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The Impacts of Green Pigovian Taxes on Urban Inequality in China*

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Abstract

Chinese officials have historically been reluctant to enact environmental policy out of concern for increasing economic inequality. However, no previous research on China has studied the distributional effect such policies would have. This paper investigates the impacts of two green Pigovian taxes on urban consumption inequality in China. It links price changes simulated by the general equilibrium Harvard-Tsinghua model (Cao, Ho, and Jorgenson 2009) to 2002 urban household data from the Chinese Household Income Project. The results show that a narrow tax on fossil fuels disproportionately burdened poorer individuals, while a broad output tax affected all individuals relatively evenly. These results extend the findings from the Harvard-Tsinghua model simulation, which previously examined the impact of the same taxes on health damages and overall economic performance. As expected, utility price increases were the primary drivers of unequal real consumption reduction. More surprisingly, lower food prices were a significant offsetting benefit that favored poor households. When examining the distributional effects of environmental taxes, policymakers and researchers should therefore also consider distributional impacts driven by price changes in non-energy consumption categories.

Table of Contents

Chapter 1: Introduction

Over the past three decades, China has quickly transformed from a centrally-planned economy into a burgeoning market-based economy. Its sustained GDP growth of almost 10% per year has pulled hundreds of millions out of poverty. This rapid economic expansion has established the country as the world's largest exporter and second largest economy (Monahan 2011). However, China's focus on economic growth has also increased both international and domestic scrutiny on two negative consequences: economic inequality and environmental degradation. To address these concerns, the Chinese Communist Party modified its development philosophy to emphasize greater social stability through economic equality, environmental improvement, and institutional reform. Announced in 2006 as the "Harmonious Society" Resolution, this philosophy was designed to lead China into the next stage of its economic and political development (Xinhua 2006; Geis and Holt 2009).

Chinese policymakers now must address three challenging goals of economic development, equality, and environmental protection. Simultaneous progress in all three areas is no easy task—addressing one of the issues often aversely impacts the other two. High economic growth has increased incomes at disproportionate rates, causing economic inequality to rise throughout the 1980s and 1990s. Though inequality stopped rising in the mid-2000s, a wide income gap still persists. Meanwhile, China's land, air, and water quality has deteriorated as the country continues to demand more fuel and resources for its growing economy.

Historically, China has been reluctant to enact climate change and pollution control policies out of fear that they would stunt economic development, poverty alleviation, and inequality reduction efforts (Heggelund 2007). The central government's continued suppression of oil and electricity prices reflects its unwillingness to raise energy prices on vulnerable households. However, Roumasset, Burnett, and Wang (2008) have pointed out that Chinese incomes are approaching the turning point on the Environmental Kuznets Curve for nitrous oxides (NO_x), particulate matter, and sulfur dioxide (SO_2). In the past several years, Chinese officials have indeed grown more concerned with the high health and economic costs from air pollution.

The Chinese government has recently taken several steps to reduce air pollutant emissions. The 11th and 12th Five Year Plans (FYP) covering 2006-2010 and 2011-2015 included binding energy intensity and pollution reduction targets. The 12th FYP also includes plans to introduce market-based pilot programs for carbon emissions trading (Hannon et al. 2011). In early 2012, China announced plans to implement a carbon tax on heavy energy consumers by the end of 2015, though its reasons for switching to a tax policy are unclear (Lee 2012).

An important strand of research has quantified the economic costs and benefits for various environmental policies in China. Another body of literature has measured and discussed the impacts of economic growth on inequality. However, to date no study has examined how an environmental policy in China would impact its economic inequality.[1] Intuitively, one would expect the primary impact on households to be through increased utility prices. This would produce a regressive effect on consumption since poorer households spend a higher share of their expenditures on utilities, which is a necessity good.

In this paper, I quantify the impact of fuel- and output-based "green" Pigovian taxes on urban consumption inequality. Extending the work of Cao, Ho, and Jorgenson (2009), I

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[1] Several studies focusing on the United States economy have addressed the distributional impact of environmental taxes. Metcalf (1999) used the U.S. Benchmark Input-Output Account to trace the direct impact of various green taxes on consumer prices. He then used the US Bureau of Labor Statistics' Consumer Expenditure Survey (CES) household data to examine distributional impacts. Jorgenson (2010) internally linked CES data with the Intertemporal General Equilibrium Model to trace carbon tax effects dynamically throughout the entire economy and its various household types.

apply the tax policy price impacts from their Harvard-Tsinghua model to a nationally representative urban household dataset from the 2002 Chinese Household Income Project (CHIP). In the first year of the policy, I find that the fuel tax decreased the consumption of the poorest quintile by two-thirds more than the consumption of the richest quintile. The output tax created more evenly distributed impacts: the difference in real consumption decline between the least and most affected quintiles was under 4%. Surprisingly, large decreases in food prices under the output tax disproportionately benefited the poor and thus offset the regressive burdens from increased utility prices.

This last finding has important implications for policymakers and future researchers. When considering the distributional effects of an environmental tax, it is not only important to analyze energy price effects, but also price changes in non-energy consumption categories. Furthermore, examination of the consumption inequality for each separate category can clarify the distributional impact of each category's price change. This particular output tax incentivized a sizeable industry shift into agricultural and food sectors. Since food expenditure was an evenly distributed necessity good, it comprised a larger share of consumption for the poor than the rich. The price decrease thus disproportionately benefited the poor.

The rest of this paper is organized as follows. Chapter 2 reviews the background literature on economic inequality, energy use, and environmental policy in China. Chapter 3 discusses the CHIP dataset, the Harvard-Tsinghua model, and my methodology in more detail. Chapter 4 presents the main results for price and inequality changes under the Pigovian tax policies, while Chapter 5 discusses the implications of my findings. Chapter 6 concludes.

Chapter 2:
Economic Growth, Inequality, and the Environment

2.1. Economic Inequality in Urban China

China's economic transition over the past three decades has had two major effects on urban incomes.[2] First, it has led to substantial income increases for all households. Second, income growth has benefited some more than others, creating higher levels of urban economic inequality. This section reviews the empirical literature behind these effects and provides background on the underlying reasons for disproportionate urban income growth.

Most empirical research on economic inequality has used more readily available income data to study household welfare. Studies using consumption data, however, have found similar results (see Wu and Perloff 2005; Cai, Chen, and Zhou 2010; Liu and Li 2011). The Chinese National Bureau of Statistics (NBS) conducts the most comprehensive annual household survey in China, but the raw data are not accessible to the public. Many researchers have thus used CHIP data, which allow access to household level micro-data from a subsample of the NBS surveys. The CHIP surveys also augment the NBS income data with additional information on subsidies and imputed rents. Gustafsson, Li, and Sicular (2008) have published a volume of studies that analyze the CHIP datasets. A series of working papers examining the new, unpublished 2007 CHIP data from editors Li, Sato, and Sicular is also available.[3]

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[2] Although I limit my discussion to urban areas, an important body of literature exists on poverty and inequality in rural areas. Absolute poverty has largely been limited to the rural areas. Thus, several government initiatives have specifically targeted poverty alleviation in the countryside. For more information, see Fan, Zhang, and Zhang (2002) and Luo and Sicular (2011).

[3] The working papers from *Rising Inequality in China: Challenge to a Harmonious Society*, edited by Li, Sato, and Sicular are available online at http://economics.uwo.ca/centres/cibc/workingpapers.asp.

The Chinese household data show that urban economic development has substantially raised incomes. Using NBS data, Benjamin et al. (2008) found that urban mean incomes steadily grew an average of 6% annually from 1991 to 2001. Using CHIP data and an income definition that included imputed rents and subsidies, Khan and Riskin (2008) calculated a similar 6.4% annual increase in urban incomes from 1995 to 2002.

This income growth benefited all households and thus pulled most out of urban poverty. Ravallion and Chen (2007), also analyzing NBS data, used a higher urban poverty line than the official threshold to account for higher urban costs of living. The authors found that the percentage of urban China in absolute poverty declined from 6% in 1981 to 0.5% in 2002, though the downward trend stagnated in the late 1980s and early 1990s. Deng and Gustafsson (2011) reported that absolute poverty levels continued to decline from 2002 to 2007 while incomes grew over 10% per year.

Urban economic inequality, however, has increased over the economic reform period. As shown in Figure 1, the urban Gini increased from around 0.22 in 1988 to 0.32 in 2007 when calculated with either CHIP income or consumption data. Since the CHIP data undercounted wealthy households due to under-coverage and underreporting of income, these Gini calculations likely underestimate inequality. Deng and Gustafsson (2011) showed that disproportionate growth in imputed housing rents and non-labor, private sector income to high income households drove income inequality upward from 2002-2007 after leveling off from 1995-2002. However, the trend in the CHIP consumption Gini in Figure 1 suggests that the income gap may be stabilizing in recent years. The most recent Gini coefficients published by the World Bank (2012) also indicate that inequality did not increase from 2002 to 2005.[4]

Underlying changes to the urban economy drove much of the disproportionate income growth. Urban areas had relatively low inequality prior to the 1978 economic reforms (Benjamin et al. 2008). The economic planners during this pre-reform period emphasized industrial growth in urban state-owned enterprises (SOEs) with resources extracted rurally. Almost all urban residents were guaranteed subsidized housing, healthcare, and lifelong jobs with the SOEs. To control the labor supply and provide population stability, the government used its *hukou* household registration policy to place tight restrictions on migration into urban areas (Chan and Zhang 1999). Most of China's poverty therefore remained in rural areas, where almost all of the population worked in large, underperforming agricultural collectives.

Starting in 1978, Chinese leaders began implementing a "dual-track" system that kept some socialist programs of the planned economy in place while gradually transitioning to a more market-oriented economy. The government specifically loosened its authority over land, labor, and capital by allowing greater market allocation of these factors of production (Gustafsson, Li, and Sicular 2008). China also opened to foreign investment, which led to an influx of foreign companies and new technologies.

These economic reforms increased both the level and dispersion of urban incomes. Private real estate markets formed in urban areas, allowing individuals to own property and earn rental income. Liberalized and more fluid labor markets allowed household income to better reflect a worker's education or skill level. However, the diminished role of SOEs also made it more difficult for the companies to provide equalizing benefits. In the mid-1990s SOEs buckled under the legacy burden of continued welfare support, leading to layoffs of

[4] The most up-to-date World Bank poverty estimates can be found online at its Poverty & Equity Database (http://povertydata.worldbank.org/poverty/country/CHN).

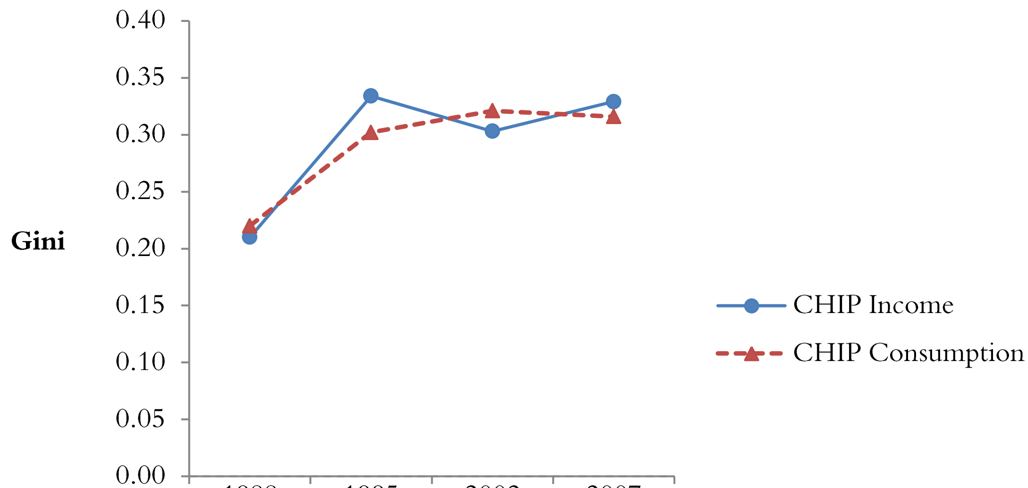
public sector workers and increased inequality (Fang, Zhang, and Fan 2002). Meanwhile, there was limited development of alternative social programs and institutions to replace the eroding social safety net (Benjamin et al. 2008; World Bank 2009).

Another major consequence of urban economic development has been the influx of long-term rural-to-urban migrants into cities. Sheng (2008) estimated that the number of migrants grew from 30 million in 1995 to 132 million in 2006. However, more recent migration has slowed as surplus rural labor supply dwindles and factories move closer inland (*Economist* 2010). Migrants compete with urban residents for low-wage jobs (Gustafsson and Ding 2011) but do not enjoy the *hukou* benefits of healthcare, education, and property ownership. Though migrants may help relieve rural poverty and inequality, they have become the unofficial urban poor, earning less than urban residents and living in poorer conditions.

Since migrants are not classified as urban residents under the *hukou* policy, they are excluded from both NBS and CHIP urban data. However, the 2002 and 2007 versions of the CHIP data include a long-term migrant sample. Li, Luo, and Sicular (2011) reported that migrant incomes rose faster than urban incomes, earning 77% of the income of urban residents in 2002 and 88% of urban incomes in 2007. For the 2002 data, Khan and Riskin (2008) calculated that including the migrant sample would increase the urban Gini by 6%. Inequality measures taken from urban residents will thus understate the disproportionately poorer conditions of migrants. This bias will likely shrink in the future as migration slows and migrant incomes continue to rise.

China's rapid economic growth raised overall income levels and led to the "greatest poverty reduction in history" (World Bank, 2008). However, the inequality created will pose continued challenges to Chinese policymakers as they seek to improve social equality in the "Harmonious Society". China has already implemented and expanded urban social insurance initiatives like pensions and the urban *di bao* program under the 11^{th} and 12^{th} FYP. However, coverage is generally inconsistent and could be expanded, particularly to migrants (World Bank 2009). China will also face increased demand for social programs as its old age dependency ratio rapidly increases over the next decade (World Bank 2012). Effects on inequality will thus remain a high priority for the Chinese government as it considers environmental taxes.

FIGURE 1: CHIP Urban Inequality, 1988-2007



	1988	1995	2002	2007
CHIP Income	0.210	0.334	0.303	0.329
CHIP Consumption	0.22	0.302	0.321	0.316

Year

Source: Deng and Gustafsson (2011, CHIP income) and Liu and Li (2011, CHIP consumption).

2.2. Energy and the Environment in China

China's economic growth has made it one of the world's most energy intensive countries (Nielsen and Ho 2007). Its energy intensity was high prior to 1978. Chinese economic planners inefficiently allocated resources into highly energy-intensive industries rather than agriculture and light manufacturing, sectors in which China had a comparable advantage in unskilled labor (Fan, Perkins, and Sabin, 1997). Between 1980 and 2000, however, China's energy intensity declined. Berrah et al. (2007) estimated a 0.43 elasticity of energy demand as energy use doubled while the GDP quadrupled over these two decades[5]. Past research on the causes of this decline pointed to structural shifts away from the most energy-intensive industries in metallurgy, refining, electricity, and chemicals; technological improvements from increased innovation and new foreign technologies; and relaxed energy price regulation (Fisher-Vanden et al. 2004; Hang and Tu 2007; Ma and Stern 2008).

From 2000 to 2005 elasticity of energy demand increased to around 1.0-1.4 as energy intensity again increased. Rosen and Hauser (2007) argued that this shift reflected shortcomings in the financial system and political economy, both of which favored development of heavy industry. State-owned banks extended loans to energy-intensive SOEs at relatively low risk: SOE operating costs were low and the companies were able to export excess capacity at will without fear of exchange rate appreciation. Local officials were promoted based primarily on economic performance and thus overlooked environmental concerns. Localities would compete for heavy industry development and the high tax revenue it generated (Roumasset, Burnett, and Wang 2008).

[5] Over-reporting of GDP and other data issues may also contribute to changes in energy intensity statistics (Fisher-Vanden et al. 2004; Nielsen and Ho 2007).

Continued government ownership of energy companies has allowed China to maintain artificially low energy prices that favor energy-intensive industries and deter efficiency improvements (Zhao, Ma, and Hong 2010). Four large state-owned oil companies dominate the oil industry and five state-owned power companies control the electricity market (Ni 2009). While the government slowly deregulated coal starting in 1994, it has continued to control oil and electricity prices while compensating the SOEs for their losses (Hang and Tu 2007; Rosen and Hauser 2007; Ni 2009). During the global oil price spikes from 2005-2008, the government tightly controlled end-consumer prices to avoid inflation, costing Chinese oil companies and the government billions of yuan but benefiting consumers. The government similarly subsidized electricity prices when coal input prices soared, keeping down price inflation for end consumers while generating substantial losses for China's power companies. Government price regulation thus highlights China's fear that higher energy prices would burden vulnerable low-income households as well as its energy-intensive industries (Hang and Tu 2007). These energy pricing regulations have protected economic growth and equality at the expense of energy efficiency and the environment.

China's growth has indeed made it the biggest energy user in the world on aggregate. In 2007 it surpassed the United States as the world's top greenhouse gas emitter, and in 2009 it passed the US as the top energy consumer (IEA 2010). It is home to the world's largest coal industry and second largest power industry (Berrah et al. 2007; Billings and Wei 2011). China relies on coal for 70% of its energy needs[6] and continues to emphasize the importance of its coal industry while it develops alternative energy sources in oil, natural gas, and renewables (Ni 2009).

[6] For comparison, the second largest share of coal consumption in the world is India, which consumed almost 55% of its energy from coal in 2004 (Table 14.3, Naughton 2007).

Recently, China's high energy use and reliance on coal has focused attention on the costs of environmental pollution.[7] A number of assessments have quantified pollution damages in China. A 2004 "Green GDP" estimate from China's State Environmental Protection Agency (SEPA) and the NBS reported that economic loss from pollution reached 3% of national GDP (Du 2006). The Ministry of Environmental Protection (MEP) later calculated economic losses of 3.8% of GDP in 2009 (Zheng 2012). Focusing on air pollution, The World Bank (2007) and SEPA estimated national health damage at 3.8% of GDP in 2003. Cao, Ho, and Jorgenson (2009) used the linked atmospheric and economic Harvard-Tsinghua model to estimate national air pollution damages at 1.8% of GDP in 2002.

China has made recent administrative changes to better implement energy and environmental policies. In 2008 the ministry-level MEP replaced SEPA, giving regulators more power to implement and enforce environmental policies. Additionally, the government has revised its promotion requirements for party officials to include compliance with environmental standards (Cao, Garbaccio, and Ho 2009).

Since 2005, China has also implemented a wide range of policies to encourage energy efficiency throughout the economy (Zhou, Levine, and Price 2010). Over the 11th FYP, China reduced its energy intensity by 19%—just short of its 20% target[8] (Hannon et al. 2011). The 12th FYP has set a binding 16% reduction target for energy intensity as well as a new 17% target for reducing carbon intensity.

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[7] High energy demand has also made the China increasingly reliant on foreign supplies in the volatile Middle East and Africa (Thomson and Horii 2009). Though not discussed here, energy security concerns are another reason for why China has promoted energy efficiency and also has continued to lean on domestic coal for fuel.

[8] Hannon et al. (2011) pointed out that in the final few months of the 11th FYP, Chinese officials scrambled to meet energy intensity targets by forcing black-outs and factory closures. While certainly not the advisable, these last-minute measures do highlight the increased pressure placed on local officials to meet environmental targets.

China has taken specific measures to reduce air pollution, particularly in urban areas. It has focused on alleviating health damages from carbon dioxide, SO_2, total suspended particulate (TSP), and NO_x.[9] The National Environmental Protection Plan for the 11th Five Years aimed to reduce carbon dioxide and SO_2 emissions by 10% and increase the urban air quality of major cities. The 12th National Environmental Protection Plan added NO_x and ammonia nitrogen to the pollution reduction goals (MEP 2012). China has levied pollution charges on various individual pollutants since the 1980s, though their effectiveness has been hamstrung by low charges, lack of compliance and other design flaws (Cao, Garbaccio and Ho 2009). Recently, Chinese officials have strongly considered implementing market-based policies to combat air pollution. The 12th FYP announced plans to create a carbon emissions trading system, though in early 2012 reports emerged that China would instead place a carbon tax on large energy users by 2015 (Wei 2012).

Several recent studies have quantified the costs and benefits of various environmental policies in China. Aunan et al (2007) used a computable general equilibrium model of the Chinese economy that specifically examined policy impacts on agricultural yields. The authors found that China could commit to reducing CO_2 emissions by up to 17.5% without suffering a welfare loss. Cao, Garbaccio, and Ho (2009) used the Harvard-Tsinghua model (discussed in detail in Chapter 3.3) to simulate the effects of two major SO_2-reduction policies: shutdowns of small power generation units and installations of flue gas desulfurization technology. They found that the policies would meet the 11th FYP SO_2 emission reduction target while achieving "unambiguously positive long-run impacts on the economy and the environment." Cao, Ho, and Jorgenson (2009) also used the Harvard-

[9] Mainly released through coal use, SO_2 emissions cause human health damages and acid rain for both China and its neighbors Korea and Japan. The smallest 2.5 micron TSP particles, designated $PM_{2.5}$, cause health problems through penetration deep into the lungs. NO_x facilitate the formation of harmful ozone and fine particles in addition to posing direct respiratory health risks (EPA 2010).

Tsinghua model to evaluate two broad Pigovian taxes: an output tax equal to the marginal health damage per unit output, and a fuel tax at 30% of marginal health damages per unit of fuel. As shown in Table 1, the authors found that the benefits created from the taxes far exceed their costs: fuel tax policy decreased health damages by 0.15% of GDP in the first year while the output tax decreased damages by 0.05% of GDP. Overall GDP and consumption, however, decreased very little to achieve those results.

Two overarching themes emerge from the existing literature. First, environmental policies often have broad impact, even when tailored to achieve specific goals. For example, the Pigovian taxes decreased health damages but also reduced SO_2 and CO_2 emissions, which were the targets for Cao, Garbaccio and Ho (2009) and Aunan et al. (2007) respectively. Second, the models indicate that well-designed environmental policies can substantially improve overall environmental outcomes at very low cost to economic growth. The impact on economic inequality, however, has never been explored directly with environmental policy scenarios.

TABLE 1: **Effects of Pigovian Taxes on the Economy and Environment, Year 1**

	Fuel Tax (%)	**Output Tax (%)**
GDP	–0.02	–0.01
Consumption	–0.17	–0.29
Investment	0.18	0.46
Coal Use	–12.0	–3.9
CO2 emissions	–3.1	–3.1
SO2 emissions	–10.3	–4.7
Reduction in damages/GDP	0.15	0.05
Changes in other tax rates	–2.1	–7.2
Pollution tax/total tax revenue	1.83	7.16

Source: Reproduced from Table 6 in Cao, Ho, and Jorgenson (2009).

Chapter 3: Data and Methods

3.1. The CHIP Data

I use the 2002 urban household dataset[10] from the Chinese Household Income Project (CHIP), an ongoing effort between NBS staff and researchers at the Chinese Academy of Social Sciences. The CHIP data draw from a subsample of the Household Income and Expenditure Survey (HIES) conducted annually by the NBS. Though the HIES is the most comprehensive survey of its kind in China, the NBS only publishes its data in aggregated tables. Furthermore, few details on the HIES methodology, quality, and comprehensiveness are released (Gustafsson, Li, and Sicular 2008). Past examination of the HIES has identified several sampling issues including inaccurate expenditure reporting by households (Gibson, Huang, and Rozelle 2003), undercounted income categories, exclusion of rural-urban migrants (Bramall 2001), and under-coverage of the richest and poorest households (Riskin, Zhao, and Li 2001).

The CHIP surveys are conducted every seven years to address some of the concerns with the HIES. The 2002 survey drew from a subsample of HIES households, covering 9,200 rural households across 22 provinces and 6,835 urban households in 12 provinces. It also contained migrant data covering 2,005 households. The households were given CHIP questionnaires that request additional income information on subsidies, imputed rental value, and public goods consumption. I use the CHIP expenditure data, which were directly copied from the HIES without additional information. It therefore has the same sampling issues as

[10] The 2002 CHIP dataset is the most recent, publicly available version. The most recent CHIP dataset from 2008 is not publicly available until late 2012.

the HIES discussed above. The data may also contain copy errors from when the numbers were transferred from NBS to CHIP records.

I use consumption rather than income[11] to capture economic welfare for two reasons. Theoretically, the Permanent Income Hypothesis argues that households maximize utility based on their unobserved permanent income (Friedman 1957). The related Life Cycle Hypothesis argues that while income levels differ depending on a person's age, consumption remains smooth across one's life (Aldo and Modigliani 1963). Consumption data are therefore a better measure of overall welfare than income because they are not as susceptible to large fluctuations (Jorgenson 1998). Methodologically, use of consumption data is the most direct way to model the impact of industry output price changes on households. Ultimately, studies by Wu and Perloff (2005) and Cai, Chen, and Zhou (2010) have shown that urban income and consumption inequality closely parallel each other.

[11] Most studies on Chinese economic inequality have focused on income. Chinese income data have historically been more reliable and thus allow for more accurate longitudinal assessments. Gustafsson, Shi, and Sicular (2008) argue that households may not have perfect access to savings or credit accounts to smooth their consumption patterns. For those households with access to savings accounts, NBS data trends have shown that expenditures have not increased as quickly as household savings rates and therefore may not capture increased permanent income (Appleton and Song 2010).

3.2. Calculation of Household Consumption

I group each urban household's consumption according to the categories from NBS consumption data tables published in Chapter 10 of the 2003 NBS Statistical Yearbook:

- Food, including tobacco and alcohol
- Clothing
- Household facilities, articles, and service
- Medicine and medical service
- Transportation and communication
- Education, culture, and recreation
- Residence, including rent, housing service, and utilities
- Miscellaneous good and services

To remain consistent with the NBS statistics, I omit in-kind expenditures and only include cash expenditures. I assign all members of a household the mean per capita expenditure.

I scale consumption figures up to national values using regional sampling weights calculated for each provincial region represented in the CHIP sample: east, west, coastal, and large metropolitan areas. The regional weights contain two ratios. The first scales the number of urban CHIP individuals sampled in region *r* to the population levels in the 0.95 per thousand 2000 census micro-sample. The second ratio scales this number up to the total 2002 urban population:

$$w_r = \frac{P_r^{census}}{P_r^{CHIP}} * \frac{P_u^{nation}}{P_u^{census}}$$

where w_r is the weight of region *r*, P_r^{census} is the population of region *r* in the 2000 census micro-sample, P_r^{CHIP} is the region population in the CHIP sample, P_u^{nation} is the 2002 national urban population, and P_u^{census} is the total urban population in the 2000 census micro-sample.

Since the CHIP dataset did not sample households for a number of provinces in each region, the weighting calculation above assumes that the sampled households were representative of the entire region. It also assumes that the urban population for each region grew at the same rate from 2000 to 2002 since I weight the regions using 2000 census proportions.

3.3. Harvard-Tsinghua Model

The Harvard-Tsinghua Model provides an integrated environmental, health, and economic assessment of the Chinese economy. Cao, Ho, and Jorgenson (2009) used the model to quantify the economic and environmental costs and benefits of two Pigovian taxes. At the center of the model is a general equilibrium component which simulates the Chinese economy. This component contains thirty-three production sectors that dynamically demand productive inputs and supply industry outputs. There is also one household sector that maximizes a utility function containing the outputs from production. The model first determines the amount of fossil fuel inputs needed in each production sector. The fossil fuel consumption is then used to calculate the emissions of three air pollutants—TSP, SO_2, and NO_x.

The atmospheric component of the model converts the emissions into spatial ambient concentrations, which depend on atmospheric conditions and emission source characteristics (i.e. emission height or velocity). These concentrations are then overlaid onto a population map to determine how many people are exposed to the pollution. The "intake fraction" of the pollutants determines the amount of emissions actually inhaled by the exposed population.

The health component of the model then uses concentration-response coefficients to estimate the health impacts due to pollution intake (Levy and Greco 2007). The economic value of the health impacts are estimated using willingness-to-pay (WTP) for changes in health risks. The WTP statistics were obtained from a 1999 contingent valuation survey in China (Zhou and Hammitt 2007) and other surveys from Western countries.

The Harvard-Tsinghua model has therefore assigned economic values of health damages to specific emissions, which can then be traced back to their output or fuel source. The levels of the two Pigovian taxes are determined by these damage calculations. The output tax equals the marginal damage caused by an additional unit of output. The fuel tax is set at 30% of the marginal damage from an additional unit of coal, oil, or gas used (Ho and Jorgenson 2007). Cao, Ho, and Jorgenson (2009) applied these taxes to the Harvard-Tsinghua model updated with industry data from the 2002 Chinese input-output table. For both tax policies, the authors maintained government revenue neutrality by offsetting generated revenue with cuts to distortionary enterprise taxes.

Given the complexity of the Harvard-Tsinghua model and the quality of data that it demands, it contains a number of uncertainties and approximations. For example, pollutant concentration and human exposure calculations are extrapolated from detailed local studies to a national level, and contingent valuation methodologies may not fully capture society's WTP for certain health benefits (Diamond and Hausman 1994). The full Harvard-Tsinghua model and its limitations are described in *Clearing the Air: The Health and Economic Damages of Air Pollution in China*, edited by Ho and Nielsen (2007).

3.4. Price Changes to CHIP Consumption

The Harvard-Tsinghua model only estimates the price effects of the Pigovian taxes on a single representative household. In this paper, I analyze how the price changes impact the consumption of every urban household in the CHIP dataset. I require two bridge tables to link the impact of Pigovian taxes on CHIP consumption: the industry-NBS bridge and the NBS-CHIP bridge.

The industry-NBS bridge[12] was calculated using the 2002 China input-output table and the United States trade and transportation margins as a first approximation. The bridge table links the 24 NBS consumption categories to the outputs from the 33 industry sectors after accounting for trade and transportation margins. I use this bridge to calculate the price changes for each NBS consumption category. The price change for any particular NBS category *n* is the weighted average of the price changes in all sector outputs linked to *n*. Thus

$$P_n = \sum_{i=1}^{33} (P_i * \beta_{n,i})$$

where P_n is the percentage price change for NBS category n, P_i is the percentage price change for industry sector i, and $\beta_{n,i}$ is the percentage of output in sector i allocated to NBS category n.

The NBS-CHIP bridge links 84 CHIP consumption categories with relevant NBS consumption categories. Though the CHIP data had been copied from consumption data used by the NBS, the CHIP data were missing a few key NBS subcategories. For example, the bridge table separates transportation into several NBS subcategories such as transportation products, fuel, and fees, each with different linkages to industry sectors in the industry-NBS bridge. However, the CHIP transportation data only include one subcategory for

[12] Unlike the US, China does not publish official trade and transportation margins. Jing Cao kindly provided me this bridge table for use in this paper.

"transportation fees". The NBS-CHIP bridge was thus constructed to proportionally divide a large CHIP category like "transportation" into the relevant NBS categories. Appendix A provides more detail on how CHIP variables were linked to the NBS categories.

I use the NBS-CHIP bridge to calculate price changes in the CHIP categories. The price change for any CHIP category *c* is the weighted average of the price changes in all NBS categories linked to it. Thus

$$P_c = \sum_{n=1}^{24} (P_n * \alpha_{c,n})$$

where P_c is the percentage price change for CHIP category *c*, P_n is the percentage price change for NBS category *n*, and $\alpha_{c,n}$ is the percentage of NBS category *n* allocated to CHIP category *c*. The price changes for each CHIP category are calculated under both tax scenarios for 2002 and 2010.

3.5. Measurement of Economic Inequality

Two changes are applied to CHIP household consumption under the policy scenarios. First, every household experiences the same percentage change in income. I obtain the income change from the household sector in the Harvard-Tsinghua Model. Second, each household faces the price change P_c for each CHIP expenditure category *c*. Each household's overall price change can be expressed as the weighted average of all the individual price changes it faces:

$$\Delta P = \sum_{c=1}^{84} (P_c * \gamma_c)$$

where ΔP is the overall percent change in prices faced by the household, P_c is the percentage price change for CHIP category *c*, and γ_c is the household's ratio of consumption in CHIP category *c* to its total consumption.

I use the changes in income and prices for each household to calculate the change in real consumption. I start with a basic equation for expenditure *E,* price *P* and quantity *Q,*

$$E = PQ$$

and for small percentage changes,

$$\Delta E = \Delta P + \Delta Q$$

$$\Delta Q = \Delta E - \Delta P \tag{1}$$

If we assume that the percentage change in household income ΔI is a change in permanent income, then by the Permanent Income Hypothesis, $\Delta I = \Delta E$ since household expenditure reflects permanent income. Furthermore, the percentage change in quantity is equivalent to a change in real expenditure ($\Delta Q = \Delta E_{real}$) since Equation (1) adjusts for price changes. Equation (1) thus becomes an equation for the percentage change in real expenditure,

$$\Delta E_{real} = \Delta I - \Delta P.$$

We can use this percentage change to obtain the new household expenditure E_{tax} under a Pigovian tax scenario:

$$E_{tax} = E_{base} * (1 + \Delta E_{real})$$

I measure consumption inequality under the base case and policy scenarios using the widely-used Gini coefficient, *G*:

$$G = \frac{2}{n^2 \bar{E}} \sum_{x=1}^{n} x(E_x - \bar{E})$$

where *n* is the total number of individuals in the weighted CHIP dataset, E_x is the total expenditure of person *x*, and $\bar{E}$ is the mean per capita expenditure (Whitehouse 1995).

I then decompose the overall Gini coefficient to explore the marginal effect of a small, isolated real consumption change in an individual category on total inequality. Building off the work of Shorrocks (1982) and Lerman and Yizhaki (1985), López-Feldman (2006) showed how the total Gini, *G*, could be decomposed using the following equation:

$$\mathrm{G} = \sum_{k=1}^{K} S_k G_k R_k$$

where S_k is the share of total consumption from category *k*, G_k is the category Gini, and R_k is the correlation between the cumulative distributions of consumption in *k* and total consumption. Marginal effects are calculated by taking the derivative of *G* with respect to a small percent change *e* in consumption category *k* (Stark, Taylor, and Yizhaki 1986):

$$\frac{\partial G / \partial e}{G} = \frac{S_k G_k R_k}{G} - S_k$$

Chapter 4: Results

4.1. Changes to Real Consumption

In the first year, the average urban household faced a decrease in real consumption of 0.15% under the fuel tax and 0.27% under the output tax compared to the base case. By 2010, the policy effect on real consumption was less negative, with a fall in consumption of 0.12% under the fuel tax and 0.21% under the output tax. Table 2 decomposes these overall real consumption changes into the specific changes for each expenditure category. The percentage change for each category is weighted by its average proportion of total expenditure in the base case. The table also presents each category change's share of contribution to the total consumption change.[13]

Real consumption of food and clothing increased under every policy scenario. The contributing share for these two categories was negative since their changes counteracted the overall decrease in real consumption. On the contrary, utility consumption changes contributed the largest share to overall consumption decrease across all scenarios. Almost all other categories experienced smaller falls in real consumption.

Under the output tax in both years, food and utility changes were greatest in magnitude but affected overall consumption in opposite directions. Compared to the fuel tax, the output tax increased real food consumption by roughly five times more. It also raised real clothing consumption substantially higher. However, for the remaining categories it generally reduced real consumption further than the fuel tax. In particular, it decreased real utilities consumption by 50% more.

[13] Category share = weighted percent change for the category / total percent change

TABLE 2: Average Real Consumption Change, by Weighted Percent and Share of Total Change

Category	2002 Fuel		2002 Output		2010 Fuel		2010 Output	
	Weighted Percent	*Share*	*Weighted Percent*	*Share*	*Weighted Percent*	*Share*	*Weighted Percent*	*Share*
TOTAL	**-0.145%**	**100**	**-0.273%**	**100**	**-0.115%**	**100**	**-0.214%**	**100**
Food	0.008%	-5.57	0.041%	-15.12	0.038%	-33.02	0.158%	-73.48
Clothing	0.000%	-0.26	0.010%	-3.56	0.007%	-6.34	0.035%	-16.20
Household Articles, Facilities, Services	-0.008%	5.53	-0.010%	3.61	-0.003%	2.21	0.002%	-0.81
Medical	-0.006%	3.86	-0.037%	13.57	-0.003%	2.30	-0.054%	25.31
Transportation	-0.006%	4.20	-0.020%	7.46	0.000%	0.14	-0.011%	4.96
Communication	-0.010%	6.68	-0.034%	12.53	-0.004%	3.27	-0.029%	13.55
Education, Culture, Recreation	-0.022%	15.24	-0.057%	20.92	-0.001%	0.79	-0.040%	18.63
Housing	-0.006%	4.30	-0.020%	7.32	0.001%	-0.69	-0.005%	2.13
Utilities	-0.093%	64.04	-0.139%	50.74	-0.151%	131.4	-0.269%	125.49
Misc. Goods and Services	-0.003%	1.97	-0.007%	2.53	0.000%	-0.07	-0.001%	0.41

Source: Author's calculations.

4.2. Changes to Consumption Inequality

The base case Gini coefficient was 0.331. In the first year, the fuel tax increased the base Gini by 0.036% while the output tax very slightly decreased the Gini by 0.009%. Both policies had a more positive effect on inequality in 2010: the fuel tax increased the Gini by 0.063%, and the output tax increased it by 0.027%. Table 3 displays the Gini coefficients and changes for all policy scenarios. Figure 2 breaks down the decrease in real consumption by quintile and tax policy in 2002. The quintiles are delineated by total per capita expenditure. Under the fuel tax, the poorest quintile faced a 66% greater reduction in real consumption compared to the richest quintile. The output tax affected all quintiles similarly: the difference in consumption reduction between the least and most affected quintiles was less than 4%.

In Table 4, I decompose the total base case inequality by expenditure share, Gini coefficient, and marginal effect for each consumption category. Food, utilities, and clothing were the most evenly distributed expenses with Gini coefficients of 0.28, 0.34, and 0.45 respectively. These categories had negative marginal effects on overall inequality. For example, holding all other consumption constant, a 1% rise in real food consumption would decrease the total Gini by 0.116%. Similarly, an isolated 1% fall in real utilities consumption would increase the Gini by 0.025%. The remaining expenditures were more unevenly distributed across the urban population and had positive marginal effects on the total Gini. In general, the magnitude of a category's marginal effect corresponded to its share: food had the highest expenditure share and also the greatest magnitude of marginal impact.

In Figure 3 I further examine the distribution of base case expenditure shares for food and utilities, which had the largest consumption changes under the output tax (Table 2). The poorest quintile of individuals spent half of their expenditures on food, while the richest quintile spent less than one-third. For utilities, the poorest individuals spent twice as much expenditure share compared to the richest. These results capture the relatively low Gini coefficients for food and utilities. On the contrary, culture, education, and recreation expenses were more disproportionately distributed with a Gini of 0.65. As displayed in Figure 3, the richest quintile spent almost double the proportion of their expenses on this category compared to poorer individuals.

TABLE 3: Gini Coefficients by Tax and Year

(Change from base case in parentheses)

	Base	30% Fuel	100% Output
2002	0.3311	0.3312 *(+0.036%)*	0.3311 *(-0.009%)*
2010	--	0.3313 *(+0.063%)*	0.3312 *(+.027%)*

Source: Author's calculations.

TABLE 4: **Decomposition of Total Gini Coefficient, Base Case**

	Share of Total Expenditure (S_k)	Gini coefficient (G_k)	Correlation (R_k)	Marginal effects (% Change)
Food	.3834	.2834	.8130	-0.116
Clothing	.0943	.4490	.6405	-0.012
Household Articles, Facilities, Services	.0644	.6383	.7145	0.024
Medical	.0697	.6484	.5840	0.010
Transportation and Communication	.1003	.5230	.7805	0.023
Education, Culture, Recreation	.1527	.6484	.7256	0.046
Housing	.0442	.8886	.7183	0.041
Utilities	.0567	.3363	.5490	-0.025
Miscellaneous Goods and Services	.0343	.5879	.7105	0.009

Source: Author's calculations.

FIGURE 2: Decrease in Real Consumption under 2002 Tax Scenarios, by Quintile

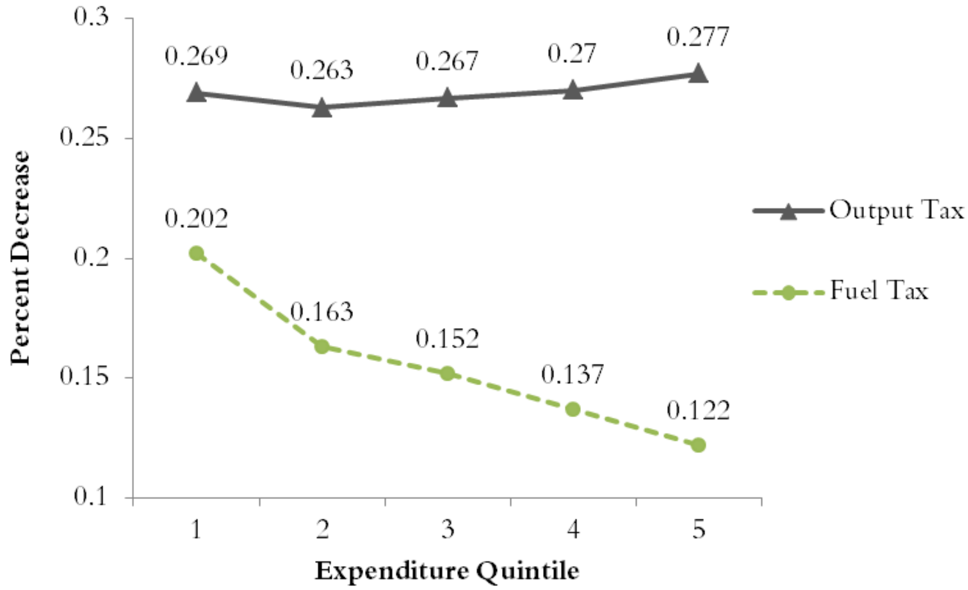
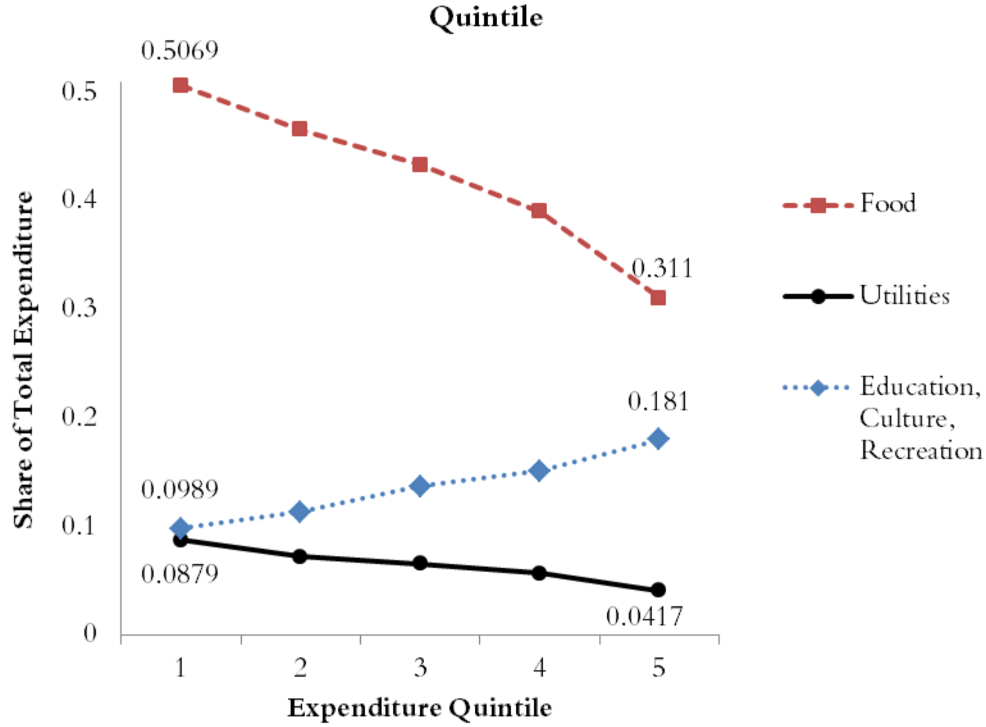


FIGURE 3: Selected Category Share of Expenditure, by Quintile



Source for Figures 2 and 3: Author's calculation.

Chapter 5: Discussion

5.1. Distributional, Economic, and Environmental Impacts of the Taxes

Differences in the changes to food and utility consumption under each policy were the primary reasons for the disparity in inequality outcomes. Since both categories were relatively evenly distributed as necessity goods, poorer individuals spent a larger share of consumption on these categories than wealthier individuals. The consumption of the poor was therefore more susceptible to changes in food and utility prices. Under the output tax, the rise in food and clothing consumption thus disproportionately benefited the poor, offsetting the regressive burden of higher utility prices. Simultaneously, the changes in consumption for the remaining categories were more negative under the output tax compared to the fuel tax. Expenditures in the remaining categories were unequally distributed, implying that consumption was proportionally higher for the rich. The fall in consumption for these categories hence hurt the rich more than the poor. Taking all the above effects together, the output tax had very little impact on inequality. On the contrary, the fuel tax had a larger impact on inequality because utility prices primarily contributed to the overall consumption decrease, while the percent changes in all other categories were much smaller.

Summarizing these findings more generally, a rise in consumption for categories with lower Gini coefficients tended to have a negative effect on total Gini, whereas a rise in consumption for categories with a high Gini tended to have a positive effect (see marginal effects in Table 4). It is also important to consider each category's share of total expenditure: a higher share would exacerbate the directional effect of the consumption change.

The distributional impacts of the tax policies highlight additional tradeoffs for policymakers to consider. Though the fuel tax produced more inequality, it did not decrease consumption as much as the output tax. The most affected quintile under the fuel tax only faced a 0.20% consumption decrease in 2002. By comparison, the least affected quintile under the output tax experienced a decrease of 0.26%, which was 30% more negative (Figure 2).[14] Drawing from the results in Cao, Ho, and Jorgenson (2009), the fuel tax also produced better environmental outcomes in the first year. The fuel tax decreased coal use by 12% and value of health damages by 9.1% (0.15% of GDP). The output tax had a much smaller impact on energy use and health damages: coal use dropped 3.9% and the value of health damages declined 3.1% (0.02% of GDP).

Analyzing differences in how each tax impacted the underlying economy helps contextualize the reasons for the disparate impacts on inequality and the environment. The fuel tax caused a greater reduction in health damages because it incentivized fuel switching, reduced energy use, and created an industry shift away from energy-intensive industries. The output tax only created a more substantial industry shift because altering fuel inputs or reducing energy use would not reduce the tax burden. This more pronounced shift increased supply and decreased prices in light industry sectors such as agriculture, food products, and textiles.

The output tax was also much broader than the fuel tax, which focused on the most energy-intensive industries. This broad coverage generated substantially more revenue but further lowered real consumption through greater price increases. Since the Harvard-Tsinghua model slashed enterprise taxes to maintain revenue neutrality, the output tax encouraged over 2.5 times more capital investment than the fuel tax in the first year. This

[14] My results for percentage consumption decrease are close to the Harvard-Tsinghua model results from Cao, Ho, and Jorgenson (2009). See Appendix C for more discussion on the comparability of my results with simulation results from the Harvard-Tsinghua assessment.

greater investment helped offset GDP loss from the tax, leading to higher investment and consumption in future years compared to both the fuel tax and base case.[15]

Across all quintiles, both policies diminished consumption by just fractions of a percent to achieve reductions in coal use and health damages over an order of magnitude higher. This high benefit-cost ratio resulted because costs to industry in highly-taxed sectors such as metals smelting, mineral products, and chemicals impacted intermediate and/or non-consumer goods. These tax impacts never reached end consumers because these goods were directed towards investment, government expenditures, and exports. Indeed, urban consumption accounted for just 14% of 2002 GDP (NBS 2007). Since average consumption decrease was small, ultimately the fuel taxes had very little impact on overall inequality as measured by the Gini (Table 4).

5.2. Model Limitations

Several constraints to both my methodology and the Harvard-Tsinghua model may have biased the findings on inequality. While significant, these limitations should not compromise the integrity of my findings because the environmental benefits far exceeded the costs to consumption and the impacts on inequality. Readers should consider the limitations as caveats to the use of the specific numbers presented in this paper.

First, impacts on inequality under the fuel tax are likely to be slightly higher because CHIP dataset did not include migrants. As discussed in Chapter 2.1, inclusion of migrants would augment the number of relatively poor urban individuals who are more sensitive to

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[15] Cao, Ho, and Jorgenson (2009) compared the policies to the base case in the twentieth year of the model. Under the fuel tax, GDP was 0.11% higher but consumption 0.04% lower. In comparison, under the output tax GDP was 0.7% higher and allowed for higher consumption and investment relative to the base case.

utility price increases. However, the CHIP dataset also underreported the incomes of the wealthy, which implies that inequality impacts would be slightly lower.

Second, methodological assumptions likely biased the 2010 inequality results upwards with the fuel tax. I applied income growth of 24% to all individuals equally from 2002-2010[16] with the assumption that individual consumption category shares would remain constant. In reality, shares of food, clothing, and utilities would decline as people gained income. A decline in utility expenditure share would close the difference in overall consumption change between the top and bottom quintiles since all would be more insulated from utility price increases. The effect of changing shares with income under the 2010 output tax scenario is unclear. Higher incomes would diminish both the losses of higher utility prices and the gains from lower food prices for the poor.

Third, data constraints to the population and emissions mapping in the Harvard-Tsinghua model prevented the distributional analysis of health impacts. It is plausible that poorer individuals lived closer to high-pollution sources and therefore would have benefit disproportionately from the tax policies. However, the population maps in the model did not include the spatial income or consumption distributions needed[17] to examine distributional health impacts.

Fourth, the Harvard-Tsinghua model did not consider adjustment lags or costs. Companies, investors, and workers would all require resources to respond to new incentives and offset the costs imposed by the tax policies. Initially, the taxes would create a greater decrease in GDP and consumption but achieve less health impact than simulated. These

[16] This assumption of equal income growth should be relatively accurate. Liu and Li (2011) found that the urban consumption Gini did not grow from 2002 to 2007. According to World Bank (2012) inequality data, China's overall inequality stabilized from 2002 to 2005.

[17] Construction of a population map differentiated by income or consumption would require detailed census-level household data by county. Currently, such data are not publicly available.

adjustment costs would temporarily increase inequality: poorer populations would be more susceptible to increased utility prices without enjoying the benefits of lower food prices from the industry shift.

Finally, minor flaws in the CHIP data and in the bridge tables linking output price changes to end user consumption may also alter the results. However, there is no clear presence of any directional bias. These concerns are discussed in greater detail in the Appendices.

5.3. Implications for Policy

When considering the Pigovian taxes, policymakers face complex tradeoffs among the competing effects on economic and consumption growth, inequality, and air pollution. Since the taxes change the underlying economy in different ways, each policy also carries political considerations. Now that officials have announced plans to implement a carbon tax by 2015, it is important to consider the political feasibility for each tax policy.

The broader output tax may garner more support because it is fair, covering most economic sectors. It also generated more revenue for the government in the model. However, a broad tax is generally more costly and difficult for the government to enforce. Furthermore, low energy-intensity industries may object and push for a narrower tax focused on heavy industry.

The fuel tax is narrowly targeted to high energy users and industries that include energy-sector SOEs and export manufacturers. As government entities, the SOEs may not be able to raise objections to taxes on their output. However, their link to the government may also provide them with an influential platform to lobby against the tax. Since the tax would impact exporters, the fuel tax may also garner domestic support because part of the costs will fall on countries that import Chinese goods.

The specific impacts of the taxes also depend on related policies. Policy efforts to encourage fuel switching, energy reduction, or worker reemployment would shorten the adjustment costs and help achieve quicker results. Improvements to economic inequality due to more generous social welfare programs, increased program coverage of migrants, or progressive income growth will further insulate households from utility price increases.

One should also consider alternative environmental policy scenarios. A different use of tax revenue could transfer all or part of the tax revenue to households as compensation for increased prices. A variation on the lump-sum transfer could provide more money to poorer households to decrease inequality as well as increase consumption. These household subsidies would trade increased consumption for lower GDP and investment in the future compared to the enterprise tax cut.

An initial, necessary step towards any tax on energy will likely require policy changes that liberalize energy markets. Currently, the government controls energy prices at below-market levels and subsidizes the energy SOEs for any losses. However, the 12^{th} FYP announced intentions to set prices closer to market level over the next few years. Allowing prices to gradually rise to market equilibrium may have impacts similar to the effects of the fuel tax, which raised energy prices above the market rates used to price energy in the Harvard-Tsinghua model.

Chapter 6: Conclusions

I have extended the research on environmental taxes in China by quantifying the effects of two Pigovian taxes on urban economic inequality. The results confirmed the concern that an increase in energy prices would place a disproportionate burden on poorer households. However, the results also highlighted the previously unexplored decrease in food prices, which offset rising utility prices by benefiting the poor. These findings present new policy tradeoffs, including one between changes in urban consumption and inequality: the fuel tax had a more disproportionate but less negative impact on consumption, while the output tax had a more balanced but also more negative impact. Overall, the environmental benefits far outweighed the very small changes to inequality, providing additional evidence for the high benefit-cost ratio found in Cao, Ho, and Jorgenson (2009).

Ultimately, the methods and findings presented this paper offer policymakers and researchers new insights for analyzing the impact of environmental policies on inequality. It is important to examine distributional impacts from price changes in non-energy consumption categories like food. This requires an analysis of the general equilibrium policy effects throughout all sectors of the economy. One can then approximate the direction and magnitude of the distributional impacts of such non-energy price changes by considering the total expenditure share and distribution of the affected consumption categories.

There are several avenues to improve this research in the future. Direct incorporation of the CHIP household dataset into a general-equilibrium system like the Harvard-Tsinghua model would allow households to experience differential income increases and dynamically change their expenditure patterns according to income level. If new data on the geographic distribution of income become available, the population and ambient concentration maps in the Harvard-Tsinghua model can be improved to study the distribution of health impacts.

This work can also be extended to include the rural CHIP dataset. Rural areas are substantially poorer than urban areas and contribute heavily to China's national inequality. Inclusion of rural household data would offer new insights into the impact of environmental taxes on rural and national inequality.

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Appendix A: Bridge Table Allocations

The NBS-CHIP bridge assigns every individual CHIP expenditure variable into relevant NBS categories. Table A1 lists the NBS categories with their assigned CHIP data variables. Detailed descriptions of the variables can be found in the 2002 CHIP documentation.

The industry-NBS bridge, which was created by Jing Cao, links price changes from the China's 33 industry sectors to price changes in NBS consumption categories after accounting for trade and transportation margins. Because China does not publish official trade and transportation margins, the bridge modifies the official U.S. data for the Chinese economy.

To check the accuracy of the bridges, I first allocate all weighted CHIP expenditures into their NBS categories using the NBS-CHIP bridge. The NBS-CHIP bridge table is structured such that for every household *h*, its expenditure on NBS category *n* is the sum of all the CHIP expenditures allocated to it. Thus

$$E_n = \sum_{c=1}^{84} (E_c * \alpha_{n,c})$$

where E_n is the household's expenditure for NBS category *n*, E_c is the expenditure for each CHIP category *c*, and $\alpha_{n,c}$ is the percentage of CHIP category *c* allocated to NBS category *n*. Once all expenditures are allocated across all households *h* = 1…6385, the total CHIP expenditures should equal the total NBS expenditures.

I then allocate the NBS expenditures into to the relevant industry sectors from which they originated. The industry-NBS bridge table links the 24 NBS consumption categories to the outputs from the 33 industry sectors after accounting for trade and transportation margins.

The table is structured such that for each household h,

$$Y_i = \sum_{n=1}^{24} (E_n * \beta_{i,n})$$

where Y_i is the output from industry sector i, E_n is expenditure in the *n*th NBS category, and $\beta_{i,n}$ is the percentage of NBS category n allocated to industry sector i. The total NBS (and CHIP) expenditures aggregated across households equals the total allocated industry sector outputs.

Table A2 compares the industry sector shares from the Harvard-Tsinghua model's 2002 social accounting matrix (SAM) with the allocated shares that I calculated. Since the 2002 SAM totals 3.6 trillion yuan sector output while I used the weighted CHIP expenditure total of 3.1 trillion yuan, I compare the percentage of allocated output for each industry sector. The table is organized from largest to smallest CHIP share and also displays the sector price changes from the Harvard-Tsinghua model output. The highlighted sectors are those that face the highest absolute price changes under the fuel and/or output tax.

The CHIP sector shares generally reflect the relative sizes of the SAM sectors. There are two major features of the CHIP data that explain why the shares do not perfectly match up. First, the consumption data from the CHIP dataset overestimated expenditures on some areas and underestimated expenditures in others. For example, the data included higher food expenditures (see Appendix B) and lower rental value of housing. Second, the CHIP data did not differentiate key subcategories like transportation equipment or fuel. I therefore assigned subcategory consumption using rough estimates from relative 2002 SAM shares or NBS aggregate data.

TABLE A1: **CHIP-NBS Variable Assignments**

NBS Category	Code	CHIP Variable Description
Food	E1	Expenditure on food, tobacco, alcohol, eating out
Clothing	F2	Expenditure on clothes
Household Articles, Facilities, and Services	F3	Expenditure on home equipment, facilities, and services
Medical	F4	Health and medical expenditure
Transportation	F514	Expenditure on transportation fees
	F5x	Expenditure on other transportation*
Communication	F522	Expenditure on communication services
	F5x	Expenditure on other communication*
Housing	F71	Expenditure on housing
	F73	Expenditure on housing services

*Note: F5x is the expenditure on transportation and communication not accounted for by F514 and F522. The category includes communication equipment, transportation equipment, fuel, and equipment fees (i.e. service and maintenance). I assign 69% of F5x to transportation and 31% to communication based on the relative 2002 SAM sector shares in refining, transportation equipment, and telecommunication equipment.

TABLE A2: **CHIP and SAM Industry Sector Shares with Price Changes**

Industry Sector	**CHIP shares**	**SAM shares**	**Price Change (Fuel)**	**Price Change (Output)**
Food products and tobacco	15.7%	12.9%	-0.04%	-0.12%
Sawmills and furniture	14.6%	17.0%	0.18%	0.88%
Agriculture	12.7%	15.2%	0.14%	0.08%
Hotels	7.9%	7.4%	0.00%	0.00%
Commerce and restaurants	6.9%	6.0%	-0.39%	-1.41%
Apparel, leather	6.7%	5.5%	0.05%	-0.06%
Transport and warehousing	4.4%	3.3%	0.19%	1.30%
Electrical machinery	4.0%	2.0%	0.15%	0.03%
Electronic and telecommunications equipment	3.3%	2.8%	0.10%	-0.10%
Business	2.9%	1.5%	0.06%	0.07%
Finance and insurance	2.9%	2.6%	0.06%	-0.14%
Post and telecommunication	2.8%	2.5%	0.12%	0.08%
Electricity	2.7%	2.5%	1.97%	4.45%
Real estate	2.6%	6.4%	0.08%	0.08%
Chemical	2.0%	2.6%	0.35%	0.49%
Other Manufacturing	1.4%	1.1%	0.12%	-0.11%
Textile goods	1.2%	1.6%	0.14%	0.20%
Gas production and supply	1.1%	0.4%	2.97%	0.71%
Build	1.0%	1.3%	0.67%	2.70%
Paper products, printing	0.8%	1.0%	0.09%	0.39%
Metals smelting and pressing	0.8%	0.8%	0.29%	0.36%
Coal mining and processing	0.4%	0.4%	12.97%	0.18%
Machinery and equipment	0.4%	0.2%	0.22%	0.08%
Petroleum refining	0.3%	0.3%	1.11%	-0.23%
Instruments	0.2%	0.2%	0.12%	-0.07%
Sawmills and furniture	0.1%	0.9%	0.18%	0.09%
Natural gas mining	0.1%	0.1%	0.15%	-0.09%
Nonferrous mineral mining	0.0%	0.1%	0.23%	0.45%
Metal products	0.0%	0.0%	0.54%	0.92%
Transport equipment	0.0%	1.3%	0.10%	-0.16%
Crude petroleum mining	0.0%	0.0%	-0.07%	-0.51%
Construction	0.0%	0.0%	0.28%	0.88%
Public Administration	0.0%	0.0%	0.11%	0.38%
TOTAL	**100%**	**100%**	**–**	**–**

Sources: Author calculations and SAM output file from Jing Cao

Appendix B: CHIP Expenditure and Gini Statistics

I first examine how closely the CHIP sample of households represented the more comprehensive NBS sample. Table B1 compares the per capita consumption calculated from the weighted CHIP data with the official NBS figures published in the 2003 *Statistical Yearbook*. The per capita expenditures calculated from the weighted CHIP data are close but slightly higher than the official NBS statistics. Interestingly, the per capita statistics calculated from the raw CHIP data were much closer to the NBS figures, although the CHIP subsample clearly was not representative of the national population. Though the more prosperous eastern provinces have double the population of the poorer western provinces, a similar number of individuals (6,037 and 5,570, respectively) were sampled from those regions. The use of regional sampling weights would increase the weights given to the under-sampled coastal provinces and inflate per capita expenditures. Furthermore, since the CHIP survey omitted households from many provinces, the CHIP regional subsamples may not accurately represent the NBS regional samples. The actual method by which the NBS selected the CHIP provinces is unclear (Song, Sicular, and Yue 2011).

The weighted CHIP data consists of 502.1 million urban individuals represented within the 6,385 sampled CHIP households, matching the official 2002 urban population. The total urban household expenditure of 3.12 trillion yuan from the weighted data exceeds the official NBS number of 2.74 trillion Yuan from the 2003 NBS Statistical Yearbook (Table 3-12), but falls short of the 3.63 trillion yuan statistic revised after the 2006 GDP revisions[18]

[18] The 2006 revision methods for household expenditure and for overall GDP have come under heavy criticism by researchers attempting to replicate the changes (Wu 2007; Holz 2008). It appears the NBS conducted two opposing revisions: a downward adjustment of urban real growth rates and a large reclassification of pollution formerly considered "rural" to "urban," with the latter revision causing the large adjustment to urban expenditure.

(2007 Statistical Yearbook). The 2003 Statistical Yearbook figure of 2.7 trillion yuan in urban household expenditure is more relevant to the CHIP data because it was calculated using the household survey data and retail sales data for commodity expenditures (Holz 2004). My higher CHIP estimate reflects the higher per capita expenditures discussed above, though both my estimate and the NBS statistics likely undercount household expenditures due to the NBS sampling and data collection issues discussed in Chapter 3.

My base case Gini coefficient (0.3311) is slightly higher than both the CHIP-based income Gini (0.303) and the consumption Gini (0.321) from Figure 1. However, my use of the data differs from the existing research in three areas that may contribute to different base case Gini calculations. These differences are unlikely to affect my results, which examine the change in Gini between the base and policy cases.

First, CHIP and NBS urban consumption data undercounted incomes of the wealthy, imputed rents, and subsidies. The latter two are more accurately addressed with the augmented CHIP definition of income.[19] Though the undercounting may change the absolute Gini coefficient, it would not significantly affect the change in Gini since housing prices changed very little compared to utility prices under the tax policies. The undercounting of wealthy incomes may also be offset by the exclusion of stable urban migrants. Second, I did not account for temporal and regional price differences within China. Adjusting for inflation and regional purchasing power parity would likely lower the Gini coefficient but it would not affect the expenditure category shares, which are the primary drivers of overall inequality change. Finally, I assigned each member within a household the mean share of their CHIP household's consumption. Liu and Li (2011) accounted for different household compositions

[19] Liu and Li (2011) include calculated imputed rents and subsidies in their definition of consumption. I only include the imputed rents present in the CHIP consumption data, and I exclude subsidies because they are transfer payments.

by applying "equivalence scales" (OECD) to yield more representative per capita data. This method would not change the relative share of total expenditure allocated to each expenditure category.

TABLE B1: CHIP and NBS Urban Cash Expenditure Per Capita

Living Expenditures		**Urban Expenditure Per Capita** (2002 Yuan)			**Difference**
		Raw CHIP	**Weighted CHIP**	**NBS**	**Weighted CHIP to NBS**
Total		6022.2	6210.3	6029.9	2.99 %
Food, Alcohol, Tobacco		2294.8	2381.2	2271.8	4.82 %
Clothing		584.9	585.9	590.9	-0.85 %
Household Articles, Facilities, Services		390.2	400.0	388.7	2.91 %
Medical		422.1	433.1	430.1	0.70 %
Transportation and Communication		602.5	622.8	626.1	-0.53 %
	Transportation	257.1	264.6	267.2	-0.97 %
	Communication	345.4	358.2	358.8	-0.17 %
Education, Culture, Recreation		919.8	948.2	902.3	5.09 %
Residence		607.3	626.3	624.4	0.30 %
	Housing	270.9	274.3	242.6	13.1 %
	Utilities	336.4	352.0	357.0	-1.40 %
Miscellaneous Goods and Services		200.7	212.9	195.8	8.73 %

Sources: Author calculations and 2003 NBS Statistical Yearbook

Appendix C:
Consumption Changes and the Harvard-Tsinghua Model

The CHIP real consumption changes (Table 2) that I calculated were slightly lower than the changes found in Cao, Ho, and Jorgenson (2009). In the first year, the average CHIP consumption decrease under the fuel tax was 13% lower and the decrease under the output tax was 7% lower than the Harvard-Tsinghua simulation. There are two primary factors that likely contributed to these differences.

First, I only used the urban CHIP dataset while the Harvard-Tsinghua model used the consumption patterns from the national accounts, which included both urban and rural households. Rural households would generally experience greater real consumption decreases. They are substantially poorer than urban households, making them more susceptible to increased utility prices. Furthermore, rural households consume proportionally more in-kind foods. They thus would not benefit as much from the decreases in food prices that disproportionately favored poor urban households.

Second, the shares of expenditure from the national accounts used to create the Harvard-Tsinghua household welfare function may not match the shares for the average CHIP individual. However, it is difficult to explain any differences because the national accounts were revised in 2006 using an unpublished revision methodology (Holz 2008).

Ultimately, these differences were small and would not produce significantly different GDP, environmental, or distributional impacts from those simulated by the Harvard-Tsinghua model. The assumptions that were used to calculate the price changes and economic effects were in the Harvard-Tsinghua model and thus exogenous to my methodology.