and welfare of the poor in future.

The combination of trade and economic growth can buffer the poor against climate change. In the richer closed economy, improving the productivity of the agricultural sector has the greatest impact on the welfare of the poor. In contrast, in the richer open economy, the non-agricultural sector plays a bigger role in driving the welfare of the poor. The implication is that changes in productivity growth in the non-agricultural sector will have a much larger impact on the welfare of the poor than mitigation of climate change (unless there are impacts unforseen in this study). By importing food and exporting non-agricultural good, in which it has relative comparative advantage, the poor can be better off.

It should be stressed that these results are the outcomes that would obtain without frictions. For instance, we assume that all foods are perfect substitutes, labor is perfectly mobile between sectors and that there are no barriers to trade. Frictions would possibly exacerbate the climate change impacts. For instance, the above analysis is carried out under the crucial assumption that there are no human capital barriers and there is a free movement of labor between agriculture and non-agriculture. Between 2009 and 2030 if labor cannot move out from the agriculture to the non-agriculture sector welfare implications for the poor will be much more severe. Non-agricultural growth and trade will be of much less help to the poor if the mobility of labor from agriculture to non-agriculture is constrained by a lack of education or other barriers. [Eswaran et al., 2009] find that despite the rapid growth of the non-farm sector, its success in drawing labor from the agriculture has been limited. They provide some evidence to suggest that lack of human capital has hindered the movement of labor to non-agriculture.

We have also assumed that the productivity change due to climate change is Hicks neutral and affects the marginal product of both labor and land in the same way. If we assume that the climate change will affect the marginal product of land more than labor, then this could require a larger sectoral shift of labor from the non-agricultural sector to the agricultural sector, and a greater increase in the food prices, and thus worsen the condition of the poor.

More research is needed in future to study the welfare implications for the poor when the assumptions in the above analysis fail to hold. This is beyond the scope of this paper but is an important issue of future research. While the quantitative investigation is geared to throw light on this issue for India, we expect the methodology of this research can be applied to other developing countries as well.

4.8 Appendix A: Open economy case

We assume that the factor markets clear locally and the goods market clear internationally. The total food production is given as $Y_{_F} = Y_{_F}^I + Y_{_F}^R$.

Here,

$$Y_{_F}^I = \theta_{_F}^I A_F^I \left(\frac{L_F^I}{A_F^I}\right)^{\alpha}$$

for I and

$$Y_{_F}^R = \theta_{_F}^R A_F^R \left(\frac{L_F^R}{A_F^R}\right)^{\beta}$$

for R.

Similarly, the total non-food production is given as $Y_T = Y_T^I + Y_T^R$. Here $Y_T^I = \theta_{_T}^I$ L_T^I for I and $Y_{_T}^R = \theta_{_T}^R\, L_T^R$ for R. Factor market clearing conditions for land and labour for I are $N_l^I = L_F^I + L_T^I$ and $A^I = A_F^I$. Similarly for R we have $N_l^R = L_F^R + L_T^R$ and $A^R = A_F^R$. We denote the wage rate by W^I in I , w^I per capita wage in I , w^R per capita wage in R and by W^R in R. We denote per unit land rent by r^I in I and by r^R in R.

On consumption side, as previously we have

$$U_{_i}^I = (f_{_i}^I - \underline{f})^{\rho}(t_{_i}^I - \underline{t})^{1-\rho}$$

for I and

$$U_i^R = (f_i^R - \underline{f})^{\rho}(t_i^R - \underline{t})^{1-\rho}$$

for R. Individuals in both regions maximize utility subject to their respective income constraints $M_i^I = w^I + r^I a_i$ for I and $M_i^R = w^R + r^R a_i$ for R. As in the previous section we can derive total demands of F and T in both the economies in the following way:

$$F_d^I = \underline{f}N^I + \frac{\rho}{P}(w^I N_l^I + rA^I - P\underline{f}N^I - \underline{t}N^I)$$

$$F_d^R = \underline{f}N^R + \frac{\rho}{P}(w^R N_l^R + rA^R - P\underline{f}N^R - \underline{t}N^R)$$

Global food demand is obtained as $F_d = F_d^I + F_d^R$

Similarly, for non-food we have

$$T_d^I = \underline{t}N^I + (1-\rho)(w^I N_l^I + r^I A^I - P\underline{f}N^I - \underline{t}N^I)$$

$$T_d^R = \underline{t}N^R + (1-\rho)(w^R N_l^R + r^R A^R - P\underline{f}N^R - \underline{t}N^R)$$

Global non-food demand is obtained as $T_d = T_d^I + T_d^R$

As in the closed economy case, we obtain optimal labour, rent and output supply from marginal conditions in both sectors of the respective economies.

In general equilibrium, all four markets clear.Land: $A^I = A_F^I$; $A^R = A_F^R$;Labour: $N_l^I = L_F^I + L_T^I$; $N_l^R = L_F^R + L_T^R$;Food: $F_d = F_d^I + F_d^R = Y_F = Y_F^R + Y_F^I$

Textile: $T_d = T_d^I + T_d^R = Y_T = Y_T^R + Y_T^I$

As shown previously general equilibrium can be obtained with textile market equilibrium condition as follows: $T_d = T_d^I + T_d^R = Y_T = Y_T^R + Y_T^I$

$$\left(\theta_T^{I\frac{\alpha}{\alpha-1}}\left(\frac{1-\alpha}{\alpha}\right)P\theta_F^{I\frac{1}{1-\alpha}}\alpha^{\frac{1}{1-\alpha}}\right)A^I - P\underline{f}N^I + \left(\theta_T^{R\frac{\beta}{\beta-1}}\left(\frac{1-\beta}{\beta}\right)P\theta_F^{R\frac{1}{1-\beta}}\beta^{\frac{1}{1-\beta}}\right)A^R - P\underline{f}N^R$$
$$+\frac{1}{(1-\rho)}A^I\left(\frac{\theta_T^I}{\alpha P\theta_F^I}\right)^{\frac{1}{\alpha-1}} + \frac{1}{(1-\rho)}A^R\left(\frac{\theta_T^R}{\beta P\theta_F^R}\right)^{\frac{1}{\beta-1}}$$
$$= \frac{\rho\theta_T^I N^I + \rho\theta_T^R N^R - \rho\underline{t}\ N^I - \rho\underline{t}\ N^R}{(1-\rho)}$$

From the above equation we determine equilibrium international price of food P.

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