Environmental Tax Reform and Economic Welfare

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Abstract

According to a new study *Environmental Performance Index (EPI)* (2012), India has the worst air pollution in the entire world. Given the severe damages caused by air pollution, it is important to explore various options to control air pollution. In *chapter 1*, I use a computable general equilibrium (CGE) model to show that a Pigouvian tax on the use of fossil fuels with cuts in existing distortionary taxes could have double dividend in India. In addition, the fuel tax policy is also progressive. Alternative Pigouvian tax on output of pollution intensive commodities has a positive effect on economic growth, but it achieves only a modest reduction in air pollution. This tax policy does not have a significant distributive impact.

Chapter 2 presents a new econometric model of aggregate demand for urban India. I create inter-area consumer price indices for India and combine them with a nationally representative consumer expenditure survey to estimate the model. The consumer expenditure data allows for substantial demographic heterogeneity. I estimate a flexible model of aggregate demand known as Translog model in the literature and report estimated model parameters, cross price elasticities and expenditure elasticities. The model is able to explain the patterns of aggregate demand in urban India and it can be useful in general equilibrium models to evaluate macro-economic impacts of a broad range of policies. The results of such general equilibrium models will be more realistic if they incorporate flexible functional form such as the one presented in the chapter.

In *chapter 3*, I evaluate the impact of three revenue neutral environmental tax policies — carbon tax, fuel tax and output tax — on consumer welfare in India. I take the results of my CGE simulations to household data to estimate the welfare impacts of the environmental policies. Demographic attributes such as household size, the education the age of household head affect the expenditure patterns and thus the individual welfare effects. As for the aggregate welfare, the impact of pollution taxes is generally very modest compared to the improvement in environment as measured by reduction in health damages due to air pollution. The output tax policy seems to offer double dividends, because the output tax policy works as a tax reform rather than an additional burden on consumers. The output tax is mildly regressive, but other policies could be mildly progressive or regressive depending on the measure of progression used.

For Mother

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Overview

According to a recent survey by Columbia and Yale universities, India has the worst air pollution in the entire world. India ranks the last among 132 countries in the 'Air effects on human health' index and the situation has worsened over the last ten years. The Indian economy has grown at 6.14% per annum over the last three decades (1980 to 2008). Though the economy has become less energy intensive, the total primary energy use (3.79%/year) and energy use per capita (1.82%/year) have increased rapidly over this period, putting significant strain on the environment. The potential of market based environmental policies to address this problem is enormous in India. At present, a variety of command and control environmental regulations are in place, mostly technology and performance-based standards. But in near future these policies will be neither sufficient nor effective. My thesis provide a rationale and a framework for quantifying the potential benefits and costs of market based environmental policies in India.

The fundamental question of my thesis is how consumers of India, who are very diverse in terms of demography and wealth levels, are going to be affected after an imposition of market based environmental tax policy—both individually and cumulatively. It is well known that market based environmental taxes are capable of achieving significant environmental improvement, but there is uncertainty if they can be implemented in a costless way as far as consumers are concerned. The possibility of a costless implementation is known as double dividends Pearce (1991). According to Pearce (1991), new environmental taxes, whose revenues are recycled back to the economy by lowering existing, distortionary taxes on capital or labor, can achieve a (strong) double dividend: a first dividend of improved environmental quality, and a second dividend of a net economic benefit, in the form of higher individual welfare, faster GDP growth spurred by investment, or employment.

The first chapter of the dissertation investigates the economic and health effects of market based environmental tax policies. In this chapter, I construct a computable general equilibrium model of Indian economy, which captures both the direct effects as well as the indirect effects arising out of interindustry transactions. The model estimates the economic costs and health benefits of two specific pollution control policies: a Pigouvian tax on fossil fuel use and a Pigouvian tax on the output of all commodities. The tax rates in the two cases are set proportional to the health damage per unit of fuel and per unit output of the commodity respectively. One advantage of these market based policies is that they are administratively easier and cheaper to implement than the first best solution— a direct tax on emissions, concentration, or damages (Portney and Stavins, 2000). Market based taxes are already used in India—even if not for environmental reasons—and so may be politically acceptable as an instrument for emission reduction too. According to my analysis, the fuel tax is much more effective in reducing pollution and health damages while the output tax has a greater positive effect on GDP and household consumption. The output tax works more as a tax reform policy than an environmental policy and may be politically more feasible as it spreads the pain across all sectors. Both taxes could have double dividends, because even though real consumption is lower in the first 7-8 years, it is consistently higher in later years.

I have also made an attempt to estimate the distributional implication of the policies by considering four occupational categories of the household sectors. These categories are rough proxies for income quantiles. I find the fuel tax policy to be progressive. The output tax policy does not seem to have a significant distributive impact according to the calculations of the chapter.

Although the first chapter provides important information of the dynamic impact of Pigouvian taxes, it still leaves a few issues unaddressed. First, it doesn't have a welfare framework that is built upon micro household data. Second, the lack of demographics in the modeling means that we cannot internalize the effect of changing demography. Third, it doesn't address the distributional effect sufficiently. The model does have 4 occupational/income categories of households. But this methodology is far from a full-fledged formal distributional analysis.

In chapter 2, I have estimated a flexible model of household welfare known as Translog model in the literature (first introduced by Christensen et al. (1975)). I report estimated model parameters, cross price elasticities and expenditure elasticities of the model. To the best of my knowledge, this is the first model of aggregate demand/welfare for India. This welfare function internalizes the enormous demographic diversity of India. The data constraints forced me to consider only the urban sector of India, so we lose one important demographic information, but we do have rich set of other demographics, such as religion, social group/caste, age of the head, education of the head, composition of the family etc. The model could be applied in general equilibrium models to evaluate the macro-economic impacts of a broad range of policies.

An important contribution of this chapter is the careful preparation of price levels for 64 of 72 state-regions of India using unpublished commodity prices collected by the Labour Bureau. I create inter-area urban price indices for India using

(1) price data on 350 commodity items and services from 91 urban centers of India collected by the Labour Bureau,

(2)a hedonic price model that I estimated using house-rent data from a national survey of household amenities (NSS 58th round survey on household amenities and condition for the year 2002).

I have exploited the large inter-regional variation of prices in India to identify the parameters of the translog model. The model reflects the consumption behavior of individual households and accounts for the heterogeneity in household behavior seen in the micro-data rather than assuming a representative consumer.

The parameter estimates of the model can be applied to a host of food and energy policy research. Simulations in a general equilibrium setup are going to be more realistic and accurate if the flexible functional form such as the above is used. Given the size and population of Indian economy, Indian energy demands and global gas emissions in coming times are going to be a global problem. So the chapter contributes significantly to future endeavors on climate policy research.

In the third and final chapter, I evaluate a variety of environmental tax policies from the perspective of consumer welfare. Apart from the two Pigouvian tax policies from above, I consider another environmental policy—Carbon tax Policy, a fixed tax policy based on the carbon content of energy fuels. The analytical framework described in this chapter not only measures the welfare effects on individual households classified by demographic attributes and wealth levels, but also combines the welfare effects into a single and convenient social welfare measure. We are able to see changes in efficiency and equity as components of change in social welfare. This framework was developed by Jorgenson et al. (1992) in order to evaluate carbon tax policy in the USA.

Depending on the demography of households, we see wide variation in the individual welfare effects. The impact on aggregate welfare is generally very modest in relation to the improvement in environment. Unlike the fuel tax and the carbon tax policies, the output tax policy shows signs of double dividends, because in this case social welfare improves after imposition of the policy. All three policies are mildly regressive according to relative measure of progressivity. But if we go by the absolute measure of progression, then except the output tax policy, the two policies are mildly progressive.

The three chapters of the thesis contribute to the understanding of air pollution and its effects on economic welfare. In totality, the three chapters set up a powerful general equilibrium framework; provide a new tool for welfare modeling; and evaluate various market based policies using the tool.

Chapter 1

Market Policies to Control Health Effects of Air Pollution in India

1.1 Introduction

According to a recent survey *Environmental Performance Index (EPI)* (2012), India has the worst air pollution in the entire world. India ranks the last among 132 countries in the "Air effects on human health" index and the situation has worsened over the last ten years. India beats the second-lowest nation by a wide margin and the situation shows little improvement in the last few years [1].

The Indian economy has grown at 6.14% per annum over the last three decades (1980 to 2008). The economy has become less energy intensive, but total primary energy use (3.79%/year) and energy use per capita (1.82%/year) have increased rapidly over this period, putting a significant strain on the environment. According to a recent report in New York Times, ambient air quality in Delhi is now significantly worse than the air quality in Beijing[2] and the real-time air monitors installed in the city regularly show PM2.5 and PM10 concentration exceeding 500ppm, which is extremely hazardous. [3] The problem is not just limited to Delhi. Using data collected from 342

[1] To see graphically the positions of all countries according to the 'Air effects on human health' index, go to the website http://epi.yale.edu/dataexplorer/countryprofiles (last checked on April 27, 2013)

[2] http://india.blogs.nytimes.com/2011/11/21/new-delhi-now-more-polluted-than-beijing/ (as seen on 15th February, 2012).

[3] Real-time pollution in ten different locations in Delhi can be tracked on: http://safar.tropmet.res.in/. I checked PM2.5 and PM10 levels on several occasions between 15th January and 15th February 2012 at different hours in the day. Both PM2.5 and PM10 concentrations were always higher than 300ppm considered hazardous in the USA.

ground level air-quality monitoring stations in 127 cities, Greenstone and Hanna (2011) show that the ambient particulate matter concentrations in India are five times the level of concentrations in the United States.

India is more densely populated than both the US and China. As India's population increases and urbanizes [4], even more people will be exposed to outdoor air pollution and the cost to health and life will increase rapidly unless special efforts are made to improve air quality. What are the most cost-effective ways to reduce health damages from outdoor air pollution in India?[5]

A variety of regulations, mostly technology and performance-based standards, have been implemented over the last four decades to reduce emission and improve air quality. Many of these policies are sector specific (like catalytic converters for motorized transport or higher smoke stacks for brick kilns) and target a few large cities. Greenstone and Hanna (2011) analyze the effect of air and water regulations in India and find that "the air regulations have led to improvements in air pollution" (page 4) reducing the average ambient concentration of particulate matter, NOx and SO2 in cities where monitoring stations are located. World Bank's World Development Indicators (WDIs)[6] also show that the average annual exposure level of the average urban resident to outdoor particulate matter (PM10) in India has declined from 110.55 ppm in 1990 to 59.23 ppm in 2008. In contrast, remote sensing data from across India shows that the average concentration PM2.5 in ambient air has increased from 2002 to 2009 (*Environmental Performance Index (EPI)*, 2012). A recent study of air pollution in six cities (Delhi, Mumbai, Chennai, Bangalore, Pune and Kanpur), sponsored by the Central Pollution Control Board (CPCB), shows that the concentration of RSPM exceeded the annual standard ($60 mg/m^3$) in five of the six cities in all the years (2000-2006), but there was no discernible trend in concentration values over time. NO2 concentrations, on the other hand, showed a definite rising trend while SO2 levels were declining in all cities, which is largely attributed to the regulation on reduction of sulfur in diesel. (Reddy and Venkataraman, 2002)

Thus, there is some evidence that technology and performance-based standards intended to reduce air pollution have worked in India, at least for some pollutants, in spite of India's limited

[4] India's urban population is growing (31.8%/decade) more than twice as fast as its rural population (12.2%/decade).

[5] I do not compare the cost-effectiveness of policies aimed at outdoor air pollution with those aimed at indoor air pollution in the present paper, although this could be an interesting direction for researchers.

[6] http://data.worldbank.org/country/india

institutional capability to enforce these standards. While standards may reduce emissions of pollutants and are important elements in the policy toolkit, they typically exact a relatively high cost (Portney and Stavins, 2000). As economists, we are interested in knowing the marginal benefits and costs of emissions reduction and whether the benefits exceed the costs. However, there is a near complete absence of information on the control costs and benefits of these regulatory policies (Greenstone and Hanna, 2011).

Economists generally prefer policies that use market-based signals rather than explicit directives for pollution control levels and methods. Market based signals like fuel taxes and subsidies or emission taxes provide better incentives to the emitter to innovate and adopt new technologies and offer more flexibility to reduce emission at the lowest cost possible. However, such instruments have not been used in India to control outdoor air pollution [7]. Much of outdoor air pollution in India results from burning coal and motor fuels (gasoline and diesel). Together they account for 87% of the total primary energy use from commercial sources and 64% of total primary energy used from all sources, including biomass. Both the central and state governments tax gasoline and diesel to raise revenues for general funds. There is some tax on coal too. These taxes could have served some environmental function, like the motor fuel taxes in EU countries (Stavins, 2003), but they do not. In fact, they are levied in ways that increase inefficiencies and are detrimental to the environment. For example, the same grade of coal is 34-36% cheaper for power utilities, the most polluting industry, compared to all other sectors of economy [8]. Similarly, diesel is about 40% cheaper than gasoline in India even though it is more polluting than gasoline.

What would be the effect on the environment and the economy if the current perverse fuel tax regime in India is replaced with 'green' taxes that are proportional to the damages? Ideally, we would like to directly tax the emission or even the damages since we are concerned with local pollutants like SO2, NO2 and particulate matter (PM). However, economy-wide actual emissions and damages cannot be measured and monitored at a reasonable cost using the present infrastructure

[7] The story is different for indoor air pollution (IAP), where the Government of India provides high levels of subsidy on Kerosene and liquefied petroleum gas (LPG) to encourage substitution away from highly polluting solid unprocessed fuels like firewood and dung-cake.

[8] Fertilizer and defense sectors also pay the same lower price as power utilities (http://www.coalindia.in/Documents/Revised_2nd_Ver_Coal_Price_for_uploading_310112.pdf)

of India.[9] Therefore, the best available tax may apply to a measurable activity that is closely correlated with emissions (Fullerton et al., 2001). I consider two such policies: first, an indirect tax on primary fossil fuels (coal, gasoline and diesel) where the tax rate is proportional to the average health damage per unit of fuel and second, an output tax that is set proportional to the marginal damage caused by per unit production of the commodity.

Both the fuel tax and the output tax policies are not as efficient as a direct Pigouvian tax on emissions because inputs and outputs are imperfectly correlated with emissions. For example, a ton of coal produces different levels of emissions and damages in different industries. An efficient externality tax would tax the sectors differently, but that may not be practically feasible (Ho et al., 2002). Even a sector differentiated fuel tax would not encourage abatement on all margins and may even remove the incentive for innovation of end-of-the-pipe abatement technologies (McMorran and Nellor, 1994). In general, an indirect tax (on fuel or output) is not desirable when pollutants are easy to monitor with standard methods and allow for effective end-of-the-pipe technologies or if there is a significant scope for input substitution (Schmutzler and Goulder, 1997). On the positive side, fuel and output taxes are administratively easier and cheaper to implement than a direct tax on emissions, concentration, or damages (Portney and Stavins, 2000). These taxes are already used in India—even if not for environmental reasons—and so may be politically acceptable as instruments for emission reduction too. Therefore, I focus on taxes on commodities and fuels in this paper.

1.2 Social Accounting Matrix and The Economic Model

I use a Solow growth model of the Indian economy to compare the costs and benefits of different environmental policies. It is a Computable General Equilibrium (CGE) model and therefore, captures feedback effects and market interdependencies that may reinforce or weaken the first-order effects of pollution taxes.

The economic model uses a social accounting matrix (SAM) that is based on 2003-04 input-output tables and was commissioned by the Ministry of Environment and Forests (MoEF) of the Government of India. The original SAM consists of 36 sectors of the economy including eight

[9] However, there is a scope for emission trading in certain states of India. Duflo et al. (2010) connects experience with emissions trading, from programs like the U.S. Rain program, to lessons for implementation of a Trading Pilot Scheme in India.

energy sectors (coal, crude oil, natural gas, petroleum products, hydro, thermal and nuclear power plants, and biomass), 3 factors of production, and 4 agents -households, private corporations, public non-departmental enterprises, and the government. Households are divided into nine occupational categories [10].

I make two adjustments in the original SAM for my analysis. First, I split the 'petroleum products' sector into two independent sectors by creating a new row and column for household fuels (Kerosene and LPG). When splitting the column (which contains entries for inputs going into Petroleum Products sector), I assume that household fuels are produced using the exact same technology as other petroleum products. For splitting the row (which contains entries for the intermediate and the final uses of household fuels), I get the aggregate household consumption of Kerosene and LPG from the Annual Reports of Ministry of Petroleum and Natural Gas and allocate it to different household categories using the data from the 61st round (2004-05) of annual consumption and expenditure survey by the National Sample Survey Organization (NSSO).[11] I do this exercise to make sure that when I impose green taxes on fossil fuels in the counterfactuals, I do not tax the household use of Kerosene and LPG. About 80% of all Indian households use biomass for cooking and heating (Pachauri and Jiang, 2008) resulting in more deaths and diseases than any other source of air pollution. Kerosene and LPG are cleaner substitutes of biomass as household fuels. Taxing them along with other petroleum products would lead to increased use of biomass, which is terrible for both environment and public health. As far as I know, this is the first paper that makes this important distinction when modeling the effect of green taxes in India in a CGE framework.

Second, I reclassify the 9 occupational categories of households in the original SAM into four groups—rural poor & rural non-poor and urban poor & urban non-poor[12]. This new classification

[10] The 9 occupational categories are: rural non-agricultural self-employed, rural agricultural labor, rural other labor, rural agricultural self-employed, rural other households, urban self-employed, urban salaried class, urban casual labor, and urban other households.

[11] I ignore the commercial use of LPG, such as use by the restaurant and catering industries. Commercial LPG is only a small fraction(roughly 10%) of the total LPG demand of India.

[12] For distributional analysis, it would have been ideal if I had households divided into income or consumption deciles. Instead, the SAM divides households into occupational categories. Among 9 categories, rural agricultural laborers, rural other laborers and urban casual laborers have average savings rate ranging from 4-7 percent: I classify them as poor. The savings rates of the remaining six household groups ranges from 26-41 percent. I group them as non-poor. I use the sharp discontinuity of savings rate as a justification for categorization of households into poor and non-poor. It is, however, possible that some households in the bottom of the 'non-poor' category may be poorer than some of the

allows me to explore the distributional impact of different environmental taxes. The classification is not as perfect as a quantile grouping, but it still manages to separate poor and nonpoor satisfactorily.

I rely heavily on Ho and Nielsen (2007) for my economic model, with two important differences. First, I do not have to a planned economy component in my model and second, I work with disaggregated household groups. Introduction of separate household groups entails specifying separate consumption patterns, savings rate and tax rates for each group. I describe below the important features of the model. More details with equations are given in Appendix A.

Each household group maximizes a Cobb-Douglass utility function that has all 37 commodities as arguments. Households derive income from labor, capital and land. In addition, a household gets its income from current transfers from the government, interest on public debt and the net current transfers from the rest of the world. Households spend on the consumption of goods and services and pay income taxes and indirect taxes on the purchase. They keep the residual income as savings.

Labor supply is inelastic and mobile across sectors. I do not embed any leisure-labor choice in the model, which is a simplification. The projection of working population provides exogenous labor supply at the beginning of every period in the simulation. The capital stock is endogenous and is owned by households and the government. Households receive dividends and the government receives profits on their respective capital stock holding. Capital services are mobile across sectors and it responds to sector specific relative returns.

The government gets its revenue from taxes on sales, imports, labor income and capital income. The government expenditure includes purchases of goods and services, subsidies and transfers, interest payments on debt. The government deficit as a share of GDP is set exogenously and projected to fall over time. Given that tax/subsidy rates and deficit are exogenous, the government expenditure on goods and services is determined endogenously from the budget equation.

The Rest of the World is modeled very simplistically. I make the conventional Armington assumption for both the import and the export markets. World relative prices are set to mimic the

richest households in the 'poor' category. I verified my classification with consumption data from 61st round (2004-05) of NSSO survey and found that 81% of rural poor households and 73% of urban poor households in my classification had monthly per capita consumption expenditure below the national median. 47% of the households I classified as rural non-poor and 34% of the households I classified as urban non-poor were also in the below median consumption expenditure category. Clearly, my classification of households in poor and non-poor categories has significant type 1 and type 2 error percentages. Of the four categories, the rural poor are the best identified category. Accordingly, I focus my distributional analysis on the impact of tax policies on the rural poor more compared to others.

SAM's domestic prices after adjusting for the domestic tax rate and tariff rates. Current Account Balance is set exogenously and it is projected to fall over time. An endogenous variable for terms of trade clears the export-import equation.

Production technology in all sectors is assumed to be Cobb-Douglas. The relevant parameters for the base year, such as input expenditure shares, come from the SAM , while the same are projected exogenously in later years. Productivity growth is introduced as an exogenous shock to production function and is assumed to be identical across all sectors.

1.3 The Environment-Health Model

1.3.1 Estimation of Emission by Sector

Particulate matter, SO2, and NOx are generated by a combination of combustion of biomass & fossil fuels and non-combustion processes (process emissions). I get the estimates of sector-wise combustion emission coefficients of these three pollutants from Garg et al. (2006), which provides the estimates for 15 sectors for SO2, 12 sectors for NOx and 7 sectors for total suspended particulate matter (TSP) at my level of classification. I modify these aggregate estimates into my more detailed sectors using fuel emission factors from both Garg et al. (2001)[13] and Lvovsky and Hughes (1997). The data on the total physical quantity of different types of fuels consumed by different sectors of the economy in 2003-04 were obtained from the TERI (2002). For process emission, I use emission coefficients from RAINS [14]-Asia database and CPCB (2007). The sources mentioned above give me data only for total suspended particulate matter while recent research shows that much of the health damage is caused by finer particles: PM2.5 and PM10. (Dockery, 2009). I assume PM10 emissions to be 54% of TSP emissions from all sectors of the economy in all parts of India (following Lvovsky and Hughes (1997) and Ho and Jorgenson (2003)). I use this crude rule of thumb because there are no estimates for particle size distribution for different sectors and regions of India. I completely ignore health effects due to PM2.5 for want of data on emission and dispersion characteristics. All emission estimates used here are based on emission factors and not on actual measurements of total emissions.

[13] http://www.decisioncraft.com/energy/papers/ecc/ei/so2.pdf

[14] (Regional Air Pollution INformation and Simulation)

There are three sources of change in total emissions, and hence health effects in my model. First, the energy efficiency of the economy improves over time resulting in lower combustion emission per rupee of output produced. This improvement in energy efficiency is exogenous. The way I accomplish this is by changing technological parameters for broad input aggregates (K,L,E,M, Land) slowly to the corresponding parameters of input-output tables of the US economy in 1982. The details of this methodology are described in Appendix B. Second, fuel tax changes relative price of fuels, which leads to substitution to cleaner fuels and inputs and hence lower emission. Third, fuel or output tax may increase the price of the energy intensive sectors and therefore lead to lower demand of outputs from these sectors in comparison to the base case. The emission coefficient (emission of pollutant per tonne of oil equivalent (TOE) of fuel used in a sector), however, remains unchanged in my model over the years. My objective in succeeding sections is to capture the effects of the second and the third sources of change (the first source affects the base case and the counterfactual in identical ways.)

1.3.2 Estimating Health Effects and Health Damages of Air Pollution

1.3.2.1 The Intake Fraction (iF) Approach

I focus on the health effects of outdoor emission of PM10 and SO2 on the urban population of India. I assume that emissions in rural areas cause little outdoor air pollution due to low population density and low ambient concentration levels and hence can be ignored. Next, I completely ignore the health effects of biomass use (and indoor air pollution) in my policy simulations because most households in India collect biomass using own family labor instead of purchasing it from the market, and therefore, the government cannot tax it even though it is highly polluting and causes more deaths and diseases than any other source of air pollution. Indirectly, the government subsidizes domestic use of LPG and Kerosene to discourage use of biomass. I make sure that these cleaner household fuels are not taxed in any of the policy counterfactuals. Moreover I report impact on biomass use in all my counterfactuals to check whether the implemented policies lead to substitution towards biomass use.

Following Ho and Jorgenson (2003), I use intake fraction (iF) approach to assess the health damages from air pollution. Intake fraction is defined as a dimensionless ratio of the amount of pollutant inhaled to the amount of the pollutant emitted (Bennett et al., 2002). Bennett et al. (2002) iterates that intake fraction is not an intrinsic property of the pollutant. Other factors like emission locations, environmental conditions, exposure pathways, receptor locations and activities, and population characteristics are important determinants of intake fraction.

Ideally, one should use India specific intake fractions, but there are no iF estimates for India. I take iF values used by Ho and Jorgenson (2003) for China and adjust them for differences in both the population levels and the population densities between India and China. However, I am unable to make adjustments for different climatic conditions and age distribution in India.

Ho and Jorgenson (2003) take their iF values from studies done by the Harvard University Center for Environment (HUCE) for five highly polluting industries (electricity, chemicals, cement, metals smelting and transportation). They take the average of the iF value of three manufacturing sectors (cement, metals smelting and chemicals) and use it as an estimate for the iF value of all manufacturing industries. Similarly, they use the iF value of the transportation sector as an estimate for the iF value of all service industries. The HUCE studies estimated iF for a 50-km domain only. Ho and Jorgenson multiply these iF values by 3 to make a simple estimate of the national iF values. The iF(SO2) estimate of manufacturing sectors is also used for transportation because it was not estimated by HUCE. This is a conservative estimate because stack heights are closer to the ground for transport emissions.

1.3.2.2 Dose-Response Function: From Exposure to Health Outcomes

The iF values allow me to link sector-wise emissions to population exposure. Next, I use linear dose-response coefficients from literature to estimate number of health cases resulting from population's exposure to emission of different pollutants [15].

Total amount pollutant x inhaled by people from emission in sector j is given by:

$$Dose_{xj} = iF * EM_{xj} = BR * C_x * POP_d$$

where C_x is the concentration of pollutant x; BR is the breathing rate and POP_d is the

[15] Even though I assume linearity of dose response function in the paper, dose response function could be nonlinear too. See Wiener (2004) for an analysis of the effects of a nonlinear dose-response function on instrument choice.

Population density.

Number of cases of health effect h from pollutant x is given by,

$$HE_h = \sum_x DR_{hx} * C_x * POP_d = \sum_x \frac{Dose_{xj}}{BR}$$

Dose Response Coefficients (DR_{hx}) measures how pollutant concentration leads to health damages (both mortality and other diseases). For morbidity I use standard coefficients from World Bank 1997 (annex. 2.1). See also **Kandlikar and Ramachandran (2000)** for a similar use of morbidity dose response coefficients in Indian context. For mortality coefficients, I use coefficients from Ho and Jorgenson (2003).

I obtain national level health effects of a pollutant x by simply adding up the number of health cases from all industries. This assumes that emissions from different industries do not interfere with each other. Finally, I put rupee value on these health damages by using VSL estimates for India from Kishore (2012). Kishore (2012) estimates the VSL for valuing cases of mortality in India. I only use the average VSL estimate from his paper and do not adjust it for people in different income categories. There are no value estimates in India for diseases caused by exposure to PM10 and SO2. So, I take values for China from Ho and Jorgenson (2003) and adjust them by the ratio of VSL estimates between the two countries (4:5). My valuation for morbidity is imprecise, but it is not a major concern because monetary valuation of mortality forms a large share of total health damages. I update the VSL and morbidity values over later years linearly with increases in per capita income, assuming income elasticity of VSL = 1[16].

1.4 Results

1.4.1 Base Case Simulations(Business as Usual)

I use Social Accounting Matrix (SAM) based on the accounting year 2003-04 to calibrate parameters and initial conditions for the economic model. My choice of the base year is constrained by the availability of a relevant SAM for my purposes. I initialize the economy with a given level of

[16] This is just a convenient choice. Robinson and Hammitt (2011) show that income elasticity of VSL could be more than one for low income countries making VSL a *luxury* commodity.

capital stock and working age population. Then the economic model calculates the production in every sector, the intermediate the final use of commodities by agents, and the savings available for investment. The model assumes full employment and flexible prices to solve for equilibrium prices clearing all the markets simultaneously. The same procedure is repeated for every subsequent years, but with a bigger capital stock (augmented by investments) and a larger projected future population. This Solow type modeling is continued till 2030, which is the last year of my projections.

The parameters that describe the future production technology, consumption pattern, and savings behavior are exogenously set in my model. Taking a cue from Ho and Jorgenson(2003, 2007), I make these parameters slowly converge to the values corresponding to the US input-output table of 1982. I do not suggest that India's economy in a few decades will resemble the US economy of 1982. But predicting India's economy in 2030 is nearly impossible. Yet choosing this benchmark allows the energy-material ratio to fall slowly over time resulting in higher energy efficiency. With this conservative benchmark for 2030, India's energy use grows at 5.6% per year during 2003-09 in the simulations (and 5.36% per year for the entire simulation period of 2003-30). India's actual energy use over the period 2003-09 has grown at 5.37% per year[17], which is very close to my simulation results.

Table 1.1 shows the changes in GDP, energy use, emissions and health damages from emissions at different points in the simulation period in the base case. In my simulations, GDP grows at 8.3% between 2003-04 and 2010-11, close to the actual growth rate in the economy during this period (8.23%), and it grows at 6.93%/year over the entire simulation period. Energy use and emissions increase rapidly with the increase in GDP even as energy intensity of the economy goes down. Emission keeps pace with energy use because I assume that there will be no change in emission factors (emission per unit of fuel used) over the years when in reality emission factors have declined in many sectors due to autonomous improvements in technology and pollution control policies. I am forced to make this limiting assumption of unchanging emission factors because there aren't any reliable projections of emission factors in India. Ho and Nielsen (2007) have addressed this problem by endogenizing emission factors using estimates of "new" technology for china in Lvovsky and Hughes (1997). I leave this refinement for future research when similar estimates are available

[17]World development Indicators

Table 1.1: Selected Variables from BAU case

a

Variable	*2003*	*2011*	*2030*	*28-year growth rate*
POPULATION(millions)	1072	1202	1448	1.11%
GDP(Bill 2003 dollars)	578	1121	3753	6.93%
Energy Use (Bill tons of SCE[b])	0.70	1.09	2.96	5.36%
Energy/GDP (tons of SCE/mill. 2003 dollars)	1211	972	789	-1.59%
Carbon Emission (Bill tons of Carbon)	0.29	0.46	1.35	5.71%
Coal Use (Mill TOE[c])	153	282	820	6.23%
Oil Use (Mill TOE)	127	171	406	4.30%
Bio Use (Mill TOE)	139	206	424	4.14%
PM10 emission - Total (k tons)	2869	4941	13514	5.74%
PM10 emission - Combustion only (k tons)	2448	4250	11462	5.72%
SO2 emission - Total (k tons)	6051	10046	26557	5.48%
NO2 emission - Total (k tons)	5610	8937	23522	5.31%
Death Count (1000s)	39	76	283	7.34%
Damage/GDP (%)	1.41%	2.43%	7.62%	

[a]Source: Author's Calculations

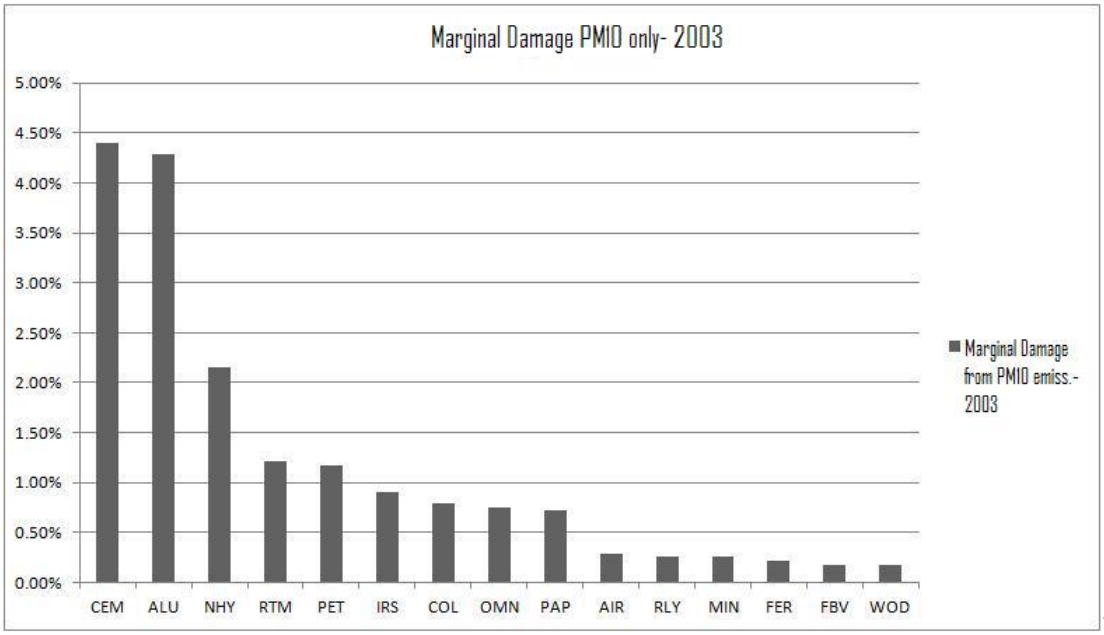
[b]*Standard Coal Equivalent.*

[c]*Tonne of Oil Equivalent.*

for India as well.

In the base case, the share of coal in total energy use increases over the years because coal is the cheapest source of energy in India and will remain so in future too. The pattern of rising coal's share in the energy mix is very similar to the projections in (World Energy Outlook, 2007) and the expert group of the Planning Commission of India.

The number of premature deaths due to air pollution rises from 39,000 in 2003 to 283,000 in 2030 in my simulations –a growth rate in excess of 7% per annum. The sharp increase in mortality is due to the increase in pollution accompanied by rapid urbanization of India's growing population. Once I include morbidity and mortality costs into my calculations, total value of health damage is 1.41% of GDP in 2003-04 and it grows to 7.62% of GDP in 28 years. Damage valuation captures not only the health incidences of pollution, but also the rising value of life over time due to rise in per capita income. These damage values are underestimated because I do not measure health damages due to other pollutants like finer particles (PM2.5), NOx, volatile organic compounds, ozone, etc.



[a]

[a]Source: Author's Calculations.

Figure 1.1: Marginal Damage by PM10 emission - Sector-wise

1.4.2 (Pigouvian) Output Tax Policy

This policy taxes the output of each sector according to the marginal health damage (MD) per unit of production. The marginal damage of a sector depends not only on the fuel used in the sector, but also on other factors like stack height, location of the plant, surrounding population density, process emission factors etc. MD valuation treats both process and combustion emission equally polluting. Figure 1.1 highlights the industries that cause maximum health damage from PM10, measured by the value of health damage as a share of the total value of the output of that industry in the first year of the base (no policy) case.

Cement (CEM), Aluminum (ALU), Thermal Power (NHY) and Motorized Road Transport (RTM) are some of the most damage intensive industries in India when it comes to health damages from particulate matter. NHY(Thermal Power plants), despite its enormous reliance on coal, turns out to be less damaging to health compared to Aluminum and Cement sectors, because it emits at a higher stack level. Under the Pigouvian output tax policy, one would impose a tax of about 4.5% on Aluminum and Cement, 2.1% on electricity produced by Thermal Power plants and similarly on other sectors just to account for the externality effects of PM10 emission.

For every year t, the output tax rate in the policy counterfactual is set as a fixed fraction λ of the full Pigouvian MD of the year $(t-1)$. This is an additional "green" tax which is levied on top of the existing indirect taxes.

$$t^x_{jt} = \lambda MD_{jt-1}$$

The output tax policy allows the economy to reallocate resources to cleaner industries. Output tax has the advantage of spreading the costs of environmental taxation over all the dirty sectors, but has the disadvantage that it is inefficient in reducing total emissions, as it fails to encourage switching to cleaner fuels. While I impose new taxes, I reduce other existing distortionary taxes like sales tax and capital tax keeping the policy revenue neutral[18]. The government expenditure remains the same with this new tax as it was in the reference case [19].

Table 1.2 shows the effect of an output tax that covers half (λ =50%) of the health damage caused by PM10 and SO2 emission as the percentage difference in key variables from the no-tax case in the first and the last year of the simulation period.

Even the halfway (λ =50%) Pigouvian policy reduces PM10 and SO2 emission by 2.01% and 1.64% respectively in the first year and by 3.36% and 3.09% respectively in the last year of my simulation. Combustion PM10 emission falls significantly faster than process PM10 emission, because Cement sector—the main source of process emissions of PM—doesn't contract as much as the Thermal Power sector. Apart from reduction in local ambient pollution, one can also see a complementary decline in carbon emissions. Percentage reduction in carbon emission exceeds the percentage reduction in energy use because the tax results in switching from coal to oil to some extent and oil is a less carbon intensive fuel.

Lower emissions of particulates and SO2 result in lower health damages. However, the decline in the value of health damages is less than the decline in the emission because emissions fall more

[18] An alternative way to repatriate green taxes back into the economic system could be give it equitably to the population as transfers. This expectedly leads to lower GDP, investment and overall consumption. Moreover this policy is very progressive because rural and urban poor class consumption goes up while nonpoor class consumption falls significantly. Clearly, we can't expect double dividends in such a tax policy, because new taxes bring new distortions on top of existing ones.

[19] Cao, Ho and Jorgenson(2007) also reduce existing distortionary taxes and keep government expenditure constant at base level

Table 1.2: Percentage Effects of Output Tax Policy

[a]

Variable	**First year**	**Last year**
Energy use	-0.21%	-0.56%
Energy/GDP	-0.27%	-1.11%
Carbon emission	-0.42%	-1.18%
Bio use	-0.08%	0.38%
Oil use	0.38%	0.56%
PM10 Emission - Total	-2.01%	-3.36%
PM10 Emission -Combustion only	-2.38%	-3.81%
SOx Emission - Total	-1.64%	-3.09%
Premature deaths	-0.65%	-1.55%
Value of Damage	-0.95%	-1.50%
Real GDP	0.08%	0.60%
Investment	0.77%	1.32%
Consumption Rural Nonpoor	-0.19%	0.14%
Consumption Rural Poor	-0.17%	0.17%
Consumption Urban NonPoor	-0.15%	0.20%
Consumption Urban Poor	-0.19%	0.16%
Damage/GDP[b]	-0.02%	-0.14%
Lambda[b]	50%	50%
Green tax/Revenue[b]	4.60%	6.00%

[a]Source: Author's Calculations

[b]These entries are changes in percentage points from the BAU case, the rest are percentage changes from the BAU case.

in industries with lower intake fraction values like the power sector (NHY) with relatively higher stack heights. Premature deaths are reduced by 0.65% and 1.55% in the first and the last years respectively. The reduction in the value of public health damage is a modest 0.02 percentage of GDP in the first year and 0.14 percentage of GDP in the final year.

There exists evidence for double dividend in this case as the counterfactual GDP is higher than the reference case GDP in all 28 years. The estimate for the first year may not be very precise, because I assume zero adjustment costs when resources shift away from dirty industries to cleaner ones. I also assume that prices are perfectly flexible to ensure full employment. These assumptions are more plausible in the long-run rather than in the short-run.

GDP in 2030 is half-a-percentage-point higher from the base case. This substantial increase in GDP is due to an increase in investment. Green tax accounts for 4.6-6% of total government revenue and its repatriation results in 10-12% reduction in capital tax which boosts investment and GDP. Household consumption does not benefit to the same extent from the tax repatriation because the existing sales tax rates were lower than the capital tax. In fact, consumers face higher prices of essential goods after imposition of output tax. As expected, consumption with output tax is lower in the initial years for all household categories (and it remains so until 2012-13). However, household consumption recovers in later years and it is 0.14%-0.20% higher in 2030 in comparison to the base case due to the increase in the total output of the economy. These effects are quite similar across household categories and I don't find a strong distributional effect of the tax. Thus the evidence of double dividends is robust across all four household categories.

The output tax is levied on a sector according to the damage caused by it and the revenue collected is recycled to different sectors in proportion to their existing tax rates. Sectors that pay a higher rate of indirect taxes in the base case, like Cement and Aluminum, get a higher share of the green tax recycling. As a result, the net incremental effect of output tax on price is not necessarily the highest for the most damaging sectors. Figure 1.2 shows the net effect of output tax on the prices and quantities demanded of different sectors in the first year, 2003-04. One can see that even though Thermal Power sector is less damaging to the economy (measured in terms of damage per rupee of output) than Cement and Aluminum industries, the net incremental effect of output tax on price is higher for Thermal Power sector.

In some cases, like Other Petroleum products (PET) and Paper (PAP), the price is even lower after output tax because they were already very highly taxed in the base case and they benefit by green tax revenue repatriation. Effects on the output levels are less straightforward because of general equilibrium effects. The Cobb Douglas demand structure of my model implies an exact opposite percentage effect on demand of a commodity after the price change, but the model also captures the indirect effects due to changes in the demand of the commodity as inputs in other sectors. As a result, Iron & Steel and Construction sectors defy the usual behavior of quantities upon price rise and their outputs rise in spite of increased prices. This rise in demand can be attributed to increased investment under the tax policy, the sector that heavily uses commodities of Iron & Steel and Construction sectors as inputs. Similarly, the general equilibrium indirect effects of Coal sector cause a fall in output levels of coal despite a fall in its price.

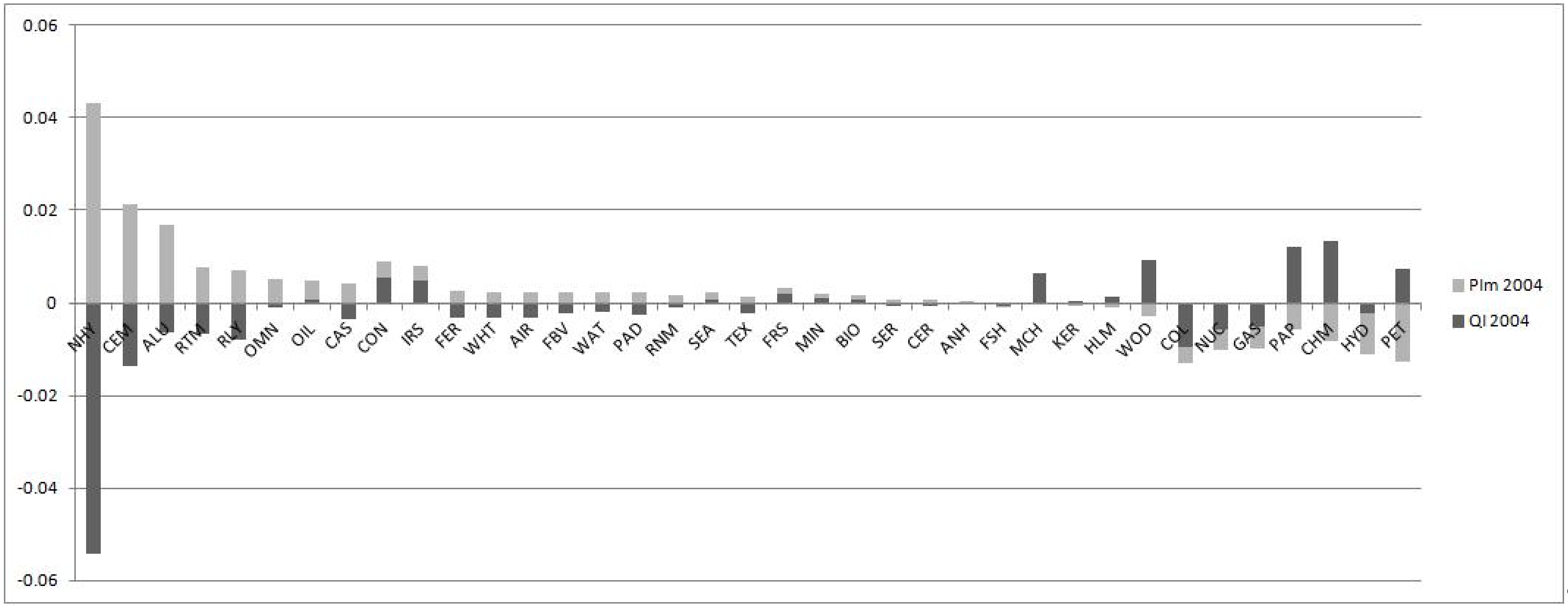
1.4.3 (Pigouvian) Fuel Tax Policy

Output tax discussed above is only moderately effective in reducing emission mainly because it is more of an indirect tax and it offers little incentive for firms to switch to cleaner fuels. Now I take up a more direct policy instrument—a tax on fossil fuels set according to their respective average damage to the overall economy. This is a narrow-based, but a better targeted policy. Apart from discouraging resources going to dirty sectors, it also discourages use of dirty fuels.

There are already some taxes on fossil fuels in India, but as mentioned earlier, the design of the taxes makes them detrimental to the environment. A tax reform is needed. I propose a Pigouvian tax, in addition to the existing taxes on fossil fuels, that is proportional to the average marginal damage caused by their use in the economy. The average marginal damage of a fuel, say coal, is calculated as the weighted average of sector-specific marginal damages caused by its use, where the weights are the quantity shares of coal used in different sectors.

$$AMD_f = \frac{\sum_j MD_j^f \times FT_{jf}}{\sum_j FT_{jf}} \qquad f = coal, oil, gas$$

where MD_j^f is the sector marginal damage of the fuel and FT_{jf} is tons or cubic meters of fuels used in sector j.



[a]Source: Author's Calculations.

Figure 1.2: Percentage change in Prices and Quantities in the first year

Table 1.3: Average Marginal Damage of fuels [a]

In 2003 dollars			
Gas (10^3cub. mt)	Biomass (1 ton)	Oil (1 ton)	Coal (1 ton)
2.29E-03	1.17	15.14	12.58

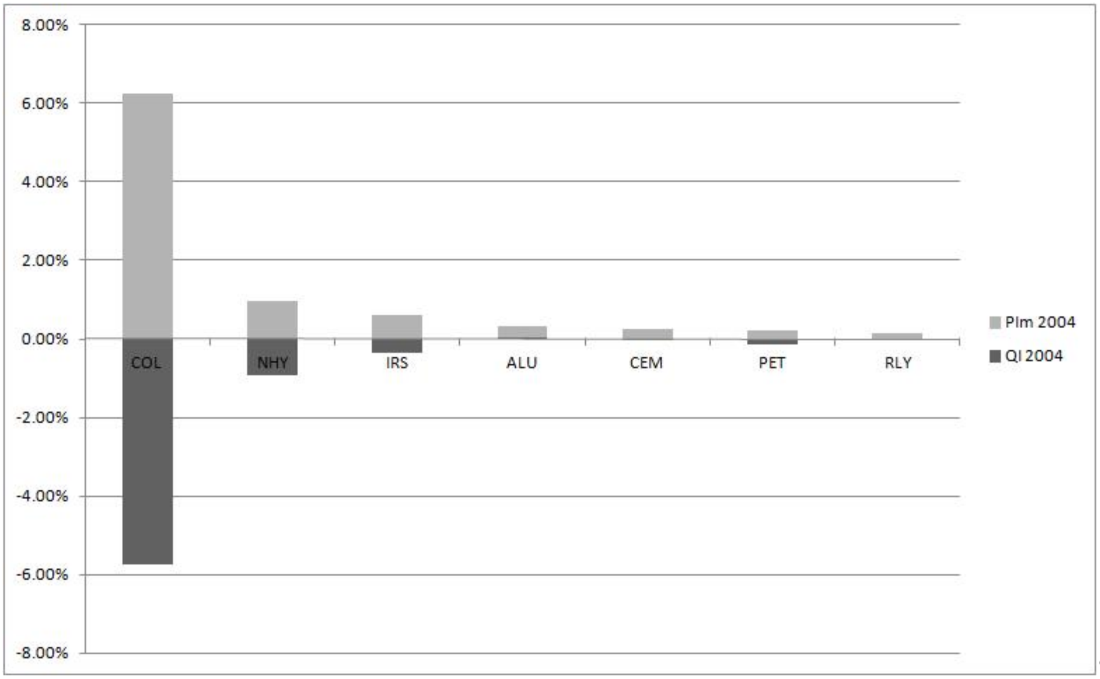
[a]Source: Author's Calculations

Since the same fuel may be more or less damaging to the environment and the public health depending upon the sector specific emission factors and intake fractions, the above averaging is necessary. For example, a priori, coal is more polluting than oil, but in India it is mainly used in thermal power plants (78% of total coal consumption) that emit at a high stack level while a significant fraction of oil is used for ground transportation (43% of total oil consumption) that emit at a low stack level. As a result a ton of oil is more damaging to health than a ton of coal. However, when compared in energy units such as tons of oil equivalent (TOE), the damage is greater from one TOE of coal than one TOE of oil. See table 1.3

The fuel tax in year t is levied as an ad valorem tax that is equal to a fraction λ (= 0.25) of the ratio of the average marginal damage of the fuel in the previous year, $AMD_{f(t-1)}$ and the price of the fuel, P_f:

$$t_{ft}^{xv} = \lambda \frac{AMD_{f(t-1)}}{P_f}$$

I exempt biomass, LPG and kerosene from the fuel tax. Biomass, though highly damaging, is not taxed because it is not a traded commodity. Most households collect it using their family labor and therefore, it is not possible to tax it. LPG and kerosene are highly subsidized in India to encourage households to switch from biomass to these cleaner fuels. Moreover, their use as household fuels causes little health damage, if any. Treating them at par with other petroleum products would be counterproductive and politically infeasible too. Therefore, I created a separate sector for LPG and kerosene, as described earlier, and leave their current pricing regime unaltered in my simulations. Fuel tax on Gas is ignored because of its insignificant AMD.



[a]

[a]Source: Author's Calculations.

Figure 1.3: Prices and Quantities Effects in the first year following a fuel tax on both Coal (COL) and other Petroleum Products (PET)

This leaves me with two fossil fuels to impose fuel tax on: Coal and Other Petroleum Products (mainly diesel and gasoline). Like in the case of output tax, here too I use the tax revenue to proportionately reduce the existing distortionary taxes. Figure **1.3** shows the net effect of additional fuel tax (after revenue recycling) on the prices the quantities of output of different sectors in the first year of my simulation period. Naturally, coal is the most affected sector after the imposition of fuel tax followed by thermal power sector. The net impact on the other petroleum products (PET) is small as compared to coal and related sectors. It is so because there was already a 30% tax on this sector in 2003-04 and so, it received a higher share of the tax recycling.

Since there is already 30% tax on other petroleum products, compared to 1% tax on coal, I carry out a second thought experiment where I levy fuel tax on coal only. In this case, the price of PET actually goes down compared to the base case.

Table 1.4 shows the effect of fuel tax on energy use, emission, economy and health damages. If both coal and PET are taxed, then the total energy use declines by nearly 6% in 2030 and the total use of coal goes down by 14% compared to the reference case. GDP remains unaffected in the first

Table 1.4: Effects of Fuel Tax Policy on Selected Variables

[a]

	Fuel tax on Coal and PET		Fuel tax on Coal only	
Variable	**First year**	**Last year**	**First year**	**Last year**
Energy use	-2.11%	-5.92%	-1.99%	-5.93%
Real GDP	0.00%	0.12%	0.01%	0.08%
Carbon emission	-3.62%	-9.70%	-3.48%	-9.70%
Bio use	-0.03%	0.10%	-0.02%	0.06%
Oil use	-0.15%	-0.45%	0.22%	0.30%
Coal Use	-6.68%	-14.01%	-6.74%	-14.17%
PM10 Emiss. -Total	-5.13%	-11.09%	-5.08%	-11.08%
PM10 Emiss.- Combustion only	-5.89%	-12.58%	-5.89%	-12.64%
SOx Emission - Total	-4.37%	-10.08%	-4.27%	-10.02%
Premature Deaths	-3.75%	-8.94%	-3.59%	-8.77%
Damage value real	-3.72%	-8.62%	-3.55%	-8.49%
Investment	0.16%	0.37%	0.08%	0.20%
Consumption Rural Nonpoor	-0.07%	0.02%	-0.06%	-0.01%
Consumption Rural Poor	-0.03%	0.04%	-0.03%	-0.01%
Consumption Urban NonPoor	-0.05%	0.03%	-0.04%	-0.01%
Consumption Urban Poor	-0.05%	0.03%	-0.05%	-0.01%
Green tax/Revenue[a]	1.30%	1.80%	0.95%	1.2%
lambda[a]	25%	25%	25%	25%

[a]Source: Author's Calculations.

[a]These entries are changes in percentage points from the BAU case, the rest are percentage changes from the BAU case.

year, but it grows by roughly 0.1% in the last year. The economy becomes more energy efficient and the energy mix of the economy shifts more towards petroleum products. This leads to a significant reduction in emission of carbon (10%), PM10 (11%), and SO2 (10%) and health damages due to air pollution (8.5-8.6%) in the last year. Household consumption is marginally lower in the first year, but it recovers towards the end of the modeling period and the rural poor fare better than the non-poor. When only coal is taxed, consumption is marginally lower even in 2030. In this case, increased investment and efficiency are not big enough to translate into higher consumption even till 2030. Additional gains from levying more tax on already heavily taxed petroleum products is at best marginal. Thus, my results suggest that fuel tax on "dirty" coal would be an environmental policy "without tears" for India. It would lead to significant reductions in emission of both local pollutants and carbon dioxide without much effect on GDP and household consumption. However, at present coal is hardly taxed in India. According to the SAM, there was just 1% net tax on coal in 2003-04. In 2011, the government imposed a cess of Rs 50 ($1.1) per ton of coal to create a clean energy fund[20] to finance research and clean energy projects to reduce India's carbon footprint. Afterwards, a 5-12% increase in price of different grades of coal in January 2012 was quickly rolled back under pressure from industrial users[21]. The sale price of coal has always been a contentious issue in India. The Ministry of Coal used to set the price till 2000 and thereafter the prices were deregulated. Even after deregulation, the prices fixed by coal companies are perceived to be "guided" by the Government(Chikkatur, 2008)[22]. Ideally coal prices should be left to the market and trading of coal should be free [23]. It will result in higher economic efficiency and probably better environmental outcomes.

[20](http://articles.economictimes.indiatimes.com/2011-04-07/news/29392656_1_national-water-mission-water-resources-clean-energy)

[21](http://economictimes.indiatimes.com/news/news-by-industry/energy/power/coal-india-cuts-coal-price-review-after-march/articleshow/11697613.cms)

[22](Chikkatur, 2008: http://www.c2es.org/docUploads/india-coal-technology.pdf)

[23](Planning Commission of India, 2006)

Table 1.5: Percentage Effects of Output Tax Policy— two $\lambda's$ [a]

	Output Tax ($\lambda = 0.5$)		Output Tax ($\lambda = 0.25$)	
Variable	first year	last year	first year	last year
Energy use	-0.21%	-0.56%	-0.11%	-0.28%
Energy/GDP	-0.27%	-1.11%	-0.14%	-0.56%
Carbon emission	-0.42%	-1.18%	-0.22%	-0.59%
Bio use	-0.08%	0.38%	-0.04%	0.20%
Oil use	0.38%	0.56%	0.19%	0.29%
PM10 Emission - Total	-2.01%	-3.36%	-1.02%	-1.70%
PM10 Emission -Combustion only	-2.38%	-3.81%	-1.21%	-1.93%
SOx Emission - Total	-1.64%	-3.09%	-0.83%	-1.57%
Premature deaths	-0.65%	-1.55%	-0.33%	-0.78%
Value of Damage	-0.95%	-1.50%	-0.48%	-0.74%
Real GDP	0.07%	0.55%	0.04%	0.29%
Investment	0.77%	1.32%	0.39%	0.68%
Consumption Rural Nonpoor	-0.19%	0.14%	-0.10%	0.08%
Consumption Rural Poor	-0.17%	0.17%	-0.09%	0.09%
Consumption Urban NonPoor	-0.15%	0.20%	-0.08%	0.11%
Consumption Urban Poor	-0.19%	0.16%	-0.10%	0.09%
Damage/GDP[b]	-0.02%	-0.14%	-0.01%	-0.07%
lambda[b]	50%	50%	25%	25%
green tax/revenue[b]	4.60%	6.00%	2.40%	3.00%

[a] Source: Author's Calculations.

[b] These entries are changes in percentage points from the BAU case, the rest are percentage changes from the BAU case.

1.5 Sensitivity Analysis

1.5.1 Nonlinearities in Output Tax

I run the same simulation as in the section on output tax, but now with a $\lambda = .25$, half of the original value. I am interested in any nonlinearities that may exist in relation to output taxation rate, but I observe none. As shown in the Table 1.5, all the effects are halved as a result of new λ. One reason for this is the broad nature of this taxation policy. The general equilibrium spillovers in the model are linear in this aspect.

Table 1.6: Effects of Fuel Tax Policy on Selected Variables—3 $\lambda' s$

[a]

	Fuel Tax on Coal and PET $\lambda = 0.5$		Fuel Tax on Coal and PET $\lambda = 0.25$		Fuel Tax on Coal and PET $\lambda = 0.125$	
Variable	first year	last year	first year	last year	first year	last year
Energy use	-3.94%	-10.54%	-2.11%	-5.92%	-1.10%	-3.16%
Energy/GDP	-3.93%	-10.70%	-2.12%	-6.04%	-1.10%	-3.23%
Carbon emission	-6.77%	-17.49%	-3.62%	-9.70%	-1.88%	-5.14%
Bio use	-0.05%	0.15%	-0.03%	0.10%	-0.01%	0.06%
Oil use	-0.36%	-1.04%	-0.15%	-0.45%	-0.07%	-0.20%
PM10 Emiss. -Total	-9.66%	-20.04%	-5.13%	-11.09%	-2.65%	-5.87%
PM10 Emiss.- Combustion only	-11.10%	-22.83%	-5.89%	-12.58%	-3.04%	-6.64%
SOx Emission - Total	-8.21%	-18.16%	-4.37%	-10.08%	-2.26%	-5.35%
count of death	-7.04%	-16.09%	-3.75%	-8.94%	-1.94%	-4.74%
damage value real	-7.00%	-15.55%	-3.72%	-8.62%	-1.92%	-4.57%
Real GDP	-0.01%	0.16%	0.00%	0.12%	0.00%	0.07%
invest	0.28%	0.59%	0.16%	0.37%	0.09%	0.21%
consumption Rural Nonpoor	-0.14%	0.01%	-0.07%	0.02%	-0.04%	0.02%
consumption Rural Poor	-0.06%	0.03%	-0.03%	0.04%	-0.01%	0.02%
consumption Urban Nonpoor	-0.10%	0.02%	-0.05%	0.03%	-0.03%	0.02%
consumption Urban Poor	-0.10%	0.01%	-0.05%	0.03%	-0.03%	0.02%
green tax/revenue[b]	2.40%	3.20%	1.30%	1.80%	0.65%	0.95%
lambda[b]	50%	50%	25%	25%	12.50%	12.50%

[a]Source: Author's Calculations.

[b]These entries are changes in percentage points from the BAU case, the rest are percentage changes from the BAU case.

1.5.2 Nonlinearities in Fuel Tax

I redo the same exercise as above and consider three $\lambda = 0.5, 0.25, 0.125$ to analyze the presence of any nonlinearities associated with fuel taxation (See Table 1.6). I report results for the case of fuel tax on both PET and coal. Every time λ is doubled, percentage effects on most of the variables increase less than doubled, be it energy use, emission, bio use or investment. There are apparent diminishing returns to higher rate of fuel tax.

There are a few exceptions, though. Oil use changes are more than doubled when λ is doubled. This is understandable, because it is oil which is taxed more with every increment in λ and there are first order impact on oil use due to this. The same is true for Coal. Another interesting exception is consumption. Comparison across last year consumption in all household types suggests that $\lambda = 0.25$ is the best in the lot, because it gives the highest future consumption. Imposing higher fuel taxes doesn't necessarily mean higher consumption in the future (despite higher GDP and investment). There exists, as it were, a golden rule λ close to 0.25 that maximizes future consumption levels.

1.5.3 Fuel Tax with a Faster Convergence towards US 1982

My results may not be robust to other approaches of projecting the SAM parameters of Indian Economy. I have converged these parameters (e.g. consumption expenditure shares, cost shares of K,L,E,M, savings rate) slowly towards those from input output tables of 1982 US Economy (described in detail in Appendix B). The convergence rate I have chosen is very conservative and Indian parameters make it only a half way towards US1982 parameters in 2030. What if Indian Economy moves faster and looks more like US 1982 Economy? Surely this is going to affect the BAU scenario fundamentally, but is it going to change the reported percentage impacts on key variables? To find this out, I raise the convergence rate in such a way that the parameters of the SAM reach as far as 87% towards those of US 1982 Economy in 2030. Note that the base year (2003) parameters are still same in both scenarios and there would be no change in the results for the first year. I do not find any marked difference in last year results too. Decline in emissions - local and global- are marginally less than that in the original case. The effects on Consumption suggest that the tax is still progressive, but by a lesser degree. The Increase in the last year consumption for the rural nonpoor is 0.05% against 0.02% (the original value). For the rural poor, the same is 0.03% against

Table 1.7: Output Tax- Comparison between alternative convergence rates. [a]

Variable	Original Convergence Percentage change Last Year	Faster Convergence Percentage change Last Year
Energy use	-0.56%	-0.49%
Carbon emission	-1.18%	-0.88%
Bio use	0.38%	0.38%
Oil use	0.56%	0.25%
PM10 Emission - Total	-3.36%	-2.21%
SOx Emission - Total	-3.09%	-2.01%
Premature deaths	-1.55%	-1.03%
Real GDP	0.55%	0.46%
Investment	1.32%	1.09%
Consumption Rural Nonpoor	0.14%	0.18%
Consumption Rural Poor	0.17%	0.21%
Consumption Urban NonPoor	0.20%	0.21%
Consumption Urban Poor	0.16%	0.20%
Damage/GDP[b]	-0.14%	-0.07%
lambda[b]	50.00%	50.00%
green tax/revenue[b]	6%	4.50%

[a]Source: Author's Calculations.

[b]These entries are changes in percentage points from the BAU case, the rest are percentage changes from the BAU case.

0.04% (the original value).

1.5.4 Output Tax with a Faster Convergence towards US 1982

Once again I consider an alternative convergence scenario as mentioned above for the output tax policy and in table 1.7, I compare last-year effects on some selected variables.

Percentage effects are quantitatively smaller for almost all the variables, but they still have the same direction. As India becomes more like a developed nation, the output tax policy gets less effective in reducing pollution. In the new scenario, the output tax is 30-35% less effective in reducing local pollutants and premature deaths and 25% less effective in reducing carbon emission. Impact on Consumption is higher while impact on investment is lower. As a result of these differences, economic value of health benefits from the output tax policy is 0.07% of GDP in 2030 in this case against a much higher estimate of 0.14% of GDP in the original case.

1.6 Conclusion

I model two market instruments to control air pollution in this paper: a Pigouvian output tax and a Pigouvian fuel tax. I find that both taxes could be good for the environment and good for the economy (if green tax revenue is used to cut specific taxes). Emission of local pollutants, carbon di-oxide, and health damages decline while GDP goes up with green taxes. The poorest households benefit marginally more than the non-poor households. We get this double dividend because both these green taxes help to reduce pre-existing distortionary taxes on investment and certain other commodities. Also, my model assumes away the costs of adjustments in technology, and hence, gives over-optimistic results in the short-run when these costs are likely to be substantial. But the result of a double dividend from green taxes remains valid in the long-term and is robust to uncertainties in the key parameters.

Between the two policies, fuel tax on coal is much more effective in reducing pollution and health damages while output tax has a greater positive effect on GDP and household consumption. The output tax works more as a tax reform policy than an environmental policy. However, it may be politically more feasible as it spreads the pain across all sectors while fuel tax affects a few large industries (coal and thermal power). I am not able to compare these two policies with the whole array of command and control policies already in use in India for pollution control. Greenstone and Hanna (2011) have shown that some of these policies have been effective in reducing urban air pollution, but I do not have data on the costs or the benefits of these policies. Such policies have an important role in controlling local air-pollution and they will continue to be important in future too.

Finally, economic analysis of environmental policies in India faces major challenges due to dearth of data on substitution elasticities between inputs, dispersion properties of pollutants, reliable dose-response function, and VSL values. There is an urgent need for further research in each of these fields for more reliable analysis.

Chapter 2

Consumer Behavior in Urban India - The Transcendental Logarithmic Model

2.1 Introduction

This paper presents a new econometric model of social welfare and aggregate demand for urban India. I create inter-area urban price indices for India using price data on 350 commodity items and services from 91 urban centers of India collected by the Labour Bureau and using a hedonic price model that I estimate using house-rent data from a national survey of household amenities (NSS 58th round survey on household amenities and condition for the year 2002). I use these inter-area urban price indices in combination with a nationally representative consumer expenditure survey conducted by India's National Sample Survey Organization (NSSO) to estimate a Transcendental Logarithmic (translog) model of aggregate demand. To the best of my knowledge, this is the first model of aggregate demand for India. The translog model, I estimate, reflects the consumption behavior of individual households and accounts for the heterogeneity in household behavior seen in the micro-data rather than assuming a representative consumer.

I exploit the large inter-regional variation in prices in India to identify the parameters of the model. This large variation in prices is mainly due to supply-side factors like high transportation costs, differences in local resources, different agro-climatic and federal structure of governance. Other studies in India have also found and used the large cross-sectional price variation in India. Das and Bhattacharya (2008) attempt to examine price convergence across various regions of India and their results show a significant presence of contemporaneous cross-sectional dependence in prices.

Next, I collapse highly detailed consumer expenditure survey into four broad commodity groups – Food, Energy, Housing and Misc. It helps in two ways. First, it gives me a parsimonious set of model parameters to estimate and second, it rules out situations of zero consumption of a commodity group. Moreover, this particular categorization makes good sense as well, because Food and Housing are the two largest components of the total expenditure of an urban Indian household (roughly two-third share) and Energy use plays a crucial role in many current policies.

The plan of the paper is as follows. In section 2, I will present current literature on the subject of aggregate demand in India and discuss a few motivating factors for this paper. Section 3 describes the underlying theoretical model in brief. In section 4, I discuss various data issues that come up in the model estimation. In section 5, I present the estimated results and their interpretations. Finally, in section 6, I conclude the discussion.

2.2 Literature Review and Motivation

Barten (1964) pioneered the literature on the estimation of demographically augmented complete demand systems using consumer surveys. Most of the literature following Barten (1964) has been based on datasets from developed countries (For example, Muellbauer (1977), Pollak and Wales (1981), Jorgenson and Slesnick (1987)), Nelson (1988) on USA; and Chatterjee et al. (1994) on Australia and New Zealand). There have been relatively few utility consistent demand analyses of consumer expenditure in developing countries. Unlike developed countries, most developing countries lack the necessary high quality consumption and price data.

India is an important exception in this respect because the necessary data has been available with reasonably high quality. Using the time series of consumer surveys and price indices in India, several authors have worked on the aggregate demand estimation (Murthy et al. (1997); Ray (1985); Coondoo and Majumder (1987)). However, most of the current work in India focus on certain commodity groups rather than the aggregate system. Filippini and Pachauri (2004) estimate three linear econometric models of electricity demand for urban India. Pachauri (2004) provides estimates of the expenditure elasticity of total per capita energy requirements. Gundimeda and Köhlin (2008) use LA/AIDS model for fuel consumption in Indian households. The other favorite commodity in the literature has been food. Abdulai et al. (1999) estimates an LA/AIDS model on various categories of food items in both urban and rural India. Swamy and Binswanger (1983) carry out a linear estimation of demand for Food in India using data over 20 years and present a set of expenditure and cross-price elasticities. Using models of complete demand system, Kumar et al. (2011) reveals a structural shift in the dietary pattern of the Indian population that has been taking place for the past two decades across different income groups. They find that the consumers are shifting their budgetary allocation from cereals based food towards high-value commodities like fruits and vegetables, milk, fish, meat and meat products, etc.

Meenakshi and Ray (1999) analyze India's food expenditure pattern taking account of regional differences in consumer preferences and in time-series consumer price indices. They also take demographic differences into account in the calculation of the demand behavioral parameters. We will also find in my paper how demographic differences such as household size and ethnicity play important roles in consumer behavior.

The welfare implication of a policy affecting either the Food or the Energy demand is an interesting direction for researchers. True elasticities and nonlinearities in the consumer behavior cannot be neglected in such research. Simplistic modeling of household behavior is likely to give misleading results. Therefore, the demand system estimated in this paper provides a crucial component in such research investigations both in a general equilibrium and a partial equilibrium framework.

This paper falls in the branch of parametric demand system estimation literature. I have applied the Translog model, but alternative models such as AIDS, the generalized Leontief, quadratic AIDS are also found in the literature. See Barnett and Serletis (2008) for an up-to-date survey of consumer demand modeling and a number of empirical approaches.

2.3 Model Description

We use a translog indirect utility function to model household demand for goods. In my model, households consume n consumption goods to maximize a one-period utility function subject to constraints. The translog indirect utility function generates Engel curves with rank two (Gorman, 1981). (See Jorgenson et al. (1997) for an elaborate discussion on many other characteristics of the model). More sophisticated specifications of the model can generate higher rank demand system, but we focus on "rank two" specification of the model in the current paper. Jorgenson and Slesnick (2008) show that while "rank three" system represents consumer behavior more adequately, the differences are not large. Our model of demand is consistent with exact aggregation and the aggregate demand we estimate is a sum of micro-level demand functions of all households in our sample. We do not assume a representative household. Our model also incorporates heterogeneity in the household behavior while aggregating demand functions.

The translog indirect utility function is of the form:

$$ln(V_k) = \alpha_0 + ln\frac{p_k'}{M_k}\alpha_p + \frac{1}{2}ln\frac{p_k'}{M_k}B_{pp}ln\frac{p_k}{M_k} + ln\frac{p_k'}{M_k}B_{pA}A_k \tag{2.1}$$

where,

p_k is the vector of prices for four commodity groups faced by household k ,

$M_k = p_k'x_k$ is total expenditure of household k.

A_k is a vector of demographic characteristics of household k.

Scalar α_o, vector α_p (size 4) and matrices B_{pp} and B_{pA} (size 4×4 and (length of demographic control vector) $\times 4$ respectively) are underlying parameters of the model.

The restrictions on the parameters of this system to ensure economic regularity are:

$B_{pp} = B_{pp}'$ (symmetry conditions of the Slutsky matrix);

$i'B_{pA} = 0$ and $i'B_{pp}i = 0$ (constraints for exact aggregation) and i is a vector of ones with size 4;

$i'\alpha_p = -1$ (Free Normalization constraint).

Note that homogeneity restriction is inbuilt in the functional specification.

For detailed discussion of all the constraints, see Jorgenson et al. (1997).

Applying Roy's Identity to Eq. 2.1, we get the following demand function for the vector of budget shares, $w_k = \left\{\frac{p_{ki}x_{ki}}{M_k}\right\}$, (where x_k is the vector of quantity demanded by the household k.):

$$w_k = \frac{1}{D(p_k)}\left(\alpha_p + B_{pp}ln\frac{p_k}{M_k} + B_{pA}A_k\right) \tag{2.2}$$

where denominator $D(p_k) = i'\alpha_p + i'B_{pp}ln\frac{p_k}{M_k} + i'B_{pA}A_k = -1 + i'B_{pp}ln(p_k)$.

The Aggregate Demand System given by equation 2.2 makes budget shares linear in logarithms of total expenditure $\{ln(M_k)\}$ and attributes $\{A_k\}$. This linearity was achieved by getting rid of terms involving attributes A_k and total expenditure M_k in the denominator using constrains of "exact aggregation". The linearity in logarithms of total expenditure $\{ln(M_k)\}$ and attributes $\{A_k\}$ is exactly what is necessary for "exact aggregation". This system also allows for non-homothetic preferences and hence non-unity full expenditure elasticities. I use this system as the econometric basis for estimating parameters α_p, B_{pp}, B_{pA}.

The concept of exact aggregation was developed by Lau (1977). A vital implication of this theory is that systems of demand functions for individuals with common demographic characteristics can be recovered uniquely from the system of aggregate demand functions. This means that one can use both aggregate welfare and individual welfare in assessing the impact of a policy shock.

2.4 Data Issues

2.4.1 The NSS Consumption Survey

The National Sample Survey Organization of India conducts periodic surveys of consumption expenditure of a large representative sample of households from all states of the country. The survey is administered every year over a smaller sample of households and every five years over a large sample, called the thick sample. The survey collects detailed consumer expenditure data on 380 commodities and services from nearly 0.12 million randomly sampled households of India using a 30-days recall period. The survey uses 365-days recall for consumer durables. I use the 61st round of the national sample survey (NSS), a thick round, conducted in 2004-05. For most consumer items, the survey asks both quantity consumed (kilos, litres or number) and total amount of money spent. This allows us to compute prices by dividing expenditure by the quantity purchased. The variation in unit prices that we observe in the consumption data is, at least in parts, also due to differences in the quality of the goods or the services consumed by households.

Apart from consumer expenditure, the survey also has information on household attributes like household size, composition (age and gender of members), religion, social group (scheduled caste, scheduled tribe, other backward castes, others), years of education and the main occupation of adult members of the household. I use this rich information on household characteristics to capture the heterogeneity in Indian households. Another nice feature of the survey is that it is representative not only at the national level, but also at the sub-state level called clusters. Each cluster covers a few districts. There could be one or more clusters in a state depending on its size. The 35 states and Union territories of India are divided into 72 NSS clusters, also called state-regions.

As mentioned earlier, we have expenditure data for 380 commodities and services from the NSS. We aggregate them into four broad consumption groups:

1. *Food*: Expenditure on all food items including tobacco, betel leaves, Areca nuts and alcohol

2. *Energy*: Expenditure on Electricity, LPG, liquid fuels, biomass fuels, etc.

3. *Miscellaneous (or Misc)* : Expenditure on all items other than Food, Energy and Housing.

4. *Housing*: House rent paid (actual or imputed)

We need this aggregation to have a small set of parameters in the model. The aggregation implicitly assumes that indirect utility functions are homothetically separable in prices of items within each group.

Some adjustments to the original data are necessary to make it conceptually consistent with the demand system.

Rescaling: For some items (such as clothing, bedding, footwear etc.), the survey collects consumption expenditure over the last 365 days, instead of the usual 30 days recall. I rescale all yearly expenditure data to monthly consumption simply by dividing it by 12.

Durable purchase vs Durable services: There is a fundamental difference between the purchase or repair of a durable good and services enjoyed by the household out of such a good. Since consumption is a flow variable, it is the latter that is consistent with the demand system. Unfortunately, the NSS survey does not provide information on the asset holdings of the household, which could have been used to estimate durables service flow. Instead, the survey asks questions about the purchase of new durables and the repair of the old ones. To convert this information into a service flow, I consider bins of households classified by certain selected household characteristics (household size, religion and social group) and the levels of total expenditure on non-durables. For every such bin, I measure the simple mean of the expenditure on durable goods (either purchase or repair). I take the simple mean of the bin to be the service flow of durables. Apparently this method brings some smoothness in the expenses on durables and addresses the discontinuity inherent in the purchase and repair of durable goods. Additionally, it keeps consistency between the National Accounts' and Consumer Survey's definition of the aggregate expenditure on durable goods. We are essentially assuming that even though individual expenses on the durable goods are not an estimate of the service flow from such goods, the aggregate expense on durable goods are a reasonable estimate of aggregate service flow from durable goods. This methodology is crude, but it is probably the best that one can do given the lack of relevant information in the survey. The service flow from durable goods as measured above are subsumed in the Misc group.

2.4.2 Consumer prices from Labour Bureau – Government of India

We need price data from an independent source to estimate our model. The NSS consumption data does allow us to compute unit prices for most commodities, but we do not know if the price variation we see in this data is due to differences in quality or due to other supply side factors. It is hard to take variation due to difference in quality out of these unit prices. Still, some papers in the literature do use unit values to get the price-levels. Coondoo et al. (2011) use unit values as prices, but only as an illustration of their methodology. Deaton and Dupriez (2011) use unit values to compute the state-level price-levels for food. To address the endogeneity issue–wealthier households consuming higher quality goods– they use full expenditure as a proxy of quality effect and adjust their estimates accordingly. Another problem with using unit values from the NSS expenditure survey is that they are not available for many non-food items. Therefore, we need price data from an alternative source.

The Labour Bureau of India publishes consumer price indices (CPI) for different cities and states of India. However, we cannot use CPI's because it is meant only for time-series comparison. I need a cross-sectional price indices for the base year, 2004-05, to estimate the model. Another problem with using the CPI's is that the weights used to compute it are outdated and non-representative of the urban population because they are based on old consumption surveys carried out by the Bureau itself. Deaton (2008) has pointed out several troublesome issues with the weights used by the Labour Bureau and their undesirable impact on the poverty estimation.

An important contribution of this paper is the careful preparation of price levels for 64 of 72 state-regions of India using unpublished commodity prices collected by the Labour Bureau. The Bureau collects data on prices of around 350 items from 91 urban centers of India every month. The list of items in the Bureau's price data matches well with the list of items for which NSS collects expenditure data in its consumption surveys. There are, however, some issues with the Labour Bureau's price data that require me to make adjustments before we can use them to create price indices.

- First, the Bureau data does not have prices of all 350 items from all 91 urban centers. On average, it reports prices of 170 items in a given center. So there are gaps in price data if we consider all possible item-city pairs. These gaps are filled by using the population weighted averages of item prices from the centers that report them. For example, if the price of milk is collected from only 50 centers, then for remaining 41 centers we do not have any price data. I take the average of the milk prices from the 50 centers (using population of the state-regions as weights) and use this average as the price of milk for the remaining 41 centers.

- Second, price data from different cities are expressed in different units. For example, some cities have the price of milk expressed in Rupees per liter while others have it in Rupees per kilogram (kg). In this case, I use the standard density of milk to convert the price of milk from Rupees per kg to Rupees per liter. In some instances, the different units used cannot be reconciled. For example, medicine per liter and medicine per strip. In such cases, I drop one of them from the analysis, generally the one with a smaller number of data points.

- Third, for some commodities like rice, the Bureau data reports price of two or more varieties. The NSS consumption survey, however, reports rice as a single commodity. In such cases, I use the cheapest variety only because it is probably the most commonly purchased variety and therefore, it would be a better candidate for comparison across cities.

- Fourth, we create price indices at the NSS cluster or state-region level–the smallest unit at which the NSS sample is representative of the population. There are 72 state-regions in NSS data while price is reported from 91 urban centers by the Labour Bureau. Thus, we have price data from more than one center in some state-regions. In such cases, I use the simple mean of city-item prices as the price for the state-region.

- Fifth, the Labour Bureau does not report prices from cities in some of the smaller states and Union Territories (UTs) of India[1]. My analysis also leaves out these states and UTs.

- Sixth, the Bureau collects price data once every month in each center. We arbitrarily pick prices for the month of August 2004 to compute our indices. Changing the month does not change our results.

- Seventh and finally, the price data that we have from the Labour Bureau, does not include real or imputed house-rents, one of the largest consumption categories for urban households. We make up for this deficiency in the Labour Bureau data by using another dataset about which we discuss more in the next sub-section.

Since the original weights used in the CPI are outdated and unrepresentative of the consumption basket of urban sector of India, I use the NSS consumption survey to get the appropriate weights for different items of consumption. Further, I compute consumption weights separately for households of different occupational categories –urban salaried class, urban self employed, urban casual laborers and urban other laborers–whose consumption baskets are different from each other. Thus, we have four different price indices for each state-region. Item price ratios are then aggregated to the level of 3 commodity groups– Food, Energy and Misc using the Tornqvist index.

In Tables 2.1 and 2.2, I present Tornqvist price indices of Food, Energy and Misc groups for Urban self-employed households from different state-regions of India. We report price indices for only one category of households to fit the table in the available space. Price indices for other categories of households, not shown here in tables 2.1 and 2.2, are quite similar. If we look at columns 3-5 of the table, we find considerable cross-sectional variations in price indices of all 3 commodity groups. I exploit this variation to estimate the econometric model. Energy prices show the maximum variation.

[1]These states account for only 1.8% of the total population of India.

Widely varying prices of electricity and firewood among states is responsible for such large variation in energy price indices.

2.4.3 Price Indices for housing – National Sample Survey 58th round-2002

Housing is one of the most important consumption items for urban households, but we do not have data on house rents in the Labour Bureau dataset that we have. We cannot use the NSS consumer survey either to create house rent indices because the survey gives only paid or imputed rent expenditure, but it doesn't have information on any of the correlated attributes of dwellings such as the floor area, number rooms in the house, or the quality of construction material, etc. Therefore, we use a different dataset to compute house rent indices for urban India. The NSSO conducted a survey on household amenities and condition in the year 2002 that covered a representative sample of close to 42 thousand dwellings from all across India. The survey collected data on a number of characteristics of dwellings including its location (slum or non-slum), floor area, number of rooms, other amenities, etc. and the real or imputed rent. We use the urban sub-sample of this rich dataset to estimate a hedonic regression equation with the logarithm of monthly rent (actual or imputed) as the dependent variable and a vector of characteristics of the dwelling as independent variables. We also include a dummy for each state-region to control for fixed location-specific characteristics not included in the vector of dwelling attributes.

$$\ln Rent_i = \alpha + \beta' A_i + \gamma' SR_i + \epsilon_i \tag{2.3}$$

where $Rent_i$ is monthly rent paid or imputed for household i,

A_i is the vector of attributes of the dwelling. (Main attributes used in the regression are number of rooms, total floor area, characteristics of drinking water facility, characteristics of bathrooms, use of the dwelling, built and condition of the dwelling, experience of flood in the past, ventilation etc.)

SR_i is the dummies for state-regions of India. (One state-region is dropped to avoid perfect multicollinearity)

The coefficients of state region dummies (γ) give us the logarithm of housing price indices in reference to Delhi, the reference state-region whose dummy is dropped in the regression. We report the exponential of these coefficients as the house price indices of different state-regions of India in column (6) of tables 2.1 and 2.2.

Again, we see a considerable variation in rent prices across state-regions of India. The Jhelum valley in Jammu and Kashmir has the highest house rents, even higher than large cities like Delhi and Chandigarh. This is probably due to a large number of restrictions on building and buying houses in this sensitive region. This region should be treated as an exception. Apart from J&K, Delhi and Chandigarh, Kerala, Maharashtra and Gujarat are other states with relatively high rents. These are also some of the most urbanized and developed states of India. Jharkhand, Orissa and Chattisgarh, some of the least developed states of India, also have the lowest house rents. There is a significant variation in house rents even within a state. For example, in Karnataka, rent index is higher for the inland south region that is home to the state's capital city, Banaglore. Similarly, in Andhra Pradesh, the index is higher in the sub-region that is home to Hyderabad, the largest city in the state. Thus, our hedonic equation yields house rent indices that seem reasonable and on the expected lines.

2.4.4 Price Indices of 4 commodity groups

Tables 2.1 and 2.2 presents the price levels for all four commodity groups in 43 state-regions of India. The missing state-regions are the ones for which we do not have price data from the Labour Bureau. We find from standard ANOVA tests (See Appendix D) that "within state" variation in prices is substantially less than the "between state" variation for the food and energy groups. The same is not true for miscellaneous items though. I assume that the population-weighted average of price indices at the state level can be used if the price indices of a particular state-region could not be estimated. For example, the state-region Karnataka:Coastal was not represented by any of the 91 city centers of Bureau price data. So we use the population weighted average of the remaining state-regions from the state Karnataka listed in tables 2.1 and 2.2 as an estimate for price levels of Karnataka:Coastal. With this rule, we are able to expand the number of state-regions for which we have price levels from 43 to 64. This allows me to keep more observations, especially those from big states for which such averages are possible to measure. The observations finally left out are from a few small states which represent less than 2 percent of the total population of India.

Table 2.1: Price Indices-North and East States only (For Self Employed Urban households only) —Year 2003-04

[a]

State (1)		*Region* (2)	*Food* (3)	*Energy* (4)	*Misc* (5)	*Housing*[b] (6)	*State PCI*[c] (7)	*Rank*[d] (8)
J & K	:	*Jhelam Valley*	1.02	1.04	1.04	1.26	14465	30
Him. Pradesh	:	*Him. Pradesh*	0.97	0.62	1.10	0.49	24480	11
Punjab	:	*Northern*	0.98	1.02	0.99	0.62	26975	5
Chandigarh	:	*Chandigarh*	1.00	0.77	0.96	1.00	56197	1
Haryana	:	*Eastern*	0.98	1.15	1.00	0.80	26353	6
Delhi	:	*Delhi*[e]	1.00	1.00	1.00	1.00	43030	2
Rajasthan	:	*North-East*	1.00	1.07	0.97	0.55	15737	29
Uttar Pradesh	:	*Western*	0.96	1.22	0.99	0.43	9993	39
Uttar Pradesh	:	*Central*	0.95	1.21	0.99	0.62	9993	39
Uttar Pradesh	:	*Eastern*	0.95	1.15	0.99	0.48	9993	39
Bihar	:	*Central*	0.87	1.01	0.88	0.41	6158	42
Tripura	:	*Tripura*	1.01	0.72	1.01	0.41	NA	NA
Assam	:	*Plains E*	0.92	0.98	1.02	0.61	13856	31
Assam	:	*Plains W*	0.97	1.00	1.00	0.65	13856	31
West Bengal	:	*Himalayan*	0.89	0.87	0.81	0.48	18231	26
West Bengal	:	*Central Plains*	0.96	0.97	1.06	0.40	18231	26
West Bengal	:	*Western Plains*	1.01	0.85	1.07	0.50	18231	26
Jharkhand	:	*Jharkhand*	0.93	0.81	1.02	0.31	11144	38
Orissa	:	*Northern*	0.96	0.84	1.04	0.21	11951	34
Chhattisgarh	:	*Chhattisgarh*	0.98	0.85	1.01	0.34	13811	33
M. Pradesh	:	*Central*	1.02	0.93	0.99	0.34	11870	35
M. Pradesh	:	*Malwa*	0.97	1.03	1.03	0.51	11870	35
M. Pradesh	:	*South*	0.92	0.98	0.95	0.38	11870	35

[a]Source: Author's Calculations

[b]This price index is same across all occupational categories.

[c]*State Per Capita Income of the year 2003-04 in 1999-2000 prices*

[d]*Rank of State Per Capita*

[e]*Reference state-region*

Table 2.2: Price Indices-West and South States only (For Self Employed Urban households only)-Year 2003-04
[a]

State (1)		*Region* (2)	*Food* (3)	*Energy* (4)	*Misc* (5)	*Housing*[b] (6)	*State PCI*[c] (7)	*Rank*[d] (8)
Gujarat	:	*Eastern*	1.03	1.23	1.03	0.59	22387	13
Gujarat	:	*Plains N*	1.02	1.29	0.99	1.00	22387	13
Gujarat	:	*Plains S*	1.06	1.35	1.03	1.00	22387	13
Gujarat	:	*Saurashtra*	1.03	1.31	0.99	0.78	22387	13
Maharashtra	:	*Coastal*	1.09	0.80	1.06	0.68	25265	7
Maharashtra	:	*Inland W*	1.02	1.09	1.00	0.44	25265	7
Maharashtra	:	*Inland N*	1.06	1.13	1.08	0.81	25265	7
Maharashtra	:	*Inland E*	1.01	1.12	1.02	0.51	25265	7
Andhra	:	*Coastal*	1.04	0.82	0.98	0.34	18961	21
Andhra	:	*Inland N*	1.00	0.83	0.94	0.65	18961	21
Karnataka	:	*Inland E*	1.01	0.96	0.97	0.38	18284	23
Karnataka	:	*Inland S*	1.04	1.06	1.03	0.67	18284	23
Karnataka	:	*Inland N*	0.96	1.00	0.97	0.37	18284	23
Goa	:	*Goa*	1.04	0.68	1.03	0.55	42206	3
Kerala	:	*Southern*	0.92	0.76	0.86	0.81	22848	12
Tamilnadu	:	*Coastal N*	1.00	0.49	0.96	0.56	20672	17
Tamilnadu	:	*Coastal*	0.90	0.51	1.00	0.50	20672	17
Tamilnadu	:	*Southern*	0.94	0.53	0.98	0.40	20672	17
Tamilnadu	:	*Inland*	0.94	0.52	0.99	0.46	20672	17
Pondicherry	:	*Pondicherry*	0.98	0.49	0.92	0.49	40338	4

[a]Source: Author's Calculations

[b]This price index is same across all occupational categories.

[c]*State Per Capita Income of the year 2003-04 in 1999-2000 prices*

[d]*Rank of State Per Capita*

According to the tables, Gujarat and Maharashtra are among the most expensive states for an urban household, while West Bengal and Tamil Nadu are among the cheapest states. Incidentally, Gujarat and Maharashtra are also among the richest states of India in terms of per capita income. So my price indices are consistent with the Balassa-Samuelson Theorem– poorer areas of a country have lower price levels in the absence of free mobility. Columns (7) and (8) of the two tables report per capita income and the rankings of the states[2]. Two major components in the urban households- Food and Housing- are strongly correlated with the per capita income of the state (Spearman Rank Correlation Coefficients are 0.47 and 0.50 respectively). However, we do not see this correlation for the other two consumption groups: energy and the Misc. A possible reason for this could be the fact that energy is a highly controlled commodity in India, with the Government of India deciding the price of electricity and energy fuels (LPG, Kerosene, Motor Fuels etc.). For Misc group, probably the assumption of free mobility is not valid.

There aren't many other studies on the measurement of regional price indices in India, which I can compare my price indices with. Deaton and Dupriez (2011) is an exception. They use NSS unit value data for food items and come up with a set inter-area food price indices at the state level after controlling for quality effects. There is a positive and statistically significant correlation between food price indices in tables 2.1 and 2.2 and Deaton and Dupriez's state price indices (ρ =0.4).

2.5 Aggregate demand system Estimation

We estimate the parameters of the translog indirect utility function using a demand system that consists of 4 commodity groups– Food, Energy, Housing, and Misc. In addition, we include demographic characteristics like the number of adults and children in the family, social group (caste) affiliation of the family, its religion, the main occupation, the region (North, South, East and West) of India it belongs to, a quadratic of the age of the household head and a quadratic of the years of education of the household head (the matrix A_k in eq 2.2) to control of heterogeneity in household behavior.

The table 2.3 contains the summary statistics of key identifying variables as well as selected demographic control variables. Food and housing account for nearly half (43.8%) and one-fifth

[2](Taken from Central Statistical Organization's data. Information at the state-region level is not available.).

Table 2.3: Summary Statistics – 2004-05

[a]

Variables	Mean	Std. Error	Min	Max
Share_Food	0.438	0.001	0.010	0.934
Share_Energy	0.096	0.000	0.000	0.368
Share_Misc	0.264	0.001	0.043	0.822
Share_Housing	0.202	0.001	0.000	0.888
Price_Food	0.990	0.000	0.852	1.098
Price_Energy	0.951	0.002	0.471	1.356
Price_Misc	0.996	0.000	0.738	1.131
Price_Housing	0.564	0.002	0.160	1.256
Total Expenditure(in Rs/month)	5222	36	145	91131
Household size	4.392	0.020	1	27
Upper Class dummy	0.465	0.004	0	1
Female Head dummy	0.102	0.002	0	1
Muslim dummy	0.138	0.003	0	1

[a]Source: The National Sample Survey and Author's Calculations

(20.2%) of the total consumption expenditure of an average urban household respectively. The high budget share of food indicates high levels of poverty in urban India. Energy expenditure accounts for approximately 10% of the budget share while nearly a quarter is spent on other things included in the Misc group. There is a great variation in the price levels of house rent and energy with maximum-to-minimum price ratio being 8:1 and 3:1 respectively. There is much less variation in the prices of food and miscellaneous groups.

We estimate that an average urban household spends Rs 5,222 (or approx. $114) per month, which translates to annual per capita expenditure (APCE) of Rs. 14,268 (or $311 in 2003). This is considerably lower than the consumption estimate from the National Accounts Statistics of India. According to National Accounts Statistics of 2003, average APCE was Rs 16,005 ($348) for all of India. Urban households earn 65-70% more than the national average, (Pradhan et al., 2000). So, average urban APCE will be around Rs 26,408-27,208 (approx. $575-592). The big gap between the consumer survey and national account survey estimates is a well known problem in the literature (Meyer and Sullivan (2012), (CSO, 2008)). Factors such as underrepresentation of high income households, underreporting of expenditure in certain categories, absence of banking, finance and insurance in the consumer survey are chiefly responsible for this. Big gaps between national accounts estimates and consumer survey estimates are common even in developed countries (Meyer and Sullivan, 2012).

I estimate the following demand system (with the error terms added) with the help of the above variables. It is a system of 4 equations where error terms are possibly correlated across the equations. Therefore, I use Non Linear Seemingly Unrelated Regression (NLSUR) model to estimate the system of equations. NLSUR allows for both a correlated error structure and restrictions across equations.

$$w_k = \frac{1}{D(p_k)}(\alpha_p + B_{pp} ln(\frac{p_k}{M_k}) + B_{pA}A_k) + \epsilon_k$$

Note that the variance matrix of the error terms is singular (since errors add to zero) and hence the multivariate normal density of the error terms is degenerate. Barten (1969) shows that any arbitrary equation of such a demand system can be dropped and the remaining 3-equations system can be estimated by NLSUR (assuming that the rank of the variance matrix is exactly one less than the full). If we impose homoskedastic and non-autocorrelated errors, the parameter estimates of the dropped equation can be recovered from the restrictions imposed on the demand system (Barten, 1969).

I estimate the reduced system of equations using Iterative Feasible Generalized Nonlinear Least Squares method. The method is identical to Full Information Maximum Likelihood method. Table 2.4 presents the regression results for different specifications that vary mainly in the demographic characteristics included in them. For example, specification (1) has categorical dummies for number of children and adults in the family as well as dummies for Head's age and education. Specification (2), however, captures these demographics by adding a continuous variable of household size and quadratics of both age and education of the head. Specification (3) and (4) also use different combinations of these dummy and continuous variables. The estimates are robust to the alternative ways of capturing demographics. I do not present coefficient estimates of demographic variables to fit the table in the limited space and focus mainly on the behavior of the coefficients of the matrix B_{pp} (these coefficients correspond to price variables in the system of equation. For example, B_{23} is the coefficient of the price of the Misc commodity group in the equation for the Energy commodity group. By the symmetry of Slutsky matrix, B_{23} is also the coefficient of the price of the Energy commodity group in the equation for the Misc commodity group).

Table 2.4: Regression Table

	(1)	(2)	(3)	(4)	(5)
$B11$	-0.00392	0.00364	-0.00290	0.00119	-0.108***
	(-0.27)	(0.25)	(-0.20)	(0.08)	(-6.07)
$B12$	-0.00409	-0.00434	-0.00486	-0.00298	-0.0165***
	(-1.48)	(-1.57)	(-1.76)	(-1.09)	(-4.71)
$B13$	-0.143***	-0.146***	-0.141***	-0.149***	-0.0174
	(-11.26)	(-11.43)	(-11.17)	(-11.67)	(-1.11)
$B14$	0.0454***	0.0431***	0.0431***	0.0449***	0.0355***
	(19.02)	(18.24)	(18.27)	(18.77)	(13.69)
$B22$	-0.0303***	-0.0288***	-0.0288***	-0.0309***	-0.0141***
	(-24.53)	(-22.75)	(-22.44)	(-25.80)	(-9.81)
$B23$	0.00217	0.00507*	0.00487*	0.00210	-0.00280
	(0.89)	(2.07)	(2.02)	(0.88)	(-0.92)
$B24$	0.00518***	0.00578***	0.00613***	0.00491***	0.00642***
	(5.78)	(6.45)	(6.90)	(5.46)	(6.62)
$B33$	0.165***	0.165***	0.162***	0.171***	0.0439**
	(14.00)	(14.04)	(13.81)	(14.47)	(3.05)
$B34$	0.0307***	0.0292***	0.0293***	0.0311***	0.0324***
	(16.84)	(15.96)	(16.04)	(17.04)	(16.49)
DUMMY CONTROLS FOR:					
Head's Age & Education	Yes	No	Yes	No	No
Number of Children & Adults	Yes	No	No	Yes	Yes
Household occupation type	Yes	Yes	Yes	No	No
Household religion	Yes	Yes	Yes	Yes	No
Social group, Sex and Marital status of the head	Yes	Yes	Yes	Yes	Yes
Regions of India	No	No	No	No	Yes
CONTINUOUS CONTROLS FOR:					
Household size	No	Yes	Yes	No	No
Head's Age and Education	No	Yes	No	Yes	Yes
Sq for Head's age and Education	No	No	No	Yes	Yes
Observations	38562	38562	38562	38562	38562
Uncentered R-sq for 4 equations	0.96	0.96	0.96	0.96	0.96
	0.90	0.90	0.90	0.90	0.90
	0.94	0.94	0.94	0.94	0.94
	0.84	0.84	0.84	0.84	0.84

t statistics in parentheses

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

In specification (5), I introduce four region dummies (North, South, East and West) as demographic variables in the system of equations. The estimates in this specification are identified by price variation only within the regions. Although most of the coefficients of B_{pp} are remarkably similar across all specifications, there are a few exceptions in specification (5). For example, coefficients associated with the price of food, such as $B12$, $B12$, $B13$ are dissimilar to those appearing in first 4 specifications. This suggests that there may be some local demand factors that are creating an omitted variable bias in the first four specifications. For example, cold climate in mountainous states may affect the energy and food consumption of the households and such a climate is also likely to affect prices of these commodities. In specification (5), region fixed effects take care of some of the omitted unobservables, specifically those which are fixed at the region level. But they would fail to take care of omitted unobservables at smaller levels, if any (For example, unobservables at the state level or the district level). Note that we cannot use fixed effects at the state-region level, because we do not have a panel and we rely on geographical variation in prices to estimate the coefficients. I will take up this problem of endogeneity in prices in the next section where we use an instrumental variable (IV) approach to mitigate this problem.

I pick specification 5 of table 2.4 and expand the regression output in table 2.5. Once again, for brevity, I do not report all coefficients for demographic controls in the table. The coefficient estimates in table 2.5 should not be interpreted in the usual way, because our model is nonlinear. Every equation in the system 2.2 has a price dependent negative divisor $D(p_k)$. Therefore, even if North dummy has a positive coefficient in the Food equation, we must conclude that households in the North region spend less on food compared to those in the reference region East.

The estimated coefficients satisfy the linear regularity restrictions such as the homogeneity conditions, the symmetry conditions, the exact aggregation conditions and the free normalization condition. Moreover, there are inequality constraints such as non-negativity and monotonicity required for economic regularity of the demand system. The non-negativity constraints were inbuilt in the estimation algorithm. Monotonicity constraint requires Slutsky matrix to be negative semi-definite. I checked this condition for every household in the sample. It turns out that less than 1% of the total sample fail to satisfy the monotonicity constraints with the estimated coefficients. Treating this small percentage of households as outliers, we can say that the estimated demand

Table 2.5: Regression Table

	(1) Food	(2) Energy	(3) Misc	(4) Housing
Constant	-1.806***	-0.362***	0.425***	0.743***
	(-56.73)	(-39.39)	(14.66)	(25.86)
Price_Food	-0.108***	-0.0162***	-0.0162	0.0350***
	(-6.04)	(-4.59)	(-1.03)	(13.58)
Price_Energy	-0.0162***	-0.0141***	-0.00235	0.00631***
	(-4.59)	(-9.84)	(-0.77)	(6.44)
Price_Misc	-0.0162	-0.00235	0.0415**	0.0322***
	(-1.03)	(-0.77)	(2.89)	(16.33)
Price_Housing	0.0350***	0.00631***	0.0322***	0.00328
	(13.58)	(6.44)	(16.33)	(1.24)
Female Dummy	0.0450***	-0.00438*	-0.00955**	-0.0311***
	(10.73)	(-2.15)	(-3.00)	(-7.84)
Married Dummy	0.0131*	-0.0221***	0.00557	0.00341
	(2.26)	(-10.55)	(1.29)	(0.64)
Widowed Dummy	0.0129	-0.0253***	0.0104	0.00201
	(1.89)	(-7.98)	(1.91)	(0.32)
Divorced/Separated Dummy	0.0152	-0.0290***	0.0102	0.00357
	(0.90)	(-5.70)	(0.75)	(0.31)
North Dummy	0.0341***	-0.00648***	-0.0108***	-0.0168***
	(12.13)	(-5.73)	(-4.76)	(-5.79)
South Dummy	0.0252***	0.0119***	-0.0273***	-0.00974***
	(8.72)	(11.41)	(-11.46)	(-3.95)
West Dummy	0.0440***	-0.000546	-0.0329***	-0.0106***
	(15.75)	(-0.52)	(-14.08)	(-3.99)
Education	0.00736***	-0.00143***	-0.00190*	-0.00404***
	(7.58)	(-3.69)	(-2.50)	(-4.23)
Education Sq	-0.0000780	0.000132***	-0.000227***	0.000173*
	(-1.00)	(4.37)	(-3.65)	(2.10)
Age	-0.00146***	-0.000998***	0.00192***	0.000535
	(-3.47)	(-6.45)	(5.60)	(1.36)
Age Sq	0.0000234***	0.00000950***	-0.0000199***	-0.0000130**
	(5.70)	(6.22)	(-5.74)	(-3.28)
Observations	38562	38562	38562	38562
R^2	0.9624	0.8999	0.9367	0.8461

t statistics in parentheses

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

Table 2.6: Elasticities

[a]

Group	Compensated	Uncompensated	Full Expenditure
Food	-0.554	-0.795	0.693
Energy	-0.809	-0.874	0.706
Misc	-0.752	-1.096	1.195
Housing	-0.585	-0.935	1.285

[a]Source: Author's Calculations

system meets all regularity conditions.

One important use of demand-system estimates is the calculation of elasticities and their use in the assessment of economic impacts following changes in prices, income and demography. The elasticities depend on the total expenditure, household characteristics and the parameter estimates of the system such as the matrix B_{pp} and B_{pA}. I report the own compensated price elasticity, the own uncompensated price elasticity and the expenditure elasticity of all four commodity groups in table 2.6 for a reference household. This reference household is chosen to be a Hindu family from North India with 2 adult members and 2 children and a monthly full expenditure of Rs 8,750. The head of the household is a 40 year old male who has finished secondary education. Food, energy and housing are price inelastic while the demand for miscellaneous group has elasticity marginally exceeding unity. The own compensated price elasticities are negative and less than unity for all 4 commodity groups. Expenditure elasticities are all positive implying that all four commodity groups are normal goods. Expenditure on food is the least sensitive to income changes, while expenditure on housing is the most sensitive.

The cross compensated elasticities between the commodity groups are presented in table 2.7. Every commodity group is a net substitute of the other three. It is due to the way individual commodities have been classified into these four groups. This classification makes it unlikely that any of the commodity groups should be complements of the others. I do not report cross price uncompensated elasticities here, but there are instances of gross complementarity in the uncompensated elasticities, especially involving Housing and Misc goods (See Appendix E for details).

Table 2.7: Compensated Elasticities

[a]

	Price of Food	Price of Energy	Price of Misc	Price of Housing
Quant of Food	-0.554	0.084	0.306	0.164
Quant of Energy	0.318	-0.809	0.290	0.200
Quant of Misc	0.368	0.093	-0.752	0.291
Quant of Housing	0.209	0.068	0.308	-0.585

[a] Source: Author's Calculations

2.6 Instrumental Variable Method

In any aggregate demand estimation, price endogeneity problems could always arise due to the interplay of demand and supply forces in the price determination. This could lead to simultaneity bias in the coefficients of interest. Often such issues are ignored by using the justification that consumers are price takers. However, price taking behavior is not sufficient to ensure exogeneity of prices. If demand of a substantial number of consumers is affected by certain local forces, this will lead to simultaneity. For example, northeast states of India are home to many diseases due the terrain and climatic conditions. So it is possible that the consumers from these states spend on medicines more than the consumers from other areas of India. This consumer behavior could increase the price of medicines in these states and hence our estimates would be underestimated.

Other than the simultaneity bias, we can imagine that certain cultural or state level factors could lead to omitted variable bias. For example, suppose a state policy encourages industrialization and urbanization in the state. This could negatively affect the agriculture of the state and may increase the price of food. In addition, this policy would encourage the population to move towards the urban industrial labor class and move away from the rural agricultural class. We can imagine that such a structural change in the composition of consumers will be reflected in their demand patterns. The urban industrial labor class would be expected to spend more on housing and less on food. In such a case, we would observe lower food consumption associated with higher food prices and we would wrongly attribute this to the price effect.

In this section, I will specifically take up the endogeneity problem associated with the food prices only. We discovered in the last section after we introduced region dummies in specification (5) of table 2.4 that estimates associated with the food prices are most likely suffering from endogeneity. This prompts me to assume that the prices of nonfood commodity groups are probably exogenous and I can focus only on the endogeneity of food prices.

Table 2.8 presents new specifications of the system of equations. For simplicity, I have considered only categorical demographic variables and avoided continuous demographic variables in the specifications of the table. Columns 1 and 4 in table 2.8 are comparable to with columns 1 and 5 in table 2.4. Comparing column 1 and 4, we see that certain coefficients associated with the price of food change between the two specifications indicating the presence of food price endogeneity. One remedy for this problem is to use an instrument for the endogenous price variable. It is well known that the monsoon rain significantly determines the agricultural supply in India. Moreover, there are often unpredictable shocks in the monsoon rain. This allows me to use the monsoon rainfall (and the pre monsoon rainfall) as an exogenous determinant of the price of food. I take district level rainfall in the months of March-July [3]. The exclusion restriction in this case would fail to hold only if the monsoon rain were to significantly affect the demand shares of commodity groups in ways other than the supply of agricultural goods. (For example, if households buy significantly more umbrellas in more rainfall prone areas (an item in Misc group) by cutting expenses on other commodity groups, then this would violate the exclusion restriction and the monsoon rainfall would be an omitted variable in the system of equations). In column 2, I check whether the monsoon rainfall is actually an omitted variable or not by adding the variable as a control. The monsoon rainfall doesn't appear to be an omitted variable, because the coefficients of price variables do not change significantly.

Using an instrument leads to interesting changes in the estimates of the price coefficients. (See column 3). But these changes are mostly similar to those in column 4 where we have used regional fixed effects. Both these specifications address the problem of price endogeneity in two independent ways. Since both give similar estimates, we can conclude that the instrumental variable method or the region fixed effects method addresses the endogeneity problem sufficiently.

[3](taken from India Meteorological Department website)

Table 2.8: Regression Table

	(1) spec5	(2) spec5w	(3) spec5wi	(4) spec5r
Constant_Food	-1.856***	-1.859***	-1.864***	-1.897***
	(-71.91)	(-70.09)	(-70.78)	(-72.98)
Constant_Energy	-0.408***	-0.403***	-0.407***	-0.410***
	(-51.49)	(-50.58)	(-50.49)	(-52.08)
Constant_Misc	0.520***	0.518***	0.521***	0.551***
	(21.24)	(20.78)	(20.87)	(22.21)
$B11$	-0.00859	-0.00472	-0.118***	-0.133***
	(-0.59)	(-0.31)	(-7.97)	(-7.50)
$B12$	-0.00258	-0.00681*	-0.00501	-0.0148***
	(-0.96)	(-2.46)	(-1.83)	(-4.23)
$B13$	-0.146***	-0.144***	-0.0389**	-0.000618
	(-11.14)	(-10.55)	(-2.79)	(-0.04)
$B14$	0.0440***	0.0423***	0.0482***	0.0357***
	(18.66)	(16.77)	(20.39)	(13.83)
$B22$	-0.0306***	-0.0279***	-0.0297***	-0.0129***
	(-25.22)	(-22.93)	(-24.73)	(-8.92)
$B23$	0.00179	0.00174	0.00301	-0.00540
	(0.75)	(0.71)	(1.19)	(-1.77)
$B24$	0.00368***	0.00542***	0.00407***	0.00514***
	(4.14)	(5.71)	(4.52)	(5.34)
$B33$	0.173***	0.170***	0.0708***	0.0345*
	(14.30)	(13.47)	(5.22)	(2.37)
$B34$	0.0335***	0.0345***	0.0279***	0.0346***
	(18.52)	(17.74)	(15.25)	(17.62)
Demographic Variables	Yes	Yes	Yes	Yes
Monsoon Rainfall as a control variable	No	Yes	No	No
Region as a control variable	No	No	No	Yes
Monsoon Rainfall used as instrument for Price_Food	No	No	Yes	No
Observations	38562	36448	36448	38562
Uncentered R-sq for 4 equations	0.96 0.90 0.94 0.84	0.96 0.90 0.94 0.84	0.96 0.90 0.94 0.84	0.96 0.90 0.94 0.84

t statistics in parentheses

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

2.7 Summary and Conclusion

In this paper, I have exploited inter-area price variation in India to measure the aggregate urban welfare function. Working on the rich cross-sectional datasets, I have been able to control for heterogeneous preferences in the urban households. Household heterogeneity is an important determinant of consumption pattern. Browning et al. (1999) discuss the need and the challenge of incorporating such household heterogeneity in aggregates used in any macroeconomic policy.

The elasticities and the parameter estimates of the model can be applied to a host of food and energy policy research. Simulations in a general equilibrium setup are going to be more realistic and accurate if the flexible functional form such as the above is used. Given the size of Indian economy and population, Indian energy demands and global gas emissions in coming times are going to be a global problem. So the paper contributes significantly to future endeavors on climate policy research.

There is still a lot to be desired in the above welfare estimation. Firstly, some kind of panel or pseudo-panel structure would have allowed more flexible functional form to capture intertemporal consumer behavior. Secondly, I have abstracted from the joint determination of leisure and goods demand. According to Jorgenson and Wilcoxen (1998), aggregate commodity demands and labor supply play crucial roles in general equilibrium models that are used to evaluate the macroeconomic consequences of energy and environmental policies. Unfortunately, labor supply is hard to estimate in India due to poor data availability. Hopefully, with better data in future, I can revisit the model to address these issues.

Chapter 3

A Distributional Welfare Analysis of Market Based Environmental Tax Policies

3.1 Introduction

Market based environmental policies have an enormous potential in India. At present, the Government of India and the state governments use a variety of command and control regulations, mainly technology and performance-based standards, to control air pollution. These policies, however, are expensive and not very effective. The 2012 Environmental Performance Index ranked India as having the poorest relative air quality out of 132 countries (*Environmental Performance Index (EPI)*, 2012) and according to the EPI report, outdoor air pollution in the country shows no signs of improvement.

I explore the welfare impact of three market based environmental policies–namely carbon tax, fuel tax and output tax policies–in the paper. These policies work by raising the prices of either the polluting fuels or the polluting industries. As a result, economic activity and consumption move towards cleaner energy sources. I simulate the impact of only small policy changes to the "business as usual" scenario and do not change the existing economic structure in a big way. With big changes, the base case parameters would cease to be appropriate for the counterfactual.

The evaluation of environmental policies is rendered complicated by the fact that such policies invariably affect the economy adversely in the short run without reducing pollution significantly. It is only in the long run, as the economy keeps converging to a steady state, that we see the benefits of the policies. This aspect necessitates a dynamic model that goes until a few decades. Accordingly, I construct a dynamic growth model that simulates Indian economy till the year 2030. Next, I take the results of simulations to the household data and estimate the welfare impacts of environmental policies. The analytical framework described below will allow us to not only measure the welfare effects on individual households classified by demographic attributes and wealth levels, but also allow us combine the welfare effects into a single and convenient social welfare measure. I am able to see changes in efficiency and equity as components of change in social welfare. The framework was developed by Jorgenson et al. (1992) in order to evaluate carbon tax policy in the USA.

The emphasis on getting individual welfare effects of environmental policies is not misplaced. By design, environmental policies raise the prices of polluting fuels or polluting industries. The change in relative prices faced by households could have significant distributional consequences. Depending on the demography of households, one could see wide variation in welfare effects. For example, the households that spend a large share of their income on energy would be more adversely affected than other households after imposition of the tax policies.

Another feature of the analysis is that it is based on the general equilibrium framework. This framework captures the interdependencies between various sectors. So, this framework assesses the full impact of policies after incorporating second and higher order effects. I am able to see the impact of the policy on all major sectors of the economy, such as investment, consumption and the government. This would not be possible in a partial equilibrium framework.

I first describe the theory of welfare measurement framework and the simulation model of the economy in sections 2 and 3 respectively. Then, in section 4, I discuss various data issues and finally, in section 5, I present results and a summary of conclusions.

3.2 Welfare Model

This section consists of three subsections in which I sequentially present the building blocks of the analytical framework. I first describe the one-period translog welfare model of individual households;

then I borrow from Jorgenson et al. (1992) an analytical setup to measure dynastic welfare (the intertemporal welfare of individual households); and then finally coalesce dynastic welfare effects into the measures of social welfare, efficiency, equity and tax progressivity. A special feature of the framework is the presence of heterogeneous preferences producing differential effects of an environmental tax on different households. See Jorgenson et al. (1997) for a detailed discussion of this framework.

3.2.1 One-period Household Welfare model

I assume that a household allocates one-period total expenditure into four commodity groups. These sub-aggregates are– Food, Energy, Housing and Miscellaneous (Misc.). The indirect utility function is given by the following translog function first introduced by Christensen et al. (1975)

$$ln(V_k) = \alpha_0 + ln\frac{p'_k}{M_k}\alpha_p + \frac{1}{2}ln\frac{p'_k}{M_k}B_{pp}ln\frac{p_k}{M_k} + ln\frac{p'_k}{M_k}B_{pA}A_k \tag{3.1}$$

where,

p_k is the vector of prices for four commodity groups faced by household k,

$M_k = p'_k x_k$ is the total expenditure of household k. Strictly speaking, this is not equivalent to the income of the household, but I will use the two interchangeably since I am not explicitly modeling savings in the paper.

A_k is a vector of demographic characteristics of household k.

Vector α_p(size 4) and matrices B_{pp} and B_{pA} (size 4×4 and (length of demographic control vector) $\times 4$ respectively) are the underlying parameters of the model.

The restrictions on the parameters of this system are:

$B_{pp} = B'_{pp}$ (symmetry conditions of the Slutsky matrix);

$i'B_{pA} = 0$ and $i'B_{pp}i = 0$ (constraints for exact aggregation) and i is a vector of ones with size 4;

$i'\alpha_p = -1$ (Free Normalization constraint). For detailed discussion on these constraints see Jorgenson et al. (1997).

Applying Roy's Identity to Eq. 3.1, we get the following demand function for the vector of budget shares, $w_k = \left\{\frac{p_{ki}x_{ki}}{M_k}\right\}$, (where x_k is the vector of quantity demanded by the household k.):

$$w_k = \frac{1}{D(p_k)}\left(\alpha_p + B_{pp} ln \frac{p_k}{M_k} + B_{pA} A_k\right) \tag{3.2}$$

where denominator $D(p_k) = i'\alpha_p + i'B_{pp}ln\frac{p_k}{M_k} + i'B_{pA}A_k = -1 + i'B_{pp}ln(p_k)$.

The above demand system 3.2 represents individual expenditure shares of commodity groups. Notice that it is linear in logarithms of total expenditure $\{ln(M_k)\}$ and attributes $\{A_k\}$ by virtue of the "exact aggregation" restrictions. This linearity is actually the necessary and sufficient condition for exact aggregation. The system allows for non-homothetic preferences and thus non-unity full expenditure elasticities. This system is the econometric basis for estimating parameters α_p, B_{pp}, B_{pA}.

Jorgenson and Slesnick (1987) show that the vector of the aggregate demand shares is given by

$$w = \frac{1}{D(p)}\left[\alpha_p + B_{pp}\ln p - \iota B_{pp} ln\bar{M} + B_{pA}\bar{A}\right] \tag{3.3}$$

where the summary statistics for log income and attributes are: (2.1) $ln\bar{M} = \sum_k n_k M_k \ln M_k / \sum_k n_k M_k$ and $\bar{A} = \sum_k n_k M_k A_k / \sum_k n_k M_k$ and n_k is the size of household type k. ι is the vector of ones.

3.2.2 Dynastic (Household level) Welfare

Individual household welfare effects following any environmental tax must have an intertemporal framework. I extend the one period welfare model to an intertemporal one by borrowing the framework of Jorgenson et al. (1992). Their theory of dynastic welfare (a dynasty being an infinitely lived household) gives a framework in which I can measure the monetary equivalent of welfare impacts. Below I reproduce the framework in brief. See Jorgenson et al. (1992) for more details.

A dynasty refers to an infinitely lived household. The household sector is made up of many such dynasties. The demographic variables in our model are used to crossclassify households and the bins made by this classification are treated as dynasties. The number of families of a bin also refers to the number of families in the dynasty. (I am going to use bin and dynasty interchangeably in this paper.)

The total expenditure of a dynasty is defined as the total expenditure of all the households in the dynasty.

$$M_{dt} = \sum_{n=1}^{N} p_{nt} x_{ndt}$$

where prices, p_{nt}, and quantity consumed by the dynasty, x_{ndt}, are indexed by commodity n, dynasty d and time t. Since prices are common for all dynasties, it has no subscript d. N is the number of commodities.

Each dynasty maximizes an additive intertemporal utility function of the form

$$V_d = \sum_{t=0}^{\infty} \delta^t \ln V_{dt}$$

where $\delta = 1/(1+\rho)$ and ρ is the subjective rate of time preference. I use an estimate of ρ from Jorgenson and Slesnick (2008)[1]. The intratemporal indirect utility function, V_{dt}, is of the form

$$\ln V_{dt} = \alpha_p' \ln p_t + \frac{1}{2} \ln p_t' B_{pp} \ln p_t - D(p_t) \ln(M_{dt}/N_{dt}) \tag{3.4}$$

$D(p_t)$ has the form $D(p_t) = -1 + \iota' B_{pp} \ln p_t$. ι is a vector of ones. $N_{dt} = K_{dt} m_0(p_t, A_d)$ is the number of household equivalent members in the dynasty at time t. It has two components. $m_0(p_t, A_d)$ is the *equivalent scale* of the household in the dynasty and K_{dt} is the number of families in the dynasty. The size of each dynasty N_{dt} is, thus, equal to the number of families in the bin times and the *equivalent scale* of the household. Jorgenson and Slesnick (1987) derives the *equivalent scale* as a function of demographic attributes A_k and prices p . It can also be interpreted as the number of equivalent members in a household. *Equivalent scales* give us an analytical tool to compare heterogeneous households. It is defined as below:

$$\ln m_0(p, A_d) = \frac{\ln m(A_d)' \alpha_p + \frac{1}{2} \ln m(A_d)' B_{pp} \ln m(A_d) + \ln m(A_d)' B_{pp} \ln p}{D(p)}$$

where the function $\ln m(A_d) = B_{pp}^{-1} B_{pA} A_d$ is a vector of *commodity specific equivalence scales.* A_d is the vector of attributes. Eq 3.4 and 3.1 are equivalent definition of indirect utility function. See Jorgenson and Slesnick (1987) for a proof.

[1] They estimate it using the US consumer surveys. Their estimate is 0.0147.

The intertemporal budget constraint is given by

$$\sum_{t=0}^{\infty} \gamma_t M_{dt}(p_t, V_{dt}, A_d) = \Omega_d$$

where

$$\gamma_t = \prod_{s=0}^{t} \frac{1}{1+r_s}$$

and Ω_d is the full wealth of the dynasty. r_s is the interest rate at time s. I skip the usual constrained maximization exercise and directly state the relevant discrete time Euler equation. For more details, see Jorgenson et al. (1992).

$$\ln V_{dt} = \frac{D_t}{D_{t-1}} \ln V_{dt-1} + D_t \ln \left(\frac{D_{t-1}\gamma_t N_{dt} P_t}{\delta D_t \gamma_{t-1} N_{dt-1} P_{t-1}} \right) \tag{3.5}$$

where I have used D_t to denote $D(p_t)$, and the aggregate price term, P_t , denotes:

$$P_t = \exp\left(\frac{\alpha_p{}' \ln p_t + \frac{1}{2} \ln p_t{}' B_{pp} \ln p_t}{D_t} \right)$$

Using the Euler equation and the intertemporal budget constraint, we arrive at the following key result (See Jorgenson et al. (1992) for details) :

$$V_d = S \ln \frac{P_0 S}{D_0} - S \ln \Omega_d + \sum_{t=0}^{\infty} \delta^t D_t \ln \left(\frac{D_0 \gamma_t N_{dt} P_t}{\delta^t D_t P_0} \right) \tag{3.6}$$

where

$$S = \sum_{t=0}^{\infty} \delta^t D_t$$

The above gives the indirect utility function of a dynasty as a function of full wealth and prices. This can be solved to get the minimum expenditure function (full wealth) as a function of prices and utility level. This will give us a way to monetize the welfare effects.

$$\ln \Omega_d(\{p_t\}, \{\gamma_t\}, V_d) = \frac{1}{S} \left[S \ln \frac{P_0 S}{D_0} + \sum_{t=0}^{\infty} \delta^t z D_t \ln \left(\frac{D_0 \gamma_t N_{dt} P_t}{\delta^t D_t P_0} \right) - V_d \right]$$

where $\{p_t\}$ and $\{\gamma_t\}$ are the time profiles of prices and interest rates respectively.

Consider an environment tax policy, that changes prices and interest rates from $\{p_t^0\}$ and $\{\gamma_t^0\}$ to $\{p_t^1\}$ and $\{\gamma_t^1\}$ and the level of welfare of the dynasty from V_d^0 to V_d^1. The equivalent variation of such a policy would be

$$\Delta W_d = \Omega_d(\{p_t^0\}, \{\gamma_t^0\}, V_d^1) - \Omega_d(\{p_t^0\}, \{\gamma_t^0\}, V_d^0)$$

3.2.3 Social Welfare

I will coalesce dynasty level welfare effects into a single social welfare measure. This measure can also be split into equity and efficiency components. Following Jorgenson et al. (1992), I define the social welfare to be the weighted sum of the average dynastic welfare and a measure of deviations from the average:

$$W = \bar{V} - \eta(\sum_{d=1}^{D} a_d |V_d - \bar{V}|^{-\mu})^{-1/\mu}$$

where $\bar{V} = \sum_{d=1}^{D} a_d V_d$

In this representation, the first parameter η is chosen to ensure that social welfare is increasing in the levels of individual welfare; this is the familiar Pareto principle. The other parameter μ is a measure of social aversion to inequality. The range of this parameter is between -1 and $-\infty$, where -1 gives the maximum weight to equity relative to efficiency. If this parameter goes to negative infinity, the function becomes a utilitarian social welfare function and gives the least weight to equity considerations.

Following Jorgenson et al. (1992), I impose the following form to the weights a_d. This particular form makes sure that all transfers from the rich to the poor will increase social welfare. It is given by

$$a_d = \frac{exp\{(\sum_t \delta^t D_t \ln(N_{dt}))/S\}}{\sum_{i=1}^{D} exp\{(\sum_t \delta^t D_t \ln(N_{lt}))/S\}}$$

The maximum level of social welfare for fixed prices and fixed total wealth is attained by reallocating wealth among dynasties to equalize dynastic welfare. This occurs when the wealth of dynasty d is $\Omega_d^\star = a_d \Omega$, where Ω is total wealth. The maximum level of social welfare (or potential welfare) can be represented as

$$W_{max} = S\ln\frac{P_0 S}{D_0} - S\ln\Omega + S\ln N + \sum_{t=0}^{\infty}\delta^t D_t(\ln\frac{\gamma_t P_t D_0}{\delta^t D_t P_0}) \tag{3.7}$$

where

$$N = \sum_{l=1}^{D} exp\{(\sum_t \delta^t D_t \ln(N_{lt}))/S\}$$

This is a representative agent version of equation 3.6 and can be interpreted as the welfare level of a dynasty with size equal to the number of household equivalent members in the whole population. Inverting this welfare function, we get aggregate wealth as a function of social welfare, initial and future prices, and interest rates:

$$\ln\Omega(\{p_t\},\{\gamma_t\},W) = \frac{1}{S}[S\ln\frac{P_0 S}{D_0} + S\ln N + \sum \delta^t D_t \ln(\frac{\gamma_t P_t D_0}{\delta^t D_t P_0}) - W]$$

This is the minimum expenditure function of a representative agent. It gives the minimum aggregate wealth needed to attain a given social welfare for given prices and interest rates. I will use this function as a money metric for welfare levels. If W^0 and $W^1$are levels of social welfare under the base case and under the counterfactual, then the equivalent variation of welfare effect is given by

$$\Delta W = \Omega(\{p_t^0\},\{\gamma_t^0\},W^1) - \Omega(\{p_t^0\},\{\gamma_t^0\},W^0)$$

This welfare effect can be split into two parts— the change due to efficiency and the change due to equity. To calculate the change in efficiency, I define W_{max}^0 and W_{max}^1 as maximum level of social welfare, i.e. potential welfare, (using equation 3.7) in the base case and in the counterfactual respectively. The monetary measure of change in efficiency is then defined as,

$$\Delta E = \Omega(\{p_t^0\},\{\gamma_t^0\},W_{max}^1) - \Omega(\{p_t^0\},\{\gamma_t^0\},W_{max}^0)$$

The other component, the change due to equity(ΔEQ), is defined as the remainder

$$\Delta W = \Delta E + \Delta EQ$$

For detailed discussion on these definitions, see Jorgenson et al. (1992).

The equity component provides the basis for getting measures of progressivity. I follow Slesnick (1986) and define the absolute and the relative index of equality as below:

$$AEQ(\{p_t^0\},\{\gamma_t^0\},W,W_{max}) = \Omega(\{p_t^0\},\{\gamma_t^0\},W) - \Omega(\{p_t^0\},\{\gamma_t^0\},W_{max})$$

$$REQ(\{p_t^0\},\{\gamma_t^0\},W,W_{max}) = \Omega(\{p_t^0\},\{\gamma_t^0\},W)/\Omega(\{p_t^0\},\{\gamma_t^0\},W_{max})$$

AEQ measures the loss due to inequitable distribution of welfare. It is nonpositive and invariant to equal absolute additions to the money metrics of potential and social welfare. REQ on the other hand lies between zero and one and it is invariant to equal proportional changes in money metrics of potential and social welfare.

Similarly, the measures of absolute and relative progressivity are defined as:

$$AP = AEQ(\{p_t^0\},\{\gamma_t^0\},W^1,W_{max}^1) - AEQ(\{p_t^0\},\{\gamma_t^0\},W^0,W_{max}^0)$$

$$RP = REQ(\{p_t^0\},\{\gamma_t^0\},W^1,W_{max}^1) - REQ(\{p_t^0\},\{\gamma_t^0\},W^0,W_{max}^0)$$

AP is identical to the measure of change in equity, ΔEQ. A positive value for AP or RP indicates progressivity, while a negative values indicates regressivity. It can be easily shown that a carbon tax that is "absolutely" progressive need not be "relatively" progressive, and vice versa.

3.3 The Simulation Model

I use a Solow growth model for the Indian economy and run yearly simulations from 2003 to 2030. The major elements of the model are similar to those in Somani (2012*b*). I reproduce a brief model description below. Please see Ho and Jorgenson (2003) and Somani (2012*b*) for full details.

3.3.1 The Economic Model

The economic model uses a social accounting matrix (SAM) based on 2003-04 input-output tables of Indian economy prepared by the Central Statistical Organization (CSO) of India. This SAM was commissioned by the Ministry of Environment and Forests (MoEF) of the Government of India. It consists of 37 sectors including eight energy sectors (coal, crude oil, natural gas, petroleum products, hydro, thermal and nuclear power plants, and biomass), three factors of production, and four agents–households, private corporations, public non-departmental enterprises, and the government. Rich information on inter-industry transactions among sectors in the SAM allows substitutability between productive inputs, especially between different fossil fuels.

To model producer behavior, I assume Cobb-Douglas technology and exogenous productivity. I am able capture the extent to which sectoral prices and outputs would move following imposition of a policy. Relevant parameters for the base year, such as expenditure shares, come from the SAM while they are projected exogenously for later years.

Consumer Behavior at the household level is already described in earlier sections. To take this sophisticated welfare model to the aggregate economy is hard. First, I do not have a Ramsey like growth model to allow intertemporal savings behavior and second, I do not have an aggregate version of the Euler equation 3.5. I do not try to address these problems, and instead, keep the savings behavior exogenous to the model. As a result of this simplifying assumption, the model fails to capture effects of an environment policy on savings behavior, if any. Consequently, consumer optimization becomes a two stage process in every period. In the first stage, the total consumption expenditure is allocated to 4 commodity groups using equation 3.3. The effects of changing demography of Indian households are captured by projections of sufficient statistics, $l\bar{n}M$ and $\bar{A}$, that appear in the equation. In stage 2, I assume nested Cobb Douglas consumption functions to determine the allocation of total consumption expenditure to each of the 37 sectors. This two stage consumer model works more realistically than other alternatives such as a simple CES model. It is a non-homothetic model and it allows patterns of expenditure on commodities to change with changes in total expenditure even when prices are same.

The remaining sub-models of the simulation are the capital formation, the Government budget and the International trade. These sub-models have standard assumptions and all of them assume perfect foresight. The capital market equilibrium is determined by the forward looking behavior of producers. The Government budget has tax revenue and capital income from government enterprises on one side and the government spending and subsidy on the other side. All tax and subsidy rates are assumed to be exogenous and are calibrated using the base year SAM. The deficit too is specified exogenously and only government purchases are endogenous in the model. Foreign Trade uses the conventional Armington assumption for both the import and the export markets. Imported goods are assumed to imperfect substitutes of their domestic counterparts. World relative prices are set to mimic the SAM's domestic prices after adjusting for the domestic tax rate and tariff rates. Current account balance is set exogenously and is projected to fall over time. An endogenous variable for terms of trade clears the export-import equation.

3.3.2 The Emission and Health Model

Particulates, SO2, and NOx are generated by combustion of biomass and fossil fuels and by non-combustion processes. In addition to these local pollutants, I also measure emission of global pollutant, CO2. I use the intake fraction methodology to measure the health effects of outdoor emission of PM10 and SO2 on the urban population of India. I completely ignore the health effects of biomass use (and indoor air pollution) in my policy simulations because most households in India collect biomass using own family labor instead of purchasing it from the market, and therefore, the government cannot tax it even when it is highly polluting and causes more deaths and diseases than any other source of air pollution in India. The government, however, subsidizes the domestic use of liquified petroleum gas (LPG) and kerosene to discourage use of biomass. I do not impose tax on these cleaner household fuels in any of my policy counterfactuals.

3.3.3 The Base Case and The Couterfactual

The base case refers to the scenario of "business as usual" with no policy shock in the current or the future years. The economic system grows in absence of any remedial steps taken by the government to control the adverse effects of air pollution. This entails making a series of the projections of parameters. The detailed description of these projections can be found in the Appendix B. Since our focus is mainly on the marginal effects of environmental taxes, most of the assumptions regarding projections are not going to affect the main results qualitatively. The base case just presents a reasonable benchmark to compare the counterfactuals with.

The counterfactuals are hypothetical policy scenarios where environmental taxes are introduced marginally. The revenue from green taxes is recycled back into the economy in the form of tax cuts in existing indirect taxes and capital taxes. Thus, the green taxes are revenue neutral. The tax cuts are proportionate to the existing tax rates in the base case. [2]

I will consider three different environmental policies as counterfactuals.

Output Tax Policy: I tax the output of each sector according to the marginal health damage (MD) per unit of production. The marginal damage of a sector depends not only on the fuel used in the sector, but also on other factors like stack height, location of the plant and the surrounding population density, process emissions, etc. The tax rate is set to be 50% of the MD of the sector output in our simulations.

Fuel Tax Policy: This is a tax on fossil fuels set according to their respective average marginal damage to the overall economy. This is a more narrow-based, but a better targeted policy. Unlike the output tax, it affects the prices of only a few fossil fuels and hence encourage switching to cleaner fuels. The average marginal damage of a fuel, say coal, is calculated as the weighted average of sector-specific marginal damages caused by its use, where the weights are the quantity shares of coal used in different sectors. Fuel tax will be set at 25% of the average marginal damage.

Carbon Tax Policy: In addition to the above two Pigouvian taxes, I also simulate the effects of a carbon tax which is levied on fossil fuels (coal and petroleum products excluding LPG and kerosene). I raise the price of fossil fuels by levying a fixed exogenous tax on them in proportion to their carbon content. I choose a carbon tax of $10/ton of carbon.

3.4 Data

The paper integrates elements of both the microlevel consumer behavior and the macrolevel simulation model of the aggregate economy. This integration poses many challenges in data analysis, which I will discuss here.

3.4.1 Using an Urban Welfare function

The translog welfare function (introduced by Christensen et al. (1975)) is fundamentally important in getting individual household welfare effects in this paper. Somani (2012*a*) has estimated such a

[2] There are other ways of recycling the revenues from green taxes too, such as, by cutting labor income tax or by making direct transfers to households. Since I have not modeled labor-leisure choice, such recycling will always lead to loss of efficiency due to distortionary effects of new taxes in my model.

function based on urban consumers of India for the year 2003-04. I borrow from Somani (2012*a*) a specification best suited for the present problem. The set of demographic variables used in this specification is given below :

Religion: Hindu+ (Hinduism, Sikhism, Jainism, Buddhism, Zoroastrianism.) and Islam+Christianity

Social_Group: Upper and Lower Castes

Age: Young(0-45) and Old(45-) Heads

Education: Low (primary or less) and High (higher than primary) Education of the Head

Sex: Male and Female Heads

No_of_Children: 0-2 and 3+

Sector: Rural and Urban

Household_size: Six categories: 1, 2, 3, 4, 5, 6+

The above set of demographics provides rich heterogeneity among households. Potentially we can identify $2^7 \times 6 = 768$ types. These household types or bins are created by crossclassification of the above demographic variables. From the consumer survey, we actually get only 569 household types with nonzero samples. The number of households is more than 1,000 for around 97% of the household types and it is more than 10,000 for roughly 85% of the bins.

Regression results of this specification are presented in table 3.1. In this specification, Somani (2012*a*) uses the instrumental variable method to estimate vector α_p(row 1); matrix B_{pp} (rows 2-5 of the regression table) and matrix B_{pA} (rows 6-16 of the table). (The district level monsoon and pre-monsoon rainfall data serve as the instrument for the price of food.).

One major limitation of the above estimates is that they are based solely on the observations of the urban sector. Rural observations were dropped, because most of them have no information on house rent. I will make the assumption that the rural and the urban consumers have identical preferences and the differences in their consumption patterns are driven solely by income differences. This assumption allows me to apply the above estimates to entire India.

Table 3.1: Regression Table

	(1) Food	(2) Energy	(3) Misc	(4) Housing
Const	-1.864***	-0.407***	0.521***	0.749***
	(-70.78)	(-50.49)	(20.87)	(29.60)
Price_Food	-0.118***	-0.00501	-0.0389**	0.0482***
	(-7.97)	(-1.83)	(-2.79)	(20.39)
Price_Energy	-0.00501	-0.0297***	0.00301	0.00407***
	(-1.83)	(-24.73)	(1.19)	(4.52)
Price_Misc	-0.0389**	0.00301	0.0708***	0.0279***
	(-2.79)	(1.19)	(5.22)	(15.25)
Price_Housing	0.0482***	0.00407***	0.0279***	-0.00129
	(20.39)	(4.52)	(15.25)	(-0.54)
Islam+Christianity	-0.0189***	0.00461***	0.0129***	0.00143
	(-8.80)	(5.29)	(7.47)	(0.65)
Upper Caste	0.00897***	-0.00210**	-0.00633***	-0.000544
	(4.86)	(-2.95)	(-4.46)	(-0.31)
Female Head	0.0394***	-0.00330**	-0.00323	-0.0329***
	(14.02)	(-3.12)	(-1.46)	(-11.17)
Old_Head(45-)	0.00655***	-0.00413***	0.00315*	-0.00557**
	(3.58)	(-6.51)	(2.29)	(-3.05)
High Education (Head)	0.0239***	-0.000568	-0.0134***	-0.00993***
	(10.70)	(-0.64)	(-7.79)	(-4.70)
HH_size 2	0.0135*	-0.0456***	0.0198***	0.0122*
	(2.43)	(-23.18)	(4.77)	(2.45)
HH_size 3	-0.0334***	-0.0508***	0.0301***	0.0541***
	(-6.23)	(-26.31)	(7.51)	(11.54)
HH_size 4	-0.0609***	-0.0543***	0.0415***	0.0737***
	(-11.54)	(-29.02)	(10.49)	(15.79)
HH_size 5	-0.0833***	-0.0558***	0.0446***	0.0945***
	(-15.34)	(-29.72)	(10.92)	(19.32)
HH_size 6+	-0.123***	-0.0568***	0.0568***	0.123***
	(-22.10)	(-28.97)	(13.41)	(23.48)
No of Children(3+)	-0.0144***	-0.0000974	0.0142***	0.000273
	(-6.14)	(-0.09)	(8.05)	(0.12)
Observations	36448	36448	36448	36448

t statistics in parentheses

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

Source: Somani (2012*a*)

3.4.2 Projection of Distribution of Total Expenditure

We need to project the distribution of total expenditure across dynasties over time. This distribution will be used to calculate distributional statistics that appear in equation 3.3 (their formulas are below) as well as to calculate the lifetime wealth of dynasties. The impact of an environmental tax would have differential impact on different dynasties and therefore it is necessary that we make these projections with as much precision as possible.

$$ln\bar{M} = \sum_k n_k M_k \ln M_k / \sum_k n_k M_k$$

$$\bar{A} = \sum_k n_k M_k A_k / \sum_k n_k M_k$$

where n_k is the size of household type k and time subscript is suppressed for simplicity. We will need projections of both n_k and M_k over all the years.

For the Base Year, I use household consumption data from a nationally representative consumer survey conducted by National Sample Survey Organization (NSSO) in 2004-05. This survey gives us the distribution of total expenditure across dynasties of only urban sector. I impose this distribution onto rural sector too, but only after scaling it down by a factor of 0.46—the ratio of national level incomes of an average rural and urban household. I use this combined distribution as the distribution of total expenditure across all 569 dynasties in the base year. I convert this into a distribution of shares of the aggregate total expenditure, $M_k / \sum_k n_k M_k$, so that the distribution adds to unity.

For Future Years, I first project of number of families, n_k, of household types. There are no official projections of families by demography in India. I, instead, use person level projections of Samir et al. (2010), which are classified by sex, education and age. Samir et al. (2010) doesn't have projections on children (aged 0-15), so I supplement population projection from the United Nations [3] to Samir et al. (2010). Samir et al. (2010) used several methodologies to make projection and I will utilize just one of them, namely GET (Global Education Trend) method.

The strategy to go from person level demographic projections to family level projections is by using a transition matrix. This matrix is prepared by using the NSS consumer survey which gives demographic information both at the family and at the person level. The rows of the transition

[3] "United Nations, Population Division, Department of Economic and Social Affairs"

matrix refer to household types classified by the original demographics, while the columns refer to individuals classified by the demographics of Samir et al. (2010). This is a 569×147 matrix. A typical cell gives proportion of population from the column person type belonging to the row household type. I assume that this base year transition matrix remains unchanged in all future years and thus for every person level projections, I get a family level projection by simply right-multiplying the transition matrix.

The size of the total population from Samir et al. (2010) and that from the NSS consumer survey are not exactly equal for the year 2003-04. It is because the consumer survey fails to represent part of the population. The survey covers a population size of 0.98 billion while the actual population at that time was 1.105 billion. For this reason I scale down all population projections of all the years by roughly 11% to make the two datasets consistent.

Next, we need to make projections of distribution of total expenditure, M_k across dynasties. I start with the base year distributions of shares of the aggregate total expenditure. Initially the share of a family in the next year is kept same as that in the base year. But since the number of families in each bin normally expands, we expect the sum of these shares to be higher than one. So I scale all shares down so as to make them add to one. Since the number of families expands differently across bins, the new distribution of income share could be very different from the previous year. I apply the same inductive process to get the distribution of shares in all the future years. This method takes a cue from the path of the total expenditure generated by the Euler equation 3.5. The Euler equation suggests that the rate of change in the total expenditure is independent of the demographic attributes of the household and the path depends only on the common factors such as prices.

3.4.3 Linking the Consumer Survey and the Input Output Tables

Input output tables (used for the SAM construction) and the NSS consumer survey record transaction in conceptually different ways. Input output tables price transactions at producers' prices, whereas the consumer survey price them at purchasers' prices. The difference between the two is due to trade commissions, transport margins and indirect taxes. For example, purchase of a new television by a household would be recorded as an expense on durable goods in the NSS, but in input-output tables, the same transaction would be recorded in the television manufacturing industry, the trade commission sector, the transport sector and the government's indirect taxes. The total of the vectors of consumption expenditure in these two datasets would still be same theoretically. To establish a link between these two vectors, I make a condensed bridge matrix in which the columns are consumer survey commodities groups and the rows are SAM industry groups. Every column of the matrix gives the split of the purchasers' price of a commodity group into contributions from the four industry groups. I use reports of the CSO [4] to get trade and transport margins, which help me make the bridge matrix. The Appendix F contains the condensed bridge matrix.

3.5 Welfare Impact

3.5.1 Long run Effects on Consumption Sector

In this section, I present how the environmental policies affect the aggregate level of consumer expenditure and prices of the four commodity groups. Although the model gives us the prices of all 37 industries, I will report the changes in the prices of four commodity groups only. Note that the prices of the commodity groups are actually a transformation of the prices of 37 industries using the Bridge matrix.

Figure 3.1 shows the time paths of percentage changes in prices under all three policy scenarios. In every scenario, changes in non-energy prices are quite modest in comparison to changes in energy prices. When compared across policies, we see that changes in non-energy prices appear to be relatively more pronounced in the case of the output tax policy. This is because the output tax is a broad based policy targeting several sectors at the same time. This figure manifests the importance of having a general equilibrium setup because we are able to internalize indirect effects of changes in the prices of non-energy goods.

Over time, the changes in energy prices become larger and larger in all three cases. In the case of Pigouvian taxes, tax rate is set according to health damages. Since the Value of Statistical Life (VSL) rises due to rise in income over years and as the exposed population also expands, we expect the tax rate to increase with time. Hence, we see larger changes in energy prices in later years. In

[4] http://mospi.nic.in/Mospi_New/upload/ftest15.htm MINISTRY OF STATISTICS & PROGRAMME IMPLEMENTATION

the case of carbon tax, I set a fixed tax rate of \$10 per ton of carbon at 2003 prices. Over years, prices of all goods fall due to productivity improvements, so the \$10 tax rate at 2003 prices also translates into higher changes in energy price in later years.

In figure 3.2, I present the paths of percentage changes in nominal consumer expenditure (aggregate) under all three policy scenarios. While the paths under the carbon tax and the fuel tax policies are similar, the path under the output tax policy is very different. The latter does not have a rising trend like the former. Note that since I am plotting the effects on the nominal consumer expenditure, we can't infer the effects on real consumer expenditure from the plots. However, the percentage changes in the nominal consumption are quite small relative to those in the prices. So it is the changes in prices that would dominate the final welfare effects. In the cases of carbon and fuel tax policies, the general price levels seems to be higher implying a possible adverse welfare impact, but in the case of output tax policy we cannot say so. It is quite possible that in this case, the fall in the prices of non-energy goods more than compensates for the rise in the prices of energy goods. This could actually enhance aggregate welfare in the long run. I will formally evaluate the policies in terms of aggregate welfare effects in the final subsection.

3.5.2 Impact on Dynastic Welfare

We are now in a position to evaluate the welfare impacts at various levels of aggregation. The smallest unit of our analysis is a dynasty. First, the demographic variables allowed us to create 569 household types with heterogeneous preferences. Let us call them demographic types. I consider 12 wealth types within each of these demographic types to expand the count of household types/dynasties to 6828. The wealth types are chosen based on the average wealth of the households within the demographic type only. I will report results for only three wealth types for each demographic type — low wealth (half the average wealth), middle wealth (the average) and high wealth (double the average). Note that different demographic types with the same wealth type could have different wealth levels, because the average wealth levels vary across demographic types. For example, the difference in welfare effects between a rural and an urban household with the middle wealth type would be driven by both the difference of demography as well as difference in average wealth levels.

Since it is not possible to report equivalent variations of each of the dynasties, I choose one

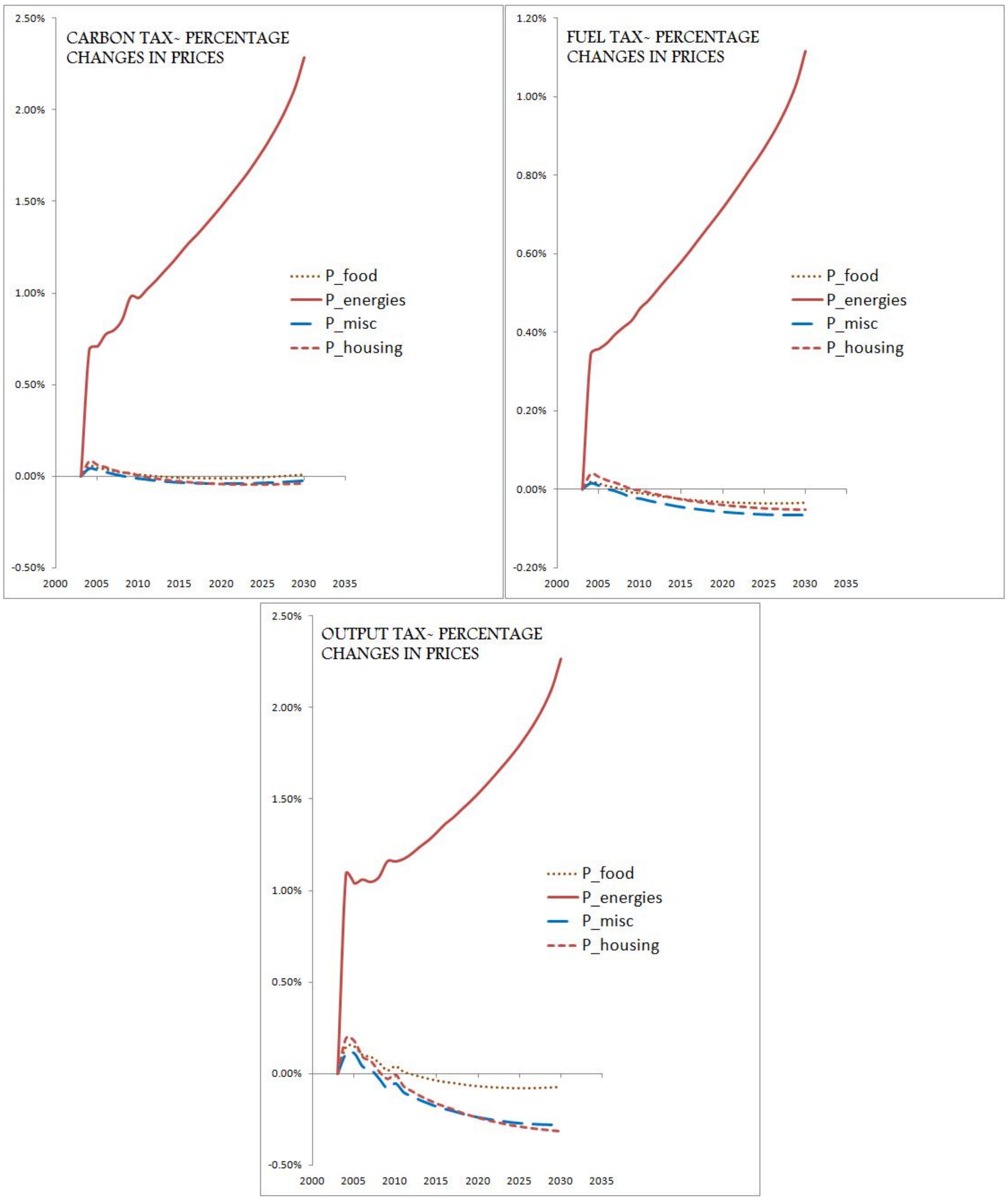


Figure 3.1: Impact on prices of commodity groups

[a]

[a]Source: Author's Calculations

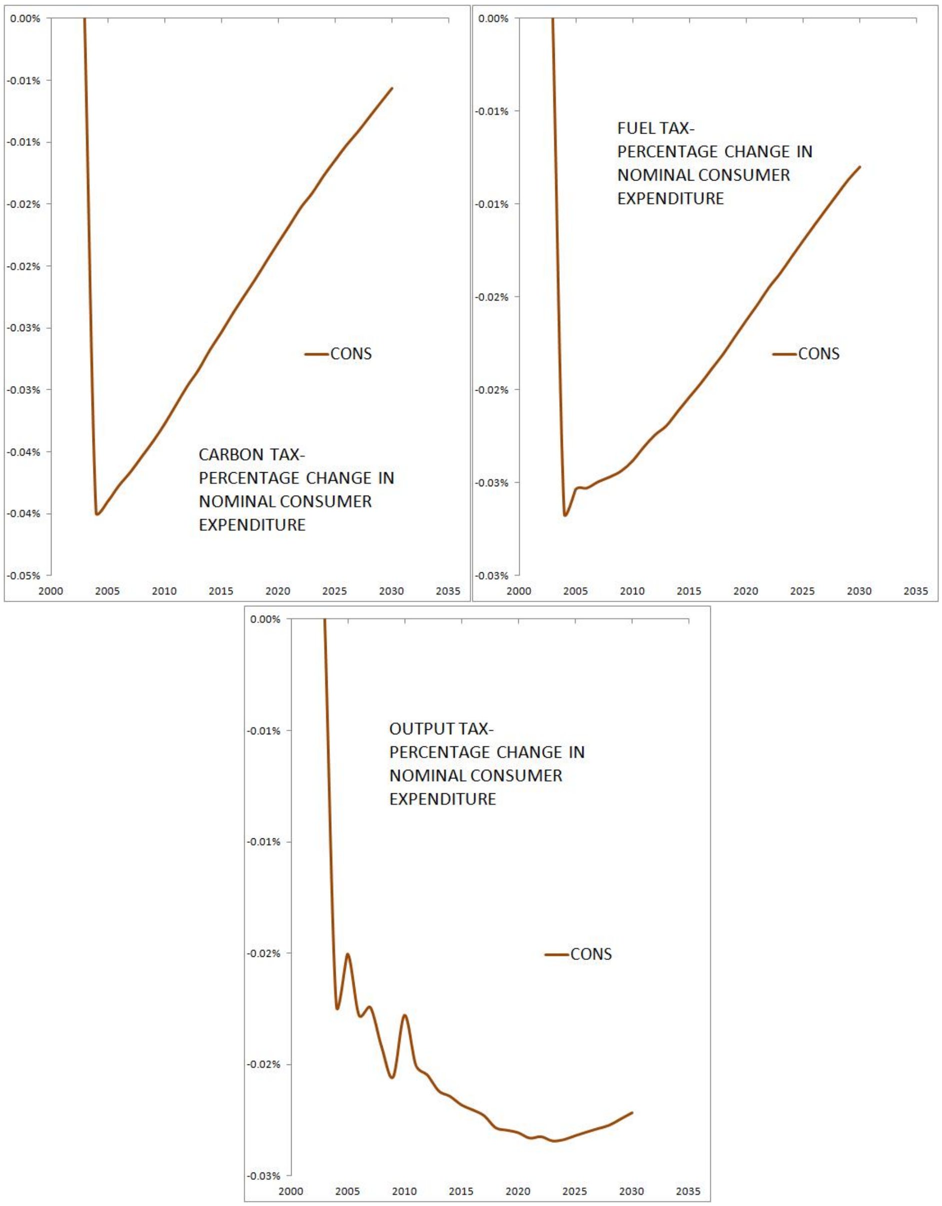


Figure 3.2: Impact on Nominal Consumer Expenditure

[a]

[a]Source: Author's Calculations

reference household for each of our policies. For example, in the case of carbon tax policy I have chosen a rural low caste Hindu family with household size 4 and number of children less than 3 as our reference household. The head of this reference family is male and of age more than 45 with a background of low eduction. I will consider, along with the reference household, only those households that differ from the reference household in only one attribute at a time.

In all the subsequent tables, I will present equivalent variations as the measures of welfare effects. They are presented both in terms of Rupees and in terms of percentages of the base case wealth. The average exchange rate between Indian Rs and US dollars in 2003 was \$1 = 46 Rs.

In table 3.2, the reference household is indicated by the bold rows. Other rows refer to the households differing in only one attribute at a time. We can see that the carbon tax policy is uniformly welfare-reducing across all the households in the table. For example, the household with size two and middle wealth level would treat the imposition of the carbon tax as a one time loss of Rs 615. With higher wealth, a family loses more in absolute terms but less in proportion to their wealth. This is true for all the demographic types in the table. For example, an upper caste family with middle wealth type would lose Rs 558 (0.302% of its wealth) following imposition of carbon tax, but the same family with high wealth type (or double the wealth of middle type) loses Rs 972 (0.263% of its wealth). Equivalent variation as a percentage of lifetime wealth consistently falls with higher wealth types for every demographic type.

Demography plays an important role in deciding who faces the brunt of the carbon tax. We cannot measure this effect by comparing equivalent variations of either low, middle or high types across demographic types. The differences would be driven by both the difference in demography and the difference in wealth levels. The table, therefore, also reports equivalent variations of an artificial wealth type called "Fixed". The wealth level of this type is set at 0.5 times the national average wealth of all households.[5] So values of this type is comparable across all demographic types, because the wealth level is controlled. The welfare effects for this type is computed using interpolation from the available 12 wealth types of every demographic type.

By comparing equivalent variations of the "Fixed" type across demographic types, we conclude

[5]The choice of wealth level for the "Fixed" type is immaterial. For all other choices of wealth level, the differences in welfare effects between demographic types would still be same, because, by design, wealth and demographic attributes do not interact in the translog welfare function. I have chosen the level in such a way that I can get welfare effects of the "Fixed" type in the table by using interpolation only and not by extrapolation.

that large households generally lose more after imposition of a carbon tax. Upper caste and educated families also end up losing more, even when they have the same wealth levels as the lower caste and low educated families. Religion of the household doesn't seem to matter in the welfare effects, but whether one lives in the rural or the urban sector does seem to matter. An urban household loses slightly more than a rural household. Families headed by a young person seems to lose less than those headed by an old person. The sex of the head also plays a role in the welfare effects.

Though, every household is adversely affected by the carbon tax, the magnitude of the effects are quite small—about one-third of a percentage point of family's lifetime wealth. In the table, the family that loses the highest percent of their wealth is the family with 3 children and 1 adult with low wealth type (a loss of 0.371%), while the least affected family is the single person family with "Fixed" wealth type, (a loss of 0.199%). It is because an adult with three children and low wealth type gives much more share to energy than an unattached adult with "Fixed" wealth type.

Table 3.3 presents dynastic welfare effects in the case of the fuel tax policy. The reference household is once again chosen to be the same as before. The level of wealth for the "Fixed" type is also same as in the carbon tax case. We can see that the magnitudes are qualitatively similar to the carbon tax case. This is understandable because both affect the economy by raising the prices of fossil fuels. Interestingly, the single person family with "Fixed" wealth type, the one that was the least affected by the imposition of the carbon tax policy, actually gains in this case. There are several other instances of positive welfare effects too (for household types not reported in the table). The effect of demography in this case (by comparing values in "Fixed" type vertically) is very similar to that in the carbon tax case.

Another interesting observation is that the fuel tax seems to be more regressive than the carbon tax, because there are many instances where the high wealth types lose less than what the medium wealth types do. The most dramatic of these instances is the urban sector household, in which a high wealth type loses almost one-seventh of the what a medium wealth type loses (Rs 11 vs Rs 67). It is not clear what is driving this peculiar nonlinearity in the wealth effect. However, we do not see this peculiarity when we compare households of low and middle wealth.

To evaluate the dynastic welfare effects in the case of output tax, I choose to start from a

Table 3.2: Welfare Impacts of Carbon Tax on Indian Households
Equivalent Variation in 2003 Rs and as a percentage of wealth

	Equivalent Variation in 2003 Rs				*Equi. Var. as a percentage*			
	Low ↔	*Medium*	*↔High*	*Fixed↕**	*Low ↔*	*Medium*	*↔High*	*Fixed↕**
Lower Caste	**-235.32**	**-417.45**	**-728.47**	**-488.50**	**-0.344%**	**-0.306%**	**-0.267%**	**-0.294%**
Upper Caste	-314.94	-557.98	-972.10	-511.01	-0.341%	-0.302%	-0.263%	-0.308%
Hindu+	**-235.32**	**-417.45**	**-728.47**	**-488.50**	**-0.344%**	**-0.306%**	**-0.267%**	**-0.294%**
Islam &Christ.	-254.62	-450.21	-782.33	-484.04	-0.336%	-0.297%	-0.258%	-0.292%
Male Head	**-235.32**	**-417.45**	**-728.47**	**-488.50**	**-0.344%**	**-0.306%**	**-0.267%**	**-0.294%**
Female Head	-260.03	-463.04	-811.95	-512.42	-0.355%	-0.316%	-0.277%	-0.309%
Low Educ	**-235.32**	**-417.45**	**-728.47**	**-488.50**	**-0.344%**	**-0.306%**	**-0.267%**	**-0.294%**
High Educ	-475.40	-839.22	-1455.19	-536.59	-0.332%	-0.293%	-0.254%	-0.323%
Household Size								
1	-95.43	-165.25	-279.27	-330.53	-0.290%	-0.251%	-0.212%	-0.199%
2	-348.51	-615.27	-1066.97	-471.86	-0.332%	-0.293%	-0.254%	-0.284%
3	-281.14	-497.82	-866.65	-481.49	-0.340%	-0.301%	-0.262%	-0.290%
4	**-235.32**	**-417.45**	**-728.47**	**-488.50**	**-0.344%**	**-0.306%**	**-0.267%**	**-0.294%**
5	-201.17	-357.58	-625.59	-498.31	-0.350%	-0.311%	-0.272%	-0.300%
6+	-153.81	-274.44	-482.51	-507.85	-0.361%	-0.322%	-0.283%	-0.306%
Rural	**-235.32**	**-417.45**	**-728.47**	**-488.50**	**-0.344%**	**-0.306%**	**-0.267%**	**-0.294%**
Urban	-493.55	-862.61	-1476.13	-508.60	-0.309%	-0.270%	-0.231%	-0.306%
Children(0-2)	**-235.32**	**-417.45**	**-728.47**	**-488.50**	**-0.344%**	**-0.306%**	**-0.267%**	**-0.294%**
Children(3+)	-152.44	-272.88	-481.70	-484.74	-0.371%	-0.332%	-0.293%	-0.292%
Young Head	-179.76	-318.35	-554.31	-457.18	-0.340%	-0.301%	-0.262%	-0.275%
Old Head	**-235.32**	**-417.45**	**-728.47**	**-488.50**	**-0.344%**	**-0.306%**	**-0.267%**	**-0.294%**

* The "Fixed" refers to equal wealth level across the above demographic types.
I set it at 0.5 of the national average wealth.
The welfare effects of the "Fixed" are, then, computed using interpolation from the available 12 wealth types.
Bold rows refer to the reference household. I change one demography at a time to get other rows.
Arrows(↔, ↕) indicate the directions of valid comparison.

Table 3.3: Welfare Impacts of Fuel Tax on Indian Households
Equivalent Variation in 2003 Rs and as a percentage of wealth

	Equivalent Variation in 2003 Rs				*Equi. Var. as a percentage*			
	Low ↔	*Medium*	↔*High*	*Fixed*↕*	*Low* ↔	*Medium*	↔*High*	*Fixed*↕*
Lower Caste	**-38.71**	**-50.40**	**-46.79**	**-52.02**	**-0.057%**	**-0.037%**	**-0.017%**	**-0.031%**
Upper Caste	-52.81	-69.12	-65.23	-67.16	-0.057%	-0.037%	-0.018%	-0.040%
Hindu+	**-38.71**	**-50.40**	**-46.79**	**-52.02**	**-0.057%**	**-0.037%**	**-0.017%**	**-0.031%**
Islam &Christ.	-40.67	-51.37	-42.81	-51.95	-0.054%	-0.034%	-0.014%	-0.031%
Male Head	**-38.71**	**-50.40**	**-46.79**	**-52.02**	**-0.057%**	**-0.037%**	**-0.017%**	**-0.031%**
Female Head	-47.03	-65.09	-72.27	-67.82	-0.064%	-0.044%	-0.025%	-0.041%
Low Educ	**-38.71**	**-50.40**	**-46.79**	**-52.02**	**-0.057%**	**-0.037%**	**-0.017%**	**-0.031%**
High Educ	-82.63	-108.62	-103.92	-88.78	-0.058%	-0.038%	-0.018%	-0.053%
Household Size								
1	-10.70	-8.41	9.18	22.54	-0.033%	-0.013%	0.007%	0.014%
2	-53.69	-65.87	-48.71	-48.67	-0.051%	-0.031%	-0.012%	-0.029%
3	-45.14	-57.55	-49.62	-49.96	-0.055%	-0.035%	-0.015%	-0.030%
4	**-38.71**	**-50.40**	**-46.79**	**-52.02**	**-0.057%**	**-0.037%**	**-0.017%**	**-0.031%**
5	-34.69	-46.65	-47.84	-57.56	-0.060%	-0.041%	-0.021%	-0.035%
6+	-29.02	-41.19	-48.69	-63.19	-0.068%	-0.048%	-0.029%	-0.038%
Rural	**-38.71**	**-50.40**	**-46.79**	**-52.02**	**-0.057%**	**-0.037%**	**-0.017%**	**-0.031%**
Urban	-65.92	-68.66	-10.91	-66.67	-0.041%	-0.021%	-0.002%	-0.040%
Children(0-2)	**-38.71**	**-50.40**	**-46.79**	**-52.02**	**-0.057%**	**-0.037%**	**-0.017%**	**-0.031%**
Children(3+)	-28.29	-40.31	-48.11	-48.12	-0.069%	-0.049%	-0.029%	-0.029%
Young Head	-27.33	-33.74	-25.68	-31.64	-0.052%	-0.032%	-0.012%	-0.019%
Old Head	**-38.71**	**-50.40**	**-46.79**	**-52.02**	**-0.057%**	**-0.037%**	**-0.017%**	**-0.031%**

* The "Fixed" refers to equal wealth level across all demographic types.
I set it at 0.5 of the national average wealth.
The welfare effects of the "Fixed" are, then, computed using interpolation from the available 12 wealth types.
Bold rows refer to the reference household. I change one demography at a time to get other rows.
Arrows(↔, ↕) indicate the directions of valid comparison.

different reference household [6]. The new reference household, as indicated by bold rows in table 3.4, is an urban upper caste family belonging to the religion category, Islam and Christianity. The family size is 5 with number of children less than 3 and the family is headed by a young male with the background of high education. The wealth level of the "Fixed" type is chosen to be 1.8 times the national average wealth.

The output tax policy is different from the other two policies, because it actually enhances the welfare of households. The wealthier types seem to benefit the most. In all instances, the rise in gain from the output tax is more that the rise in wealth. As a result, percentage changes are higher for wealthier types. For example, for the reference household with middle wealth type, the equivalent variation is Rs 1,346, but for the same household with high type (or double the wealth of middle type), the equivalent variation rises close to three times, Rs 3,513.

If wealth level is controlled, then the gains are higher for smaller families. Age and education of the head seem to matter too, because families headed by young and low educated persons gain more than those headed by old and high educated persons. However, sex of the head does not seem to matter significantly. Upper caste and Hindu families gain less than lower caste and Islamic/Christian families.

Considering gain as a percentage of wealth, the single person family with "Fixed" wealth type seems to benefit the most (0.355%), while the rural household with low wealth type benefits the least (0.087%) in the table.

The welfare enhancing impact of the output tax policy indicates the presence of double dividends. It also shows that the existing distortions in the economy (due to high taxes on capital and sectors like cement, construction, iron and steel etc.) are substantial. These sectors are vital for infrastructure investments and a shift of tax burden away from these sectors boosts investment and, in the long run, raises consumer welfare.

[6] I do this only because I want to see the results from the perspective to a new reference household. The results would still be "almost" similar for other choices of reference household, because, by design, we do not have interactions between demographic variables in the translog function. Any differences, if present, would be driven by the differences in projections of the populations of demographic types.

Table 3.4: Welfare Impacts of Output Tax on Indian Households
Equivalent Variation in 2003 Rs and as a percentage of wealth

	Equivalent Variation in 2003 Rs				*Equi. Var. as a percentage*			
	Low ↔	*Medium*	↔*High*	*Fixed*↕*	*Low* ↔	*Medium*	↔*High*	*Fixed*↕*
Lower Caste	356.14	1051.72	2782.78	1025.90	0.117%	0.173%	0.229%	0.172%
Upper Caste	**467.43**	**1345.60**	**3513.07**	**993.67**	**0.127%**	**0.183%**	**0.239%**	**0.166%**
Hindu+	697.19	2036.53	5358.06	743.24	0.121%	0.177%	0.233%	0.124%
Islam &Christ.	**467.43**	**1345.60**	**3513.07**	**993.67**	**0.127%**	**0.183%**	**0.239%**	**0.166%**
Male Head	**467.43**	**1345.60**	**3513.07**	**993.67**	**0.127%**	**0.183%**	**0.239%**	**0.166%**
Female Head	1015.80	2719.62	6815.46	976.22	0.165%	0.221%	0.277%	0.164%
Low Educ	297.72	815.80	2072.54	1436.30	0.151%	0.207%	0.263%	0.241%
High Educ	**467.43**	**1345.60**	**3513.07**	**993.67**	**0.127%**	**0.183%**	**0.239%**	**0.166%**
Household Size								
1	211.22	534.46	1293.08	2121.10	0.211%	0.267%	0.323%	0.355%
2	330.81	929.15	2393.65	1266.13	0.138%	0.194%	0.250%	0.212%
3	401.52	1155.49	3016.22	1068.16	0.127%	0.183%	0.239%	0.179%
4	378.59	1090.50	2848.02	1092.80	0.127%	0.183%	0.239%	0.183%
5	**467.43**	**1345.60**	**3513.07**	**993.67**	**0.127%**	**0.183%**	**0.239%**	**0.166%**
6+	668.00	1915.38	4990.08	837.37	0.129%	0.185%	0.241%	0.140%
Rural	125.46	413.08	1150.63	1197.60	0.087%	0.142%	0.198%	0.201%
Urban	**467.43**	**1345.60**	**3513.07**	**993.67**	**0.127%**	**0.183%**	**0.239%**	**0.166%**
Children(0-2)	**467.43**	**1345.60**	**3513.07**	**993.67**	**0.127%**	**0.183%**	**0.239%**	**0.166%**
Children(3+)	304.07	840.92	2147.65	1379.89	0.146%	0.202%	0.258%	0.231%
Young Head	**467.43**	**1345.60**	**3513.07**	**993.67**	**0.127%**	**0.183%**	**0.239%**	**0.166%**
Old Head	543.84	1615.70	4287.86	799.83	0.115%	0.171%	0.227%	0.134%

* The "Fixed" refers to equal wealth level across all demographic types.
I set it at 1.8 of the national average wealth.
The welfare effects of the "Fixed" are, then, computed using interpolation from the available 12 wealth types.
Bold rows refer to the reference household. I change one demography at a time to get other rows.
Arrows(↔, ↕) indicate the directions of valid comparison.

3.5.3 Equivalent Scale of a Dynasty

Before combining individual welfare effects into a single social welfare effect, I would like to present the weights each household type gets in the social welfare. Table 3.5 presents *commodity specific equivalent scales* and *general equivalent scales* of households, which are also the weights (or number of equivalent members) of households in the social welfare [7]. Similar to the previous section, the table contains a reference household indicated by bold rows as well as the households that differ in one attribute at a time from the reference household.

The table has many interesting results. The most interesting of them is the behavior of equivalent scales for larger households. The equivalent scales monotonically increase when household size gets bigger. This is true for all the commodity specific and for the general equivalent scales. The rise in the general equivalent scales is less than proportionate to size of the families in most cases, indicating the presence of scale economies in consumption. In certain cases, we see instances of diseconomies of scale too. For example, when household size goes from two to three, food specific, housing specific and general equivalent scales rise more than proportionately.

The upper caste families has slightly bigger equivalent scale than the lower caste families, while Hindu families have substantially bigger equivalent scales than Muslim or Christian families. Sex, education and age of the family head also determine the value of equivalent scales. Families headed by male, young and low educated persons have higher equivalent scales. If number of children is higher, while the household size is fixed, then the number of equivalent members goes down. All these results are reasonable and consistent with the general theory of equivalent scales. These general equivalent scales signifies the weights of the household in the aggregate welfare and they are produced entirely by household behavior reflected by the parameter estimates of the welfare model, α_p, B_{pp} and B_{pA}.

Note that I am not able to make comparisons between a rural and an urban household, because I am assuming identical preferences for them, which is same as assuming that their equivalent scales are identical.

[7] For full description on the concept of *equivalent scale* of the translog function, see Jorgenson and Slesnick (1987).

Table 3.5: Equivalent Scales of Households

[a]

	Food	*Energy*	*Misc*	*Housing*	*General*
Lower Caste	**3.05154**	**8.15791**	**1.39257**	**8.07754**	**3.36062**
Upper Caste	3.30650	8.82085	1.19416	10.54551	3.56766
Hindu+	**3.05154**	**8.15791**	**1.39257**	**8.07754**	**3.36062**
Islam and Christianity	2.60512	6.87726	1.91033	4.69799	2.96894
Male Head	**3.05154**	**8.15791**	**1.39257**	**8.07754**	**3.36062**
Female Head	1.54701	8.98106	1.29706	3.30715	2.05381
Low Educ	**3.05154**	**8.15791**	**1.39257**	**8.07754**	**3.36062**
High Educ	2.93375	8.33353	1.05164	9.62306	3.19950
Household Size					
1	0.85818	1.15147	1.03292	0.82059	0.90731
2	1.00790	5.80902	1.00769	1.86694	1.34977
3	2.27015	7.15341	1.15019	5.85610	2.59673
4	**3.05154**	**8.15791**	**1.39257**	**8.07754**	**3.36062**
5	4.68013	8.71571	1.43960	14.95518	4.67043
6+	7.52840	9.14686	1.80133	25.30662	6.81821
Rural	**3.05154**	**8.15791**	**1.39257**	**8.07754**	**3.36062**
Urban	3.05154	8.15791	1.39257	8.07754	3.36062
Children(0-2)	**3.05154**	**8.15791**	**1.39257**	**8.07754**	**3.36062**
Children(3+)	2.53795	8.11791	1.87952	4.85819	2.99332
Young Head	3.55584	7.08476	1.34819	9.84362	3.66077
Old Head	**3.05154**	**8.15791**	**1.39257**	**8.07754**	**3.36062**

[a] Source: Author's Calculations

3.5.4 Impact on Social Welfare

The evaluation of all three environmental policies requires coalescing individual dynastic welfare effects into a single social welfare effect. I present money equivalent changes in social welfare in table 3.6 for all three cases. The inequality aversion parameter (μ) of social welfare function can range from -1 to $-\infty$. The higher the absolute value of μ, the lesser the social welfare function gives weight to equity considerations. I consider two cases, where μ is equal to -1 and -2, in table 3.6. (-2 is a good approximation of $-\infty$, because of the fast convergence of the social welfare function.)

The first conclusion one gets from the table is that while the tax policies targeted on fossil fuels (carbon tax and fuel tax) reduce the social welfare, the broad based output tax policy targeted on polluting industries increases it. This conclusion is independent of the choice of inequality aversion parameter. The changes, however, are actually quite small in comparison to the aggregate wealth of the economy. Take fuel tax for an example. Though the policy reduces the social welfare, the reduction is as low as 0.02% the aggregate wealth.

The positive change in social welfare in the case of output tax policy signals potential presence of double dividends. The double dividends arise in this case because the output tax policy works as a tax reform rather than an additional burden on consumers. It shifts tax burden to more polluting industries without compromising efficiency, because it does not place the tax burden only on energy sectors. It simultaneously reduces other existing distortionary taxes such as indirect taxes and capital taxes. In the table, the measure of increase in efficiency following the output tax policy is 105 billion Rupees. On the other hand, the carbon tax policy reduces efficiency by 175 billion Rupees and fuel tax policy by 15 billion rupees.

Decomposing the change in social welfare into two components – change in efficiency and change in equity – gives us further insights. The component of efficiency, by construction, is independent of μ. The component of efficiency and equity are of opposite sign. The component of equity expectedly depends on the inequality aversion parameter (μ). If we choose a higher absolute value of μ, the social welfare function gives less weight to equity and so the money metric value of change in equity becomes smaller because . As a result, absolute values of the change in social welfare and that of μ are positively related.

Qualitatively, carbon tax and fuel tax have very similar welfare effects, but since fuel tax is a targeted policy, designed to tax the most polluting fuels, the value of reduction in environmental damage measured by the health effects from local pollutants is the highest in this case[8]. Carbon tax would result in a higher loss of welfare in order to achieve similar reduction of environmental damage. Output tax doesn't achieve high reduction in environmental damage, because it tries to share the burden of green taxes on many sectors rather than targeting only fossil fuels. However, in all cases the reduction in environmental damage is significantly more than the change in welfare.

Environmental taxes are feared in developing nations, mainly because they are believed to be regressive. At least in the relative sense, the table confirms this fear. The measures of relative progression fall in every case. This decline, however, is very marginal when compared with the base value of the index of relative equality, which is 0.78. (It means that the money metric social welfare is 0.78 of money metric potential welfare in the base case.) If one considers the absolute measure of tax progressivity, then we have a different story. The changes in equity in table 3.6 can be interpreted as measures of absolute progression. The carbon and the fuel tax policies are "absolutely" progressive, whereas the output tax policy is "absolutely" regressive. This is true irrespective of the value of μ.

In summary, the three cases of environmental taxes present three different approaches of addressing the problem of pollution in India. These taxes work by inducing changes in the industry prices and hence encouraging firms and households to substitute away from certain targeted sectors. We see that they would have different implications on consumer welfare and the environment. The impact on welfare is generally very modest in relation to the impact on the environment. The results are based on the long run adjustments of the economic system and may not hold if there are significant short run adjustment costs. One method to avoid short run costs would be to phase in new policies gradually over time.

I also present simple decomposition of welfare impact into efficiency and equity components. Efficiency component is dominant and dominates the overall effect of social welfare. All three policies are mildly "relatively" regressive. However, if we consider the absolute measure of progression, then except the output tax policy, the other two policies are mildly progressive.

[8]The estimate of reduction in health damages comes from the simulations. The simulations give us period-wise value of health damage of the base case and the counterfactuals in 2003 Rs. I get the present value of the change in health damages using interest rates as discount factors (or γ_t).

Table 3.6: Change in Social Welfare [a]

		Change in Social Welfare (in bill. 2003 Rs)			*Change in Social Welfare (as percent of wealth)*			*Tax Progressivity*	*Change in Damage (in bill. 2003 Rs)*
Environmental Policy	*Inequality aversion par.(μ)*	*Welfare*	*Efficiency*	*Equity*	*Welfare*	*Efficiency*	*Equity*	*Relative Progression*	
Carbon Tax	-1	-91.2	-174.9	83.7	-0.14%	-0.26%	0.12%	-0.000183	-1802.0
	-2	-142.7	-174.9	32.3	-0.21%	-0.26%	0.05%	-0.000093	-1802.0
Fuel Tax	-1	-11.5	-15.0	3.4	-0.02%	-0.02%	0.01%	-0.000071	-1513.6
	-2	-13.6	-15.0	1.4	-0.02%	-0.02%	0.00%	-0.000028	-1513.6
Output Tax	-1	37.6	105.1	-67.5	0.06%	0.16%	-0.10%	-0.000146	-242.6
	-2	79.8	105.1	-25.4	0.12%	0.16%	-0.04%	-0.000033	-242.6

[a]Source: Author's Calculations

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Appendix A

Description of Economic Model

I work with a multi-sector dynamically recursive model of Indian economy. I borrow heavily from the economic model in Ho and Nielsen (2007). The model is a standard Solow growth model (dynamically recursive). Every period savings rate is exogenously fixed. Investment equals savings and capital accumulates over years through successive investments. The economic model will integrate economic activity and energy use with the pollution emission and subsequent health damage. This enables me to allocate the health damage value between various sectors of the economy as well as on different fossil fuels.

A.1 Production

There are 37 sectors in the economy (after splitting household fuels from Petroleum Products sector in the original SAM). Each produces output using capital, labor, land and intermediate inputs. Intermediates can be broadly divided into energy and materials. The technology is assumed to be Cobb-Douglas. Technological progress increases overall productivity over time and is exogenous to the model.

$$QI_{jt} = QI_j(TD_j; KD_j; LD_j; QP_{jE}; QP_{jM}; t)$$

where TD, KD, LD are demands for land, capital, and labor. The intermediate inputs are aggregated to either energy and material (non-energy) categories. 9 of the 37 sectors (coal, gas, crude oil, household fuels, other petroleum products biomass, nuclear energy, hydel power, thermal power) are categorized as energy and the rest are non-energy sectors. I will use the following index sets for industries and commodities:

$$I_{IND} = \{1, 2, ..., 37\}$$

$$I_{COM} = \{1, 2, ..., 37\}$$

The Cobb-Douglas function, profit maximization and perfect competition simplify marginal condition. To model producer's behavior, it is convenient to work with dual price functions. The industry output price corresponding to the above quantity is (henceforth I will suppress subscript t wherever possible to keep equations reader-friendly):

$$lnPO_j = \alpha_{Kj}ln(PKD_j) + \alpha_{Lj}ln(PLD_j) + \alpha_{Tj}ln(PTD_j) +$$

$$\alpha_{Ej}ln(PP_{jE}) + \alpha_{Mj}ln(PP_{jM}) + \alpha_{j0} + \alpha_j g(t)$$

$$ln(PP_{jE}) = \sum_{i \in E} \alpha_{ij} ln(PS_i)$$

$$ln(PP_{jM}) = \sum_{i \in M} \alpha_{ij} ln(PS_i)$$

The prices for the intermediate input bundles(Energy/Non-energy) are functions of the corresponding individual commodity prices(PS_i) of Energy/Non-energy inputs. S in PS stands for supply. Supply Prices PS are different from output prices, PO. The supply price is the price faced by intermediate input buyers after taking account of indirect taxes and import competition and the industry output price PO is the price received by the sellers. The industry price PI paid by buyers includes various indirect subsidies and taxes (both ad valorem and unit taxes).

$$PI_j = (1 + tt_j^f)PO_j$$

$$PI_j = (1 + tt_j - ts_j + tf_j.xi\_f_j)PO_j + to_{jt}$$

where

$$tt_j^f = (1 + tt_j - ts_j + tf_j.xi\_f_j) + \frac{to_{jt}}{PO_j}$$

tt_j is the indirect sales tax; ts_j is the subsidy rate on sales; tf_j is fuel taxes set proportional to marginal damage of each type of fuel use (in couterfactual simulation); and to_j is the output taxes set proportional to sector level marginal damage (also in couterfactuals only).

To go from industry prices to commodity prices, I need a MAKE matrix. To keep things simple, I treat industry and commodity as identical and assume each commodity is solely produced by the corresponding industry. This would be the case if actual MAKE matrix is diagonal.

The cash flow of each sector is defined as enterprise income after deducting the land, labor and intermediate costs. Cash flow includes earning attributable to the capital services of the industry and also interest and transfer payments from the government to the enterprises ($G_{ENT,j}$).

$$CF(K_j) = (1 - tv_j)PKD_jKD_j + G_{ENT,j}$$

$$= PO_jQI_j - PTD_jTD_j - PLD_jLD_j - \sum_i PS_iQP_{ji} + GENT_j$$

I have introduced $G_{ENT,j}$, to denote direct grants from the government to enterprises. This is merely for accounting consistency. While these grants or subsidies are mostly for loss making enterprises, I ignore this aspect and treat them exogenously, keeping them only to match the data on government expenditures and the cash resources of each sector in the sample period.

RE_j is defined as retained revenue net of capital income tax. Dividends are received by households as a fraction of cash flow of each sector. This dividend payout ratio is set to match the data of SAM 2003-04 of India and it remains constant over years.

A.2 Households

Ideally Households should be modeled based a micro level survey providing us with the data on consumption, hours worked, education level, work experience etc. I leave this option for the future research. For the present model, I have households modeled in a way very similar to Solow growth model. Savings rate is set exogenously in the model. For simplicity leisure-consumption choice is not modeled. Labor supply is fixed in every period and grows with population exogenously over subsequent years. One immediate implication of this assumption is that income tax is a nondistortionary tax.

I write labor supply as a function of working population, annual labor hours worked and labor quality. All three components are calibrated to match the SAM of 2003-04 and then projected.

$$LS_t = POP_t^w \times hr_t \times q_t^L$$

There are 4 household groups with independent consumer behavior and with different shares in labor input. The disposable income for a representative household in each household group consist of their respective shares in labor income (net of labor income taxes), land income and distributed profits (dividend), interest payments from government to households (G_I), government transfers to individuals ($G_{transfer}$), and unrequited transfers from the Rest of the world ($R_{transfer}$). Each of these shares come from the SAM values and they don't change over years.

$$Y^{p,hh} = Y_{LS}^{hh} + (1 - tv)PT.TD^{hh} + DIV^{hh} + G_I^{hh} + G_{transfer}^{hh} + R_{transfer}^{hh}$$

where

$$Y_{LS}^{hh} \equiv (1 - t_L^{hh}) \sum_j PLD_j.LD_j^{hh}$$

where t_L^{hh} is labor income tax of household type hh.

Out of disposable income, an exogenous share goes to private household savings:

$$S^{p,hh} = s^{hh} Y^{p,hh}$$

I let household savings rate to project over years exogenously. The household maximizes a utility function defined over the 37 commodities subject to the budget constraint:

$$(1 - s^{hh})Y^{p,hh} = \sum_i PC_i C_i^{hh} \equiv C_{Exp}^{hh}$$

where PC_i is the market price of commodity i to the household sector and may include further consumption taxes or subsidies:

$$PCi = (1 + tc_i^{hh})PS_i \quad i \in I_{COM}$$

With Cobb-Douglas utility function,$U^{hh} = \sum_i \alpha_{iC}^{hh} ln(C_i^{hh})$, C_i is

$$C_i^{hh} = \alpha_{Ci}^{hh} \frac{C_{EXP}^{hh}}{PC_i}$$

Once again α_C^{hh} are obtained from the SAM.

A.3 Capital Accumulation

Capital accumulation follows standard Solow path where investment adds to existing capital stock and depreciation reduces it.

$$K_t = (1 - \delta)K_{t-1} + \psi_I II_a \quad \text{(A.1)}$$

K_t is the aggregate capital stock summed over different industries; $\delta$is the depreciation rate; II_a is the aggregate investment in the economy which is then converted into capital units from investment units[1]. The rate of return to the aggregated capital comes from the theory of cost of capital by Jorgenson (1963):

$$r_t PK_{t-1} = (1 - t_k)(1 - t_v)PKD_t + \delta PK_{t-1}$$

In the above equation, PKD_t is the price of capital services(aggregated over all industries), PK_{t-1} is the price of capital stock and r_t is the rate of return. The above equation implies that

[1]This is needed to take into account the fact that composition of investment might differ from composition of existing capital stock. In the base year, this parameter is normalized to 1 while for future years it is projected to a higher number on the assumption that future year investment would be on higher quality capital type.

people are indifferent between putting their money in banks for interest and investing in production with returns equal to after tax income plus capital appreciation.

I do not distinguish between inventory and fixed investment. The aggregate investment is allocated between 36 sectors according a Cobb-Douglas function as below:

$$(1+t_i)PS_iI_i = \alpha_{iI}PII_a.II_a$$

$$ln(PII_a) = \sum_i \alpha_{iI} ln(1+t_i)PS_i$$

PK and PII_a are related to each other due to the fact that one unit of investment can be converted into ψ_I unit of capital stock

$$PK = PII_a$$

A.4 Rest of the World

I keep the modeling for rest of the world simple. I make standard Armington assumption (Armington, 1969) and treat goods imported from other countries as imperfect substitutes of the domestically produced commodities. In other words, domestically consumed goods can be expressed as CES aggregate of domestically produced and imported goods. This means that the prices of importables and domestic prices play their roles in determining the demand of both varieties. A similar assumption on the exportables means that the export demand is dependent on the relative prices of both foreign and domestic prices.

Imports

Let PM_i^* be the world price of importable good i. The price to domestic buyers needs adjustment to tariffs, and pollution taxes (only in counterfactual):

$$PM_i = e(1+tr_i+tx_{vi})PM_i^* + tx_{ui} \qquad i \in I_{COM}$$

e is the exchange rate.

The supply price PS_i is the aggregate price index for a commodity-domestic or imported.

$$PS_i QS_i = PC_i QC_i + PM_i M_i$$

QS_i is defined as a CES aggregate of two varieties- domestically produced goods QC_i and imports M_i:

$$QS_i^{\rho_i} \equiv \frac{QC_i^{\rho_i}}{d_i} + \frac{M_i^{\rho_i}}{m_i} \qquad i \in I_{COM}$$

The dual definition of PS_i is:

$$PS_i^{r_i} = [PC_i^{r_i} d_i^{r_i} + PM_i^{r_i} m_i^{r_i}]$$

$$\rho_i > 1 \quad r_i = \rho_i/(\rho_i - 1) \quad \sigma_i = 1/(1 - \rho_i)$$

d_i and m_i are domestic and import share coefficients respectively. These are subject to change over time, but they are not indexed by time here for simplicity.

Exports

To keep the modeling simple, I write the export demand as a function of base export level and a function of relative prices.

$$X_i = EX_i[\frac{(1 + tr_i^*)PC_i}{e(1 + se_i)PE_i^*}]^{\eta_i}$$

EX_i is set exogenously at base exports, t_i^* and PE_i^* are the international tariff rate and price level of the ROW variety good, se_i is the export subsidy

Current Account and Foreign Debt

Current account balance has been assumed to be exogenous. CA is defined as follows:

$$CA = \sum_i \frac{PC_i X_i}{1 + se_i} - \sum_i PM_i M_i - NFY - G_{IR}(B^*) + R_{transfer}$$

NFY is net factor payments abroad, $R_{transfer}$ is unrequited transfers from ROW and G_{IR} is interest payments on stock of debt as defined below:

$$B_t^* + B_t^{G*} = B_{t-1}^* + B_{t-1}^{G*} - CA_t$$

Above equation adds both private and government debt together. I do not attempt to explain the division between two sources. All these elements mentioned above enter exogenously in the model and they are projected over years.

A.5 Government revenue and Expenditure:

Government sector plays a big role in India. Revenue is given by

$$REVENUE = R_{SALES} + R_{TARIFF}\text{-}R_{REBATE} + R_{CONSUMP} +$$

$$R_{VAT} + R_K + R_L + R_{EXT} + TAXN_{hh} + TAXN_{ent}$$

Most of the above taxes have been discussed earlier, so I do not elaborate on them. For example, R_{SALES} is sales tax collection that is levied on industry output at its output prices. R_{EXT} is the hypothetical externality tax revenue which can be either ad valorem or unit tax and they are imposed on both domestic production and importables. R_{VAT} is levied on value of primary factor contribution in every sector and so on. The last two terms are non tax receipts from households and enterprises and they are assumed to proportional to GDP over years.

Public expenditure consists of broad items like government purchases of goods and services; transfers, grants, subsidy, interest payments (to households, to enterprise or to ROW). Transfers from government include items like retirement payments and welfare payments, so they are set as proportional to existing population.

$$EXPEND = VGG + G_{SUBSIDY} + \sum_j G_{ENT,j} + G_{hh,I} + G_{IR} + G_{transfer}$$

where VGG is value of total government purchases and $G_{SUBSIDY}$ is subsidy to different sectors. I model allocation of VGG exactly the way I model consumption.

$$PS_iG_i = \alpha_{Gi}VGG$$

Public deficit is defined as :

$$DEFICIT \equiv EXPEND - REVENUE$$

This deficit is exogenous and projected over years in such as a way that deficit-GDP ratio falls slowly over time. VGG is determined endogenously, since tax rates are fixed, revenue depend on economic activity.

Government debt follows a path given by this equation:

$$B_t + B_t^{G*} = DEFICIT_t + B_{t-1} + B_{t-1}^{G*}$$

Appendix B

Projections of Exogenous Parameters

My projections of various exogenous parameters involve using various sources and also a lot of "guesstimating". This exercise affects the Business as Usual (BAU) scenario fundamentally, but the comparisons between BAU and counterfactual are hardly affected.

Labor force depends not only on working population, but also on participation rate and labor quality. I consider a single coefficient for these components which converts working population into labor hours supplied. For the base year, this is set to match the data from SAM, but over years I raise it for the first few few years by 0.4%; then at 0.3% and finally flatten to a constant. I take Census of India's projections of total population and working age population (age: 20-60 years). I estimate health effects only for the urban population and the projections of urban population also comes from Census of India.

Same as labor, future capital should also see improvement in quality or composition. Investments in future years are adjusted by a quality parameter ψ^I which initially rises at 1.4% and then falls to zero growth in 15 years.

Supply of land is fixed in the model. It is owned by rural households only and it is used as inputs only in 4 agricultural sectors. Land is assumed to be immobile across sectors.

There are four household groups and hence four representative households in the model. Over years, within rural or urban sectors, there is very little movement across these occupation groups. But overall urban sector is growing roughly at 0.7 % per annum, while rural sector is shrinking. I apply this rate of urbanization on various shares of 4 household types. For example, population shares of both urban poor and non-poor rise at 0.7%, while population share of rural poor and non-poor fall in such a way so that total of shares equal one. I do the same with other shares of household types, such as, share in labor income, share in dividend income, share in the government transfer and share in foreign transfer.

I have one savings rate for each of the household. I keep it constant over years. There are no signs of falling savings rate in India. Some projections predict a rising savings rate. To keep things simple, I let household type's savings rate constant over time, but aggregate savings rate still changes with more urbanization. It rises from 27.7% in 2003 to 28.6% in 2030. Dividend as a share of total cash flow is taken from the SAM as 0.57 and it is not changing over years.

The current account balance as a share of GDP is introduced exogenously in the model. Current Account balance in India can be very erratic. They oscillate from year to year. I use actual numbers of CA till 2010 and then project future CA balances to slowly fall to zero. The model needs estimates of Indian Exports demands in future. In absence of any information about future preferences on Indian exports, I do not project exogenous demand for exports in all sectors. I keep this constant over years, but model endogenously gives growth in exports driven by rising technological progress and falling prices.

The government deficit is set at 6.8% in the base year and it falls steadily by 10% over years and finally become zero in 2030. Total stock of debt is obtained from Budget 2003-04 and RBI website. This stock is made to fall slowly over time with its growth rate falling as well.

Technical progress is exogenous and exponential in nature. Technical growth rate is 1.8% for all the sectors.

Tax rates come from the SAM. In the SAM I have, one can only observe net indirect taxes (sales tax minus subsidy). Tariff collection is not separated from sales tax collection. As a result, I follow some thumb rules to determine these components in my analysis. Sectors with positive net tax values are assumed to receive zero subsidy and likewise I assume sectors with negative net tax are not taxed at all.

Cost share parameters of K,L,E,M and Land are slowly made to converge to corresponding parameters from US 1982 input output tables. The rate of convergence is slow in the sense that parameter from India SAM reach half way towards US1982 parameters in 2030, the last year of simulations. Similarly consumption pattern (α_C^{hh}) for every households, investment expenditure values shares (α_I) and government expenditure values shares (α_G) are also converged slowly to US 1982.

Appendix C

Sectors and Acronyms

Table C.1: Sector Names with their codes

S. No.	Sector Name	Sector Code
1	Paddy Rice	PAD
2	Wheat	WHT
3	Cereal, Grains, Other Crops	CER
4	Cash Crops	CAS
5	Animal Husbandry & prod.	ANH
6	Forestry	FOR
7	Fishing	FSH
8	Coal and Lignite	COL
9	Crude Oil	OIL
10	Natural Gas	GAS
11	Minerals n.e.c.	MIN
12	Food & beverage	FBV
13	Textile and Leather	TEX
14	Wood	WOD
15	Petroleum & Coal-tar Products(exc. Household Fuels)	PET
16	Household Fuels(Kerosene and LPG)	KER
17	Chemical, Rubber and Plastic Products	CHM
18	Paper & Paper Prod.	PAP
19	Fertilizers & Pesticides	FER
20	Cement	CEM
21	Iron and Steel	IRS
22	Aluminum	ALU
23	Other Manufacturing	OMN
24	Machinery	MCH
25	Hydro	HYD
26	Thermal	NHY
27	Nuclear	NUC
28	Biomass	BIO
29	Water	WAT
30	Construction	CON
31	Road transport motorized	RTM
32	Road transport non-motorized	RNM
33	Rail Transport	RLY
34	Air Transport	AIR
35	Sea Transport	SEA
36	Health & Medical	HLM
37	All Other Services	SER

Appendix D

ANOVA Test on Price indices

Table D.1: ANOVA Test on Food Price indices

ANOVA Test on Food Price indices					
Source of Variation	Partial SS	df	MS	F	Prob > F
Factor(state_code)	0.285780804	23	0.012425252	16.49	0
Residual	0.111503586	148	0.000753403		
Total	0.397284390	171	0.002323301		

Table D.2: ANOVA Test on Energy Price indices

ANOVA Test on Energy Price indices					
Source of Variation	Partial SS	df	MS	F	Prob > F
Factor(state_code)	7.806966350	23	.33943332	56.34	0
Residual	0.891620730	148	.006024464		
Total	8.698587080	171	.05086893		

Table D.3: ANOVA Test on Misc Price indices

ANOVA Test on Misc Price indices					
Source of Variation	Partial SS	df	MS	F	Prob > F
Factor(state_code)	0.298042187	23	.012958356	6.58	0
Residual	0.291301185	148	.001968251		
Total	0.589343372	171	.003446452		

Appendix E

Uncompensated Price Elasticities

Table E.1: Uncompensated Price Elasticities

	Uncompensated Price Elasticities			
	Price of Food	Price of Energy	Price of Misc	Price of Housing
Quant of Food	-0.717	0.016	0.065	-0.028
Quant of Energy	0.050	-0.886	0.122	0.022
Quant of Misc	-0.111	-0.010	-1.051	-0.036
Quant of Housing	-0.245	-0.047	-0.065	-0.932

Appendix F

Bridge Matrix

Table F.1: Bridge Matrix

	Food	*Energy*	*Misc*	*Housing*
Other Services(SER) + Transport	0.09670502	0	0.665666595	1
Food related industries	0.90329498	0	0	0
Energy related industries	0	1	0	0
Remaining Industries	0	0	0.334333405	0