# Three essays on environmental engel curves and international trade

by

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B.S., Shandong University of Political Science and Law, 2014

M.S., State University of New York at Buffalo, 2016

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AN ABSTRACT OF A DISSERTATION

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# Abstract

This dissertation comprises three chapters that investigate the correlation between household consumption choices and environmental consequences in the context of evolving after-tax incomes, with a specific focus on foreign content. Utilizing Engel curves, we analyze this relationship and subsequently decompose the composition effect to further estimate the contributions of changing consumption patterns.

In the first chapter, we estimate Engel curves to analyze the influence of foreign content (outsourcing) and foreign environmental taxes embedded in the consumption of final goods and services in the United States (U.S.). Using U.S. household income and consumption data spanning from 1996 to 2011, we observe that Engel curves exhibit concave shapes, gradually shifting downward over time in relation to the foreign content of goods and upward in response to foreign environmental taxes. Our findings indicate a decrease in the foreign content of U.S. household consumption bundles over time, primarily driven by significant income growth, leading to a shift in consumption towards goods with higher domestic content. This shift represents a movement along the Engel curve. Conversely, the greater share of U.S. household consumption of goods utilizing foreign inputs sourced from countries with higher environmental taxes is attributed to factors beyond income. Consequently, these factors contribute to the upward shift in this Engel curve.

In the second chapter, we examine the role of household consumption decisions in the generation of industrial waste and dust emissions. This inquiry stems from the association between manufacturing activities and environmental concerns, particularly regarding industrial waste and dust. Despite recent comprehensive policies in China effectively reducing emissions of atmospheric pollutants such as SO2, NOx, CO, PM10, and VOC, industrial waste and dust remain significant issues in Chinese metropolitan areas. Employing environmental Engel curves, we explore this relationship over time. Our findings indicate that Chinese households have contributed to lower industrial waste and dust emissions over time, primarily due to changes in the relative

supply and demand of pollution-intensive goods. This shift is reflected in a change in the Engel curve, accounting for 76% of the decline in industrial waste and dust emissions embedded in the consumption of goods in China.

In the third chapter, we conduct a systematic examination of Environmental Engel curves (EECs) to discern disparities between developed and developing countries based on their respective environmental stringency levels. Recognizing the substantial variability in environmental regulatory frameworks across nations, our empirical findings reveal that developing nations significantly contribute to the pollution embedded within U.S. household consumption patterns. This finding contrasts with the fact that developed countries primarily serve as the leading trade partners of the United States of America. Additionally, our study finds that pollution levels would have decreased over time, even without changes to production techniques. This decline can be attributed roughly equally to two trends: household income growth, reflected by movements along inelastic EECs, and economy-wide changes represented by downward shifts in EECs over time.

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# Dedication

To my beloved parents, Zhencong Li and Lian Jiang, for their boundless love, unwavering support, and countless sacrifices for me.

# Chapter 1

# Engel Curves on Outsourcing and Foreign Environmental Taxes: A Valued-Added Approach

## 1.1 Introduction

The integration of the world economy has achieved unprecedented levels during the 2000s.[1] It has essentially reshaped the global economy linking markets and consumers at a scale unimaginable just a few decades ago. An important facet of this integration process is the fragmentation of the production process across national borders (Antràs and Helpman, 2004; Koopman et al., 2014), a phenomenon better known as global sourcing. This important phenomenon is consequential in many dimensions, an essential one being the challenge of linking consumption decisions to the domestic production of goods using national input-output tables. By definition, the presence and growth of foreign outsourcing mean that domestic consumption choices may be related to imports of foreign-sourced inputs used in producing domestic goods and services for final consumption. In

[1] Bagwell et al. (2016) show that the most-favored-nation tariffs applied by developed countries on manufactured products decreased, on average, by 85 percent. Likewise, Nicita et al. (2018) argue that the average tariff faced by world exporters averaged around 2.6 percent in 2006. See their column at "https://cepr.org/voxeu/columns/trade-war-will-increase-average-tariffs-32-percentage-points".

this paper, we investigate the relationship between U.S. household incomes and the foreign content of the final goods and services they consume. Moreover, we also study the relationship between household incomes and the associated foreign environmental taxes embedded in their consumption bundles. We rely on the concept of Engel curves to study these relationships since our focus is the effects of consumption decisions. In the former case, we call this relationship the Engel curve on the foreign content of goods, while, in the latter case, we label it the Engel curve on the foreign environmental taxes.

The numbers on the fragmentation of production processes leave no margin for doubts about the importance of this topic. Johnson and Noguera (2017) show that the ratio between value-added and gross exports fell by 20 percentage points in manufacturing sectors between 1970 and 2009.[2] This finding implies that countries increasingly rely on foreign inputs to produce exported goods and services. Importantly, Antràs and Staiger (2012) indicate that most of the growth in international trade flows occurred through differentiated inputs. Thus, they confirm the importance of process fragmentation across borders and highlight that the uniqueness of inputs being traded challenges the multilateral trade system since bilateral negotiations may be needed to overcome holdup problems. Most recently, policy concerns with international integration have resurfaced, primarily since the election of former U.S. President Donald J. Trump.[3] These concerns with production fragmentation have also become intertwined with environmental policy. The U.S. Inflation Reduction Act of 2022 promotes the consumption of fuel-efficient vehicles (e.g., electric and hybrid cars) while promoting domestic production (or imports from preferential U.S. partners) of auto batteries and their components.[4] It then represents a key recent policy where economic integration and environmental policies intertwine. Notice that a central pillar of these policies is consumption behavior, where policy makers try to influence with various policy tools, which we study in this

[2] Wolszczak-Derlacz and Parteka (2018) confirm a substantial rise in offshoring in recent decades. The manufacturing offshoring intensity in 40 countries measured as the ratio of imported intermediate inputs to the value-added rose from 0.24 in 1996 to 0.30 in 2008.

[3] It is well documented that former President Trump initiated various trade skirmishes, some multilateral (e.g., tariffs on steel and aluminum) and some geared towards specific countries (e.g., tariffs on Chinese products via U.S. Section 301). For a timeline of these events, see https://www.piie.com/blogs/trade-and-investment-policy-watch/trumps-trade-war-timeline-date-guide.

[4] For more information, see U.S. President Joseph Biden's statement on electric vehicles and battery manufacturing at https://www.whitehouse.gov/briefing-room/statements-releases/2022/10/19/fact-sheet-biden-harris-administration-driving-u-s-battery-manufacturing-and-good-paying-jobs/

paper via estimation of Engel curves.[5]

Our econometric strategy to estimate these Engel curves follows the approach adopted by Levinson and O'Brien (2019). Our source of information about U.S. household incomes, expenditures, and demographic characteristics is the Consumer Expenditure Survey (CEX) from the Labor Bureau of Statistics, which is also used in their study. Instead, information on the production of final goods and services and input-output linkages is provided by the World Input-Output Database (WIOD). In this case, we can map the U.S. production of final goods and services to their foreign input sources, a point not explored in Levinson and O'Brien (2019). Notice that this mapping strategy allows us to measure the U.S. household exposure to the foreign content of the final goods and services they consume. Importantly, we can also use these production linkages to relate foreign inputs to their country of origin's environmental taxes by using the OECD Environmentally Related Taxes (ERT) database. This strategy enables us to measure U.S. households' exposure to foreign environmental taxes. This matter is undoubtedly vital since the acceleration of international trade has led to concerns about the potential adverse effects of international trade on the environment (Bombardini and Li, 2020; Tosun and Knill, 2009).

We use non-parametric and parametric econometric strategies to estimate these two Engel curves yearly, covering the period from 1996 to 2011. Their main characteristics are very robust regardless of the econometric strategy and whether or not we control for other household characteristics besides their income. The estimated Engel curves are concave and display a quadratic shape relative to income. Thus, their shape implies that high-income U.S. households may consume a bundle of goods and services with lower foreign content intensity than middle-income households. Likewise, high-income U.S. households consume more products that rely on foreign inputs from countries with lower environmental taxes than middle-income households. Importantly, we show that the Engel curve on foreign content shifts downwards over time while the Engel curve on foreign environmental taxes moves upwardly over the years. These shifts suggest that U.S. household consumption decisions have moved in the opposite direction to globalization by choosing goods

[5] Chai and Moneta (2010) find that Engel's work contains some interesting features in juxtaposition to both modern and classical literature. Then, they offer a few thoughts about the contemporary literature spawned by Prais and Houthakker (1955) and how it built upon Engel's research. Their paper does not include a discussion about foreign content.

with lower foreign content intensity over time. Instead, the results imply that the same decisions have favored goods and services relying on foreign inputs from countries with more lenient environmental policies, as signaled by their lower taxes.

The factors explaining these results borrow heavily from the literature investigating the evolution of U.S. pollution emissions. For example, in a seminal paper, Levinson (2009a) decomposes and measures the evolution of U.S. pollution into a scale effect, a composition effect, and a technique effect.[6] His results show that despite an increase in income, which produces a positive scale effect, the change in consumption choices towards cleaner goods (negative composition effect), and, primarily, because of decreases in pollution intensity (negative technique effect), emissions of major pollutants due to U.S. manufacturing activity have been reduced, on average, by twenty-five percent from 1987 to 2001. Besides, Shapiro and Walker (2018) confirm the prominence of the technique effect in explaining the reduction in the emission of major pollutants during manufacturing activity. But, most importantly, they show that the implicit cost of environmental regulations is primarily responsible for these significant emission reductions. In contrast, increases in firm-level productivity and reductions in trade costs do not play important roles in explaining this phenomenon.

Our paper focuses on the contribution of consumption decisions in explaining the foreign content and environmental taxes embedded in the consumption of goods and services. For this reason, we keep the input-output linkages and foreign environmental taxes at their 2002 levels. This decision essentially mutes the technique effect discussed above, corresponding to a decision also present in Levinson and O'Brien (2019). Notice that our measure for the average (across U.S. households) exposure to foreign content on consumption bundles decreases by about 9 percent over the years, while its counterpart involving exposure to foreign environmental taxes increases by about 2 percent. These effects seem economically meaningful. In addition, we find that changes in the composition effect cause 60 percent of the effect related to foreign content, i.e., as U.S. household incomes grew, they shifted to consuming goods with lower foreign content (negative composition effect). This effect represents a movement along the Engel curve. On the contrary, most of the impact related to the increase in exposure to foreign environmental taxes is driven by

[6]This decomposition is originally proposed in Copeland and Taylor (1995).

other (non-income effects) factors causing a shift in the Engel curve. Moreover, we consider the effects of income redistribution on consumption decisions. We conclude that income redistribution may lead to a shift in imports of inputs towards countries with higher environmental taxes. At the same time, it may lead to more economic integration as measured by the foreign content used to produce final goods and services.

Our paper is strongly related to the literature that uses the concept of Engel curves to study different economic phenomena.[7] As suggested above, Levinson and O'Brien (2019) use Environmental Engel curves to study how U.S. consumption decisions have affected pollution emissions.[8] They conclude that the composition effect and other non-income factors[9] (price changes and availability of goods) are equally responsible for the reduction in average emissions embedded in U.S. household consumption bundles. Sager (2019) estimates Environmental Engel curves to relate U.S. household incomes to the (carbon dioxide) $CO_2$ emissions embedded in their consumption choices. He can then estimate the effects of redistribution of income on $CO_2$ emissions, concluding that it may lead to greater emissions and create an "equity-pollution dilemma." A vast literature has studied the effects of aggregate (national) income on aggregate pollution levels across countries using Kuznets curves.[10] The general finding is that pollution emissions increase to a certain income point and then decrease. This relationship then displays an inverted U-shaped form. More recently, Kacprzyk and Kuchta (2020a) used a novel dataset[11] to proxy for development levels and estimate this curve for $CO_2$ emissions using data from 1992 to 2012. They find that the income threshold, beyond which increases in income lead to declines in pollution, is smaller and more stable than the

[7] Dunbar et al. (2013) use Engel curves to identify how total household resources divided up among household members. They find that large shares of resources are devoted to children, and the share increases with the number of children.

[8] They estimate separate Engel curves for five main pollutants, namely: particulates smaller than 10 microns (PM10), volatile organic compounds (VOCs), nitrogen oxides ($NO_x$), sulfur dioxide ($SO_2$), and carbon monoxide (CO).

[9] Non-income factors cause shifts in the Engel curve. On the contrary, income changes cause a movement along the curve.

[10] Torras and Boyce (1998) bring 'political and social economy' in environmental Kuznets curve and find that the growth of per capita income can be accompanied by improvements in at least some important dimensions of environmental quality in the developing countries. Hettige et al. (2000) suggest that the evidence on the inverted-U relationship only applies to a subset of environmental measures. By measuring the effect of income growth on three determinants of industrial water pollution, the environmental Kuznets curve rises rapidly through middle-income status and remains roughly constant thereafter.

[11] They use the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) nighttime light imagery as a proxy for the income level.

previous thresholds discussed in the literature. Notice that these papers neither focus on household exposure to the foreign content of consumption bundles nor rely on the WIOD to link household consumption to the sourcing countries accurately nor control foreign environmental taxes.[12]

The rest of the paper unfolds as follows: section 2 describes the data and methodology; section 3 presents the nonparametric estimates; section 4 explains the empirical strategy and discusses the results for parametric estimation of the Engel Curves; section 5 discusses the average decomposition of the average index values over time, and applies the estimated Engel curves to evaluate the effects of income redistribution efforts. Finally, section 6 concludes.

## 1.2 Data and Methodology

### 1.2.1 Data

Our key objective is to understand the relationship between household income, consumption, and the degree to which U.S. production of final goods relies on foreign-sourced inputs. These datasets enable us to estimate the Engel curve on the foreign content of goods. Likewise, we want to relate the U.S. consumption of final goods to the environmentally related taxes of the countries exporting inputs used in the U.S. production of final goods. This information enables us to estimate the Engel curve on foreign environmental taxes. Essentially, this effort requires detailed information on individual household consumption, the use of foreign-sourced inputs in the U.S. production of final goods, and foreign environmentally related tax rates of countries exporting inputs to the U.S. Importantly, our data on consumption and incomes cover the years from 1996 and 2011.

Our data with detailed information on household consumption choices and income is provided by the Bureau of Labor Statistics (BLS) in two quarterly surveys: the Interview Survey for major and recurring items and the Diary Survey for more minor or frequently purchased items. The CEX provides information on itemized household expenditures, incomes, and demographic char-

[12] Cole et al. (2014) combines production data with international environmental outsourcing data for Japanese firms. They conclude that Japanese firms outsource the dirtier stages of production to minimize domestic environmental regulation costs.

acteristics. Following Levinson and O'Brien (2019), we exclude households with expenditures on nursing homes, students, and the top and bottom 1 percent of households based on after-tax income. In addition, the sample is reweighted by age groups and homeownership status to deal with the potential bias caused by the sample size reduction. The CEX captures around 80 to 95 percent of total household expenditures and is categorized by about 850 universal classification codes (UCCs).

The estimated Engel curves relate household income over time to foreign outsourcing and foreign environmental tax indexes derived from the U.S. production of final goods and services. Notice that input-output matrixes allow researchers to connect the production value of domestic goods to the value added from inputs originating from different industries. The World Input-Output Database (WIOD) extends it to consider value-added from inputs originating domestically and from different countries and industries. Thus, it enables us to trace the contribution of foreign inputs (outsourcing) to the U.S. production of final goods. Information from CEX allows us to relate household income to house expenditure across industries. The combination of both datasets allows us to relate household income to foreign inputs embedded in U.S. household consumption. A similar rationale can be extended to the relation between U.S. household consumption and foreign environmental taxes as detailed below.

This strategy requires us to concord UCCs to the industries used in the World Input-Output Database (WIOD). This concordance proceeds in two steps. First, we follow Levinson and O'Brien (2019)'s strategy to concord UCCs to the industries in the U.S. Input-output (IO) matrix. Second, we expand on their work by constructing a concordance connecting IO codes to the WIOD codes, thus bridging the linkage between CEX and WIOD codes.[13] Numerous IO codes may correspond to the same WIOD code owing to the restricted number of sectors (35 sectors and 40 countries) in the World Input-Output Database.[14] The WIOD provides a set of national input-output tables connected by bilateral international trade flows. Then, the WIOD provides for a given user, defined at the country and industry level, the information about the distribution of the output of different industries across countries. Therefore, the gross output of each U.S. industry is equal to the sum

[13] We provide further details on the concordance between the UCCs and the WIOD industries in the supplemental appendix A.

[14] See Timmer et al. (2015b) for details on the WIOD.

of the uses of foreign countries and the uses of other U.S. industries.

Our approach focuses on the relationship between household income levels and their consumption decisions. For this reason, we maintain technology and foreign environmental taxation constant for our baseline results while accommodating discussions on potential technology changes and income redistribution as extensions. Notice that Levinson and O'Brien (2019) estimates EECs using a similar assumption.[15] Our strategy to keep technology constant during the baseline analysis allows us to discern whether shifts in consumption patterns are affected by factors like consumer preferences or policy alterations. Our analysis then uses the WIOD and ERT databases to incorporate the more realistic and important assumption that technology and environmental taxes vary across countries. This strategy allows us to consider the potential impact of (different) foreign environmental tax policies on U.S. household consumption via the usage of imported intermediate products.

It is well understood that aggregate pollution levels generated by U.S. production have decreased over time (Levinson, 2009a; Shapiro and Walker, 2018). At the same time, the usage of imported intermediate products (foreign outsourcing) has become more critical for the U.S. economy and across the globe. For instance, basic manipulation of the WIOD suggests that the foreign content share (i.e., the ratio between the value of imported inputs over the value of shipments) for U.S.-produced goods rose from 8 percent to 14.3 percent between 1996 and 2011. In the case of pollution, the main channel leading to reductions in the emission of the main pollutants has been the technique effect. This effect represents reductions in pollution intensity via increases in productivity across firms and policies that directly affect the decision of firms to control their emission intensity via abatement investments.[16] Instead, we are primarily interested in how U.S. household income affects consumption and, consequently, relies on imports of outsourced foreign inputs whose foreign environmental taxes are embodied in them. We follow Levinson and O'Brien (2019) by keeping the technology (the technique effect) constant by using the 2002 WIOD-based

[15] Technology changes are an important extension of our baseline results. For instance, Duarte et al. (2013) argue that technology changes can influence consumption patterns, production processes, and trade dynamics, affecting environmental outcomes.

[16] Shapiro and Walker (2018) show that the implicit taxes on pollution via U.S. regulatory norms doubled on average between 1990 and 2008. Thus, their paper explains the bulk of the U.S. pollution reduction through the technique effect.

I-O linkages for our analysis. Notice that this strategy still captures any production-oriented taxes that may affect consumption decisions through price changes and goods availability.

Fig. 1.1 shows the foreign content share by industry using the 2002 WIOD. It is clear that, within a particular industry, the prevalent dependence on a notable proportion of intermediate goods can be ascribed to the sector's inherent attributes and intricate production procedures.[17] According to the figure, the largest foreign share in 2002 was 37.42 percent for "Coke, Refined Petroleum and Nuclear Fuel." This conclusion is a direct result of the fact that Energy-Intensive Trade-Exposed (EITE) manufacturing industries are heavily fossil-fuel-reliant and very reliant on international trade. Chen et al. (2018) argue that global economic integration allowed the transfer of the less-environmental friendly (dirtier) segments of these EITE industries to relocate across borders, enabling then firms located in developed countries to meet stringent domestic environmental targets. This process of international fragmentation explains the high foreign share for EITE industries. The second greatest foreign content share applies to the industry "Electricity, Gas and Water Supply" with 19.26 percent. In this case, Feenstra and Hanson (1996) indicate that many utility companies are choosing to outsource their information technology (IT), distribution, and even their manufacturing operations to lower operating costs and increase the quality of service. Based on Feenstra and Hanson (1996), companies can save up to 30 percent when delegating parts of their operation to foreign suppliers, which explain the relatively high foreign share for this sector. On the other hand, the sector "Private Households with Employed Persons" only sources domestically.

As discussed above, we also want to examine the evolution of the foreign environmental tax embedded in the U.S. household consumption of goods produced in the U.S. economy. The ERT measures used in this study are part of the Policy Instruments for the Environment (PINE) database, which serves as a repository, systematically aggregating quantitative and qualitative data from 3,200 distinct instruments adopted across OECD countries and numerous other nations (OECD, 2023). Environmentally related taxes within this database are pivotal in signaling market dynamics capable of shaping the conduct of both producers and consumers. Constituting approximately one-

[17] We use the word outsourcing to refer to the share of foreign content on an industry's shipment value. A more accurate definition refers to the share of imported inputs by firms that originate in the same sector that these firms operate. Hummels et al. (2014) use a similar definition of foreign outsourcing.

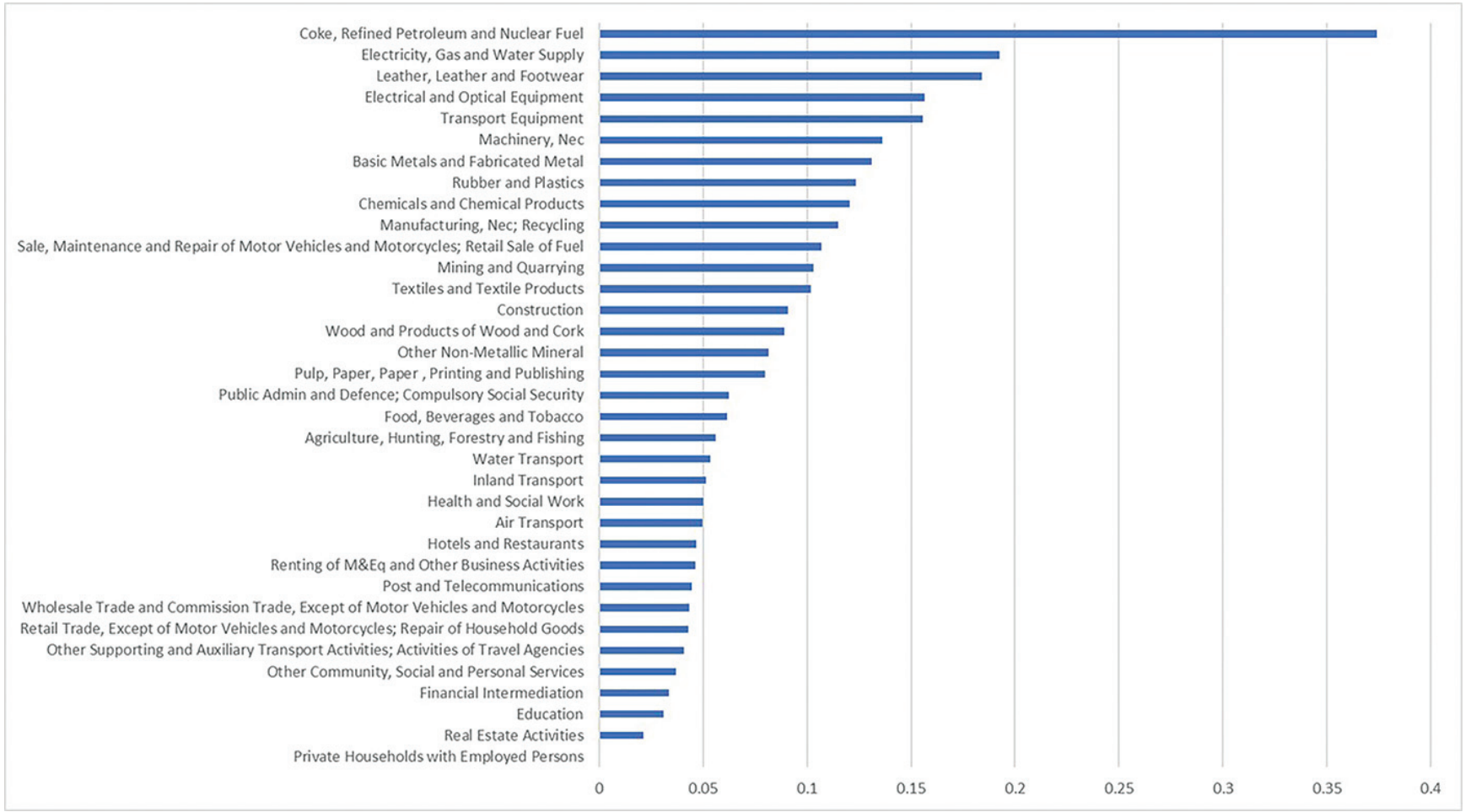



**Figure 1.1**: *Foreign Content Share By Industry in 2002 WIOD*

third of the instruments cataloged in the PINE database, environmentally related taxes manifest in a diverse array, exceeding 1,400 in variety (Ancapi, 2021). We measure environmental tax rates by taking the ratio between the tax revenue and the value added to each country and industry.[18] These environmental taxes aim to capture and elucidate the impact of environmentally related taxes on consumption patterns.

Environmental policies have experienced a growing momentum propelled by heightened awareness and the gravity of environmental issues. Our data on ERT reveals that the U.S. revenue related to environmental taxes witnessed a 10.94 percent increase (from $120,741.69 to $133,954.08 million) from 1996 to 2011.[19] Likewise, China's environmentally related tax revenue experienced a substantial growth of 30.14 percent during the same period. Since our analysis focuses on household consumption and its evolution over time, we rely on the 2002 ERT information and, therefore, we keep environmental taxes constant in our analysis. Fig. 1.2 shows that several European Union members (e.g., Netherlands, Greece, Austria, Denmark) and Mexico reported the highest environmental-related taxes in 2002. These two trade entities represented two of the largest U.S. trading partners. Instead, according to the WIOD, Canada, Mexico, Great Britain, Japan, and China were responsible for the largest foreign content shares of U.S. imported inputs in 2002.

The case of Canada and Mexico is revealing since it is a member of the North American Free Trade Area (NAFTA).[20] Conconi et al. (2018) explain that NAFTA's rules of origin promote trade of intermediate products among its members, thereby diverting imports of inputs from the rest of the world and increasing the foreign content of Canadian-sourced inputs in the production of U.S. goods. To the extent that environmental taxes tend to be higher in the European Union members and Mexico, the significant contribution of inputs originating in Mexico and these developed countries represents a force propelling heightened environmental awareness and higher foreign environmental taxes embedded the U.S. production of final consumption goods. However, Ancapi

[18]The tax revenues for the sectors with missing information were computed by applying a weighted average approach to the tax rates of analogous industries in comparable countries, determined through the utilization of the Country Similarity Index (CSI), accessible at https://objectivelists.com/. Additional information can be referenced in the supplemental appendix A.

[19]The values are expressed in millions of U.S. dollars (USD) adjusted for inflation and cost of living differences across countries using the Purchasing Power Parity (PPP) method, with the base year being 2015.

[20]As is well known, the Trump administration promoted the review of NAFTA's original agreement, and its updated version was then relabeled the USMCA.

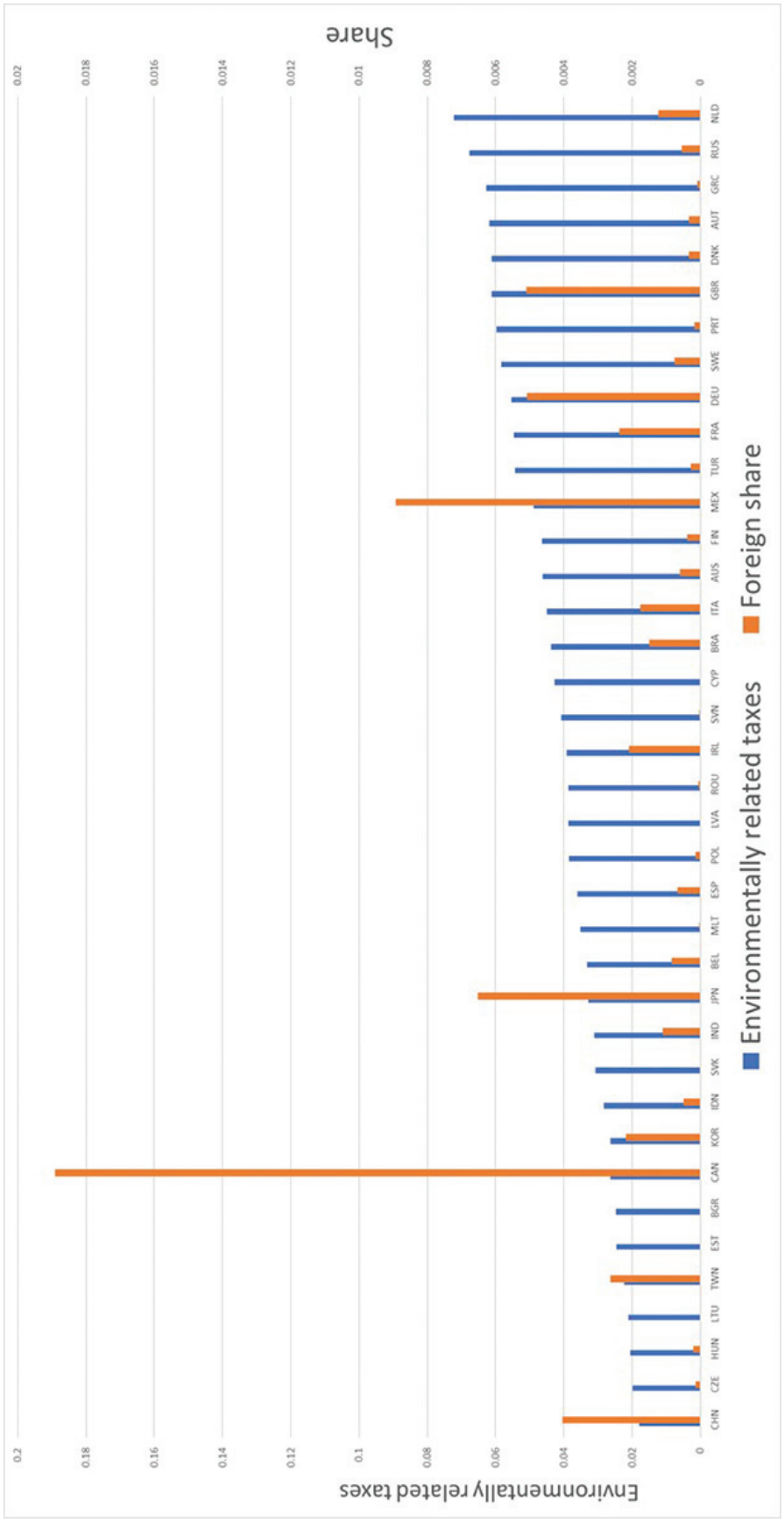



**Figure 1.2**: *Average Environmentally Related Taxes and Foreign Content Share By Country in 2002*

(2021) explains that the composition changes to consumption bundles as income rises may counter the pure scale effect of income increases on consumption choices. Section 5 discusses these effects in detail.

In Fig. 1.3, the environmentally related tax index by industry for the year 2002 is visually presented. Notably, the "Coke, Refined Petroleum, and Nuclear Fuel" sector stands out with the highest average foreign environmental tax. Huang et al. (2023) argue that this industry is characterized by resource-intensive processes and substantial energy consumption, leading to a heightened environmental impact, thereby leading to higher environmental taxes. The "Other Supporting and Auxiliary Transport Activities" ranks second in environmentally related tax revenue in Fig. 1.3. Froehlich et al. (2009) suggest that this is due to its inherent connection to consumer travel, known for its environmental impact through emissions, waste, and resource consumption. Thus, environmental taxes are heightened in this sector to encourage sustainability and responsible practices, especially in transport services, which are primary emission sources.

### 1.2.2 Methodology

We estimate the Engel curves on the foreign content of final goods and foreign environmental taxes using two household-level exposure measures. Economic integration is usually not measured in terms of absolute total trade values. Instead, the degree of integration usually refers to trade values (or other measures) relative to specific variables such as aggregate income or production values.[21] As indicated in Fig. 1.1 and Fig. 1.2, the fragmentation of production across countries is an emblematic sign of modern economies. Notice that Hofmann et al. (2019) and Laget et al. (2020) relate the intensity of trade in inputs across countries to the presence of global value chains and the formation of preferential trade agreements. As such, our measure of exposure to the foreign content of goods is the foreign content share. i.e., it represents the ratio between the value of

[21] Some examples from popular media may shed light on the importance of relating trade values to aggregate income. For instance, recent material published by the Wall Street Journal (WSJ) suggests that the degree of globalization peaked in 2007 using total trade (sum of imports and exports) over the GDP. See their report at "https://www.wsj.com/story/the-messy-unwinding-of-the-new-world-order-b43d7e45?mod=Searchresults_pos1&page=1". Another measure of de-globalization is the fall between the value of foreign inputs on manufacturing production since 2011. Again, see WSJ's "https://www.wsj.com/articles/globalization-inflation-tariffs-buy-american-11638635122?mod=Searchresults_pos6&page=1".

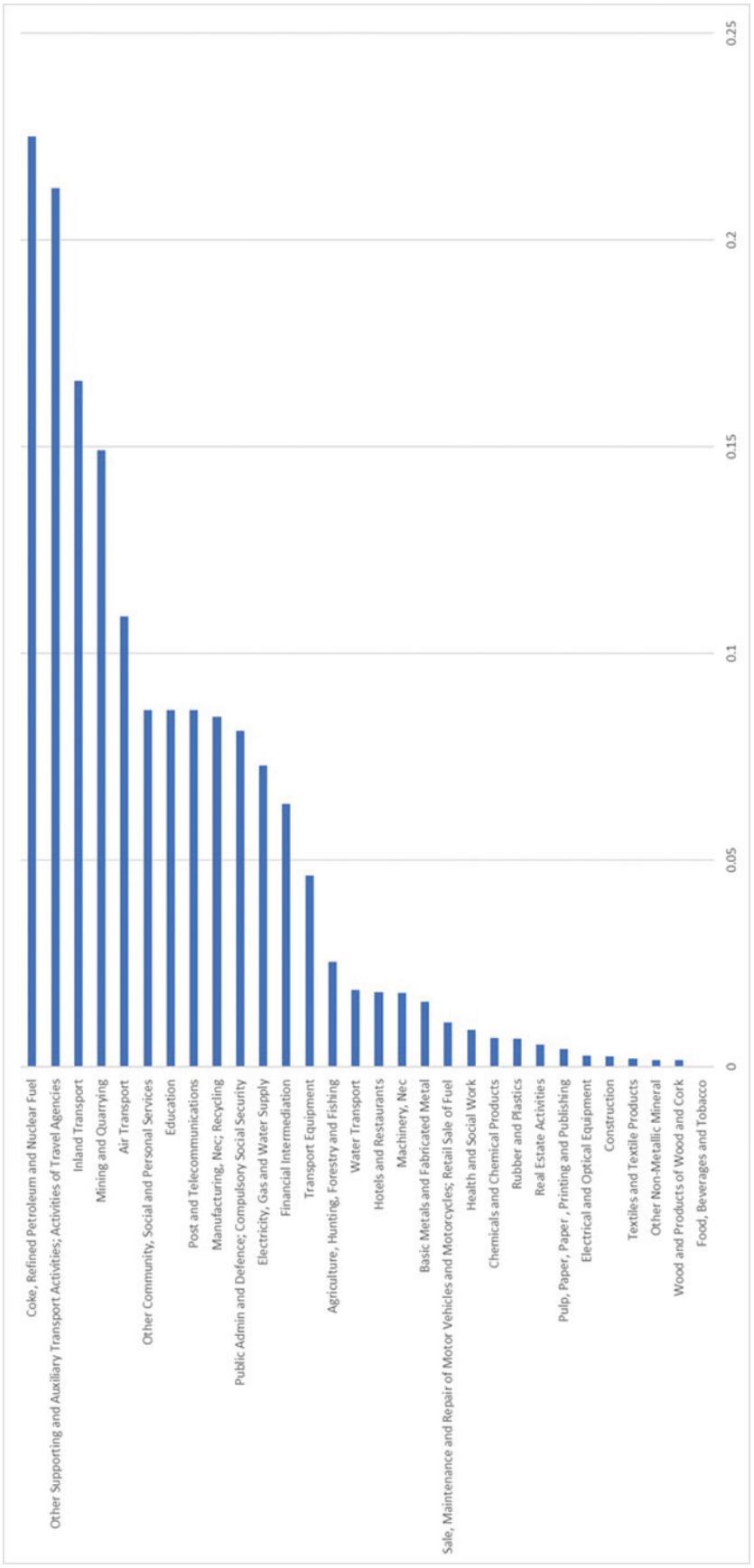



**Figure 1.3**: *Environmentally Related Taxes in 2002 by industry*

imported inputs and the value of shipments by U.S. industry $j$. We use the I-O direct linkage requirements based on the 2002 WIOD to measure this share and label it $FS_j$. Likewise, we use the 2002 OECD ERT and denote the environmental tax applied by country $c$ in industry $j$ by $ERT_{jc}$.

The household $i$'s index of exposure to outsourcing ($EO_{it}$) can be described by the following formula:

$$\frac{\sum_j (FS_j \times expenditure_{ijt})}{TOTexpenditure_{it}} = EO_{it} \tag{1.1}$$

where $expenditure_{ijt}$ corresponds to the household $i$'s expenditure in industry $j$ at year $t$. We notice that outsourcing exposure ($EO_{it}$) should be a positive number less than 1. Essentially, expression (1.1) corresponds to the household $i$'s expenditure-weighted average of the foreign content shares.

We proceed with a two-step approach regarding exposure to foreign environmental taxes. First, we measure the average foreign environmental tax ($FET_j$) that goes into foreign inputs used to produce a U.S. final good in industry $j$. Second, we calculate the household $i$'s consumption index of exposure to foreign environmental taxes ($EFET_{it}$) using the composition of an individual $i$'s consumption basket across industries.

The average industry level of exposure to foreign environmental taxes ($FET_j$) is obtained by the following expression:

$$\frac{\sum_c (ERT_{jc} \times s_{jc})}{FS_j} = FET_j \tag{1.2}$$

where we noticed that $s_{jc}$ corresponds to the foreign content share specific to country $c$ in U.S. industry $j$. This fact implies that $FS_j = \sum_c s_{jc}$. Thus, expression (1.2) corresponds to an industry-level weighted average of the foreign environmental taxes applied by country $c$ in industry $j$, $ERT_{jc}$. Notice that expression (1.2) corresponds to the first step outlined above. Then, individual $i$'s exposure to foreign environmental taxes ($EFET_i$) can be represented as an expenditure weighted-average of the industry level exposures according to the following expression:

$$\frac{\sum_j (FET_j \times expenditure_{ijt})}{TOTexpenditure_{it}} = EFET_{it} \tag{1.3}$$

Expression (1.3) ensures that industries with higher household $i$'s expenses significantly impact the overall $EFET_{it}$ calculation, accurately reflecting the household's consumption patterns. The evaluation of $EFET_{it}$ is a significant tool used to gauge households' exposure to foreign environmental taxes based on their consumption patterns. This index is a composite measure that takes into account both the foreign content share in consumed goods and the environmental taxes associated with that foreign content. It is not a cardinal variable, meaning it does not represent an absolute quantity but provides a comparative exposure assessment. This weighted average approach aligns with the economic reality that households spend varying amounts on different industries, making it an appropriate method for assessing exposure to foreign environmental taxes concerning consumption patterns. In line with it, comparing the exposure regarding $EO_{it}$ and $EFET_{it}$ across households measures the intensity with which their consumption bundles rely on foreign content (inputs) or foreign taxes rather than the value of foreign inputs or tax revenue embedded in their consumption.

Fig. 1.4 provides the schematics for calculating the indexes expressed in expressions (1.1) and (1.3) and some measures mentioned above. At the top, we can see the three primary sources of data: consumption (CEX), production (WIOD), and environmental-related taxes ($ERT_{jc}$). According to Fig. 1.4, the information from CEX is used to obtain the expenditure by household across industries ($expenditure_{ijt}$). The WIOD provides information on domestic production (value of shipments) and I-O domestic and international linkages. In particular, it allows us to obtain foreign content shares ($FS_j$). At the leftward bottom of the graph, we notice that the interaction between household expenditures and foreign content shares yields the household index of outsourcing exposure ($EO_{it}$). Likewise, back to the right middle section of Fig. 1.4, we notice that the interaction between the information on foreign content shares and the $ERT_{jc}$ yields the average industry level of exposure to foreign environmental taxes ($FET_j$). We then interact this information with household expenditure across industries to obtain the index of household exposure to foreign environmental taxes ($EFET_{it}$).

Table 1.1 shows the average household $i$'s values for the two exposure indexes described in

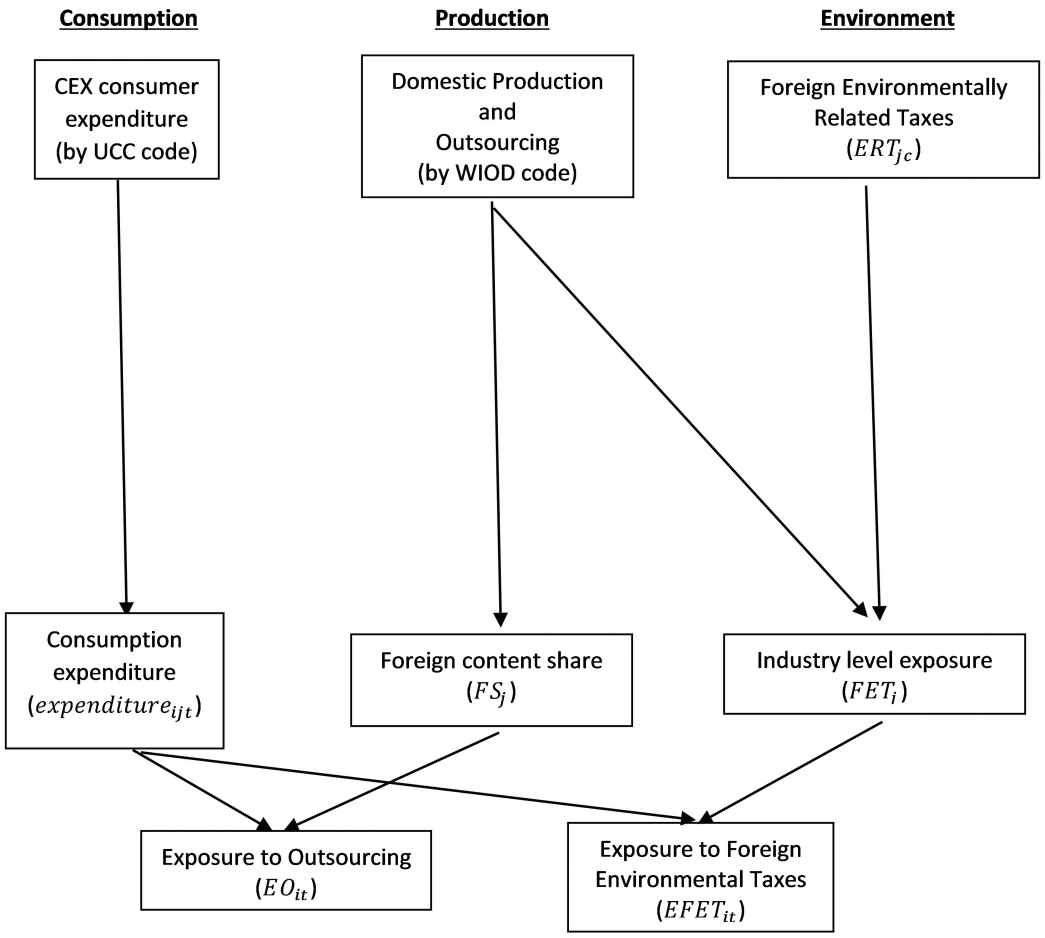



**Figure 1.4**: *Summary of Data Procedure*

expressions (1.1) and (1.3) in percentage points (multiplied by 100). In addition, this table provides crucial information on average household income and other household characteristics for 1996 and 2011, our series's first and last years. For example, the index of exposure to outsourcing ($EO_{it}$) decreased significantly between 1996 and 2011, from 7.746 to 7.039, and the exposure to foreign environmental taxes ($EFET_{it}$) rose slightly from 3.881 to 3.973. The decrease in the average value of $EO_{it}$ is possible due to our keeping the technology used in our measures at their 2002 values since we have observed above that the share of production supplied by foreign countries increases over time.[22] We explore the role of technology in household exposure as one of our extensions. As we explain below, the changes in the composition of U.S. consumer bundles of goods, price changes, and the changing availability of consumption goods over time also contribute to this trend. A similar explanation also applies to household exposure to foreign environmental taxes ($EFET_{it}$) since, in this case, we keep technology and foreign environmental taxes at their 2002 values.

In Fig. B.1, we plot the evolution of the Consumer Price Index (CPI) components from 1980 to 2014. It is clear that some CPI elements (fuel and gasoline) became cheaper during the first half of our sample (the mid-1990s and early 2000s) and became significantly more expensive during the commodity boom of the 2000s. On the other hand, the cost of electricity to U.S. households relatively falls substantially during our time frame. These trends allow for considerable changes to the composition of U.S. household consumption bundles, with consumers moving away from products heavily reliant on fossil fuels and moving towards products intensive in electricity, possibly cleaner goods whose foreign-sourced inputs are subject to higher environmental taxes. These trends seem broadly in line with the timid average increase in exposure to foreign environmental taxes, as suggested by Table 1.1.

## 1.3 Nonparametric Estimates

In this initial step, we plot the Engel curves on outsourced goods and foreign environmental taxation without controlling for other household characteristics. The former relates household

[22] Moreover, the average household became smaller, older, less likely to be married, better educated, more urban, more likely to live in the Northeast and West.

**Table 1.1**: *Average Values for Selected Variables*

| | Cross Section | | |
|---|---|---|---|
| | 1996 | 2011 | Difference |
| Variable | (1) | (2) | (3) |
| Outsourcing index (2002 technology) | | | |
| Exposure to Outsourcing | 7.746 | 7.039 | -0.707 |
| | (0.035) | (0.026) | (0.044) |
| Exposure to Foreign Environmental Taxes | 3.881 | 3.973 | 0.092 |
| | (0.010) | (0.009) | (0.013) |
| After-tax income | 4.009 | 4.521 | 0.512 |
| ($10,000 in 2002 dollars) | (0.062) | (0.066) | (0.091) |
| Household size | 2.608 | 2.545 | -0.063 |
| | (0.032) | (0.027) | (0.042) |
| Age of household head | 48.17 | 50.04 | 1.87 |
| | (0.375) | (0.331) | (0.500) |
| Head is married (share of population) | 0.556 | 0.523 | -0.033 |
| Race of head is black | 0.117 | 0.111 | -0.006 |
| Education of head (share of population) | | | |
| Elementary only | 0.182 | 0.135 | -0.047 |
| High school | 0.292 | 0.252 | -0.04 |
| Some college | 0.272 | 0.301 | 0.029 |
| College | 0.171 | 0.204 | 0.033 |
| More than college | 0.084 | 0.108 | 0.024 |
| Region | | | |
| Northeast | 0.180 | 0.185 | 0.005 |
| Midwest | 0.230 | 0.218 | -0.012 |
| South | 0.367 | 0.354 | -0.013 |
| West | 0.223 | 0.234 | 0.011 |
| Rural | 0.138 | 0.079 | -0.059 |
| Observations | 2,571 | 3,624 | |

*Notes: Values calculated using sample weights. Standard erros in parentheses. After-tax income measured in $10,000. Nominal income adjusted using the CPI for all items: nominal expenditures adjusted using the corresponding price series for food and beverages, gasoline, electricity, fuel oil, and core expenditure. Sample size for 1996 is small caused by the deletion of the observations that are students.*

income levels to their index of exposure to outsourcing ($EO_{it}$), while the latter relates household income levels to their index of exposure to foreign environmental taxes ($EFET_{it}$). This step approaches this problem (plotting the Engel curves) in a nonparametric way. First, we use the 1996 version of the CEX to split households into 50 groups based on after-tax income, which will not be influenced by tax policy. Second, we measure the average value of these two indexes for each of these 50 household groups. The share of households in each income bin can be found in Fig. B.2. We can get a nonparametric Engel curve on the foreign content of goods by plotting 50 combinations of average after-tax income and the average value of the $EO_{it}$ index per household group. This methodology can also be applied to measure this Engel curve for different years. Likewise, obtaining a nonparametric version of the Engel curve on foreign environmental taxes is similarly applicable.

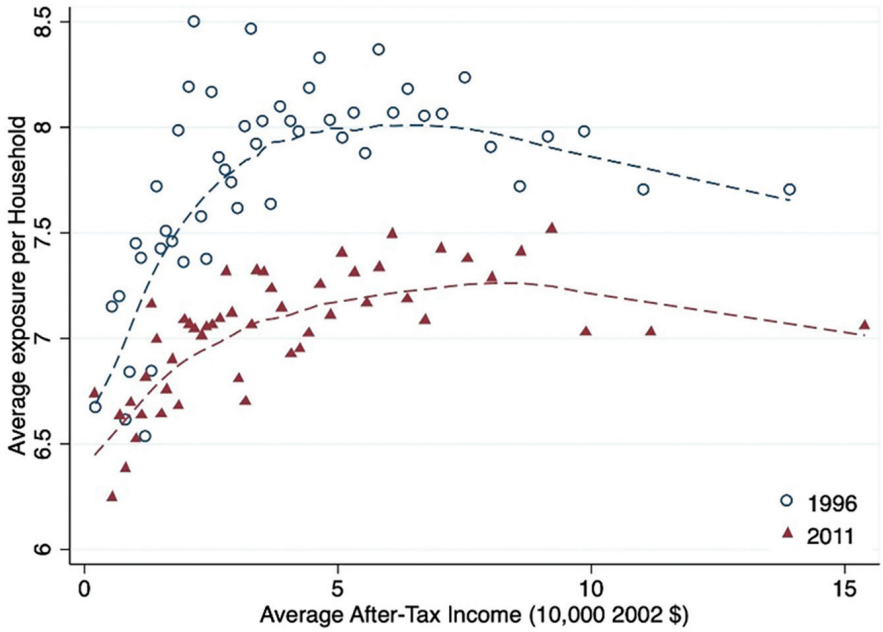
Panel (a) of Fig. 1.5 shows the nonparametric Engel curve on the foreign content of goods for 1996 and 2011. This panel reveals a consistent pattern:

1. Engel curves are concave, meaning that increasing household income will cause the exposure to the outsourcing index ($EO_{it}$) first increase and then decrease. In particular, this figure shows that middle-income households prefer to purchase goods and services more reliant on outsourced foreign inputs.

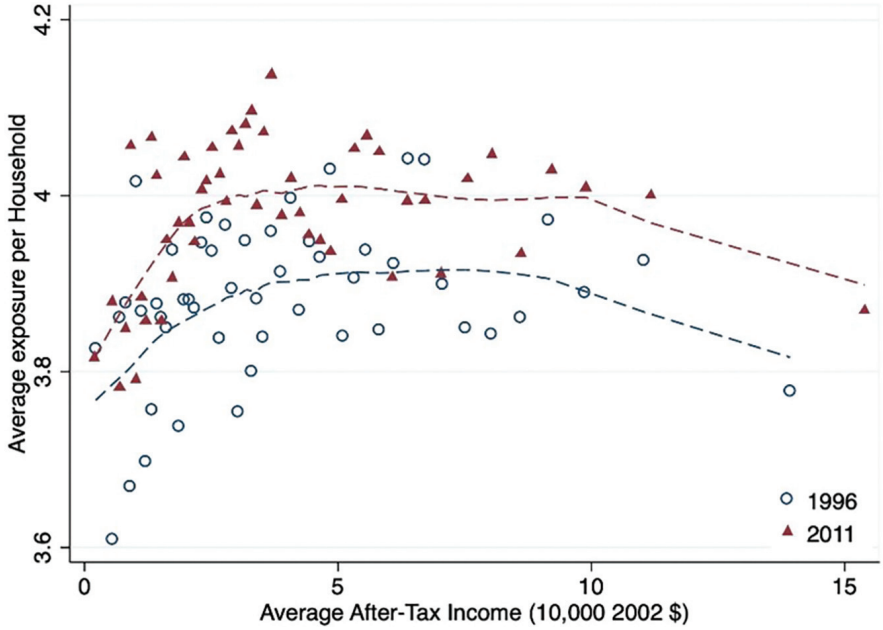
2. When the household income is relatively very high, households tend to consume more domestically produced goods that are less reliant on foreign inputs.

3. An important point is that this type of Engel curve tends to shift downward over time, as can be seen by comparing the curves for 1996 and 2011. The decrease in the outsourcing index over time for given income levels relates to changes in prices and availability of goods.

On the other hand, panel (b) of Fig. 1.5 focuses on the nonparametric Engel curve on the foreign environmental taxes. This panel shows that this Engel curve shifts upward over time and indicates a concave shape. Its general message is that middle- and high-income households will tend to buy U.S.-produced goods and services that rely more on outsourced foreign inputs from countries with higher environmental taxes.




(a) Exposure to Outsourcing Index




(b) Exposure to Foreign Environmental Taxes Index

Notes: Income is adjusted for inflation using the all-items CPI. Consumption expenditure is adjusted using the core CPI with food, fuel, gasoline, and electricity adjusted separately using the corresponding CPI. Each pair of dots represents an income level corresponding to 2% of the 1996 CEX sample, with the highest and lowest 1% of households trimmed based on after-tax income.

**Figure 1.5**: *Foreign Environmental Taxes Embodied in Household Consumption*

In Fig. 1.5, we notice several evident outliers, raising the question of their origins and influence on the plotted Engel curve. Several factors contribute to the presence of these outliers. Firstly, within a designated income group, notable variability exists in the exposure to foreign content. This variability can be attributed to differing consumption patterns, preferences, or other unobserved factors, resulting in a deviation from the anticipated trend represented by the Engel curve.[23] Secondly, a typical consumption behavior among specific households within their income group can significantly impact the calculated Engel curve, leading to notable deviations. These variations might stem from unique consumption preferences or circumstances peculiar to those households.[24] In the subsequent analysis, we excluded these outlier observations and reestimated the Engel curves for both indexes. The outcomes of this reevaluation are detailed in Fig. B.3.[25] Notably, removing outliers did not unduly skew or distort the non-parametric Engel Curves and the subsequent parametric analysis.

We test the robustness of the nonparametric estimates shown in Fig. 1.5 in different ways. The panels in Fig. B.4 and Fig. B.5 plot Engel curves based on total household expenditure and household pre-tax income, respectively. The Engel curves in these figures maintain the same properties discussed for panels (a) and (b) of Fig. 1.5. According to Harrell (2001), the location of changes in the curvature of Engel curves can be set at specific points known as knots. We re-estimate Engel curves based on five knots placed at equally-distanced percentiles.[26] Panels (a) and (b) of

[23]To exemplify, in the year 2011, within the lowest income bin, after-tax income displayed a substantial range, spanning from $94.5 to $4,213 (using $10,000 in 2002 dollars). Additionally, the age of households within this income group ranged from 19.5 to 87 years, further illustrating the multifaceted nature of this variation.

[24]An illustrative example can be found in the behavior of households within the lowest income bin. While the majority of these households typically allocate a significant portion of their income to "Food, Beverages, and Tobacco," there are exceptional cases, such as a household that deviates from this pattern by directing their expenditures toward "Mining and Quarrying." The unique preferences and priorities of this particular household drive this deviation.

[25]Mahalanobis distance was employed to assess the deviation of specific data points, representing income and exposure index values within different income bins, from the expected trend represented by an Engel curve. Mahalanobis originally introduced this distance measure in Mahalanobis (1930) as part of his investigations into racial similarity. Over time, it has matured into a pivotal and indispensable tool in statistics and data analysis, especially in situations involving diverse sets of measurements (McLachlan, 1999). By calculating the Mahalanobis distance for each data point, we can identify those income bins that exhibited substantial dissimilarities from the Engel curve, indicating potential outliers in the dataset.

[26]Harrell (2001) recommends placing knots at equally-spaced percentiles of the original variable's (after-tax income) marginal distribution. In this application, we choose the 5th, 27.5th, 50th, 72.5th, and 95th percentile as knots. When using a restricted cubic spline, one obtains a continuous smooth function that is linear before the first knot, a piecewise cubic polynomial between adjacent knots, and linear again after the last knot. By estimating Engel curves using restricted cubic splines (over income), we can observe the relationship between income and exposure index as a piecewise cubic polynomial.

Fig. B.6 present the variation in household spending reflected by 95 percent confidence intervals (shaded area). Generally, the Engel curves displayed in these panels share similar characteristics and evolution over time with their counterparts shown in Fig. 1.5.

The approach depicted in Fig. 1.5 may not precisely explain the relationship between the household exposure indexes ($EO_{it}$ and $EFET_{it}$) and household income due to the missing household characteristics. Lewbel and Pendakur (2009) show that the standard Engel curve varies with consumer characteristics, accounting for both shape and changes over time. Moreover, the law of one price may not hold across U.S. regions, given the continental dimension of its economy. For example, suppose some U.S. regions have considerably higher household incomes. In that case, it may present higher relative prices for goods that rely more heavily on foreign inputs imported from countries with higher environmentally related taxes. If this situation applies, then the shape of the Engel curve in panels (a) and (b) will be influenced by the combination of income elasticities and price differences. Likewise, if incomes and relative prices have changed over time at different rates across regions, the Engel curves may be biased by this price effect.

Thus, we now turn to parametric estimates to access the degree to which these demographic changes account for the shape and movements in the Engel curves.

## 1.4 Parametric Estimation

The main challenge in estimating the relationship between household income and the indexes of consumption exposure described in expressions (1.1) and (1.3) is that it may be affected by demographic characteristics with varying effects over the years. As a result, this relationship varies across years, producing shifts and changes in the form (concavity) of the Engel curves over time. This section describes our empirical strategy for addressing the difficulty mentioned above. In the next section, we investigate the variation in the average exposure indexes in terms of movements along the Engel curve and the shifts in this curve.

We can then estimate the relationship between exposure and household income in the following way, similar to the approach used by Levinson and O'Brien (2019). We estimate the following expression to measure the Engel curve on the foreign content of goods in year $t$:

$$EO_{it} = \alpha_t Y_{it} + \beta_t Y_{it}^2 + \delta_t X_{it} + \varepsilon_{it} \tag{1.4}$$

The dependent variable $EO_{it}$ represents the exposure index described in expression (1.1). $Y_{it}$ and $Y_{it}^2$ represent the after-tax income and its quadratic value in year $t$, respectively. $X_{it}$ denotes the vector of household characteristics that control for demographics, among other factors. Estimation of expression (1.4) per year allows us to graph the Engel curve on a yearly basis. Notice that a similar process allows us to estimate its counterpart on the foreign environmental taxes. In this case, we replace the dependent variable in expression (1.4) with the exposure index $EFET_{it}$ described in expression (1.3).

Panel (a) of Fig. 1.5 describes (different) Engel curves that share a strictly concave shape similar to the curves estimated by Levinson and O'Brien (2019). In column 1 of Table 1.2, we regress $EO_{it}$ only on the value of income and its quadratic value. The estimated shape is concave since the coefficient for the variable measuring quadratic income is negative (-0.021) and statistically significant.[27] Notice that the estimated effects are economically relevant. The numbers in column 1 of Table 1.2 suggest that, on average, a one-standard-deviation increase in income (based on 1996 values) leads to an increase in $EO_{it}$ of 0.009, corresponding to approximately 26 percent of a standard deviation (0.035 based on 1996 values) in this index according to Table 1.1.[28] Measuring the direct effect of income on exposure through standard deviation units facilitates straightforward comparison and interpretation, especially in scenarios involving variables with varying units or scales. It also provides a tangible measure of the impact of income changes on the index, aiding in informed policy decisions. This approach bridges the gap between statistical significance and real-world relevance, enhancing the applicability of our research to policy-making (Vossler and Evans, 2009).

Still, since the specification used in column 1 does not control for other household characteristics, there may be endogeneity concerns related to missing variables. For instance, educational attainment correlates with income and also correlates with environmental awareness (consumption preferences), posing an endogeneity challenge to estimate the effects of household income on $EO_{it}$.

[27] The joint test for income and its squared value is also statistically significant.
[28] Calculations use the standard deviations in the index and income for 1996.

**Table 1.2**: *Parametric Engel Curves for Exposure to Outsourcing*

| Dependent vairable: | 1996 | | 2000 | 2005 | 2011 |
|---|---|---|---|---|---|
| Exposure per Household | (1) | (2) | (3) | (4) | (5) |
| After-tax income | 0.319*** | 0.214*** | 0.119*** | 0.105*** | 0.105*** |
| ($10,000 in 2002 dollars) | (0.033) | (0.035) | (0.027) | (0.021) | (0.021) |
| After-tax income squared | -0.021*** | -0.014*** | -0.007*** | -0.005*** | -0.005*** |
| | (0.002) | (0.002) | (0.002) | (0.001) | (0.001) |
| Household size | | 0.289*** | 0.065 | 0.308*** | 0.244*** |
| | | (0.074) | (0.071) | (0.073) | (0.061) |
| Household size squared | | -0.025*** | -0.0006 | -0.030*** | -0.017** |
| | | (0.008) | (0.009) | (0.009) | (0.007) |
| Age | | 0.059*** | 0.082*** | 0.037*** | 0.055*** |
| | | (0.013) | (0.011) | (0.011) | (0.009) |
| Age squared | | -0.0005*** | -0.0007*** | -0.0003*** | -0.0005*** |
| | | (0.0001) | (0.0001) | (0.0001) | (0.0001) |
| Married | | 0.255*** | 0.414*** | 0.324*** | 0.157** |
| | | (0.087) | (0.071) | (0.074) | (0.064) |
| Race: Black | | -0.596*** | -0.365*** | -0.285*** | -0.336*** |
| | | (0.099) | (0.085) | (0.102) | (0.083) |
| Race: Asian | | -0.429** | -0.616*** | -0.428*** | -0.623*** |
| | | (0.197) | (0.149) | (0.150) | (0.121) |
| Race: Other | | 0.596 | 0.523** | 0.330* | 0.143 |
| | | (0.438) | (0.247) | (0.181) | (0.234) |
| Education: High school | | 0.119 | 0.204** | 0.354*** | 0.327*** |
| | | (0.102) | (0.090) | (0.103) | (0.090) |
| Education: Some college | | 0.069 | 0.208** | 0.241** | 0.303*** |
| | | (0.108) | (0.092) | (0.098) | (0.089) |
| Education: College | | -0.209* | -0.163 | -0.060 | -0.023 |
| | | (0.114) | (0.101) | (0.107) | (0.102) |
| Education: Graduate | | -0.498*** | -0.196 | -0.251** | -0.131 |
| | | (0.130) | (0.123) | (0.121) | (0.113) |
| Region: Midwest | | 0.458*** | 0.373*** | 0.216*** | 0.324*** |
| | | (0.098) | (0.080) | (0.080) | (0.075) |
| Region: South | | 0.722*** | 0.583*** | 0.589*** | 0.494*** |
| | | (0.092) | (0.077) | (0.081) | (0.072) |
| Region: West | | -0.013 | 0.189** | 0.067 | -0.175** |
| | | (0.100) | (0.083) | (0.083) | (0.077) |
| Rural | | 0.809*** | 0.789*** | 0.919*** | 0.488*** |
| | | (0.093) | (0.094) | (0.118) | (0.107) |
| Constant | 6.993*** | 4.642*** | 4.434*** | 4.966*** | 4.344*** |
| | (0.089) | (0.320) | (0.302) | (0.302) | (0.253) |
| F-test of income coefficients | 49.40 | 18.83 | 10.05 | 12.98 | 13.33 |
| Observations | 2,571 | 2,571 | 3,714 | 3,703 | 3,624 |
| R-squared | 0.043 | 0.204 | 0.167 | 0.141 | 0.138 |

*Notes: The dependent variable is Exposure to Outsourcing ($EO_{it}$) described in expression (1.4). Robust standard errors in parentheses. Household exposure calculated by multiplying itemized household consumption with 2002 WIOD outscourcing index or foreign environmental taxes index for each type of good and summing for each household. Ater-tax income measured in $10,000. Nominal incomes adjusted using the CPI for all items; nominal expenditures are adjusted using the corresponding core, food and beverage, gasoline, electricity, and fuel oil CPIs.*
**** for 1%, ** for 5%, * for 10%*

Thus, the specifications used in columns 2 through 5 additionally control for household characteristics, such as age, household size, race, and region of residence. Furthermore, each specification focuses on a particular year, whose estimates allow us to plot the parametric version of the Engel curve for different years. For example, the specification used in column 2 focuses on CEX data for 1996, while the specifications used in columns 3 through 5 focus on CEX information for 2000, 2005, and 2011, respectively.

In column 2, the coefficients corresponding to educational attainment levels, specifically high school and some college, demonstrate a positive relationship. This implies that households with these levels of education tend to select consumption bundles characterized by a higher proportion of foreign inputs. Conversely, the coefficients demonstrate a negative association for higher educational levels, such as college and graduate degrees, signifying a preference for consumption bundles with a reduced proportion of foreign content. Furthermore, household size, age, marital status of the household head, and living in rural areas positively affect household exposure to the foreign content of goods.

Unsurprisingly, including controls for household characteristics affects the relationship between income and household exposure. The results in column 2 indicate that using CEX data for 1996, the linear coefficient on income and its quadratic value are statistically significant and point to a strictly concave Engel curve. Moreover, the income effects continue to be economically relevant: if income increases by one standard deviation, then the index of exposure to the foreign content of goods ($EO_{it}$) also increases by 0.006 on average, equivalently, 18 percent of a standard deviation. The effect of other household characteristics is meaningful as well. For instance, households residing in the Southern region, on average, exhibit an exposure to outsourcing that is 0.26 percentage points higher compared to households in the Midwest region. Differently, a one-standard-deviation increase in age (0.375 based on 1996 levels) leads to a slight increase in the index value of 0.004 or the equivalent of about 11 percent of its standard deviation.[29]

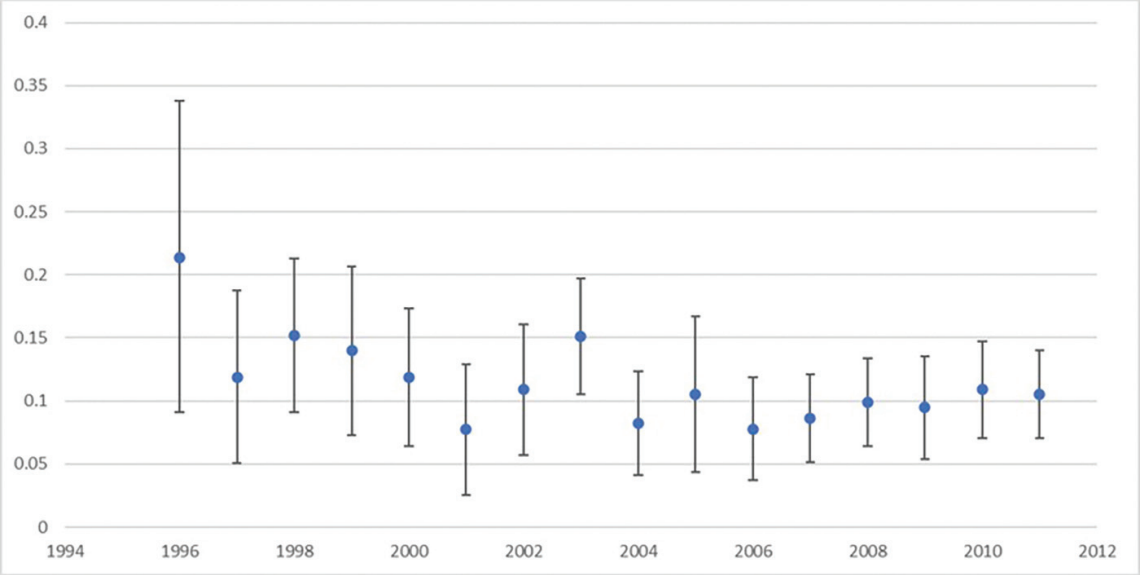
Similar conclusions apply to the specifications in columns 3 through 5 of Table 1.2. As explained above, these specifications rely on different years for the CEX information. In these cases,

[29]People form consumption habits based on past consumption patterns. Therefore, as presented in Table 1.2 and Table 1.3, age and age-squared variables are included in expression (1.4) as part of the vector of controls $X_{it}$. This strategy aims to control for problems caused by the "habit persistence" effect on consumption decisions.

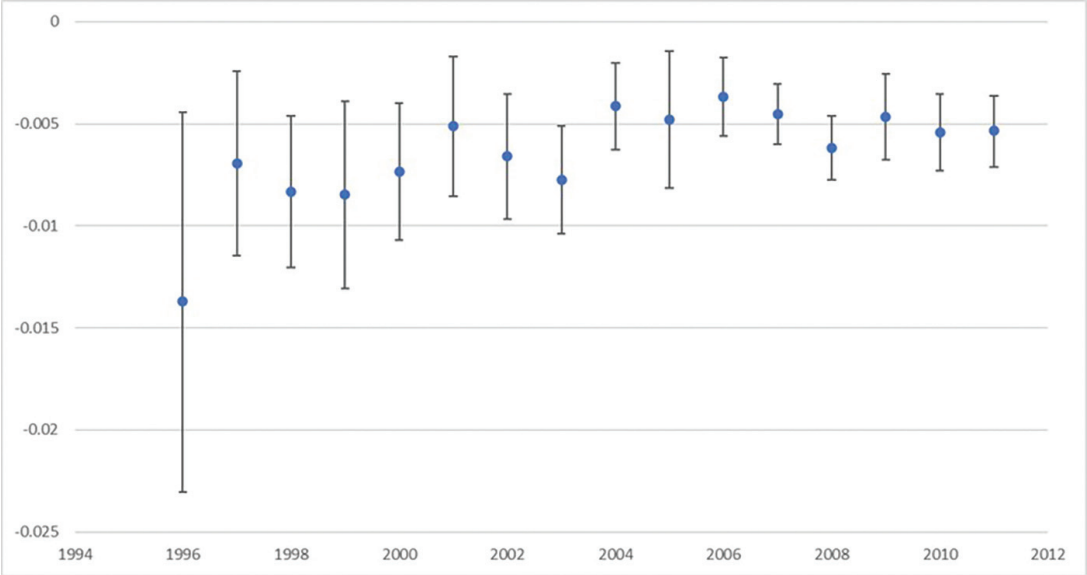
the coefficients for income and its quadratic value are positive and negative, respectively, and both are statistically significant. These results confirm the presence of strictly concave Engel curves across the years. Notice that the sign of coefficients used as controls coincide across columns 2 through 5. However, the size of these coefficients varies significantly across columns, suggesting potential important changes in the degree of concavity and shifts in the Engel curve across years. For example, if we focus on column 5, the results suggest that a one-standard-deviation increase in income (0.066 based on 2011 levels) leads to an increase in the index of exposure to the foreign content of goods of 0.0039 on average, which corresponds to 15 percent of its standard deviation based on the 2011 CEX (0.026 according to Table 1.1). The comparison with a similar analysis for column 2 reveals a decrease in the effect of income on the foreign content embedded in consumption. Fig. 1.6 shows the estimated linear coefficient of income (upper section) and its squared value (lower section) yearly from 1996 to 2011. Notice that coefficients vary over the years but are statistically significant.[30]

Table 1.3 shows the estimation of expression (1.4) using the index of exposure to foreign environmental taxes ($EFET_{it}$) as the dependent variable. It follows the exact specifications across columns used in Table 1.2, except for the dependent variable. Generally, results tend to follow a similar pattern as described for the index $EO_{it}$. For instance, the linear effect of household income on $EFET_{it}$ tends to be positive, while its quadratic value displays a negative effect. Both coefficients are statistically significant even using the parsimonious model described in column 1 of Table 1.3. If we focus on column 2, when using the 1996 CEX data, on average, a one-standard-deviation increase (0.062 based on 1996 values) in income leads to an increase of 0.0017 in household exposure to foreign environmental taxes. This effect corresponds to an increase equivalent to 17 percent of the standard deviation of the exposure index (0.010 based on 1996 values, according to Table 1.1). As we move across columns, this effect is consistent with what

[30]Following Sager (2019), we conducted a comparative analysis by juxtaposing equation 1.4 with more versatile semiparametric models. Specifically, we employed a Gaussian kernel-weighted local polynomial approach to model the influence of income while maintaining linear control over other covariates. In line with the test proposed by Hardle and Mammen (1993), for each polynomial degree, we test the null hypothesis that the adjustment of degree n+1 is appropriate. Our objective was to pinpoint the minimum polynomial degree where the null hypothesis remained unchallenged (failed to reject). The findings affirm that the quadratic model for 2011 emerges as the optimal choice. This result is available from the authors upon request.




(a) Engel Curve After-Tax Income Coefficients




(b) Engel Curve After-Tax Income Squared Coefficients

Notes: The figure illustrates the regression analysis results examining the relationship between income quadratic terms and the value of exposure to the outsourcing index over time. The dot represents the estimated coefficients in Table 1.2, while the line indicates the corresponding confidence intervals.

**Figure 1.6**: *Income coefficients over time – Exposure to Outsourcing*

we described in Table 1.2. If we focus on the 2011 CEX data, column 5 indicates that an increase of one standard deviation in income (0.066 based on 2011 values) causes an increase in the index $EFET_{it}$ of 0.0006 on average. This effect corresponds to 7 percent of the standard deviation of this index (0.009 based on 2011 values). Fig. 1.7 indicates the yearly estimated linear and quadratic income coefficients from 1996 to 2011. These estimates confirm the statistical significance of the income-related coefficients in Table 3.[31]

Fig. 1.8 presents the parametric Engel curves based on results in Table 1.2 (panel (a)) and Table 1.3 (panel (b)). It illustrates the relationship between income and the two indexes ($EO_{it}$ and $EFET_{it}$) for 1996 and 2011 using the control variables outlined in expression (1.4) and represented by $X_{it}$. The two thick lines in panel (a) use the estimated coefficients displayed in columns 2 (1996 CEX) and 5 (2011 CEX) of Table 1.2. Likewise, the two thick lines in panel (b) are constructed using the results in columns 2 (1996 CEX) and 5 (2011 CEX) of Table 1.3. We also plot each Engel curve without matrix $X_{it}$ covariates for comparison purposes. In sum, the parametric versions of Engel curves in Fig. 1.8 are similar to their counterparts in Fig. 1.5. First, all parametric Engel curves are concave. Second, the curve related to exposure to foreign environmental taxes ($EFET_{it}$) tends to shift upward over the years, while the curve pertaining to exposure to outsourcing ($EO_{it}$) exhibits the opposite pattern. We investigate as an extension to which degree these shifts remain under technological progress. Last, the degree of concavity of Engel curves in panels (a) and (b) decreases from 1996 to 2011.

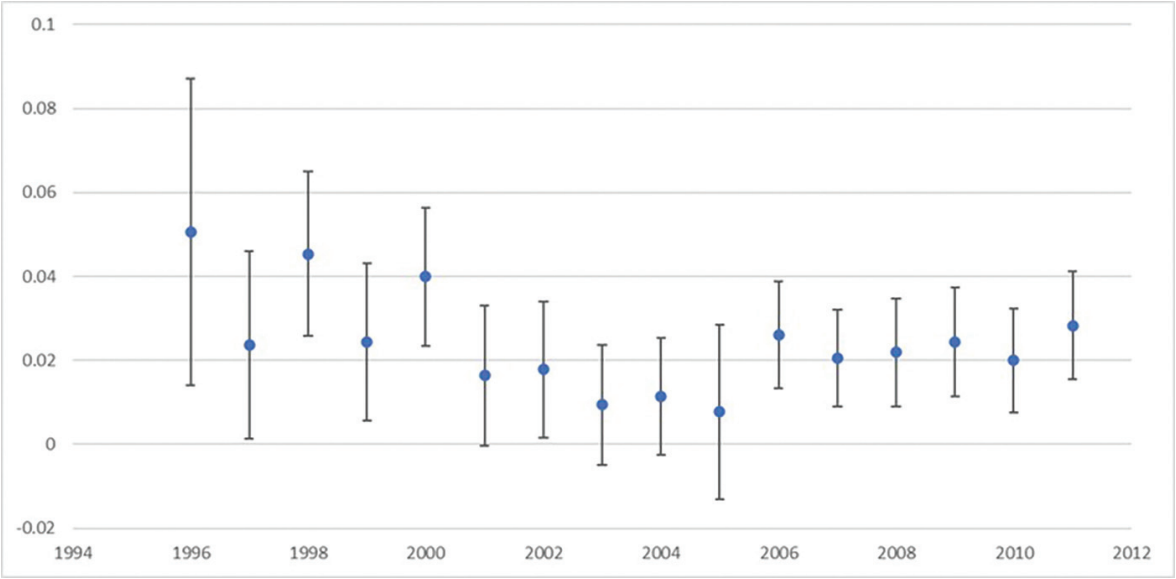
From Panel (a) of Fig. 1.8, we observe that the low-income households' exposure to foreign content intensity in their consumption (left section of the graph) is greater than high-income households' exposure intensity. This feature is in line with expectations. Chan and Gruber (2010) argue that low-income households are more price-sensitive than their higher-income counterparts. Furthermore, Buxey (2005) and Miroudot et al. (2009) underscore the critical role of foreign intermediate goods in bolstering price competitiveness. These findings explain why price-sensitive low-income households consume lower-priced goods with greater foreign content intensity than

[31] We can observe several outliers using the non-parametric estimates of the Engel Curves described graphically in both panels of Fig. 1.5. Then, we consider the methodology suggested in Levinson and O'Brien (2019) to select and re-estimate expression (1.4) for the two indexes ($EO_{it}$ and $EFET_{it}$ ) considered in Table 1.2 and Table 1.3 while dropping these outlier observations. The results are listed in Table B.1, they are qualitatively similar to those described in Table 1.2 and Table 1.3.

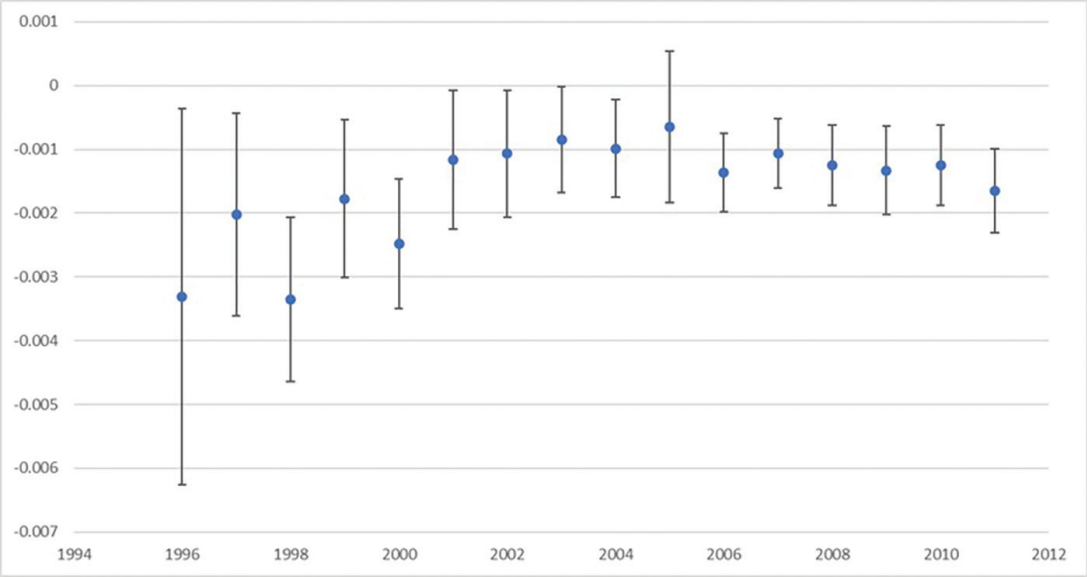
**Table 1.3**: *Parametric Engel Curves for Exposure to Foreign Environmental Taxes*

| Dependent vairable: | 1996 | | 2000 | 2005 | 2011 |
|---|---|---|---|---|---|
| Exposure per Household | (1) | (2) | (3) | (4) | (5) |
| After-tax income | 0.041*** | 0.051*** | 0.040*** | 0.008 | 0.028*** |
| ($10,000 in 2002 dollars) | (0.010) | (0.011) | (0.008) | (0.007) | (0.007) |
| After-tax income squared | -0.003*** | -0.003*** | -0.002*** | -0.0006** | -0.002*** |
| | (0.0008) | (0.0008) | (0.001) | (0.0003) | (0.0004) |
| Household size | | -0.041 | -0.036* | -0.043** | -0.020 |
| | | (0.026) | (0.021) | (0.021) | (0.021) |
| Household size squared | | 0.004 | 0.003 | 0.006** | 0.0006 |
| | | (0.003) | (0.002) | (0.002) | (0.003) |
| Age | | 0.011*** | 0.008** | 0.006* | 0.012*** |
| | | (0.004) | (0.004) | (0.003) | (0.003) |
| Age squared | | -0.001*** | 0.0001* | 0.0003 | 0.0001*** |
| | | (0.00003) | (0.00003) | (0.00003) | (0.00001) |
| Married | | 0.009 | 0.051** | 0.048** | 0.044** |
| | | (0.028) | (0.024) | (0.022) | (0.022) |
| Race: Black | | -0.022 | -0.003 | 0.065** | 0.022 |
| | | (0.034) | (0.027) | (0.031) | (0.032) |
| Race: Asian | | 0.035 | 0.043 | 0.155*** | 0.063 |
| | | (0.068) | (0.062) | (0.054) | (0.041) |
| Race: Other | | -0.023 | 0.095 | -0.064 | -0.022 |
| | | (0.159) | (0.079) | (0.065) | (0.062) |
| Education: High school | | -0.046 | 0.033 | 0.050* | 0.070** |
| | | (0.031) | (0.028) | (0.030) | (0.030) |
| Education: Some college | | -0.075** | 0.012 | 0.051* | 0.004 |
| | | (0.032) | (0.028) | (0.030) | (0.030) |
| Education: College | | -0.054 | 0.030 | 0.060* | -0.030 |
| | | (0.036) | (0.033) | (0.034) | (0.033) |
| Education: Graduate | | -0.066 | -0.005 | 0.103*** | -0.037 |
| | | (0.041) | (0.042) | (0.037) | (0.038) |
| Region: Midwest | | 0.082*** | 0.066** | 0.095*** | 0.090*** |
| | | (0.030) | (0.027) | (0.026) | (0.025) |
| Region: South | | 0.036 | 0.085*** | 0.114*** | 0.148*** |
| | | (0.029) | (0.025) | (0.025) | (0.023) |
| Region: West | | 0.10*** | 0.110*** | 0.036 | 0.137*** |
| | | (0.031) | (0.028) | (0.026) | (0.025) |
| Rural | | 0.131*** | 0.114*** | 0.130*** | 0.017 |
| | | (0.033) | (0.032) | (0.038) | (0.043) |
| Constant | 3.789*** | 3.506*** | 3.501*** | 3.640*** | 3.485*** |
| | (0.026) | (0.098) | (0.103) | (0.090) | (0.086) |
| F-test of income coefficients | 8.45 | 9.85 | 11.25 | 4.01 | 10.76 |
| Observations | 2,571 | 2,571 | 3,714 | 3,703 | 3,624 |
| R-squared | 0.008 | 0.038 | 0.032 | 0.032 | 0.038 |

*Notes: The dependent variable is Exposure to Foreign Environmental Taxes ($EFET_{it}$) described in* expression *(1.3). Robust standard errors in parentheses. Household exposure calculated by multiplying itemized household consumption with 2002 WIOD outscourcing index or foreign regulation index for each type of good and summing for each household. Ater-tax income measured in $10,000. Nominal incomes adjusted using the CPI for all items; nominal expenditures are adjusted using the corresponding core, food and beverage, gasoline, electricity, and fuel oil CPIs.*
**** for 1%, ** for 5%, * for 10%*



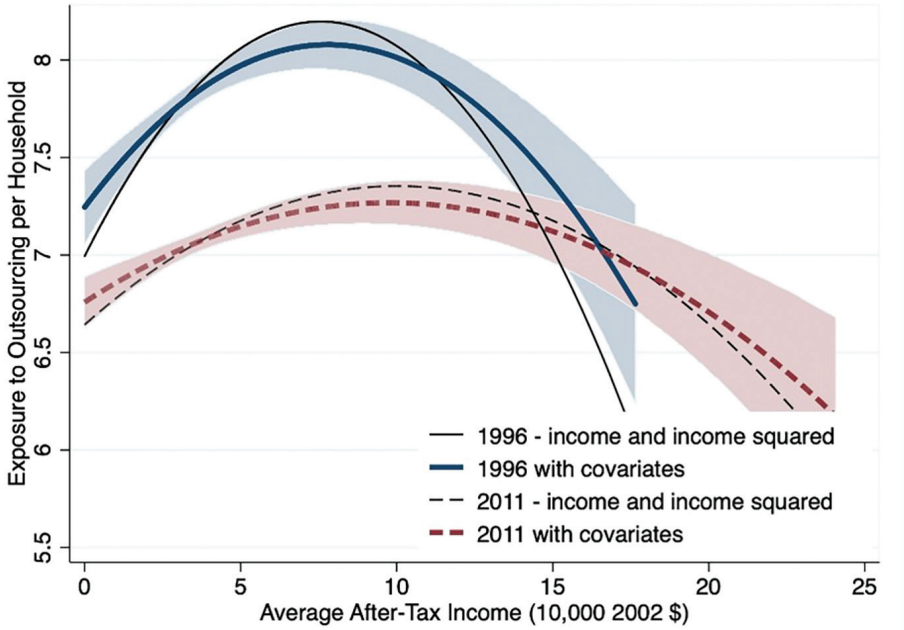

(a) Engel Curve After-Tax Income Coefficients



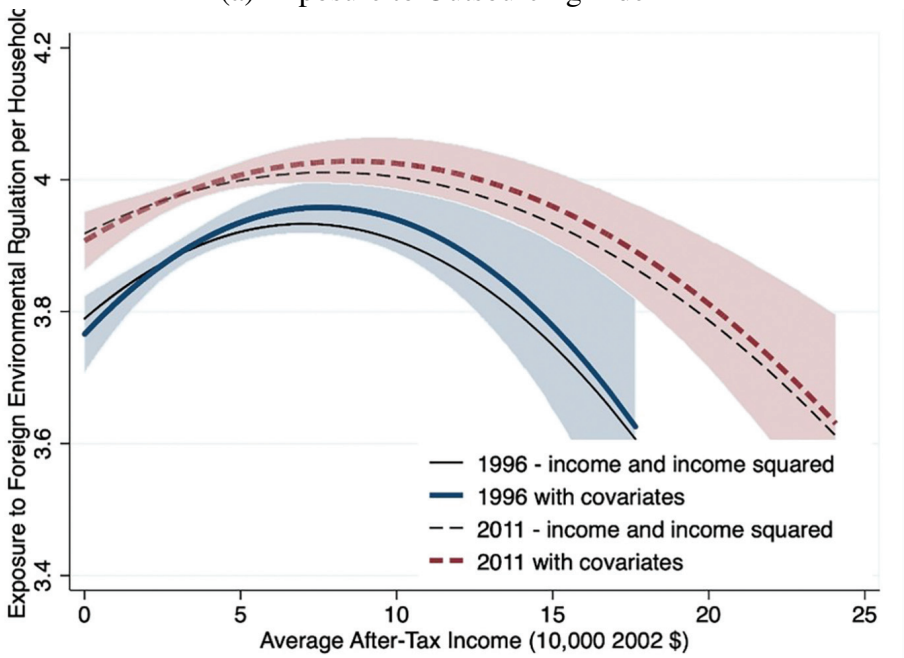

(b) Engel Curve After-Tax Income Squared Coefficients

Notes: The figure illustrates the regression analysis results examining the relationship between income quadratic terms and the value of exposure to the outsourcing index over time. The dot represents the estimated coefficients in Table 1.3, while the line indicates the corresponding confidence intervals.

**Figure 1.7**: *Income coefficients over time – Exposure to Foreign Environmental Taxes*




(a) Exposure to Outsourcing Index




(b) Exposure to Foreign Environmental Taxes Index

Notes: All other covariates are fixed at their mean values. Inflation adjustments as in Fig. 1.5. Standard errors for the two outsourcing indexes are not estimated. So, 5% confidence intervals (shaded) reflect variations in household spending.

**Figure 1.8**: *Engel Curves Based on Parametric Estimates*

their high-income counterparts. Likewise, Panel (b) exhibits similar patterns. de Groot (2003) illustrates that as consumers become wealthier, their consumption patterns tend to evolve. In the early stages of income growth, there's a shift towards manufacturing products characterized by larger emission intensity. As income continues to rise, consumers tend to favor services known for their smaller environmental footprint. Consequently, this implies that low-income households, as their income increase, might gravitate toward goods with higher environmental impact, therefore with potentially higher environmental taxes. In contrast, higher-income households may opt for goods with lower environmental impact and, possibly, lower environmental taxes.

Notice that the thin lines in Fig. 1.8 plot the regression of expression (1.4) for the two indexes on income and income-squared alone. The baseline results remain the same, although adding the covariates in matrix $X_{it}$ changes the shape of the Engel curves. Moreover, we conclude again that the Engel curves shift down for the index of exposure to outsourcing ($EO_{it}$). In contrast, they shift up for the exposure to foreign environmental taxes ($EFET_{it}$). The downward shift in Engel curves on the foreign content of goods can be attributed to policy changes and modifications in consumer behavior. Palley (2008) argues in favor of additional policies to address social concerns given the increase of foreign outsourcing, representing a new form of competition. The US-Central America and Dominican Republic Free Trade Area (CAFTA-DR) was signed into law in 2005. It was the first FTA involving the U.S. with enforceable labor requirements in line with the argument outlined in Palley (2008). Instead, Goldberg and Campa (2006) bring to the forefront that final consumption goods intensive in foreign intermediate inputs may have more volatile prices since their contents are more affected by exchange rate swings. As a result, consumers may switch to products with lower-foreign content and, therefore, less subject to price fluctuations.

On the other hand, Engel curves on the foreign environmental taxes shift upward, possibly due to increasing awareness of environmental issues. Gadenne et al. (2009) show that greater environmental awareness increases the environmental-friendly business practices and consumer options. Butler (2018) refers to a 2017 study on corporate social responsibility, revealing that 87% of consumers will have a more positive image of a company that supports social or environmental issues, and 87% of consumers would buy a product with a social and environmental benefit if given the opportunity. Thus, Americans increasingly expect companies to be engaged making an

impact on social and environmental matters. Likewise, Acemoglu et al. (2012) show that regulatory and policy frameworks are pivotal in shaping a consumption trend. They argue that nations placing a greater emphasis on environmental considerations frequently implement incentives to encourage adopting eco-friendly practices. These incentives encompass tax reductions, subsidies, or other economic encouragements for enterprises employing cleaner and sustainable production approaches. Consequently, products originating from such countries are often perceived by consumers as more sustainable and environmentally responsible.

So far, we have presented the estimation of the Engel curves and have observed whether they shift upwards or downwards over time. Next, we will decompose the effects of changes in these indexes in terms of movements along the curve and shifts of the Engel curve.

## 1.5 Applications

### 1.5.1 Decomposing the Changes Over Time

Table 1.1 indicates that the average value of the index measuring household exposure to the foreign content of goods ($EO_{it}$) decreased by 0.707 points, the equivalent of about 9 percent, from 1996 to 2011. Instead, this table suggests that household exposure to foreign environmental taxes ($EFET_{it}$) increased by 0.092, representing a 2 percent rise. It is then important to explain the forces behind these average changes. These forces can be divided into two groups. First, some forces explain a movement along the Engel curve, while others cause shifts in each curve. Movements along the curve are related to changes in after-tax income and represent the combination of scale and composition effects following Levinson and O'Brien (2019)'s definitions. Below, we detail how to measure and explain these two specific effects. On the other hand, shifts in the Engel curve can be caused by changes in other household (demographic) characteristics over time or by unexplained factors not modeled in expression (1.4).[32]

[32] Levinson (2009a) shows that the conventional way to explain the evolution of pollution emissions generated by producing goods and services is to decompose it in terms of scalar, composition, and technique effects. Our objective here is different as we aim to understand the foreign environmental taxes embedded in the foreign content of goods consumed by U.S. households. For instance, we keep technology constant at 2002 levels, meaning that we shut down the changes due to the technique effect.

As indicated above, we are trying to explain the evolution of the average values (across households) for our indexes described in expressions (1.1) and (1.3) over the years. We apply the Oaxaca-Blinder decomposition to separate components related to the movement along Engel curves and the shift in them. Then, focusing on the household exposure to outsourcing ($EO_{it}$), the average level of this index at year $t$ can be described, with the assistance of expression (1.4), by the following expression:

$$\overline{EO}_t = \alpha_t \bar{Y}_t + \beta_t \bar{Y}_t^2 + \delta_t \bar{X}_t \tag{1.5}$$

Expression (1.5) relates the average level of $EO_{it}$ to the after-tax average income and its squared value ($\bar{Y}_t$ and $\bar{Y}_t^2$) while controlling for the average of other included covariates ($\bar{X}_t$). By construction, the average OLS error is 0. Therefore the error term is not included in equation (5). We also adopt a similar strategy to investigate the factors behind the evolution of the average value for the index of exposure to foreign environmental taxes $EFET_{it}$.

We use expression (1.5) to measure changes in the average value of the exposure to outsourcing between 1996 and 2011 in the following way:

$$\begin{aligned} \overline{EO}_{11} - \overline{EO}_{96} = {} & \alpha_{96}(\bar{Y}_{11} - \bar{Y}_{96}) + \beta_{96}(\bar{Y}_{11}^2 - \bar{Y}_{96}^2) && \text{(Term 1)} \\ & + (\alpha_{11} - \alpha_{96})\bar{Y}_{11} + (\beta_{11} - \beta_{96})\bar{Y}_{11}^2 && \text{(Term 2)} \\ & + \bar{X}_{11}(\delta_{11} - \delta_{96}) + (\bar{X}_{11} - \bar{X}_{96})\delta_{96} && \text{(Term 3)} \end{aligned} \tag{1.6}$$

Term 1 of expression (1.6) considers changes in after-tax average income levels while holding constant the estimated coefficients ($\alpha_{96}$ and $\beta_{96}$). Thus, it reflects a movement along the Engel curve for 1996 prompted by the increase in income between that year and 2011. Term 2 represents changes in estimated parameters between 1996 and 2011 while keeping average incomes constant at their 2011 levels. Thus, it means shifts in the Engel curves. Finally, Term 3 captures the changes on the average index related to all other covariates.

Table 1.4 presents the decomposition results for the change in the average indexes $\overline{EO}_t$ (column

1) and $\overline{EFET}_t$ (column2) between 1996 and 2011. Term 1 of expression (1.6) is calculated by multiplying the change in average values of income (see column 3 of Table 1.1) by the 1996 OLS coefficients (see column 2 of Table 1.3 and Table 1.3). Term 3 follows a similar approach for other control variables. Thus, the summation of these effects across individual variables corresponds to Term 1 (movements along the Engel Curve) and Term 3 (changes due to other covariates) of expression (1.6). We know from Table 1.1 the value for the left-hand-side variable (e.g., $\overline{EO}_{11} - \overline{EO}_{96}$), and measuring Term 1 and Term 3 then allows us to obtain Term 2 as the difference between the left-hand-side change and the summation of Terms 1 and 3.

**Table 1.4**: *Movement Along Parametric Engel Curves for Outsourcing Indexes*

| | Exposure to Outsourcing | Exposure to Foreign Environmental Taxes |
|---|---|---|
| Dependent Variable: | (1) | (2) |
| after-tax income ($10,000 in 2002 dollars) | 0.110*** | 0.026*** |
| | (0.026) | (0.007) |
| After-tax income squared | -0.133*** | -0.032*** |
| | (0.029) | (0.009) |
| Household size | -0.018 | 0.003 |
| | (0.013) | (0.002) |
| Household size squared | 0.008 | -0.001 |
| | (0.008) | (0.002) |
| Age | 0.111*** | 0.021** |
| | (0.038) | (0.009) |
| Age squared | -0.093*** | -0.017 |
| | (0.034) | (0.008) |
| Married | -0.009* | -0.0003 |
| | (0.005) | (0.001) |
| Race dummies | 0.005 | -0.002 |
| Education dummies | -0.022 | -0.004 |
| Regional dummies | -0.063 | -0.008 |
| **Total change due to income (movement along EC)** | -0.0230 | -0.0061 |
| **Total change due to other demographics** | -0.0804 | -0.0063 |
| **Unexplained difference (shift in EC)** | -0.6036 | 0.1044 |

*Notes: Estimates based on Oaxaca-Blinder decompositions. Robust standard errors in parentheses. Movements along each Engel curves described in expression (1.6) Term 1.* Total change due to other *demographics described in expression (6) Term 3. Shifts in Engel curves described in expression (1.6) Term 2. The value of index based on 2002 production technology for all years. Ater-tax income measured in $10,000.*
**** for 1%, ** for 5%, * for 10%*

Focusing on column 1 of Table 1.4, we conclude that the increase in average after-tax income leads to a hypothetical increase of 0.110 in the average index value.[33] On the other hand, the average increase in the after-tax squared value of income is responsible for a decline in the average index of 0.133. Then, we can add up the two effects related to income to find that Term 1 in expression (1.6) contributes to an average decrease in the index ($\overline{EO}_t$) of 0.023. Similar analysis measures Term 3 of expression (1.6). In this case, the overall effects of changing demographic characteristics contribute to a hypothetical decrease of 0.0804 (see bottom of Table 1.4) in the average value of $\overline{EO}_t$ between 1996 and 2011. According to Table 1.1, the average value of the exposure index to the foreign content of goods and services ($\overline{EO}_t$) decreased by 0.707 between 1996 and 2011. The difference between 0.707 and the summation of Terms 1 and 3 is -0.6036 (i.e., $-0.707-(-0.023-0.0804)$). Thus, this amount corresponds to the contribution of Term 2 (shifts in the Engel curve) to the change in the average index. The contribution related to Term 2 (shifts in the Engel curve) is more significant than the contributions related to Term 1 (movements along the curve) and Term 3 (changes in other covariates).

Similarly, we use the results in column 2 of TTable 1.4 to decompose the forces behind the change in the average exposure to foreign environmental taxes ($\overline{EFET}_t$). The summation of the effects related to the change in average income and its squared value tends to decrease the average index value by 0.0061 (equal to 0.026 - 0.032 following column 2), corresponding to Term 1 of expression (1.6). Likewise, the summation of the effect due to changes in the average value of demographic characteristics equals -0.0063 (Term 3 in expression (1.6)). Therefore, it contributes to a potential decline in the average value of index $\overline{EFET}_t$. We know from Table 1 that the average value of this index increases by 0.092. As such, we conclude that shifts in the Engel Curve on the foreign environmental taxes (Term 2) lead to an increase in this index of 0.1044 (i.e., 0.092-(-0.0061-0.0063)). Again, shifts in the Engel curve (Term 2) are the main contributors to the average increase observed in $\overline{EFET}_t$.

Levinson (2009a) and Shapiro and Walker (2018) use a well-established decomposition model to explain the evolution of pollution emissions from U.S. production of goods and services. These

[33] This corresponds to the change in average income (0.512) found in column 3 of Table 1.1 times the 1996 OLS coefficient described in column 2 of Table 1.2 (0.214). A Similar analysis applies to other values.

papers show that pollution emission is affected by scale, composition, and technique effects. The scale effect suggests that pollution tends to rise, as production grows given the same combination of goods produced and technology. On the contrary, the composition effect focuses on the evolution of the mix of goods produced over time. In our analysis, the technology effect is kept constant as explained before using the 2002 WIOD information. Still, we can uncover the influence of scale and composition effects by observing the evolution of our index when income changes, i.e., when we consider movements along the curve, as established by Term 1 of expression (1.6). Panels (a) and (b) of Fig. 1.8 make it clear that the composition of goods consumed across households of different incomes must change since the household exposure varies among low-, middle-, and high-income households.

Following Levinson (2009a), Shapiro and Walker (2018), and Levinson and O'Brien (2019), we can define the scale effect as a proportional change of the average exposure index in 1996 relative to income. More specifically, we can focus on the exposure to the foreign content of goods and services to express the scale effect ($SC_t$) for year $t$ relative to 1996 in the following way:

$$SC_t = \overline{EO}_{96} \times [(\bar{Y}_t - \bar{Y}_{96})/\overline{Y}_{96}] \tag{1.7}$$

Next, we use the fact that Term 1 of expression (1.6) represents a movement along the curve, which, therefore, corresponds to the summation of the scale effect ($SC_t$) and the composition effect ($CC_t$). Accordingly, we can define the composition effect at year $t$ relative to 1996, with the assistance of expression (1.7), in the following way:

$$\begin{aligned} CC_t &= \text{Term } 1_t - SC_t \\ &= \alpha_{96}(\bar{Y}_t - \bar{Y}_{96}) + \beta_{96}(\bar{Y}_t^2 - \bar{Y}_{96}^2) \\ &\quad -\overline{EO}_{96} \times [(\bar{Y}_t - \bar{Y}_{96})/\overline{Y}_{96}] \end{aligned} \tag{1.8}$$

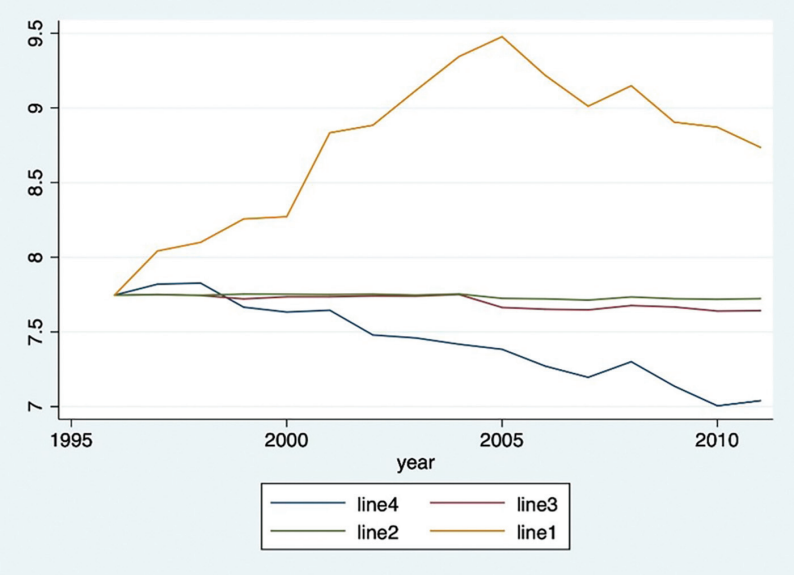
Panels (a) and (b) of Fig. 1.9 show the decomposition effects overtime for the average indexes $\overline{EO}_t$ and $\overline{EFET}_t$, respectively. Line 1 corresponds to the scale effect ($SC_t$) defined in expression

(1.7). Instead, line 2 represents the effects of movements along the curve, or, equivalently, Term 1 of expression (1.6), which describes the sum of the scale effect ($SC_t$) and the composition effect ($CC_t$) described in expressions (1.7) and (1.8), respectively. Line 3 combines Terms 1 and 3 of expression (1.6), i.e., the sum of the effects related to movements along the curve (Term 1) and changes in demographic characteristics (Term 3). Instead, line 4 shows the sum of effects summarized by Terms 1, 2, and 3 over time. These joint effects equal the average change in indexes found in Table 1.1.

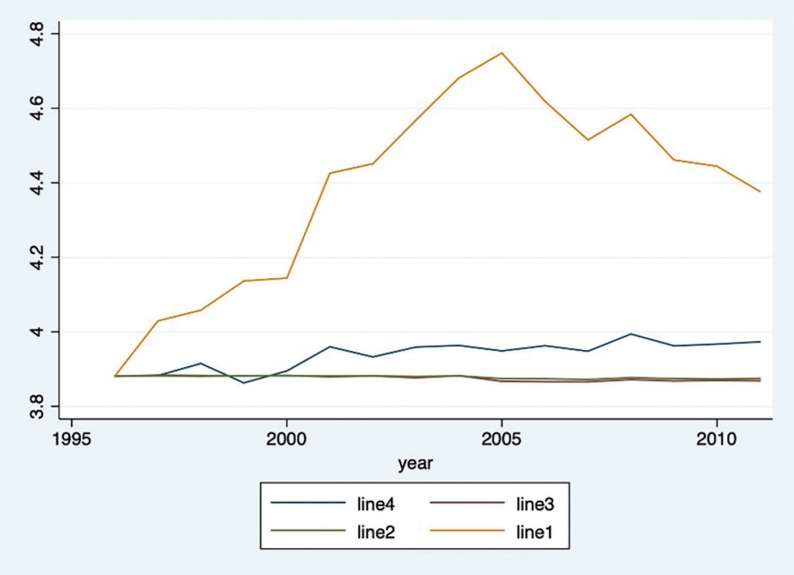
First, we focus on panel (a) of Fig. 1.9. Table 1.1 suggests that household incomes have increased. Thus, the scale effect for $\overline{EO}_t$ described in line 1 increases, according to expression (1.7), as long as average income rises, which does happen until the financial crisis of 2007. However, line 2 lies significantly below line 1. The difference between these two lines is the composition effect ($CC_t$), according to expression (1.8), which, therefore, is substantially negative and tends to reduce the average index. Lines 3 and 4 lie below line 2, suggesting that the shifts in the Engel curve (Term 2) and changes due to demographic characteristics (Term 3) are negative and decrease the average index, as discussed above. The exact contribution of each of these factors can be found in Table 1.5. We can then use expressions (1.6), (1.7), and (1.8) to disentangle the different effects on $\overline{EO}_t$ based on Table 1.5 as follows:

$$\begin{aligned} \overline{EO}_{11} - \overline{EO}_{96} &= \text{Term } 1_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \\ \overline{EO}_{11} - \overline{EO}_{96} &= SC_{11} + CC_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \\ -0.707 &= 0.9896 - 1.0125 - 0.6036 - 0.0805 \end{aligned} \tag{1.9}$$

Expression (1.9) reveals the relative contribution of the different terms in expression (1.6) to the change in the average value of $\overline{EO}_t$ between 1996 and 2011. It confirms that shifts in the Engel curve (Term 2) are the main contributor to the reduction in this index between 1996 and 2011, as discussed above. However, expression (1.9) reveals that the small (net) contribution of movements along the curve represents strong opposing forces between the scale ($SC_{11}$) and composition ($CC_{11}$) effects. The former tends to (strongly) increase the exposure to outsourcing while the lat-




(a) Exposure to Outsourcing Index




(b) Exposure to Foreign Environmental Taxes Index

Line (1) Scale Effect; Line (2) Movement Along Engel Curve;
Line (3) Movement Along Engel Curve and Demographic Changes; Line (4) Index Predicted

Notes: The changing index calculates the scale effect in proportion to real after-tax income growth. Movements are long and shifts in the Engel curve are calculated by estimating the value of indexes each year using the 1996 Engel curve coefficients. Household exposure is estimated by matching itemized consumption expenditure in each year with the corresponding industries' 2002 WIOD outsourcing index or foreign regulation index.

**Figure 1.9**: *Decomposition of Predicted Outsourcing Indexes from Household Consumption*

**Table 1.5**: *Outsourcing Offset Due to Composition Changes in Household Consumption*

| | | | | Offset by Movement along Engel Curve | | Offset by Demographic Changes | | Offset by Shifts in Engel Curve | |
|---|---|---|---|---|---|---|---|---|---|
| | Total Change | Scale Increase | Total spread (2) - (1) | Value | Share of Spread | Value | Share of Spread | Pounds | Share of Spread |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Exposure to Outsourcing | -0.71 | 0.99 | 1.70 | 1.01 | 0.60 | 0.081 | 0.047 | 0.603 | 0.36 |
| Exposure to Foreign Environmental Taxes | 0.09 | 0.50 | 0.40 | 0.50 | 1.24 | 0.006 | 0.016 | -0.105 | -0.26 |

*Notes: The total change in the value of index is predicted using CEX, WIOD data, and ERT data based on 2002 production technology and environmental taxation (Table 1). The scale (SC) in the value of index is calculated by multiplying index level in 1996 by the proportional increase in after-tax income between 1996 and 2011 (Expression (1.7)). The total spread is calculated as the difference between the predicted change from the coefficients and the predicted change due to the scale effect. Offset in column 4 (CC) are calculated by subtracting the predicted value of index including scale effects and movements along the Engel curve from the scale effect alone (expression (1.8)). Offsets due to demographic changes (expression (1.6) Term 3) are calculated in an analogous manner. Offsets due to shifts in the Engel curve (expression (1.6) Term 2) are calculated as the residual and the offsets in columns 4,6 and 8 sum to column 3 by construction. After-tax income measured in $10,000.*

ter (strongly) decreases this exposure by shifting consumption choices towards goods with lower foreign content as income rises. This combination of effects highlights that the composition effect counters to a great extent in the scale effect, and is the main factor leading to an average decrease in the exposure to foreign content of goods and services.

Next, we use expressions (1.6), (1.7), and (1.8) to disentangle the contribution of the different effects on $\overline{EFET}_t$ according to the results displayed in Table 1.5. These effects can be outlined as follows:

$$\begin{aligned} \overline{EFET}_{11} - \overline{EFET}_{96} &= \text{Term } 1_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \\ \overline{EFET}_{11} - \overline{EEFT}_{96} &= SC_{11} + CC_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \\ 0.092 &= 0.4958 - 0.5020 + 0.1044 - 0.0063 \end{aligned} \tag{1.10}$$

Expression (1.4) provides information about the relative contribution of the different terms to the change in the average value of $\overline{EFET}_t$ between 1996 and 2011. Similar to the results in expression (1.9), shifts in the Engel curve (Term 2) are an important contributor to the index's increase. The scale effect ($SC_{11}$) increases the exposure to foreign environmental taxes, while the composition effect ($CC_{11}$) has the opposite impact, leading to a small contribution of movements along the Engel curve. These findings point to shift factors (Term 2) as the primary contributor to the increase in the exposure to foreign environmental taxes as a direct comparison of the absolute value of the different elements in expression (1.10) indicates it.

Table 1.5 provides further details about the contribution of the different terms mentioned above to the change in the average value of the two indexes. Column 1 of Table 1.5 shows the changes in the average value of the two exposure indexes between 1996 and 2011 (see also Table 1.1), holding technology and foreign environmental taxes fixed at their 2002 levels. Column 2 presents the scale effects ($SC_{11}$). The difference between columns 1 and 2 (column 3) represents the value of each index changes net of scale effect. Following expressions (1.9) and (1.10), it can be explained by the composition effect ($CC_{11}$), changes in household demographics (Term 3), and shifts in Engel curves over time (Term 2).

For the index of exposure to foreign environmental taxes ($\overline{EFET}_t$), the total average positive change in column 1 is mainly explained by shifts in the Engel curve (Term 2) since the composition effect basically counters the size of the scale effect, while the changes due to demografics tends to decrease this index. On the contrary, for the index of exposure to outsourcing ($EO_t$), the value of the index decreased significantly, meaning that households tend to consume more domestically produced goods and services with less foreign content. The increasing household income will lead to substantial growth in consumption according to the scale effect (see column 2). Therefore, column 3 is partly offset by the composition effect ($CC_{11}$), which tends to decrease the consumption of goods more reliant on foreign inputs as income rises, and shifts in Engel curves (see column 8). Instead, the difference is mostly unaffected by demographic changes, according to column 6. Based on Table 1.5, we observe that the composition effect explains about 60 percent of the reduction in the average value of the index (see column 5). In comparison, shifts in the Engel curve explain about 36 percent (see column 9) of this reduction.[34]

### 1.5.2 Income Redistribution

The U.S. government engages in a multitude of social programs, including insurance (e.g., Medicaid, unemployment, and disability), education (e.g., pre-schooling, job and vocational training, college), tax and in-cash transfers (e.g., earned-income tax credits, child tax credit), and in-kind transfers (e.g., housing and food stamps). Most of these programs transfer income (directly or indirectly) from U.S. high-income households to targeted household groups. For example, some programs benefit low-income households (e.g., Medicaid) or contain income thresholds that prevent segments of the U.S. middle class from taking up benefits (e.g., child tax credits). Hendren and Sprung-Keyser (2020) analyzes 113 U.S. social programs, some of which include layouts of hundreds of billions of dollars each year. This fact makes it evident that social programs and income redistribution play a significant role in advanced economies.

[34]This conclusion can be seen by taking the value of the composition effect in expression (1.9) or Table 1.5 (-1.0125) and dividing it by the sum of its value with the value of shifts in the Engle curve (-0.6036 for Term 2) and changes due to demographic characteristics (-0.0805 for Term 3). A similar approach applies to finding the relative contribution of shifts in the Engle curve. The 4 percent remaining is due to changes in the average value of demographic characteristics.

In this section, we apply our parametrically estimated Engel curves to measure the degree to which redistribution affects U.S. consumption decisions. In turn, these decisions may affect the foreign content ($EO_t$) and the foreign environmental taxes ($EFET_t$) embedded in the final consumption of goods and services. We focus on the coefficient estimates for 2011, which can be found in column 5 of Tables 1.2 and 1.3. Our first exercises involve targeted transfers from the rich- to the low- or average-income households in line with typical U.S. social programs since they may encompass transfers only to one of these household groups. Next, we consider economy-wide transfers involving all 3,624 (see Table 1.1) households in our sample. In this case, we consider partial and complete redistribution, where the latter involves transfers to keep all households at the average income level of $45,210 (see Table 1.5).

Our first redistribution plan considers transfers of $5,000 and $10,000 from the one hundred top households based on income to the two hundred households at the bottom of the post-tax income schedule. Alternatively, we consider transfers to the two hundred households at the middle of the income schedule. Our redistribution plan is a theoretical construct that mimics some redistribution proposals. For instance, Charles Murray's plan involves in-cash transfers of about $10,000, which can be interpreted as a Universal Basic Income (UBI).[35][36] Thus, the transfers used in our redistribution exercise were chosen strategically to align with the theoretical construct of a UBI and to facilitate a comprehensive exploration of the effects of wealth redistribution, serving as a reasonable representation within the context of our study. These redistribution plans then mimic U.S. social plans that mostly target low-income households (e.g., Medicaid) versus those more catered to middle-income households (e.g., college grants and college loan subsidies). They are also economically meaningful: The mean income for the two hundred lowest-income households is $4,163, implying that these transfers ($2,500 and $5,000 for each) would correspond to an increase between 60 percent and 120 percent relative to their average after-tax income.

Notice that Fig. 1.8 indicates that the estimated Engel curve for the indexes $EO$ and $EFET$

[35] Charles Murray, a scholar at the American Enterprise Institute, suggests converting federal spending on programs like Social Security and Medicare into direct payments of $10,000 annually or $13,000 with a $3,000 health insurance deduction until a person's annual income exceeds $30,000. Murray aims to simplify the system, ensuring direct financial assistance reaches individuals, potentially saving administrative costs.

[36] Kearney and Mogstad (2019) argues that this approach could be more effective in aiding the most financially vulnerable and have fewer work disincentives than current programs.

are concave and quadratic (inverted U-shaped). To the extent that lowest income households have greater income with transfers, their individual indexes tend to grow as we move from the left side to the center of the estimated Engel curve for each index.[37] A similar fact happens to the richest households as we move from the right to the center of each panel in Fig. 1.8 unless some of these wealthiest households have income below the peak of the estimated curve. Therefore, the graphical analysis suggests an average increase in these indexes with redistribution. Table 1.6 provides numerical confirmation for these graphical conclusions. The transfers of income from the rich to the poor households lead to an average increase in the $EO$ index between 0.04 percent and 0.075 percent, while a similar analysis for the $EFET$ index causes an increase between 0.029 and 0.051 percent. This table also reveals that transfers from the rich- to the middle-income households yield similar albeit smaller average increases in these indexes.[38]

**Table 1.6**: *Results of Income Redistribution*

| | Income Redistribution | $EO$ | $\%\Delta EO$ | $EFET$ | $\%\Delta EFET$ |
|---|---|---|---|---|---|
| Original Value | | 7.0390 | | 3.973 | |
| To poorest | 0.25 | 7.0418 | 0.04 | 3.974 | 0.0291 |
| | 0.5 | 7.0443 | 0.0747 | 3.975 | 0.0514 |
| To average | 0.25 | 7.0408 | 0.0254 | 3.974 | 0.0229 |
| | 0.5 | 7.0440 | 0.0712 | 3.9745 | 0.0389 |
| All households | Marginal Redistribution | 7.082 | 0.605 | 3.986 | 0.332 |
| | Full Redistribution | 7.065 | 0.372 | 3.984 | 0.275 |

*Ater-tax income measured in $10,000*

We have also investigated the consequences of income redistribution involving all households. In this case, we follow Sager (2019) and consider marginal (small) changes in income involving

[37] Expression (1.1) controls for many household characteristics that can be correlated with income. Still, our lack of information about the same households over time may cause biases in our estimates due to missing variables. Thus, results in Section 1.5.2 are best viewed as conditional correlations between income and exposure measures rather than a casual relationship.

[38] The income range for high-income households is between $146,243 and $240,703, while the income level corresponding to the $EFET$'s Engel curve peak is $147,561. Instead, the estimated Engel curve for the $EO$ index peaks at an income level of $97,576.

two randomly chosen households. Likewise, we also consider the case of full redistribution, where transfers ensure that all households have the same average income of $45,210. The effect of former transfers can be approximated by the expression $-2 \times \beta_2 \times \Psi$ where $\Psi$ represents the dispersion of each index across households and $\beta_2$ describes the curvature of the Engel curve. The marginal redistribution mechanism increases the average $EO$ index by 0.605 percent while it raises the $EFET$ index by 0.332 percent. The low value of the estimated Engel curve's curvature ($\beta_2$) is an important piece in explaining the limited effect of redistribution on both indexes. Instead, full redistribution increases the $EO$ and $EFET$ indexes by 0.372 and 0.275 percent, respectively. In this case, several households with income just below the level that maximizes each index have to pay transfers to poorer households, thereby leading to individual decreases in their indexes. This fact limits the full redistribution effects on the estimated indexes.

In sum, income redistribution leads to movements along estimated Engel curves and, in our case, causes increases in the average foreign content of final goods consumed in the U.S. Likewise, it causes an increase in the foreign environmental taxes embedded in U.S. final goods and services. In this case, redistribution and consumption decisions are in sync with governments that want to promote trade with countries with a more robust environmental agenda, as signaled by higher environmental taxes. However, redistribution also leads to greater foreign content in final consumption. This result sheds light on a possible use of income redistribution to promote economic integration and reverse some of the de-globalization taking place (less offshoring), a movement centered in our object of study, the United States of America.

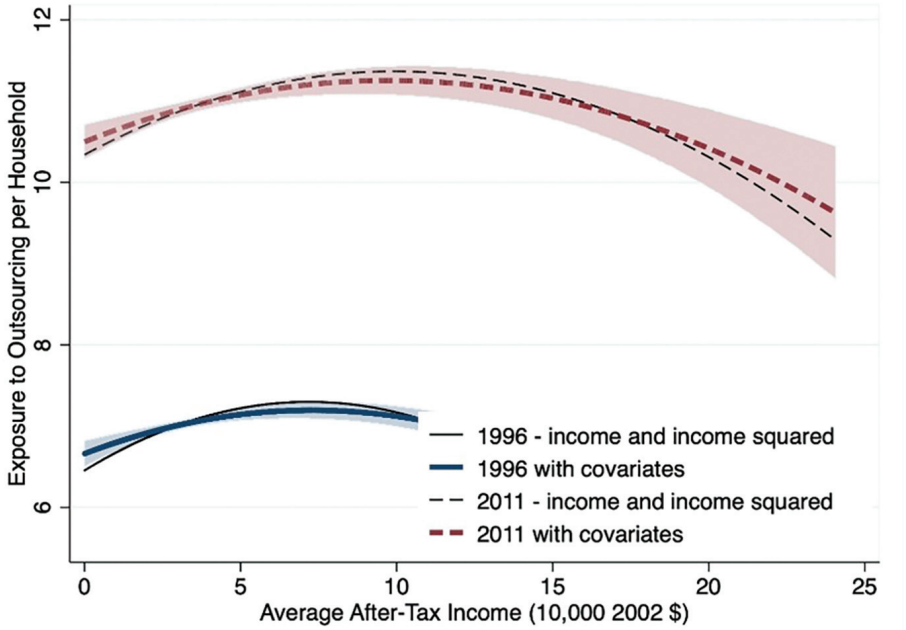
### 1.5.3 Technological Change

In the preceding section, we examined the shifts in two indexes while maintaining technological factors (IO linkage) at a constant level. This section extends our discussion to the shifts in these indexes while using information from the WIOD across the years. Notice that we keep environmentally related tax revenues constant at 2002 levels. Otherwise, our methodology closely aligns with the parametric estimations used to plot the Engel curves, as depicted in Fig. 1.8. These newly estimated Engel curves can be found in panels (a) and (b) of Fig. 1.10, which maintain a consistent

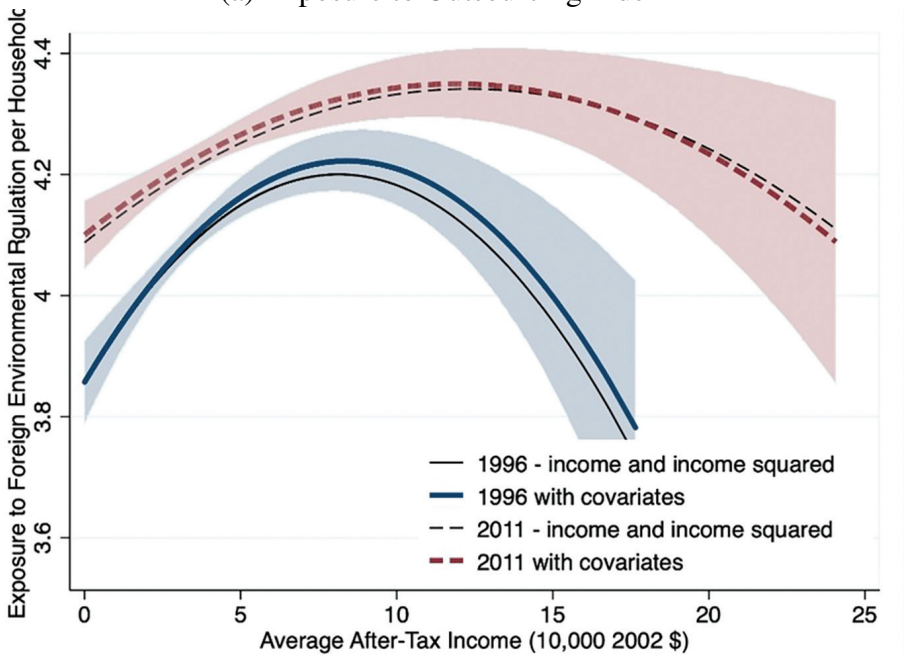
concave shape yet exhibit a differing shift pattern for the exposure to foreign content (panel (a)). Notably, for the outsourcing exposure index $EO$ (panel (a)), the Engel curve shifts up over time, a contrasting pattern to the downward shift observed in Fig. 1.8, panel (a). This shift implies a growing inclination among U.S. consumers to consume goods with a higher foreign content share as time advances. Compared to Fig. 1.8, this contrasting pattern emphasizes technology's substantial role in influencing consumption patterns concerning the share of foreign content in goods.

The rise in the share of foreign content in domestically produced goods over time can be attributed to a host of critical technological factors. Thatcher (2011) argues that advances in communication technologies have greatly facilitated global business coordination and collaboration, streamlining supply chain management by seamlessly integrating foreign intermediate goods into domestic production processes. Likewise, Hummels (2007) discusses that transportation systems have witnessed significant advancements, enhancing ease and cost-effectiveness in moving goods across borders. Moreover, Baier et al. (2014) show that preferential trade agreements (e.g., NAFTA and CAFTA-DR) promote trade between members, while Johnson and Noguera (2017) link these agreements to the fragmentation of production processes. Essentially, all these policy and technological changes affect the IO coefficients over time in the sense of leading to a greater share of foreign content in domestic consumption. They explain the upward shift of the Engel curve in this case.

In contrast, the index reflecting exposure to foreign environmental taxes $EFET$ displays an upward shift like in the baseline results, as seen in panel (b) of Fig. 1.10, but with a more pronounced shift magnitude. This upward trend in the index is influenced by the varying changes in foreign content shares over time, driven by distinct countries and industries. Fig. 1.11 elucidates these shifts in foreign content share by country from 1996 to 2011 utilizing the time-variant WIOD. Notably, specific countries, such as China, Germany, and Mexico, have increased their contribution to the U.S. foreign share and exhibit substantial environmental-related taxes, as reflected in Fig. 1.2. Consequently, the considerable rise in foreign content share associated with significant tax contributes to the average increase in the exposure to foreign environmental taxes, $EFET$. Conversely, Japan has shown the most significant decrease in U.S. foreign content share




(a) Exposure to Outsourcing Index




(b) Exposure to Foreign Environmental Taxes Index

Note: All other covariates are fixed at their mean values. Inflation adjustments as in Fig. 1.5. Standard errors for the two outsourcing indexes are not estimated. So, 5% confidence intervals (shaded) reflect variations in household spending.

**Figure 1.10**: *Engel Curves Based on Parametric Estimates with Technology Changes*

from 1996 to 2011.[39] The below-average environmental taxes in Japan, combined with the reduction in participation in the U.S. foreign content share, contribute to an increase in the index value.[40]

In Table 1.7, we delved into the outcomes of income redistribution in conjunction with technological changes. The findings exhibit a comparable pattern to those presented in Table 1.6. Specifically, redistributing income from wealthier to poorer households results in a minor increase in the $EO$ index, ranging from 0.035 to 0.065 percent. A similar analysis applied to the $EFET$ index yields an increase ranging from 0.02 to 0.041 percent. When employing the marginal redistribution mechanism involving the entire sample, the average $EO$ index experiences a rise of 0.54 percent, while the $EFET$ index sees an increase of 0.33 percent. Conversely, full-scale redistribution leads to a 0.23 percent increase in the $EO$ index and a 0.18 percent increase in the EFET index. Hence, the effects of income redistribution are not qualitatively affected by the choice of maintaining the World Input-Output Database (WIOD) at the 2002 level, enabling a more consumption behavior-focused analysis. This approach facilitates a more evident determination of whether alterations in consumption patterns predominantly stem from technological advancements or are influenced by factors such as shifts in consumer preferences or policy changes.

## 1.6 Conclusion

In this paper, we contribute to understanding the interplay between after-tax income and two critical features of final consumption goods and services. First, notice that modern economies

[39]The composition of Japan's intermediate goods imports by country underwent significant alterations between 1996 and 2011. According to data from the World Integrated Trade Solution (WITS) at https://wits.worldbank.org/CountryProfile/en/Country/JPN/Year/2011/TradeFlow/Import/Partner/all/Produ ct/UNCTAD-SoP2, the proportion of intermediate goods from Japan imported by the United States constituted a substantial share, accounting for 19.47 percent in 1996. In contrast, China's share was notably lower at 7.69 percent. However, by 2011, the share of Japan's intermediate goods imported by China experienced a substantial increase to 20.67 percent, consequently reducing the percentage imported by the United States to 13.55 percent.

[40]The shift observed in the $EFET$ in panel (b) can be linked to alterations in foreign content share across industries over the temporal span, as depicted in Fig. 1.12. Notably, the sectors of "Mining and Quarrying," "Electrical and Optical Equipment," and "Basic Metals and Fabricated Metal" display the most substantial increases in foreign content share between 1996 and 2011. Morrissey and O'Donoghue (2012) argue that marine resources have a role in climate change and food production, and there has been an increased focus on marine policy abroad, which may explain higher taxes in this sector .

**Figure 1.11**: *Foreign Content Share by Country between 1996 and 2011*

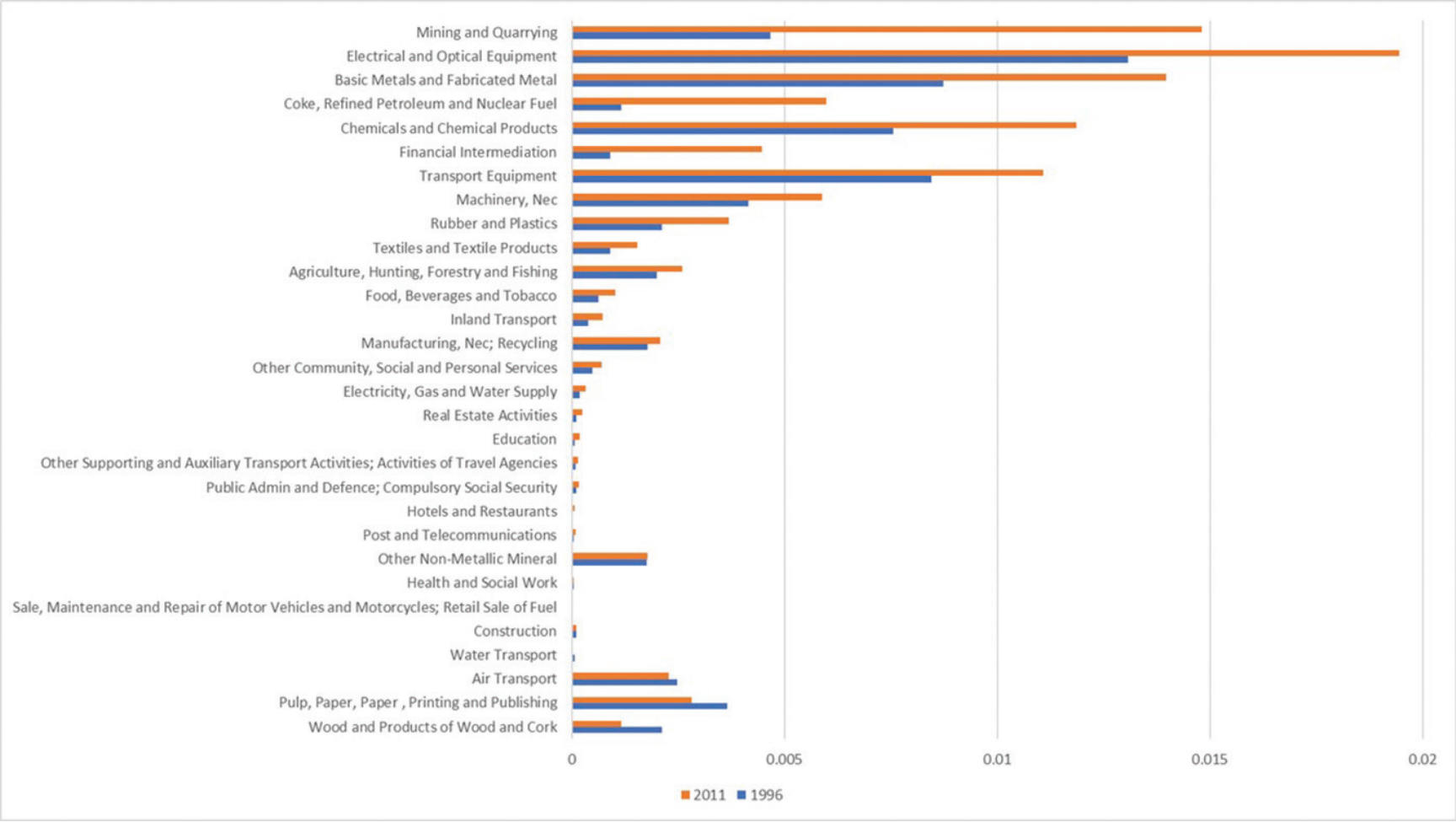



**Figure 1.12**: *Foreign content Share By Industry between 1996 and 2011*

**Table 1.7**: *Results of Income Redistribution with Technology Changes*

| | Income Redistribution | $EO$ | $\%\Delta EO$ | $EFET$ | $\%\Delta EFET$ |
|---|---|---|---|---|---|
| Original Value | | 10.9144 | | 4.216 | |
| To poorest | 0.25 | 10.9181 | 0.0346 | 4.217 | 0.0202 |
| | 0.5 | 10.9215 | 0.0652 | 4.218 | 0.0411 |
| To average | 0.25 | 10.9172 | 0.0257 | 4.217 | 0.0161999 |
| | 0.5 | 10.9198 | 0.0495 | 4.217 | 0.03003 |
| All households | Marginal Redistribution | 10.973 | 0.537 | 4.230 | 0.332 |
| | Full Redistribution | 10.940 | 0.234 | 4.224 | 0.184 |

*Ater-tax income measured in $10,000*

carry out critical levels of international trade, including the trade of inputs. Thus, we estimate Engel curves to better understand the relationship between household income and the foreign content of their consumption choices. Likewise, we are interested in better understanding how U.S. households are exposed to foreign environmental taxes via their consumption choices. Our strategy estimates Engel curves on the foreign content of goods and services and the foreign environmental taxes embedded in consumption. We find that Engel curves are concave, shift down for the exposure to outsourcing ($EO$), and shift up over time for the index of exposure to foreign environmental taxes ($EFET$). Moreover, these Engel curve features are present using different methodologies (parametric and nonparametric) and income measures.

Our decomposition analysis based on Engel curves suggests that changes in the composition of consumption bundles (movement along Engel curves) account for about 60 percent of the exposure to outsourcing index ($EO$) reduction. Instead, the increase in the exposure to foreign environmental taxes ($EFET$) is caused primarily by shifts in this curve. These results may shed some light on potential income redistribution and outsourcing trade-offs. For example, suppose significant swats of income are redistributed from high-income to low-income households. In that case, that policy may increase the consumption of goods with greater foreign content, as shown in the previous section. Likewise, our estimated Engel curve on foreign environmental taxes suggests that substantial

income redistribution to low-income households goes hand-in-hand with importing inputs from countries with more robust environmental taxes.

Our dataset does not allow a distinction between consumption of final goods produced in the U.S. or imported from abroad. Thus, our analysis assumes that imported final goods and services are produced using the same technology, including the choice of source for inputs, as final goods produced in the United States. Accounting for the relationship between U.S. household consumption of imported final goods and the content of third-country inputs used in the production of imported final goods is beyond the scope of this paper but an interesting question to pursue in the future.

# Chapter 2

# Understanding Household Consumption and Environmental Quality in China: A Study of Industrial Waste and Dust Emissions using Engel Curves

## 2.1 Introduction

Industrialization has concurrently contributed significantly to the socioeconomic growth of nations' environmental pollution[1]. Between 2010 and 2014, Chinese household expenditures increased by 15%, which is far higher than the average worldwide household expenditure growth. Similar to many developing countries, addressing environmental pollution has become crucial to China's economic policies. However, there have been discrepancies in policy treatments for different pollutants. Commonly studied pollutants such as sulfur dioxide (SO2), nitrogen oxides (NOx), carbon monoxide (CO), particulate matter (PM10), and volatile organic compounds (VOCs) have

[1]Ever since the establishment of the People's Republic of China, the manufacturing sector has consistently served as a vital impetus for the nation's economic progress, while simultaneously being a leading source of carbon emissions (Wang and Su, 2019). According to Cherniwchan (2012), the process of industrialization serves as a significant predictor of the observed alterations in emissions. Specifically, a 1% rise in the industry's proportion of overall output corresponds with an 11.8% increase in the per capita level of emissions.

received strong policy attention, whereas industrial waste and dust have been relegated to a secondary position in China's economic policy (Yang and Li (2017), Guo et al. (2021), and Nie et al. (2020)). Consequently, China has experienced a significant surge in industrial waste and dust discharge. In contrast, emissions of other air pollutants (SO2, NOx, CO, PM10, and VOCs) have gradually decreased over time. This study examines the relationship between household consumption decisions and the resulting industrial waste and dust pollution in China during this timeframe.

We investigate the relationship between pollution emissions and household income by estimating environmental Engel curves (EECs). This study's methodology for EEC estimation follows the strategy of Levinson and O'Brien (2019). In our study, we use data from the Chinese Family Panel Studies (CFPS) from 2010, 2012, and 2014 on household income, consumption, expenditure, and demographic characteristics. The data on two industrial waste emissions (industrial wastewater (IW) and industrial solid waste (ISW)) and industrial dust (ID) were collected from Chinese Environmental Statistical Yearbook (CESY). We apply the World Input-Output Table (WIOT) to measure the pollution intensity of industrial waste and dust. We then compute the pollution embedded in household consumption by pairing its itemized consumption with the 2010 total pollution intensity by industry.

We estimate the EEC for China using non-parametric and parametric econometric strategies for 2010, 2012, and 2014. Levinson and O'Brien (2019) previously estimated the relationships among pollution, income, and consumption across U.S. households with annual data from 1984 to 2012 and found three results: EECs slope upward, have income elasticities less than one (i.e., EECs are concave) and shift down over time. On the contrary, our analysis yielded environmental Engel curves (EECs) with straight shapes instead of concave shapes, which we attribute to inadequate policy controls and insufficient public education regarding industrial waste and dust. Furthermore, we find that EECs shift down over time. The primary cause of the shift can be attributed to a decrease in pollution emissions, accounting for 76% of the change. More specifically, this pollution reduction is driven by a decrease of 54% in industrial waste, 82% in industrial solid waste, and 90% in industrial dust. The shape of the EECs indicates that wealthier households are responsible for more significant pollution emissions, which have decreased over time. Regardless of whether household characteristics other than income are included, the main features of the profiles remain

highly robust.

The factors underlying our results draw extensively from the literature on the evolution of pollution emissions in China. As per the terminology established by Copeland and Taylor (1995), the evolution of pollution can be categorized as follows: i) the scale effect, whereby a rise in income proportionally leads to an increase in consumption; ii) the composition effect, which relates to the shift in the economic activities; and iii) the technique effect, which relates to the efficiency of production and recycling enhancing environmental conditions. Yunfeng and Laike (2010) study partitions of trade-embodied emissions into these three components. The results reveal that the scale effect (the growth in export volumes) and composition effect (the changes in export structure) increased CO2 emissions embodied in China's export. In contrast, the technical effect (the improvement of emission factor) offset a minor portion. Moreover, Shapiro and Walker (2018) argues in their recent study for the U.S. economy that the technique effect plays a significant role in accounting for the decline of major pollutants emissions in U.S. manufacturing activities. A study by Cole and Zhang (2019) showed that from 2013 to 2015, the Chinese economy had grown by a factor of six, while SO2 emissions from the manufacturing sector had only increased by 1.5 times, mainly due to significant advancements in the technique effect. Our study aims to investigate the role of consumption decisions in explaining industrial waste and dust in China; thus, we maintain the WIOT at 2010 levels to mute the technique effect.

Our study contributes to examining the discrepancy between policies implemented towards air pollutants (namely, SO2, NOx, CO, PM10, and VOC) vis-a-vis industrial waste and dust on pollution levels. As our estimates show that there is a linear correlation between ID, IW, and ISW emissions and income, households' consumption decisions are unaffected by the concern of releasing these pollutants stemming from the production process. Yang and Li (2017) determined that the total factor efficiency (TFE) of wastewater control in the industrial domains remains suboptimal. Moreover, in some industries, inadequate efficiency in wastewater control has emerged as a significant barrier to their sustainable development. Guo et al. (2021) suggest that solid waste management in China has undergone a comprehensive transformation from insufficient funding and a non-standard approach to a progressively improved policy framework[2]. Conversely, Chinese SO2

[2]Geng et al. (2007) further suggests that in the planning of the solid waste management system in the Tianjin Eco-

emissions were estimated to decrease by approximately 14.29% during the 11th Five-Year Plan (FYP) period (2006-2010) (Zheng et al. (2015a), and Li et al. (2022)). Moreover, China aimed to continue reducing air pollutant emissions by implementing the National Total Emission Control (NTEC) Program during the 12th FYP (2011-2015)[3]. The comparatively weaker and less effective policies in place to address industrial waste and dust emissions, compared with other major air pollutants, suggests that the public lacks awareness. Consequently, their consumption patterns are less likely to be influenced by industrial waste and dust emissions involved in producing goods.

Our research is closely connected to existing literature employing the concept of Engel curves to investigate various economic phenomena. As noted above, Levinson and O'Brien (2019) ) use EECs to investigate the impact of U.S. consumption patterns on pollution emissions. They indicate that the composition effect and other non-income determinants, such as price fluctuations and product availability, contribute equally to decreased average pollution emissions associated with US household consumption decisions. The Engel curve form can represent the demand for luxuries and necessities, implying that what is a luxury for the poor may be a necessity for the rich (Aitchison and Brown, 1954). The EEC framework allows changes in individual preferences for environmental quality when income increases to be evaluated when holding technologies constant (Pearce, 2003). In investigating the relationship between income inequality and consumption's CO2 content using EECs, Sager (2019) notes that progressive income redistribution may increase aggregate greenhouse gas emissions demand, resulting in the "equity-pollution dilemma."

Feng et al. (2020) previously estimated household food-related carbon emissions 1992 and 2007 using parametric estimates of EECs, and the results indicate that economic expenditure on food consumption increased, while food-related carbon emissions per capita decreased. Based on their findings, the coefficient estimates for squared income are statistically significant but minimal. Thus, their study indicates that EECs in China exhibit concavity and affluent households tend to consume less emission-intensive food. Moreover, the curves have become less concave and shift

nomic Development Area (TEDA), the development of capacity has been identified as a critical objective. Nevertheless, many stakeholders in this endeavor lack the requisite expertise, human resources, financial capacity, technological resources, equipment, and a forward-thinking perspective to achieve effective solid waste management.

[3]Xue et al. (2013) predicted that predicted that the implementation of NTEC during the 12th FYP will lead to reductions in the average SO2 and NOx concentrations across all Chinese cities by 9.28% and 10.61% respectively by 2015.

down over the last 15 years, implying that households indirectly contributed to fewer carbon emissions in 2007 than households with equivalent income levels in 1992. Furthermore, households in the upper-income deciles are inclined to consume less emission-intensive food.

The usual (concave) pattern of EECs follows the shape of an environmental Kuznets curve (EKC), which represents the relationship between environmental quality and per capita GDP (Bimonte and Stabile, 2017a). The estimated EKC's inverted U-shape suggests that pollution emissions tend to increase to a particular income threshold before declining. By estimating the EKC for CO2 in Canada, He and Richard (2010) find that the oil shock of the 1970s significantly impacted progress toward less-polluting technology and production. The EKC hypothesis may suggest that developing countries should pursue rapid economic growth instead of implementing pro-environmental policies. However, Rashid Gill et al. (2018) conclude that the EKC growth strategy of "grow now clean later," is resource-intensive and has a substantial environmental cost that the planet may be unable to absorb in the future.

The remainder of this paper is organized as follows. Section 2 details the dataset and methodology used in this study. Section 3 presents a nonparametric estimate of the relationship between pollution emissions and income by plotting the data. In Section 4, we provide parametric estimates and elucidate our empirical strategy while also presenting the decomposition effects. Finally, Section 5 concludes the paper with policy implications drawn from our findings.

## 2.2 Data and methodology

### 2.2.1 Data

The dataset utilized in this study contains information on household income, expenditure, and socio-demographic characteristics obtained from the Chinese Family Panel Studies (CFPS 2010, 2012, and 2014). The CFPS is an ongoing longitudinal social survey conducted throughout nearly all regions of China and designed to provide comprehensive data on a wide range of social phenomena in modern China (Xie and Lu, 2015). The data collection process involves computer-assisted in-person interviews with all household members. The CFPS sample includes individuals

from 25 provinces, encompassing 94.5% of the total population of Mainland China (Xie and Hu, 2014). Household income and expenditure data were adjusted using the all-item Consumer Price Index (CPI) to account for inflation. The Households with expenditure on students, the bottom 1% of household-based on after-tax income, and missing data are excluded, reducing the sample size from 422,648 to 406,372.In addition, household expenditures are manually categorized using World Input-Output Database (WIOD) codes. The observed statistical discrepancy in wage, non-agricultural operation, and transfer income between the 2010 and 2012 questionnaires is attributed to significant changes in the family economic questionnaire since 2010. Thus, employing comparable income helps mitigate income changes stemming from differences in questionnaire content (Shen et al., 2022).

The Chinese Environmental Statistical Yearbook (CESY) provides information on the discharge of industrial wastewater (IW), industrial solid waste (ISW), and industrial dust (ID) generated by various industries, classified according to WIOD codes. The pollution intensity per yuan for each sector is computed by dividing the total disposal amount at the industry level, as reported in the 2010 CESY, by the total sales obtained from the 2010 WIOD. The 2016 WIOD release encompasses intersectoral linkages across 56 industries in 43 nations and a framework for the remainder of the world, covering 2000 to 2014 (Timmer et al., 2015b). In the World Input-Output Table (WIOT), a collection of national input-output tables is linked through bilateral international trade flows, allowing researchers to access data on the distribution of industry output. In this study, we match the CFPS with pollution intensities from the CESY to calculate the pollution caused by producing goods and services associated with itemized expenditures. However, only the pollution generated during the production of each final product has been reported. We also want to consider the production of intermediate goods used to produce the final goods. The WIOT is used to calculate all upstream pollution. By applying the analysis method conducted by Leontief (1970), direct pollution intensities are transformed into total disposal coefficients for each industry.

Fig. 2.1 shows the discharge quantities of industrial wastewater (IW), industrial solid waste (ISW) and industrial dust (ID) in 2010. Based on the findings illustrated in Fig. 2.1, the "manufacturing of paper and paper products" industry contributes the highest amount to industrial wastewater disposal. In contrast, the "manufacturing of other nonmetallic mineral products" sector gener-

ates a significant amount of industrial dust. The "mining and quarrying" industry is responsible for the highest amount of industrial solid waste disposal. Technological advancements have played a crucial role in reducing pollution emissions in China. Industrial wastewater, particularly that from chemical and pharmaceutical production, poses a substantial threat to the ecological environment and human health (Leonhauser et al., 2014). Membrane technology, which generates stable water without adding chemicals, has been used in China because of the increasing demand for wastewater treatment and reuse (Zheng et al., 2015b). Similarly, the technical levels of industrial solid waste and industrial dust recycling have increased since 2010. Therefore, the same 2002 WIOD-based indices are applied to all years of the consumption data.

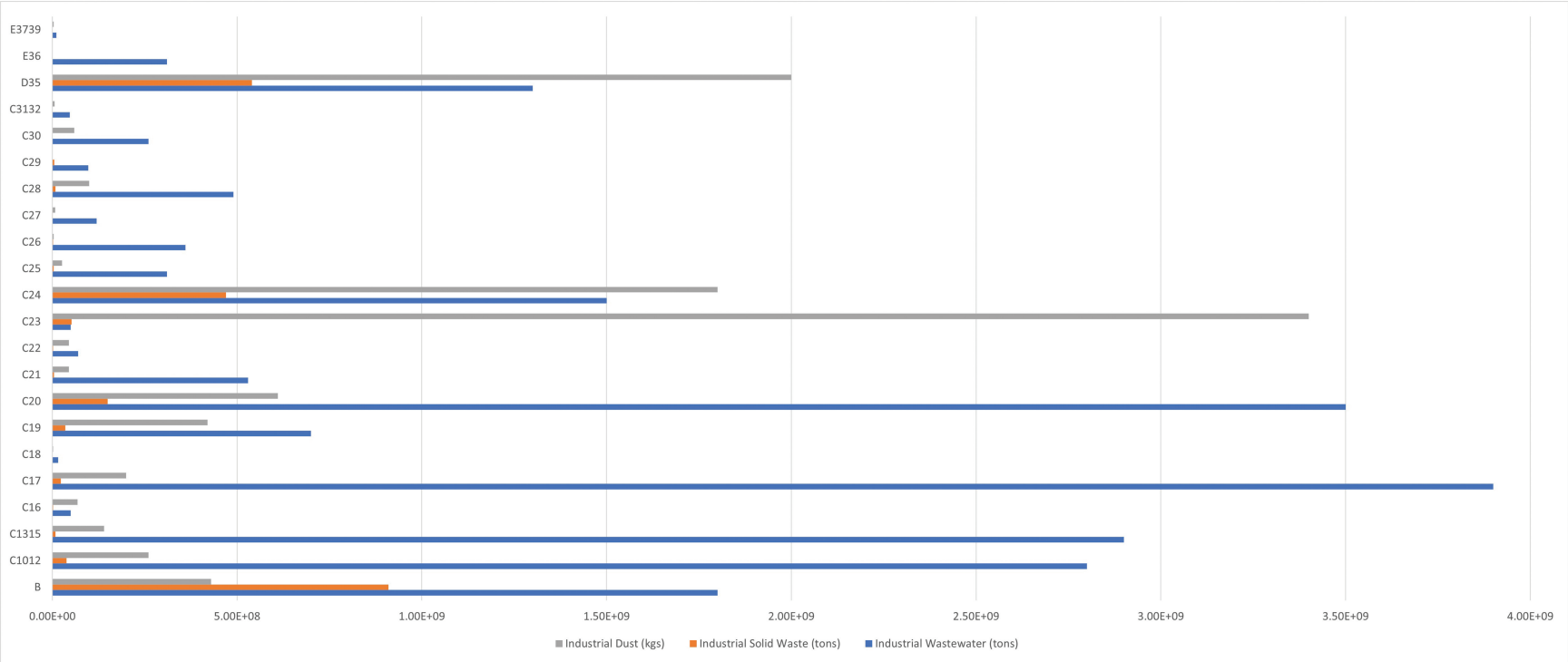
### 2.2.2 Methodology

Following the data procedure shown in Fig. 2.2, we use each industry's pollution emissions divided by total sales collected from the WIOT to calculate the direct pollution coefficients for the production. In addition, we apply the WIOT to obtain indirect pollution coefficients to account for all upstream inputs. Therefore, the total pollution coefficients by industry are calculated by summing the direct and indirect coefficients. In the WIOT, total output is the sum of all upstream inputs and inputs for the production of final goods. This relationship can be formulated as follows:

$$X = [I - A]^{-1} \times Y \tag{2.1}$$

where X is the economic output, and I is the identity matrix. Y represents the final consumption. T=$[I-A]^{-1}$ is the Leontief total requirements matrix, illustrating the dollar amount of industry i used to produce one dollar of output in industry j. Total pollution intensity coefficients are calculated using the total requirements matrix, and we observe Y collected from the CFPS.

Household income, expenditures, and demographic characteristics are available for consumption analysis. A detailed breakdown of household consumption is obtained by categorizing household expenditures by WIOD codes. Hence, household pollution is calculated by multiplying itemized household consumption by the 2010 pollution production intensity for each type of good and household.




Notes: The WIOD code used for this analysis is provided in Fig. C.1, which includes the corresponding code names and descriptions for reference.

**Figure 2.1**: *Amount of Disposal by Industry*

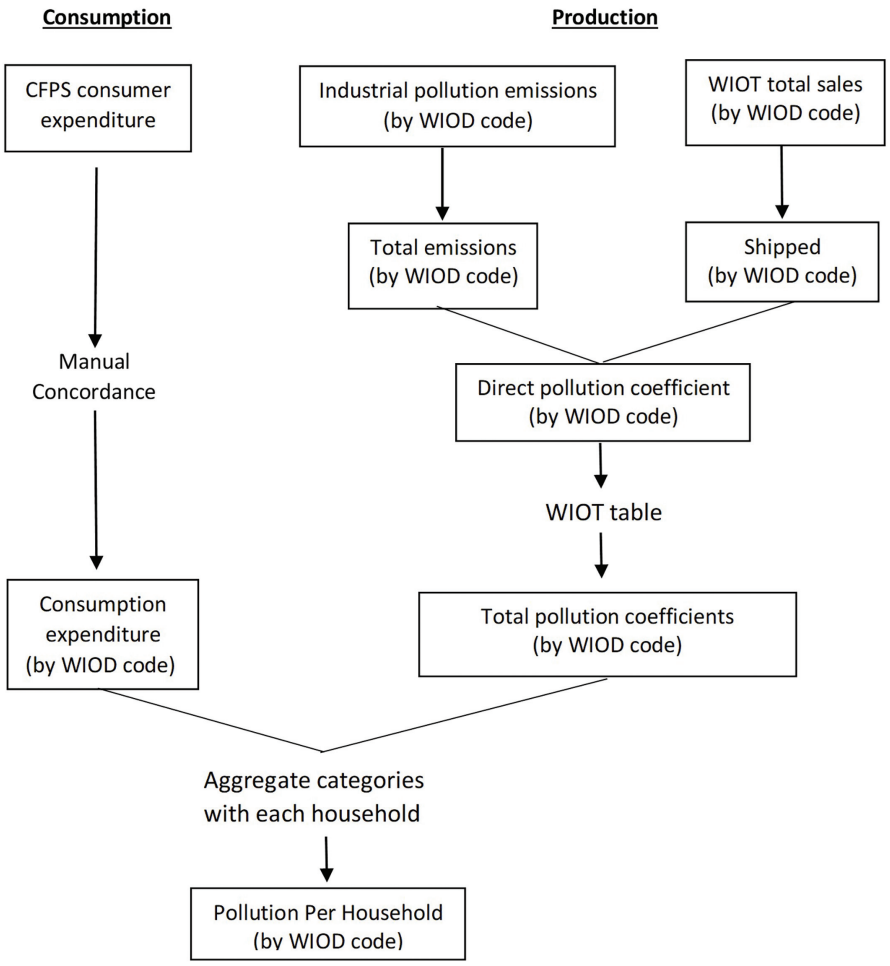



**Figure 2.2**: *Summary of Data Procedure*

Table 2.1 provides an overview of the primary variables we use in our analysis. Notably, we observe a decline of approximately 8% in the discharge of IW embodied in household consumption, from 0.775 tons in 2010 to 0.712 tons in 2014. In contrast, SO2 and NOx emissions in China showed a substantial reductions of 9.6% and 16.9%, respectively, over the same period[4]. In addition, the amount of ISW disposal decreased from 28.7 kgs to 17.09 kgs during the same period, while ID discharge decreased by 75%. The substantial decrease in industrial dust discharge can be attributed to growing public concern regarding the health risks associated with inhaling air pollutants such as SO2, soot, and dust particles, which can cause respiratory illnesses. Consequently, Chinese authorities have focused their efforts on reducing ID pollution by implementing numerous measures, significantly reducing emission levels. Setting technology as unchanged, the observed changes in Table 2.1 are affected by the composition and quantity of household consumption. Over time, household income and the age of the household head increased. We use CPI to adjust the nominal income for all items. Moreover, households tend to be on the northwest, central, and northern coasts, which were the main regions with constructions and house maledictions in 2003-2013[5]. When rural houses are demolished, the city government offers free flats or cash compensation. Furthermore, the high compensation for demolition incentives provided to households in rural areas explains the decreased number of urban variables shown in Table 2.1.

Considering the influence of international trade, we adopt a methodology that assumes all goods are produced in China, and all production uses Chinese technology with China's emission intensities. According to Levinson (2009b), the net imports of pollution-intensive goods increases are too small to explain pollution reduction resulting from changing the mix of goods produced. Therefore, shifting China's imports played a minor role in the clean-up of China's manufacturing sector.

[4]National Bureau of Statistics of China. http://www.stats.gov.cn/english/.

[5]There are 8 regions classified in this paper: Northeast (Heilongjiang, Jilin and Liaoning), NorthMunicipalities (Beijing and Tianjin), North Coast (Hebei and Shandong), Central Coast (Shanghai, Jiangsu and Zhejiang), South Coast (Guangdong, Fujian and Hainan), Central(Henan, Shanxi, Anhui, Jiangxi, Hubei and Hunan), Southwest (Guangxi, Chongqing, Sichuan, Guizhou, Yunnan and Tibet) and Northwest (Inner Mongolia, Shanxi, Gansu, Qinghai, Ningxia and Xinjiang).

**Table 2.1**: *Average Values for Selected Variables*

| | Cross Section | | |
|---|---|---|---|
| | 2010 | 2014 | Difference |
| Variable | (1) | (2) | (3) |
| Pollutant (2010 technology) | | | |
| Industrial Wastewater (tons) | 0.775 | 0.712 | -0.063 |
| | (0.013) | (0.012) | (0.02) |
| Industrial Solid Waste (kgs) | 28.70 | 17.09 | -11.61 |
| | (1.07) | (0.254) | (1.096) |
| Industrial Dust (kgs) | 0.475 | 0.119 | -0.356 |
| | (0.023) | (0.002) | (0.023) |
| After-tax income | 3.272 | 3.809 | 0.537 |
| (¥10,000 in 2010 yuan) | (0.024) | (0.034) | (0.041) |
| Household size | 2.716 | 3.101 | 0.385 |
| | (0.012) | (0.016) | (0.02) |
| Age of household head | 46.87 | 51.06 | 4.19 |
| | (0.131) | (0.158) | (0.21) |
| Head is married (share of population) | 0.891 | 0.888 | -0.003 |
| Education of head (share of population) | | | |
| Elementary only | 0.714 | 0.692 | -0.022 |
| High school | 0.189 | 0.171 | -0.018 |
| Some college | 0.0606 | 0.0476 | -0.013 |
| College | 0.0343 | 0.0278 | -0.0065 |
| More than college | 0.530 | 0.406 | -0.124 |
| Region | | | |
| Northeast | 0.189 | 0.179 | -0.01 |
| NorthMunicipalities | 0.0143 | 0.0109 | -0.0034 |
| North Coast | 0.102 | 0.118 | 0.016 |
| Central Coast | 0.127 | 0.0850 | -0.042 |
| South Coast | 0.100 | 0.0776 | -0.0224 |
| Central | 0.242 | 0.263 | 0.021 |
| Northwest | 0.110 | 0.137 | 0.027 |
| Urban | 0.530 | 0.406 | -0.124 |
| Observations | 112,536 | 76,836 | |

Notes: Standard erros in parentheses. Nominal income adjusted using the CPI for all items.

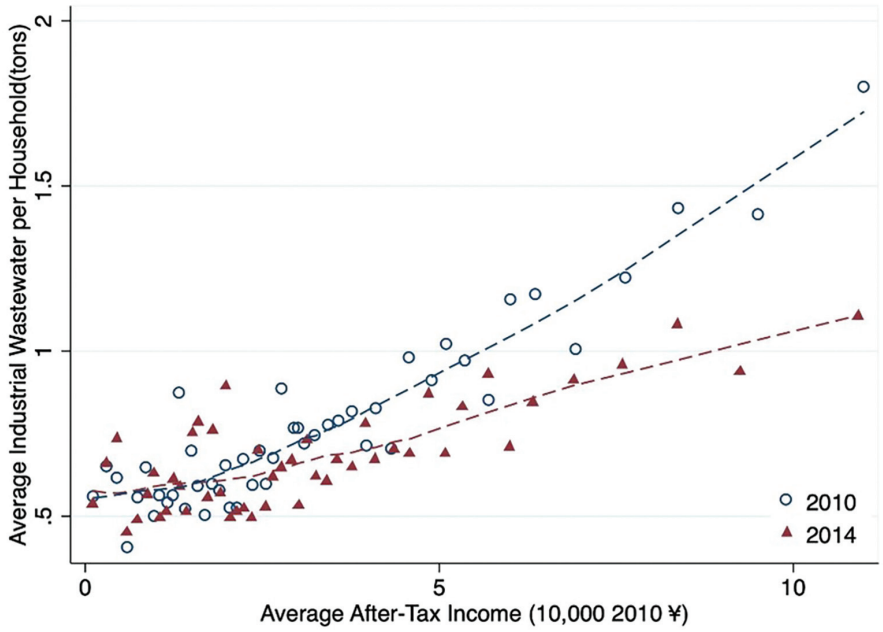
## 2.3 Nonparametric estimate

We simply plot EECs that reflect the relationship between pollution embodied in consumption and income levels without controlling for other household characteristics. Based on after-tax income, which is not influenced by tax policy, the 2010 cross-section of the CFPS is divided by household into 50 groups. Meanwhile, average pollution is calculated for each of these 50 groups associated with the consumption. In Fig. C.1, we plot the share of households in each income bin for 2010 and 2014. By plotting 50 combinations of average after-tax income and average IW emissions per household, we obtain nonparametric EECs for 2010 and 2014. For the 2010 EEC, a household in the median income bin (¥27,000 to ¥28,500 after taxes, in 2010 dollars) would have been indirectly responsible for 71.79 tons of IW on average. To analyze the shift of EEC over time, for the same income bin cutoff values, households with 2014 after-tax income in the 2010 median bin (¥27,000 to ¥28,500) would have been indirectly responsible for 70.46 tons of IW discharge on average.

Fig. 2.3 shows that the EECs for IW have a positive slope, implying that as household income increases, so does household consumption of goods and services, leading to higher pollution emissions. In addition, we find that the EECs shift downward over time. Households in the 2010 EEC were responsible for more pollution than their corresponding counterparts with the same income in the 2014 EEC. The same 2010 emission intensities are applied to control for the influence of technological improvement. The shift in EECs can be explained by changes in consumption composition resulting from regulations and social norms. Fig. 2.4 shows the same nonparametric EECs for ISW and ID, and the findings align with those of the EECs for IW, demonstrating an upward slope with a downward shift over time.

We also plot Engel curves based on total expenditure as a robustness check. Fig. C.2 shows the relationship between the average volume of IW discharge and average total expenditure. The Engel curves exhibit a similar pattern to those in Fig. 2.3 and Fig. 2.4. Similarly, Engel curves based on the total expenditure for ISW and ID are shown in Fig. C.3 and display similar trends.

Although the approach depicted in Fig. 2.3 offers a general idea of the movement along the EEC and shift in EECs, it's still unable to precisely explain the relationship between pollution

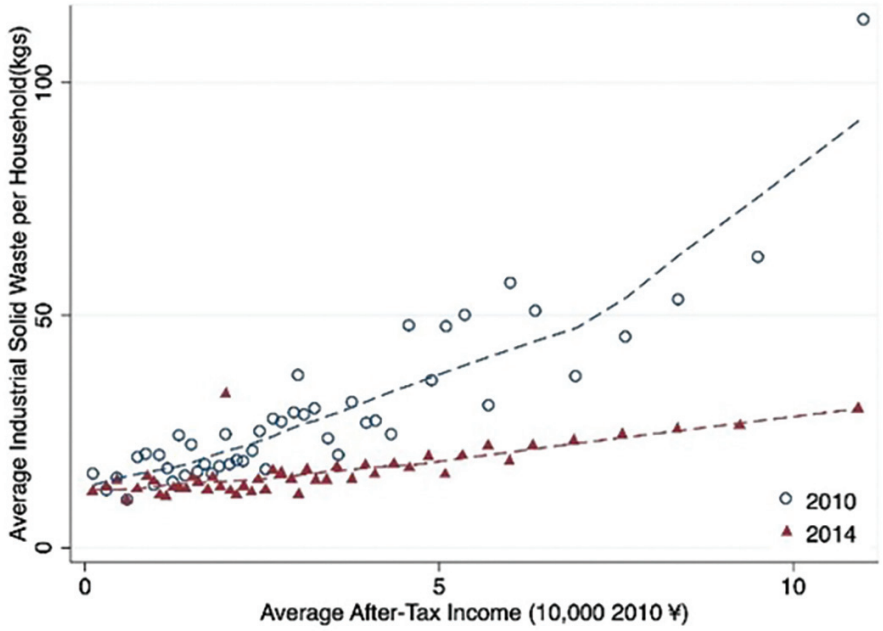



Notes: Income is adjusted for inflation using the all-items CPI. Each pair of dots represents an income level corresponding to 2% of the 2010 CFPS sample, with the highest and lowest 1% of households trimmed based on after-tax income.)

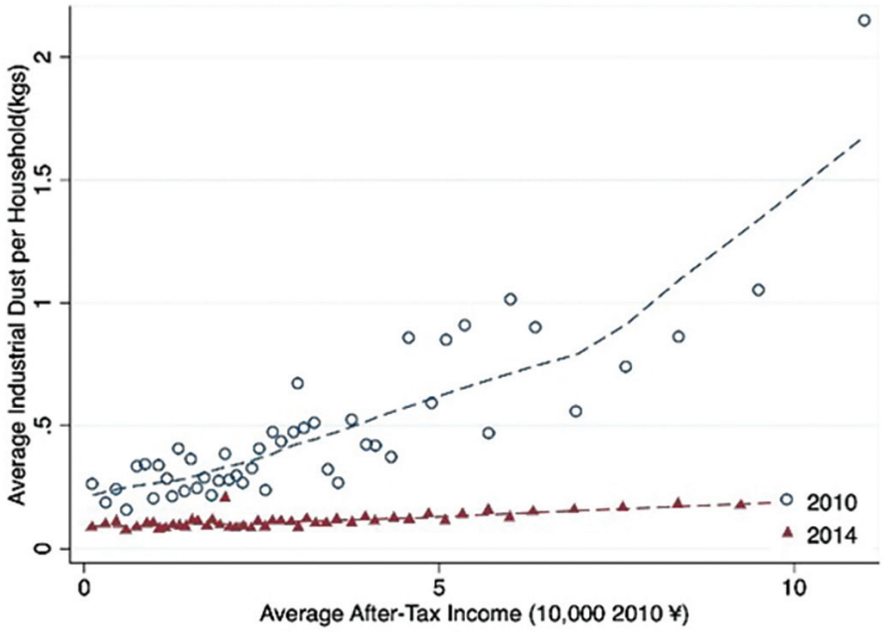
**Figure 2.3**: *Pollution Embodied in Household Consumption: Industrial Wastewater (IW)*

emissions and household income due to the missing household characteristics. For example, different household sizes, ages of the household head, and education levels may play different roles in household consumption behaviors, further changing the pollution embodied in consumption. Moreover, the law of price may not hold in Fig. 2.3. Price effects will cause movements along and shifts in EECs biased due to changing incomes and relative prices for pollution-intensive goods and services.

Table 2.1 shows some key household characteristics along with the estimated pollution emissions. Between 2010 and 2014, IW disposal decreased by 8%, whereas average after-tax income increased by 16.4%. Moreover, average households became larger, older, less likely to be married, and more likely to live in the northern coastal, northwestern, and central regions. In the next section, we describe the use of parametric estimations to examine whether these demographic changes account for the shifts in and movements along the EECs.




(a) Industrial Solid Waste (ISW)




(b) Industrial Dust (ID)

Notes: Income is adjusted for inflation using the all-items CPI. Each pair of dots represents an income level corresponding to 2% of the 2010 CFPS sample, with the highest and lowest 1% of households trimmed based on after-tax income.

**Figure 2.4**: *Pollution Embodied in Household Consumption*

## 2.4 Empirical strategy

### 2.4.1 Parametric estimate

We need to separate the components of income growth and economy-wide changes represented by movement along and shifts in the EECs over time to assess the compositional effects of the change in the volume of total pollution emissions. First, we consider a simple case in which pollution emissions are treated as the dependent variable in the regression to help understand the decomposition, while holding other demographic changes constant, as follows:

$$P_{it} = \alpha_t Y_{it} + \delta_t X_{it} + \varepsilon_{it} \tag{2.2}$$

The dependent variable, $P_{it}$ , is the amount of pollutants discharged during year t. $Y_{it}$ is the after-tax income in year t. $X_{it}$ denotes the vector of covariates that we motivate and discuss when we present the results. The equation captures the shape of and change in EECs over time.

Table 2.2 reports the results of the abovementioned regression. Column 1 indicates the coefficient outputs when we regress the total amount of IW discharge on after-tax income only. It shows that, when income increases by ¥10,000, the IW discharge level increases by 0.104 tons. Columns 2 through 4 report the regression results for the total IW volume on the after-tax income and all other household characteristics, such as age of the household head, household size, race, and region, for three years. Most of the covariates are statistically significant. Using the 2010 CFPS, the estimated coefficients of income, household size, education level, and urban are positive and statistically significant. If income increases by ¥10,000, the pollution emissions for IW increase by 0.07 tons. Moreover, when household size increases by one unit, the amount of IW discharge increases by 0.08 tons. By comparing columns 1 and 2, our basic conclusions regarding the decomposition of pollution emission changes in relation to movements along and shifts in EEC still hold with additional observable demographic factors.

Furthermore, columns 2 through 4 apply the same regression as column 2 using the 2012 and 2014 CFPS, enabling us to compare EECs across time. As shown in column 6, after-tax income and households in urban areas had a minor impact on pollution in 2014, compared with

**Table 2.2**: *Parametric environmental engel curves for IW*

| Dependent vairable: | 2010 | | 2012 | 2014 | Coefficient change. 2010-2014 |
|---|---|---|---|---|---|
| Exposure per Household | (1) | (2) | (3) | (4) | (5) |
| After-tax income | 0.104*** | 0.0747*** | 0.0348*** | 0.0323*** | -0.0424*** |
| (10,000 in 2010 yuan) | (0.007) | (0.008) | (0.004) | (0.006) | (0.010) |
| Household size | | 0.0839* | 0.0874*** | 0.156*** | 0.0721 |
| | | (0.034) | (0.023) | (0.035) | (0.049) |
| Household size squared | | -0.00354 | -0.00481 | -0.0102* | -0.0067 |
| | | (0.005) | (0.003) | (0.004) | (0.006) |
| Age | | -1.09e-05 | -0.003 | -0.009 | -0.009 |
| | | (0.006) | (0.005) | (0.007) | (0.009) |
| Age squared | | 3.65e-06 | 6.18e-05 | 9.41e-05 | 0.0001 |
| | | (5.70e-05) | (4.54e-05) | (6.53e-05) | (6.53e-05) |
| Married | | -0.0191 | 0.110** | -0.0855 | -0.0664 |
| | | (0.054) | (0.034) | (0.079) | (0.095) |
| Education: High school | | 0.0834* | 0.139*** | 0.0470 | -0.0364 |
| | | (0.034) | (0.024) | (0.028) | (0.044) |
| Education: Some college | | 0.224*** | 0.482*** | 0.216*** | -0.008 |
| | | (0.064) | (0.068) | (0.062) | (0.089) |
| Education: College | | 0.369*** | 0.403*** | 0.363 | -0.006 |
| | | (0.083) | (0.057) | (0.079) | (0.114) |
| Education: Graduate | | 0.657 | 0.718** | 0.235 | -0.422 |
| | | (0.386) | (0.259) | (0.179) | (0.425) |
| Region: Northeast | | 0.0399 | 0.159*** | 0.00840 | -0.0649 |
| | | (0.035) | (0.031) | (0.034) | (0.049) |
| Region: NorthMunicipalities | | 0.316 | 0.306*** | 0.244* | -0.0315 |
| | | (0.180) | (0.0733) | (0.123) | (0.218) |
| Region: North Coast | | 0.0715*** | 0.0352 | 0.0326 | -0.0389 |
| | | (0.059) | (0.030) | (0.042) | (0.072) |
| Region: Central Coast | | 0.207 | 0.372*** | 0.357*** | 0.15 |
| | | (0.057) | (0.051) | (0.082) | (0.100) |
| Region: South Coast | | 0.0812 | 0.231*** | 0.0339 | -0.0473 |
| | | (0.046) | (0.050) | (0.043) | (0.063) |
| Region: Central | | 0.0570 | 0.0829** | 0.0955* | 0.0385 |
| | | (0.030) | (0.026) | (0.041) | (0.051) |
| Region: Northwest | | 0.136** | 0.0923** | 0.0476 | -0.0884 |
| | | (0.040) | (0.035) | (0.039) | (0.056) |
| Urban | | 0.0997*** | 0.00416 | 0.0348*** | -0.072*** |
| | | (0.026) | (0.016) | (0.009) | (0.027) |
| Constant | 0.436 | 0.164 | 0.0213 | 0.362 | 0.198 |
| | (0.0243) | (0.124) | (0.134) | (0.158) | (0.158) |
| F-test of income coefficients | 208.8 | 90.83 | 63.31 | 32.48 | |
| Observations | 112,536 | 112,536 | 130,380 | 76,836 | |
| R-squared | 0.004 | 0.005 | 0.004 | 0.004 | |

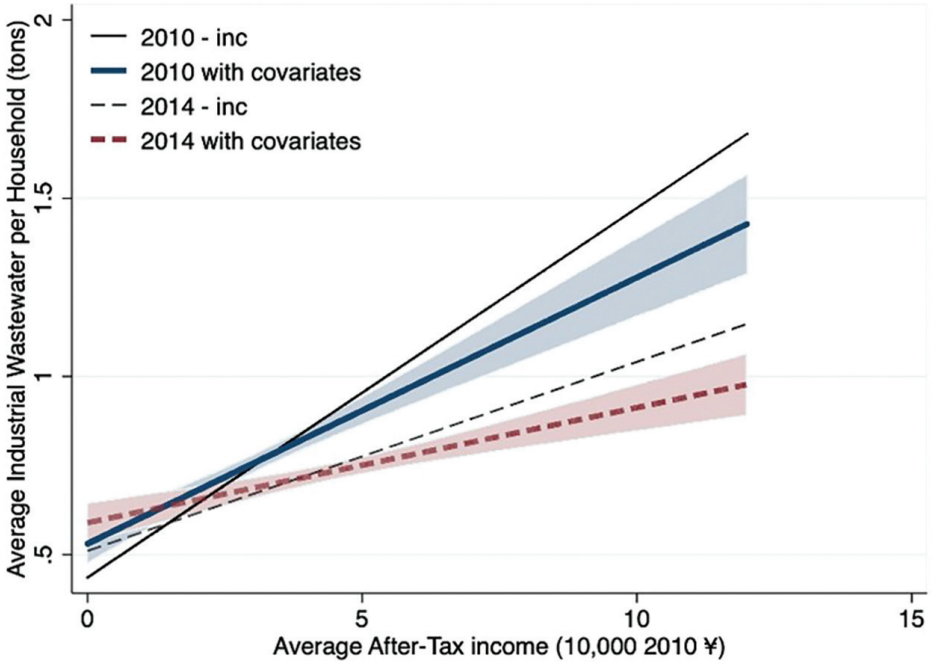
Notes: Robust standard errors in parentheses. Household pollution calculated by multiplying itemized household consumption with the 2010 WIOD pollution intnesity for each type of good and summing for each household. Includes upstream pollution based on a Leontief input-output calculation. Nominal incomes adjusted using the CPI for all items.
**** for 1%, ** for 5%, * for 10%*

in 2010. Consistent with the findings of Levinson and O'Brien (2015), most of the effects of demographic factors on the strike are determined to be statistically insignificant. Using parametric estimations of EECs to assess food-related carbon emissions from households in 1992 and 2007, Feng et al. (2020) report that EECs demonstrate a concave pattern that shifts downward over time. The statistical analysis shows that the estimated coefficients of income squared are statistically significant but exhibit a minute effect. Additionally, the EECs became less concave from 1992 to 2007 and almost reached a linear trend in 2007, which is consistent with our findings.

Additionally, we apply an estimation model that adds income quadratic terms to the regression, based on Levinson and O'Brien (2019). The outputs are listed in Table C.2. The estimation coefficients for income are statistically significant only for 2012, whereas the joint test for income and income squared indicates that they are statistically significant. In this study, we aim to explore the relationship between after-tax income and the corresponding pollution emissions embodied in consumption. By adding the income-squared term, the results cannot strongly support our analysis, although the joint test is statistically significant. Therefore, our regression model excludes the after-tax income-squared term to more precisely explore the EEC.

Fig. 2.5 presents the predicted relationship between after-tax income and IW discharge, based on the estimations in Table 2.2. The thick lines represent the results from columns 2 and 4 of Table 2.2, which explain the income expansion paths while holding other household characteristics constant. Similar to the EECs shown in Fig. 2.3, the EECs slope upward and then shift downward over time. The two thin lines reflect the regression results that only include income. Comparing the two sets of lines, we observe consistent results even with more independent variables. The EECs exhibit similar patterns, in that they slope up and then shift down over time.

Controlling for other variables, the movements along an EEC only depict the association between pollution emissions and income. Thus, we can observe that affluent households bear greater responsibility for the higher discharge of IW than their less affluent counterparts. According to the findings in Fig. 2.6, the expenditure of households in the realm of "construction" was the highest in the industry in 2010. However, in 2014, the monetary allocation to this industry significantly decreased. Conversely, household consumption has increased within the "manufacturing of food products, beverages, and tobacco products" and "insurance, reinsurance, and pension fund-




Notes: All other covariates are fixed at their mean values. Inflation adjustments as in Fig. 2.3. Standard errors for pollution intensity of production are not estimated. So, 5% confidence intervals (shaded) reflect variations in household spending.)

**Figure 2.5**: *Engel Curves Based on Parametric Estimates: Industrial Wastewater (IW)*

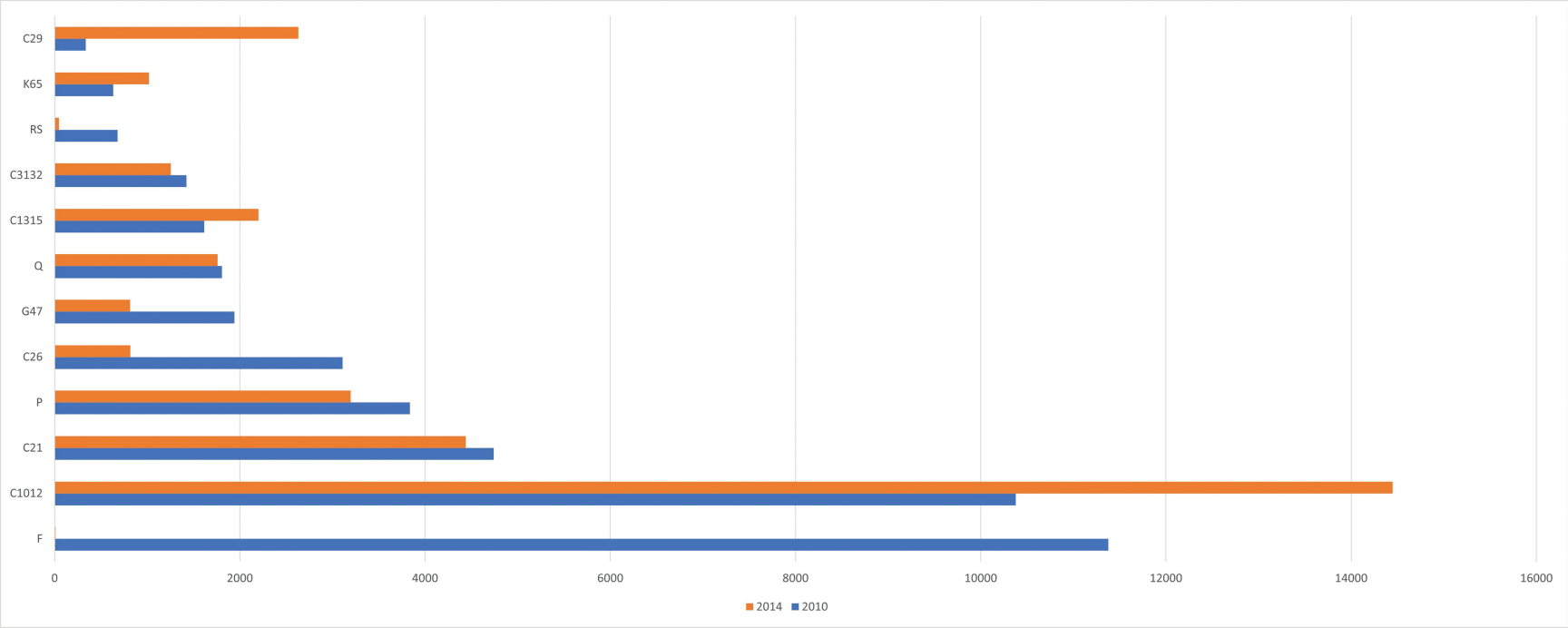
ing, except compulsory social security" industries. This growth can be attributed to the outbreak of Influenza A Virus Subtype H7N9 (H7N9) that began in February 2013 in China[6]. H7N9 influenza virus is a significant threat due to its virulence in poultry and potential to cause human disease, influenced by population immunity and transmission potential (Qiu et al., 2018). Following the outbreak of severe acute respiratory syndrome (SARS) in 2003, consumers modified their consumption behavior by increasing purchases of goods and medical products due to negative experiences and feelings associated with the virus. According to Qiu et al. (2018), over 50% of respondents reported changes in their health and consumption habits due to the need to prevent human infection with H7N9.

The food security problem in China has also drawn public attention, resulting in changes in household food-related behaviors. Affluent people with high food-purchasing power will cause a new food waste problem related to food security (Hao et al., 2017). Households with higher incomes tend to consume a large variety of goods and services. According to Hosoe and Naito (2006), using a wide variety of manufactured household goods adversely affects the environment. Compared with lower-income households, affluent households consume goods and services that require more upstream inputs for production, leading to higher pollution emissions.

Moreover, EEC shifts reflect changes in the relative supply and demand of pollution-intensive goods. The reduction in IW emissions is more extensive for wealthier households than for those with lower incomes. The close relationship between national pollution regulations and income results from mutually reinforcing factors. High-income households have larger budgets for regulatory monitoring and enforcement, and then, higher environmental standards are enforced by higher-income communities (Wheeler, 2002).

Table C.2 shows the EECs based on the parametric estimates, including income quadratic terms (Fig. C.4). Fig. C.4 depicts a convex EEC in 2010 and a straight EEC in 2014 that retain the same results; the EECs slope up and shift down over time. Existing studies have documented that air pollution has a significant negative influence on consumer decision-making behavior in

[6]As of November 13, 2015, the World Health Organization (WHO) had reported 681 laboratory-confirmed cases of human infection with H7N9 in Eastern China. Out of these cases, 275 resulted in fatalities, yielding a case fatality rate of 40.1% (Qiu et al., 2018).




Notes: The WIOD code used for this analysis is provided in Table C.1, which includes the corresponding code names and descriptions for reference.

**Figure 2.6**: *Expenditure by Industry*

addition to its considerable disruptive impact on physical health (Qiu et al., 2020)[7]. Consumers pay less attention to industrial waste concerns, which in turn causes a linear relationship between industrial waste discharge and household income. A lack of policy regulations resulted in linear (convex) EECs for industrial waste and dust in China. Consumption patterns are not influenced by concerns regarding pollution emissions associated with producing goods and services. Thus, affluent households account for an equal or a more significant proportion of industrial waste and dust discharge.

Table 2.3 lists coefficient estimates for the two other pollutants, based on the 2010 and 2014 CFPS. The results show that the coefficients on after-tax income are positive and statistically significant for all the cases. Based on the 2010 CFPS, if after-tax income increases by ¥10,000, ISW disposal will increase by 5.3 kgs, while ID discharge will increase by 0.1 kgs. Over time, households who live in center coast has a larger impact on the disposal of ISW. While the highest education level of the head of households being some college influenced pollution discharge less in 2014 compared with 2010. Furthermore, the sign and significance of other covariates in estimating ISW are consistent with those in the EECs for ID. In line with the results in Table 2.2, most of strikes of demographic factors are statistically insignificant.

Persistent consumption habits may make EECs less flexible than expected for individuals whose income grows over time. Including age quadratic terms enables us to compare the consumption choices of households with different incomes but the same age. We have so far illustrated both nonparametric and parametric estimates, and next, we will identify the movements along and shifts in the EECs by decomposing the composition effects.

### 2.4.2 Decomposing the composition effects

Movements along the EECs represent correlations between income and pollution emissions, with other covariates held constant, while, shifts demonstrate the effects of price changes on the production and consumption of pollution-intensive goods. When other demographic changes re-

[7]Prior research reports that air pollution can significantly affect the sales of insurance contracts, stock market returns, willingness to pay for small urban green infrastructures using the behavior of energy-efficient lights, and a large intention to pay for reduced PM2.5 (Liu et al., 2022).

**Table 2.3**: *Parametric environmental engel curves for other pollutants*

| | ISW | | Difference | ID | | Difference |
|---|---|---|---|---|---|---|
| Dependent vairable: | 2010 | 2014 | 2010-2014 | 2010 | 2014 | 2010-2014 |
| Exposure per Household | (1) | (2) | | (3) | (4) | |
| After-tax income | 5.339*** | 1.050*** | -4.289*** | 0.100*** | 0.007*** | -0.093*** |
| (¥10,000 in 2010 yuan) | (0.817) | (0.102) | (0.823) | (0.018) | (0.001) | (0.018) |
| Household size | 0.032 | 3.210*** | 3.168 | -0.028 | 0.023*** | 0.051 |
| | (2.827) | (0.592) | (2.89) | (0.063) | (0.005) | (0.063) |
| Household size squared | 0.159 | -0.173* | -0.332 | 0.005 | -0.001* | -0.006 |
| | (0.373) | (0.073) | (0.38) | (0.008) | (0.0006) | (0.008) |
| Age | 0.419 | -0.0532 | -0.472 | 0.008 | -0.0008 | -0.009 |
| | (0.567) | (0.124) | (0.572) | (0.013) | (0.0009) | (0.013) |
| Age squared | -0.007 | -0.0001 | 0.007 | -0.0001 | 6.21e-06 | 0.0001 |
| | (0.005) | (0.001) | (0.005) | (0.0001) | (8.91e-06) | (0.0001) |
| Married | 0.884 | -0.313 | -0.571 | 0.022 | -0.007 | -0.029 |
| | (4.330) | (1.077) | (4.46) | (0.096) | (0.010) | (0.097) |
| Education: High school | 0.138 | 2.240*** | 2.102 | -0.026 | 0.0120 | 0.038 |
| | (2.571) | (0.639) | (2.65) | (0.057) | (0.004) | (0.057) |
| Education: Some college | 24.62** | 6.467*** | -18.15* | 0.484* | 0.040** | -0.444* |
| | (9.430) | (1.198) | (9.51) | (0.209) | (0.008) | (0.209) |
| Education: College | 25.09* | 15.02*** | -10.04 | 0.447 | 0.087*** | -0.36 |
| | (10.66) | (2.951) | (11.06) | (0.236) | (0.017) | (0.237) |
| Education: Graduate | 114.2 | 16.94 | -97.26 | 2.453 | 0.083*** | -2.37 |
| | (69.87) | (11.80) | (70.86) | (1.554) | (0.058) | (1.56) |
| Region: Northeast | -3.258 | -0.018 | 3.24 | -0.081 | -0.0003 | 0.081 |
| | (2.988) | (0.588) | (3.05) | (0.066) | (0.0045) | (0.066) |
| Region: NorthMunicipalities | 25.94 | 3.217 | -22.72 | 0.563 | 0.0303 | -0.533 |
| | (28.69) | (1.927) | (28.75) | (0.637) | (0.016) | (0.637) |
| Region: North Coast | -0.693 | 0.820*** | 1.513 | -0.022 | 0.005*** | 0.027 |
| | (3.291) | (0.764) | (3.38) | (0.073) | (0.006) | (0.073) |
| Region: Central Coast | -3.951 | 9.163 | 13.114** | -0.135 | 0.063 | 0.198* |
| | (4.558) | (1.385) | (4.76) | (0.101) | (0.011) | (0.102) |
| Region: South Coast | -4.271 | 1.477 | 5.75 | -0.117 | 0.009 | 0.126 |
| | (3.393) | (0.896) | (3.51) | (0.075) | (0.006) | (0.075) |
| Region: Central | -1.014 | 2.520*** | 3.534 | -0.037 | 0.016** | 0.053 |
| | (2.630) | (0.694) | (2.72) | (0.058) | (0.005) | (0.058) |
| Region: Northwest | 2.436 | 0.924 | -1.512 | 0.041 | 0.006 | -0.035 |
| | (3.071) | (0.740) | (3.16) | (0.068) | (0.005) | (0.068) |
| Urban | 1.065 | 0.868** | -0.197 | -0.007 | 0.006 | 0.013 |
| | (1.765) | (0.284) | (1.79) | (0.039) | (0.0017) | (0.039) |
| Constant | 3.810 | 5.164 | 1.354 | 0.096 | 0.047 | -0.049 |
| | (11.15) | (3.234) | (11.61) | (0.247) | (0.023) | (0.248) |
| F-test of income coefficients | 42.70 | 106.1 | | 30.71 | 75.23 | |
| Observations | 112,536 | 76,836 | | 112,536 | 76,836 | |
| R-squared | 0.003 | 0.011 | | 0.002 | 0.008 | |

Notes: See notes for table 2

main constant, Blinde-Oaxaca decomposition provides a mechanism for separating movements and shifts in EECs. Based on Tables 2.2 and 2.3, we define the average level of pollution in a given year as follows:

$$\bar{P}_t = \alpha_t \bar{Y}_t + \delta_t \bar{X}_t \tag{2.3}$$

The dependent variable, $P_t$ is the average total pollution emissions in year t. $Y_t$ is the after-tax income during year t. $X_{it}$ denotes the vector of the covariates. By construction, the error term equals zero, owing to the properties of ordinary least squares (OLS). This equation captures the changes in the EECs.

Next, we calculate the change in average total pollution emissions between 2010 and 2014 to identify the different components of the composition effects as follows:

$$\begin{aligned} \bar{P}_{14} - \bar{P}_{10} = {} & \alpha_{10}(\bar{Y}_{14} - \bar{Y}_{10}) && \text{(Term 1)} \\ & + (\alpha_{14} - \alpha_{10})\bar{Y}_{10} && \text{(Term 2)} \\ & + \bar{X}_{14}(\delta_{14} - \delta_{10}) + (\bar{X}_{14} - \bar{X}_{10})\delta_{10} && \text{(Term 3)} \end{aligned} \tag{2.4}$$

The first term in expression (2.4) represents the change in pollution emissions caused by income changes, holding the 2010 OLS coefficients constant. This captures the movement along the 2010 EEC. The second term explains the impact of changing the coefficients on pollutant disposal quality, which refers to the shift in EECs. The last term captures the effect of changing covariates.

Table 2.4 shows the decomposition results for the change in the average disposal of IW, ISW, and ID. We use the 2010 OLS coefficient estimates reported in Tables 2.2 and 2.3 to multiply the average value changes in Table 2.1 to calculate the changes owing to different factors. From Table 2.1, the average income increased by 0.537 (¥10,000 2010 yuan), and the coefficient of income in the 2010 OLS is 0.0747. Thus, a movement along the 2010 EEC is 0.04 tons (Term 1) for IW. Simultaneously, demographic changes lead to a reduction of 0.001 tons (Term 3). The shift in EEC (-0.102) will be computed by the difference between the change of average volume of IW

disposal (-0.063) and the sum of the changes we previously calculated (Terms 1 and 2). Columns 2 to 3 apply the same strategy for ISW and ID. Both cases have total positive changes due to income, while demographic changes have opposite effects. An increase in average after-tax income leads to a hypothetical increase of 2.86 kgs in average ISW emission, which corresponds to Term 1 of expression (2.4). Term 2 has a strong negative impact on the ISW discharge compared to Term 3. For ID, an increase in average after-tax income causes a 0.05 kgs increase in pollution emissions. Term 3 decreases ID disposal by 0.02 kgs, which is smaller than the impact of Term 2 (0.39 kgs). We find that shifts in EECs have a larger impact on total pollution than the other two factors.

**Table 2.4**: *Movement Along Parametric EECs for Pollutants*

| | IW | ISW | ID |
|---|---|---|---|
| Dependent Variable: | (1) | (2) | (3) |
| after-tax income (¥10,000 in 2010 yuan) | 0.04 | 2.863 | 0.054 |
| | (0.004) | (0.443) | (0.010) |
| Household size | 0.032 | 0.012 | -0.011 |
| | (0.013) | (1.090) | (0.024) |
| Household size squared | -0.009 | 0.392 | 0.0124 |
| | (0.012) | (0.919) | (0.020) |
| Age | -0.00005 | 1.756 | 0.034 |
| | (0.024) | (2.378) | (0.053) |
| Age squared | 0.0015 | -2.841 | -0.054 |
| | (0.023) | (2.244) | (0.050) |
| Married | 0.00006 | -0.0026 | -0.00006 |
| | (0.00016) | (0.013) | (0.0003) |
| Urban | -0.012 | -0.131 | 0.0009 |
| | (0.0032) | (0.218) | (0.005) |
| Education dummies | -0.0069 | -0.483 | -0.0087 |
| Regional dummies | -0.0062 | 0.240 | 0.0073 |
| **Total change due to income (movement along EEC)** | 0.040 | 2.863 | 0.054 |
| **Total change due to other demographics** | -0.001 | -1.057 | -0.019 |
| **Unexplained difference (shift in EEC)** | -0.102 | -13.416 | -0.391 |

Notes: Estimates based on Oaxaca-Blinder decompositions. Robust standard errors in parentheses. Movement along each Engel curve calculated by multiplying in the coefficients in table 2 by corresponding changes in table 1. Total changes calculated by summing the individual changes. Pollution based on 2010 production technology for all years. Values for education and regional indicators are the combined effect for each category.

Higher-income households tend to purchase more goods and services; however, are purchased

by richer households, whereas they also tend to consume less pollution-intensity products. These two factors play opposite roles in pollution emissions, which can be further categorized further by scale effect and composition effects. Following Levinson and O'Brien (2019) and Shapiro and Walker (2018), we establish a decomposition model to explain industrial waste discharge from the Chinese production of goods and services. Following these previous studies, we use income in each year divided by income in 2010 to assess the growth rate. Then, we calculate the scale effect by multiplying the volume of pollution discharge in 2010 by the income growth rate. The scale effect ($SC_t$) for year t relative to 2010 is defined as follows:

$$SC_t = \overline{P}_{10} \times [(\bar{Y}_t - \bar{Y}_{10})/\overline{Y}_{10}] \tag{2.5}$$

Based on the definition of movement along the EEC (Term 1 of expression (2.4)), we define the composition effect as Term 1 minus the scale component ($SC_t$) of expression (2.5). Thus, the composition effect in year t relative to 2010 can be expressed as follows:

$$\begin{aligned} CC_t &= \text{Term } 1_t - SC_t \\ &= \alpha_{10}(\bar{Y}_t - \bar{Y}_{10}) - \overline{P}_{10} \times [(\bar{Y}_t - \bar{Y}_{10})/\overline{Y}_{10}] \end{aligned} \tag{2.6}$$

Fig. 2.7 presents the decomposition of predicted pollution from household consumption. Line 1 shows the sale effect ($SC_t$) corresponding to expression (2.5). When the household consumption basket is unchanged, the expected pollution emissions are depicted by the orange line. Line 2 (green line) shows movements along the 2010 EEC, which corresponds to Term 1 of expression (2.4). Line 3 (red line) represents the influence of changing demographics and income (Terms 3 and 1). Demographic factors lead to a net increase in pollution emissions in 2010 and 2012, causing line 2 to fall below line 3. In contrast the reduction impact on pollution emissions in 2014 results in line 2 being slightly above line 3. Line 4 shows the level of industrial wastewater disposal, which is explained by the left-hand side of expression (2.4) (summarizing Terms 1-3). According to expression (2.5), income growth directly influences the scale effect. The scale effect

described in line 1 increased slightly from 2010 to 2012 and decreased in 2014, owing to the spread of H7N9 and concerns of food security problems. The difference between lines 1 and 2 is offset by the composition effect ($CC_t$), whereas demographic changes (Term 3) offset the gap between lines 2 and 3. The deviation of line 4 from line 3 explains the offset by shifts (Term 2) in the EEC. The corresponding results in Table 2.5 are described as follows:

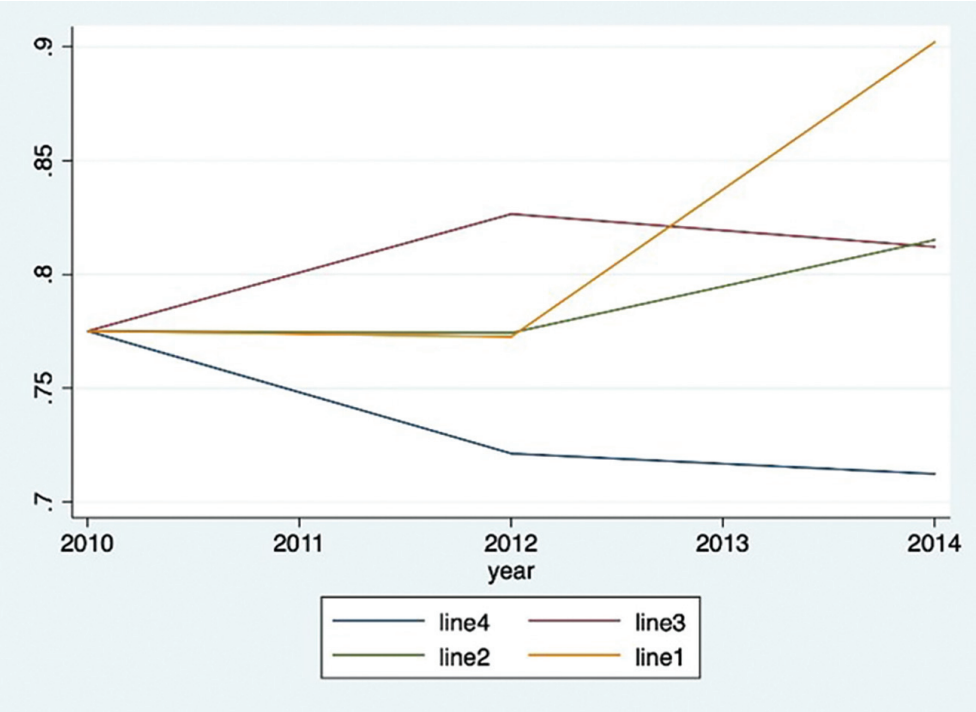
$$\begin{aligned} \overline{P}_{14} - \overline{P}_{10} &= \text{Term } 1_{14} + \text{Term } 2_{14} + \text{Term } 3_{14} \\ \overline{P}_{14} - \overline{P}_{10} &= SC_{14} + CC_{14} + \text{Term } 2_{14} + \text{Term } 3_{14} \\ -0.06 &= 0.127 - 0.087 - 0.103 - 0.001 \end{aligned} \tag{2.7}$$

The contributions of the different terms in expression (2.4) to the change in the average amount of IW discharge between 2010 and 2014 are explained by expression (2.7). This indicates that shifts in the Engel curve (Term 2) largely contribute to reduced pollution emissions. Additionally, opposing forces exist between the scale ($SC_t$) and composition ($CC_t$) effects, leading to a net contribution of movement along the EEC. In our analysis, the composition effect accounts for a smaller offsetting effect on the reduction of IW disposal, relative to the shift in the EECs (Term 2).

Next, we apply the same methodology to identify the contributions of the different effects the average levels of ISW and ID discharge.

$$\begin{aligned} \overline{P}_{14} - \overline{P}_{10} &= \text{Term } 1_{14} + \text{Term } 2_{14} + \text{Term } 3_{14} \\ \overline{P}_{14} - \overline{P}_{10} &= SC_{14} + CC_{14} + \text{Term } 2_{14} + \text{Term } 3_{14} \\ -11.61 &= 4.704 - 1.841 - 13.420 - 1.056 \qquad \text{(ISW)} \\ -0.36 &= 0.078 - 0.024 - 0.391 - 0.019 \qquad \text{(ID)} \end{aligned} \tag{2.8}$$

The results present similar patterns similar to the calculations in expression (2.7). The scale effect ($SC_t$) increases pollution emissions because households with higher incomes consume more




Line (1) Scale Effect; Line (2) Movement Along Engel Curve;
Line (3) Movement Along Engel Curve and Demographic Changes; Line (4) Index Predicted

Notes: The scale effect is calculated by increasing pollution proportionally to real after-tax income growth. Movements are long, and shifts in the EEC are calculated by estimating pollution each year using the 2010 Engel curve coefficients. Pollution predicted is estimated by matching itemized consumption expenditure in each year with the corresponding industry's 2010 pollution intensity.

**Figure 2.7**: *Decomposition of Predicted Pollution from Household Consumption: Industrial Wastewater (IW)*

**Table 2.5**: *Pollution Offset due to Compositional Changes in Household Consumption*

| | | | | Offset by Movement along EEC | | Offset by Demographic Changes | | Offset by Shifts in EEC | |
|---|---|---|---|---|---|---|---|---|---|
| | Total Change | Scale Increase | Total spread (2) - (1) | Value | Share of Spread | Value | Share of Spread | tons/kgs | Share of Spread |
| Pollutant | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| IW | -0.06 | 0.127 | 0.190 | 0.087 | 0.458 | 0.000 | 0.001 | 0.103 | 0.541 |
| ISW | -11.61 | 4.704 | 16.317 | 1.841 | 0.113 | 1.056 | 0.065 | 13.420 | 0.822 |
| ID | -0.36 | 0.078 | 0.434 | 0.024 | 0.056 | 0.019 | 0.044 | 0.391 | 0.900 |

Notes: The total change in the value of index is predicted using CFPS and WIOD data, based on 2010 production technology.

goods and services than those with lower incomes. Meanwhile, the composition effect had the opposite impact on pollution discharge. The shift in the EECs (Term 2) has a larger negative influence on the average level of pollution emissions relative to the composition effect.

Column 1 in Table 2.5 shows the change in pollutant discharge estimated in Table. The scale effects ($SC_t$) calculated in Fig. 2.7 are listed in column 2. The total spread is the difference between the total change and scale effects. Columns 4, 6, and 8 illustrate the offsets by composition effects ($CC_t$), demographic changes (Term 3), and shifts in EEC (Term 2), respectively. The spread shares are calculated as the proportion of offsets to the total spread. The total spread is 0.19, offset by compositional effects (0.087 by movement along the EEC and 0.103 by shifts in the EEC). The remaining part is offset by demographic changes, which is 0. Based on the findings presented in Table 2.5, the reduction in pollution emissions is mainly due to shifts in EECs, which account for 54-90% of the decrease. Meanwhile, movements along the EECs and demographic changes generally contribute to environmental improvements. Table 2.5 also reports the pollution offsets for the other two pollutants, for which similar patterns are observed.

## 2.5 Conclusion

Industry in China has substantially expanded the rapid rise in household expenditures. According to Ma (2004), the industrial structure in China lacks closed loops and other structural efficiencies, resulting in low efficiency in the production process and very high pollution emissions. Total wastewater emissions reached 58.9 billion tons in 2010, approximately 175% more than in 1990 (Geng et al., 2014). However, efficient policies for other major air pollutants (SO2, NOx, CO, PM10, and VOCs) have resulted in significantly reduced emissions. The policy discrepancies between industrial waste, dust, and other significant air pollutants leads to variations in consumption habits, further affecting the shape of EECs. This study investigates the interaction between household-level income and industrial waste and dust emissions.

Our study shows that EECs slope up and shift down over time. Holding other factors constant, higher-income households are responsible for higher pollution emissions by consuming more products. Moreover, among households with similar income ranges, the richer households contribute to

a larger reduction in pollution emissions over time. This is probably because of the higher environmental standards enforced by the community. Furthermore, by comparing scale and compositional effects, we conclude that high-income households are proportionally responsible for more pollution. In addition, shifts in EECs are responsible for reduced pollution emissions by approximately 76%, while movements along EECs offset it by 21% and demographic changes account for 4%.

As shifts in EECs are driven by changes in the prices of goods and alterations in the relative supply and demand of pollution-intensive products, our analysis offers policymakers insightful evidence regarding the impact of household consumption on pollution emissions. To reduce emissions, both the production and consumption systems can be improved. Further implementation and extended policies, such as the circular economy, are needed to avoid the path toward high emissions taken by today's developed countries (Peters et al., 2007).

One of the limitations of this study is that only three years are included in the dataset, although the CFPS is held every year and the 2016 WIOD release covers from 2000 to 2014. Each year has a large number of observations; however, changes in EECs over time may be biased. In addition, 28 industries are covered in our analysis, accounting for 70.3% of the goods and services produced domestically. Most of the industries in our study are related to manufacturing, such as "manufacturing of food products, beverages, and tobacco products" and "manufacturing of textiles, apparel, and leather products," and industries related to water, gas, and electricity are also included. In contrast, service-related industries, education, and industries related to activities are excluded because of the limited categories in the dataset for industrial waste emissions. To comprehensively understand the effects of consumer behavior on industrial waste and dust emissions, additional research must be conducted to investigate the additional value of products consumed by households with varying incomes and the influence of regulations on the relative prices of pollution-intensive goods.

# Chapter 3

# Imported Pollutants and US Household Consumption: A Study Using Environmental Engel Curves

## 3.1 Introduction

The rapid progression of globalization, urbanization, and industrialization has elevated environmental concerns in developing countries.[1] This underscores the pressing need to address environmental challenges on a global scale, emphasizing their urgency and significance. The European Union (EU) plans to implement a system of carbon tariffs on imported products, such as steel, cement, fertilizers, aluminum, and electricity, beginning in 2026. This action aims to safeguard the competitiveness of European industry from the threat of low-priced products from countries with less stringent environmental regulations (Devarajan et al., 2022). Although this policy ostensibly targets goods that emit higher pollution levels during production, its primary focus appears to be on developing countries, particularly China. According to (Timmer et al., 2015a), the predominant

[1] According to Nazeer et al. (2016), environmental pollution has become an inherent cost of economic growth, propelled by heightened industrialization, urban expansion, mechanization, intensified use of fertilizers and pesticides in agriculture, and the mismanagement of human waste. This predicament is particularly pronounced in developing countries, where environmental regulations are comparatively less stringent. Consequently, a positive correlation exists between economic growth and pollution levels in these developing nations.

share of U.S. trade is conducted with developed nations; however, it is observed that developing countries contribute disproportionately higher levels of pollution. This study utilizes Environmental Engel curves (EECs) to assess the extent of pollution generated by U.S. household consumption decreases in both developed and developing countries.

Our study employs the methodological framework advanced by Levinson and O'Brien (2019) to estimate the Environmental Engel curves (EECs), which depicts the association between U.S. households' income and the emissions of pollutants. The data on U.S. household income, expenditure, and demographic information were gathered from the Consumer Expenditure Survey (CEX) administered by the Labor Bureau of Statistics. To delineate the contribution of pollution embedded in U.S. consumption originating from developed versus developing countries, we employ World Input-Output Tables (WIOT). WIOT has proved valuable for analyzing global supply chain trade and exploring the formation of regional production clusters in the world economy. This facilitates mapping the production of final goods and services across various countries and industries.[2] We estimate the pollution generated in U.S. household consumption when goods are imported from other countries. By comparing the EPS of other countries with that of the United States, we can estimate the direct pollution generated by producing similar products with different environmental stringencies.[3]

Our investigation utilizes non-parametric and parametric econometric approaches to estimate the Environmental Engel curves (EECs) for developed and developing countries from 1995 to 2011. The results are consistent with the research conducted by Levinson and O'Brien (2019), as we observed similar patterns in which the Environmental Engel curves (EECs) exhibit an upward slope, concavity, and a downward shift over time. Furthermore, our study emphasizes that the pollution embedded in U.S. household consumption primarily originates from developing countries

[2]WIOT is essential for identifying the origin of value-added in pollution, offering insights into whether it emanates from domestic or international sources. Within the context of our study, let us consider the automobile industry. Suppose the United States imports components crucial for car assembly, such as engines or electronic parts, from developed countries. In that case, the pollution generated during the production of these components is embedded in the value-added of the final product (assembled cars). Through the use of WIOT, we can pinpoint the origin of this pollution, determining whether it predominantly stems from the developed countries supplying the components or from the U.S. during the final assembly.

[3]For instance, if a country's policy is 10% more stringent, the estimated pollution generated is approximately 10% less.

(61%), contrasting sharply with the relative significance of developed countries as sources of traded goods in the U.S. (67%). This situation underscores the transition of developed countries towards producing cleaner goods while still having the capacity to import "dirty" goods from the developing world with lower environmental standards. Thus, pollution emission tariffs or taxes may primarily target developing countries, particularly China.

We conduct separate analyses for global pollutants carbon monoxide (CO), nitrogen oxides (NOx), and volatile organic compounds (VOC) and local pollutants (particulate matter with a diameter of 10 micrometers or less (PM10) and sulfur dioxide (SO2)). Leibensperger et al. (2011) support the categorization of pollutants into global and local dimensions based on their transport characteristics and impacts on air quality. Global pollutants like NOx, CO, and VOCs have widespread effects. In contrast, local pollutants such as PM10 and SO2 are more confined in their impact within national borders, underscoring the commitment of nations to their air quality objectives (Unger et al. (2006); Amann et al. (2013); Heald et al. (2006)).

The factors underlying these results draw heavily from the existing literature examining the changes in pollution emissions in the United States. Employing the language introduced by Copeland and Taylor (1995), pollution evolution can be classified into three categories. First, the scale effect refers to the proportional consumption increase resulting from rising income. Second, the composition effect describes the shift in economic activities. Finally, the technique effect characterizes variations in the pollution intensity of specific activities, such as refining petroleum or generating electricity.

Furthermore, Levinson (2009a) analyzed the evolution of U.S. pollution by decomposing it into the three effects mentioned above. The study found that despite an increase in income leading to a positive scale effect, emissions of major pollutants due to U.S. manufacturing activity were reduced by an average of 25% from 1987 to 2001. This reduction was primarily attributed to changes in manufacturing techniques and offsetting compositional effects. Shapiro and Walker (2018) argue that the technique effect plays a crucial role in explaining the decrease in emissions from major pollutants in manufacturing activities, with reductions primarily driven by changes in emissions intensity within products rather than shifts in output or product composition. Additionally, they find that changes in environmental regulations, rather than shifts in productivity and trade, are the main

drivers of emissions reductions. Ling et al. (2015) examines the effects of trade liberalization on CO2 emissions with a focus on Malaysia. They disintegrate the trade effect into scale, technique, composition, and comparative advantage effects to assess the environmental impact of trade at four distinct transition points, verifying the existence of cointegration. Their study reveals that beyond a threshold income level, the scale effect positively impacts CO2 emissions, while the technique effect shows a negative influence, confirming the environmental Kuznets curve hypothesis. Furthermore, trade openness enhances environmental quality by reducing CO2 emissions through the composition effect.

This study contributes to the ongoing discourse on the implications of policies related to environmental tariffs and taxes. The decision of the European Union to apply a pioneering tariff on imports of polluting goods based on their carbon dioxide emissions has received support from member countries. Implementing a border levy seeks to establish an "equal playing field" by imposing the exact CO2 costs on both EU and foreign firms. Additionally, trade policy tools could be utilized more broadly to penalize countries that do not participate in global efforts to address climate change, also known as "free-rider" countries (Devarajan et al., 2022). By thoroughly examining pollution sources in both developing and developed countries, our research offers valuable insights, extending its contribution to the global discussions on environmental challenges. These findings provide a foundation for well-informed global strategies addressing environmental issues, emphasizing the need for a holistic understanding and proactive mitigation on a global scale.

The analysis of the correlation between commodity expenditure and income, commonly known as the Engel curve, has been a key focus in the field of applied microeconomic welfare research since the early works of Engel (1895), Working (1943), and Leser (1963). The studies of Muellbauer (1976) and Deaton and Muellbauer (1980) made a significant contribution by integrating the Working-Leser Engel curve specification within consumer theory. Moreover, several empirical studies on Engel curves have shown that some expenditure share equations require additional terms in income while others do not. Examples of such studies include Atkinson et al. (1990), Hausman et al. (1995), and Banks et al. (1997). The environmental Engel Curves (EECs) framework enables the assessment of alterations in people's desire for environmental quality as their income rises while technology remains unchanged (Pearce, 2003). Sager (2019) examines the correlation

between income inequality and consumption's carbon dioxide (CO2) content through the utilization of Environmental Engel curves. The author highlights the potential paradox of redistributing income in a progressive manner, which may increase the demand for greenhouse gas emissions, resulting in what he refers to as the "equity-pollution dilemma."

The typical shape of Environmental Engel Curves (EECs) exhibits a concave pattern that minimizes the shape of the Environmental Kuznets Curve (EKC), which illustrates the correlation between environmental quality and per capita GDP Bimonte and Stabile (2017b). The mechanics of the relationship between economic development and environmental degradation is based on Kuznets' hypothesis, which suggests that an increase in economic development, typically measured by income per capita, leads to an increase in environmental degradation, often measured by the level of air pollution emissions until a certain threshold is reached, after which the relationship becomes negative (Kuznets, 1955). Kacprzyk and Kuchta (2020b) investigate whether there is a non-linear, inverted U-shaped association between income and carbon dioxide (CO2) emissions from fossil fuels, utilizing panel data from 161 countries spanning 1992-2012. Their findings suggest a turning point in the relationship between income and CO2 emissions from fossil fuels, after which emissions start to decrease as income increases. They estimate that this turning point is at 44 thousand US dollars in 2011 constant dollars.

Section 2 comprehensively describes the dataset and methodology employed in our study. In Section 3, we present both nonparametric and parametric estimations and elucidate the decomposition effects for the Rest of the World (ROW). Section 4 delineates the estimations across regions, distinguishing between developed and developing countries, specifically focusing on the developing country, China. Lastly, Section 5 outlines the policy implications derived from the outcomes of our research.

## 3.2 Data and Methodology

### 3.2.1 Data

The primary aim of this investigation is to scrutinize the proportional origins of pollution embedded within U.S. households' consumption patterns, which entails exploring the contributions from developed and developing nations. These datasets empower us to derive estimates for Environmental Engel curves about both domestically produced and imported final goods, which are subsequently consumed by households in the United States. This endeavor necessitates comprehensive information on individual household consumption and pollution generated during the production of final products. It also entails examining trade flows to identify the origins of value-added from different countries and industries.

The Consumer Expenditure Survey (CEX), conducted by the U.S. Bureau of Labor Statistics (BLS), is designed to analyze U.S. consumer spending patterns. These surveys offer a distinctive approach to gathering data on consumer expenditures, income, and demographics, which facilitates the examination of how consumer expenditures and income relate to the characteristics of consumer units. The CEX comprises two quarterly surveys: the Interview and Diary surveys [4].The combined data from these surveys provide a comprehensive overview of consumer unit expenditures across various categories. We follow the data cleaning process conducted by Levinson and O'Brien (2019), which involved excluding households with expenditures on nursing homes and students, the top and bottom 1% of households based on after-tax incomes, and any households with incomplete income data. Furthermore, the sample undergoes a reweighting process based on age groups and homeownership status. This approach is employed to mitigate potential biases stemming from the reduction in sample size. The universal classification codes (UCC) used in the CEX categorize household expenditures into broad categories such as housing, food, transportation, and healthcare. These codes cover around 80% to 95% of total household expenditures, allowing for a relatively comprehensive analysis of household spending patterns.

[4]The Interview Survey captures data on substantial or recurring expenditures, typically three months or more. In contrast, the Diary Survey targets frequently purchased items, such as food and beverages, which can be challenging to recall within a few weeks (Attanasio and Weber, 1995).

Given the household expenditure data obtained from CEX for the consumption side, we utilize the National Emissions Inventory (NEI) and aggregated industry-level emissions, along with the World Input-Output Tables (WIOT), to calculate pollution emissions on the production side.

The National Emissions Inventory (NEI) provides detailed estimates of air pollution emissions in the United States, categorized by facilities and classified by NAICS industry.[5] This data undergo release every three years and heavily depends on data provided by State, Local, and Tribal air agencies concerning sources within their respective jurisdictions. Supplementary data is incorporated from the U.S. Environmental Protection Agency (EPA). The NEI is constructed through the utilization of the Emissions Inventory System (EIS). In the NEI, point sources involve emissions estimates for more extensive sources at fixed, stationary locations. Conversely, nonpoint sources in the NEI encompass emissions estimates for sources that, individually, are too small in magnitude to be reported as point sources. Following Levinson and O'Brien (2019), we conduct calculations by consolidating emissions data at the industry level from the 2002 NEI to determine the emissions intensity per dollar for each industry. This involves dividing the aggregated industry-level emissions by the total sales reported in the 2002 economic and agricultural censuses. It's noteworthy that nonpoint sources of air emissions, which lack specific industry assignments in the NEI, are encompassed in our emissions intensity assessments.

The NEI documents the direct pollution generated during the production of each final products in the United States. By consuming goods, U.S. households not only generate pollution in the production of final goods produced in the U.S. but also are responsible for pollution generated in other countries, as they use intermediate goods produced elsewhere, contributing to pollution in those countries. Thus, our analysis estimate pollution emissions not only from the production of final products but also from the manufacturing of inputs to those final products, their subsequent inputs, and so forth along the supply chain. This is based on direct pollution emissions calculated using NEI.

To estimate the entirety of this upstream pollution, we rely on the World Input-Output Table (WIOT). Leveraging the WIOT is also a methodological strategy for elucidating the precise origins

[5]Detailed information can be obtained from the United States Environmental Protection Agency (EPA) website: https://www.epa.gov/air-emissions-inventories/national-emissions-inventory-nei.

of pollution-related value. The WIOT 2013 release encapsulates input-output linkages among 35 sectors across 40 countries, complemented by a model for the remaining nations, spanning 1995 to 2011 (Timmer et al., 2015a). A WIOT can be conceptualized as aggregating national Input-Output (IO) tables interlinked through bilateral international trade exchanges. In contrast to a standard IO table, the WIOT presents a detailed breakdown of imports based on their country of origin and the industry involved. This level of granularity allows for the tracing of the source country.

The WIOT broadens the scope to incorporate pollution from various countries, including producing each final product and manufacturing all its upstream inputs. Leveraging information from the CEX, we establish a connection between household income and expenditure across various industries. The integration of both datasets enables us to establish a relationship between household income and diverse sources of pollution embedded in U.S. household consumption. This approach necessitates the harmonization of UCCs with the industries employed in the WIOT. The concordance process is executed in two steps, as outlined in the paper by Li et al. (2023). In our prior research, we developed a concordance that establishes a linkage between IO codes and WIOT codes. This concordance serves to connect the CEX with the codes used in the WIOT. We extend this work based on the methodology proposed by Levinson and O'Brien (2019).

Our approach examines the correlation between household income levels and pollution emissions. To achieve this, we hold technology constant at the 2002 level in our baseline results. Notably, Levinson and O'Brien (2019) also estimate EECs under a similar assumption. Our choice to maintain technological constancy in the baseline analysis enables us to isolate the influence of factors such as consumer preferences or policy changes on shifts in consumption patterns.

Fig. 3.1 illustrates the distribution of input sources for production in the United States from 1995 to 2011. Based on data from the WIOT for the respective years, the analysis reveals a discernible shift in the composition of intermediate inputs. In 1995, Canada, Japan, and the United Kingdom identified the principal contributors to foreign inputs. However, by 2011, a notable transformation occurred, with China, Canada, and Mexico emerging as the predominant foreign sources of inputs. This transition underscores dynamic changes in global sourcing patterns over the examined period. According to Krugman et al. (2021), the establishment of the North American Free Trade Area (NAFTA) has drawn attention to trade in intermediate goods and offshore sourcing

within the framework of preferential trade liberalization. PTAs are purportedly designed to facilitate more efficient cross-border production processes among member countries and NAFTA, in particular, has contributed to Canada and Mexico becoming top trading partners with the United States. Therefore, understanding the origin of products and intermediate goods is crucial as it informs policymakers and stakeholders about the dynamics of international trade, facilitates the assessment of trade agreements' effectiveness, and helps identify opportunities for enhancing economic efficiency and competitiveness within global supply chains.

The methodology described, utilizing the NEI and WIOT, is focused on assessing the pollution inherent in the consumption of domestically produced goods by U.S. households. However, it is crucial to acknowledge that a substantial portion of consumed goods originates from foreign countries. Therefore, it becomes imperative to estimate discrete pollution emissions originating from other countries due to the production of imported goods. However, the availability and complexity of data pose challenges, as comprehensive pollution emission data by industry for each country may not be readily accessible. Nevertheless, it is known that countries with more stringent environmental policies tend to generate less pollution in the production of similar goods. Leveraging this insight, the Environmental Policy Stringency (EPS) index can be employed to approximate pollution emissions in all other foreign countries using direct pollution emissions in the United States. Subsequently, by applying the World Input-Output Tables (WIOT), we can discern the origins of pollution generated by producing imported goods from other countries.

The EPS provides information on foreign environmental standards. This measure represents a country-specific and internationally-comparable measure of environmental policy stringency. In this case, environmental stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior. The calculation of the index is based on the degree of stringency of 14 environmental policy instruments and ranges from 0 (not existing) to 6 (most stringent).[6] The EPS index covers 29 out of the 40 major countries included in the WIOD, leaving 11 countries unmatched. The eleven unmatched countries account for a small proportion (0.081 percent) of the U.S. share of output supplied by a foreign country. Therefore, these unmatched countries have little influence on the results.

[6]See details in Botta and Koźluk (2014).

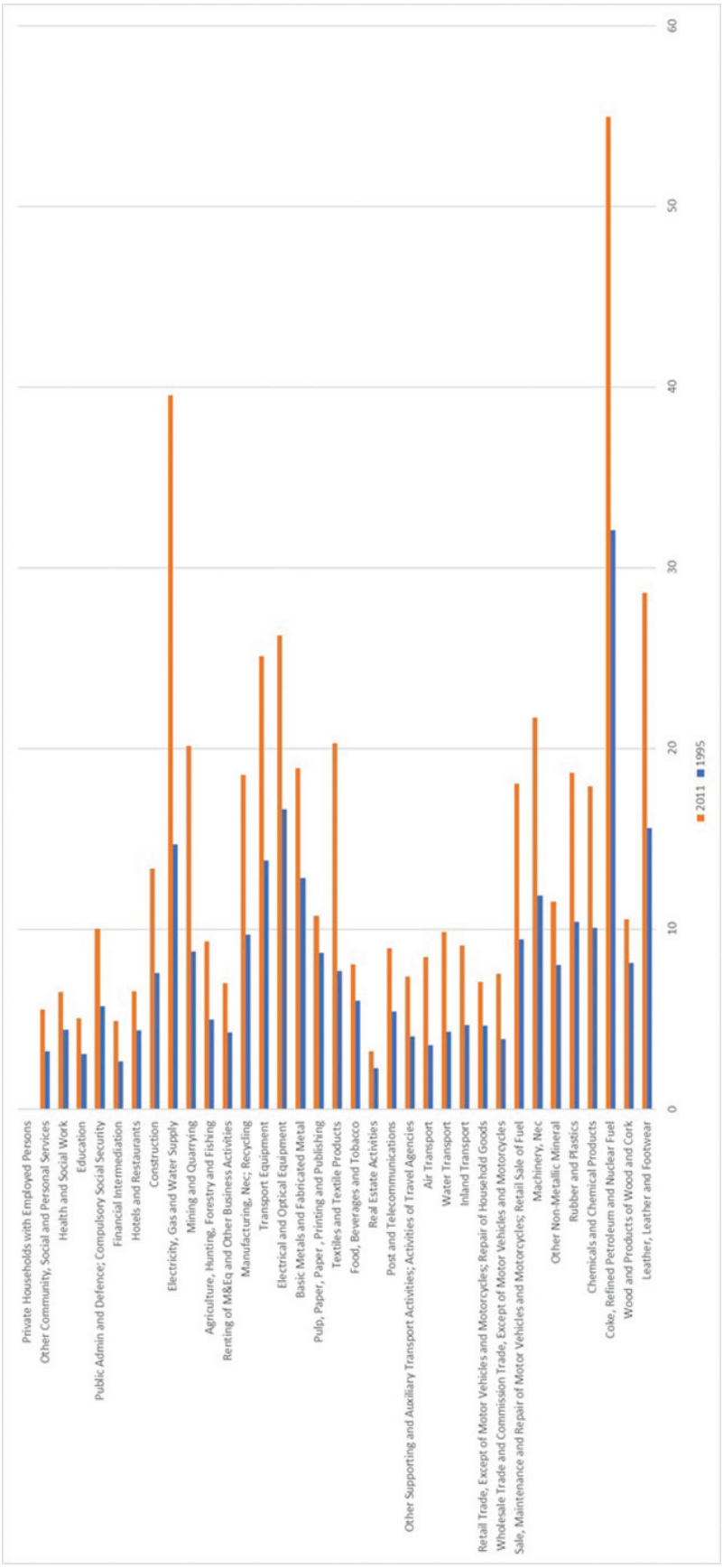



**Figure 3.1**: *Foreign Content Share By Industry*

Environmental policies have become increasingly stringent over the last two decades—for instance, the GDP-weighted average of the EPS index increased by 115.12 percent (from 1.14 to 2.45) between 1995 and 2011. Since our analysis focuses on household consumption and its evolution over time, we rely on the 2002 EPS index and, therefore, we keep environmental stringency constant in our analysis at 2002 level. Fig. 3.2 shows that the members of the European Union (Austria, Sweden, Germany, Spain, Denmark, Hungary, Finland, Netherlands, and Greece) and Japan had the most stringent environmental standards in 2002. Notice that these two trade entities represented two of the largest U.S. trading partners.

As mentioned above, we utilize EPS to compare different countries' environmental policies to that of the U.S.. For example, if the EPS for the U.S. is 1.22 and Australia's EPS is 1.14, then Australia's policy is approximately 6.6% (calculated as (1.14 - 1.22) / 1.22) less stringent than that of the U.S., potentially leading to 6.6% higher pollution levels. To estimate the actual pollution emissions generated by foreign countries for these imported goods consumed by U.S. households, we also require the share of imported goods. Continuing with the example, if the pollution emissions for industry AtB in the U.S. are 100 units and the U.S. imports goods double the size of its domestic production in this industry from Australia, then the pollution emissions for this industry will be estimated as 213.2.

Our analysis employs the consumption-to-Gross Domestic Product (GDP) ratio to estimate the proportion of imported goods.[7] This choice is grounded in the rationale that GDP signifies the overall economic output, and the consumption-to-GDP ratio serves as a comparative indicator of the influence of consumption on economic activity. Drawing on our assessment of the share of imported goods consumed by U.S. households, our findings reveal that the goods consumed by U.S. households are predominantly of domestic origin. In 2002, the highest share of imported goods was attributed to Canada, amounting to 1.72%, followed by China at 1.12% and Japan at 1.05%. On January 1, 1994, the North American Free Trade Agreement (NAFTA), which integrated the antecedent Canada-U.S. Free Trade Agreement (CUSFTA), was implemented. Notably, NAFTA stands as the preeminent free-trade accord beyond the European Union and represents a groundbreaking reciprocal free-trade agreement, marking the inaugural instance of such an arrangement

[7] Data available from World Integrated Trade Solution (WITS).

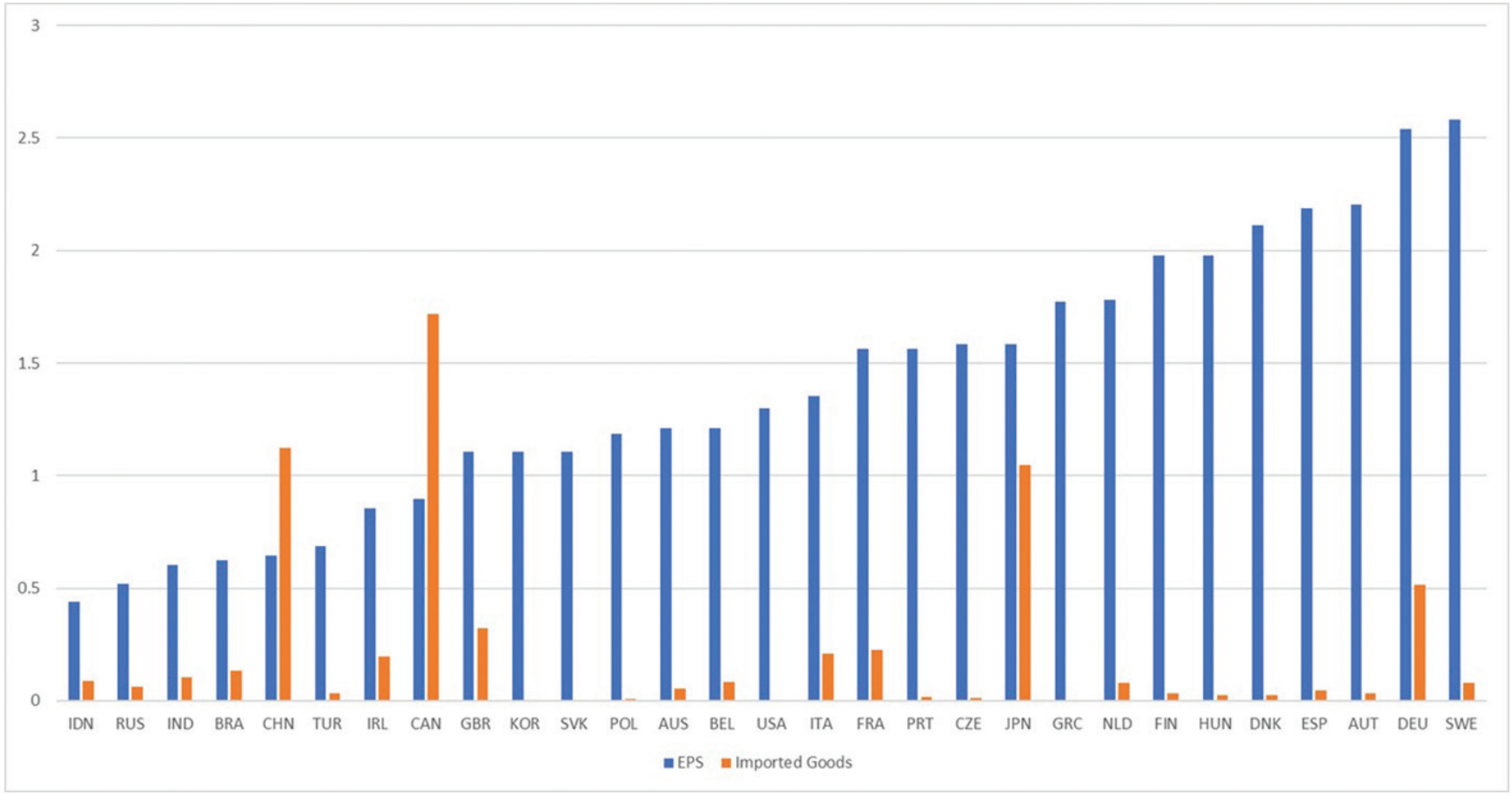



**Figure 3.2**: *OECD Environmental Policy Stringency Index and Share of Imported Goods by Country in 2002*

between a substantial developing country and developed economies (Conklin, 1994).

### 3.2.2 Methodology

Fig. 3.3 delineates the intricate process employed to isolate and identify pollution sources within our study's context. For the final products consumed by U.S. households, as depicted in Fig. 3.2, the majority is domestically produced, with a minor fraction imported from other countries. Our analysis begins with the left side of Fig. 3.3. The production of these goods leads to direct pollution within the United States (A). Moreover, it induces indirect pollution, as some of the intermediate inputs used in producing these goods are also domestically produced in the United States (B). The goods imported and produced in other countries also cause indirect pollution emissions in the U.S. since the outsourced inputs from the U.S. were used to produce them (E). Thus, the pollution embedded in the consumption of U.S. households originating from the U.S. is A + B + E.

We estimate the direct pollution intensity coefficients for other countries by utilizing the EPS relative to the U.S. (1.3). In 2002, the EPS for Canada was 0.9. The environmental policy in Canada is 30.77% ((0.9-1.3)/1.3) less stringent than in the U.S. Consequently, we can infer that Canada's direct pollution intensity coefficients are 30.77% higher. This implies that Canada's pollution levels are higher than in the U.S. By applying this method to each country, we can calculate the direct pollution emissions associated with goods imported and consumed by U.S. households (D). Using a similar approach described earlier, importing goods also contributes to pollution in foreign countries, as some intermediate goods are locally produced (F). Additionally, outsourced inputs used in producing goods in the U.S. (C) also contribute to pollution in the rest of the world (ROW). Thus, the pollution embedded in the consumption of U.S. households originating from the rest of the world (ROW) is represented by the sum of C, D, and F.

According to the methodology outlined in Levinson and O'Brien (2019), the initial step involves the computation of direct pollution intensity coefficients using NEI. This process entails determining the pollution intensity per dollar of production by aggregating the total emissions linked to each industry and dividing it by the corresponding total sales. Utilizing data from the EPA

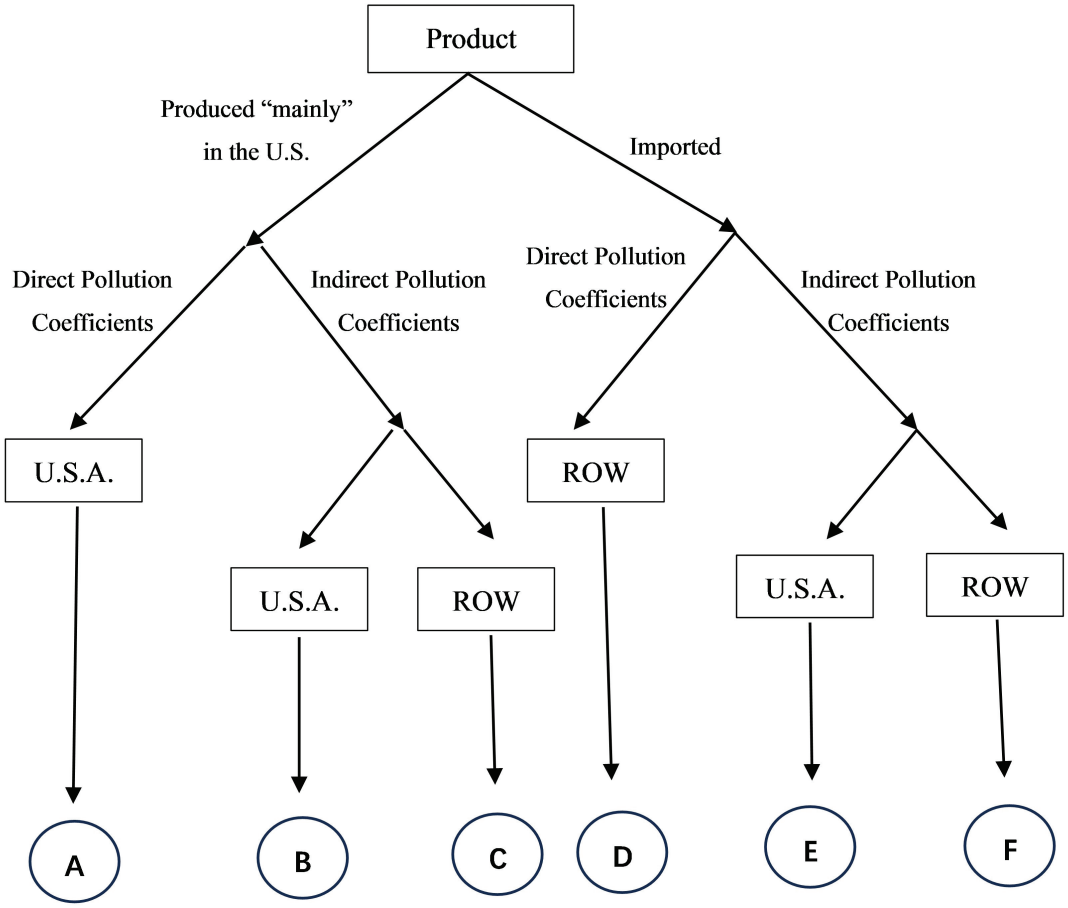



**Figure 3.3**: *Process of Isolating Pollution Sources: A Detailed Overview*

National Emissions Inventory for air pollution emissions and the Economic Census and Census of Agriculture for sales data, these calculations are performed within the NAICS industry framework. To align with the WIOT industries, sales and pollution data are aggregated accordingly.

Subsequently, the computation of total pollution intensity coefficients is undertaken. While the direct coefficients account for emissions tied to each industry's output, they exclude upstream emissions linked to the production of inputs. By employing WIOT and conducting a Leontief (2018) analysis, we convert the emissions intensities from the NEI into total emissions coefficients. These coefficients encompass the pollution generated in the manufacturing of each final product and throughout the production of all its inputs.

In the WIOT, the total output is the aggregation of all upstream inputs and the inputs utilized to produce final goods. We compute the total pollution linked to each household's consumption based on the 2002 production technology. For each household, we multiply the itemized consumption at the 2002 level by the dollar amount of pollution calculated previously to determine the pollution associated with each specific consumption category. Summing up pollution from all categories within a household's annual consumption provides the total pollution attributable to that household.

$$X = [I - A]^{-1} \times Y \tag{3.1}$$

Here, X denotes the economic output, and I represents the identity matrix. Y stands for the final consumption. T=$[I - A]^{-1}$ is the Leontief total requirements matrix, depicting the dollar amount of industry i required to produce one dollar of output in industry j. And we observe Y collected from the CEX.

To compare consumption expenditure across different years with the per-dollar pollution intensity coefficients from 2002, we adjust all expenditures to real 2002 dollars using the Consumer Price Index. After adjusting consumption to 2002 dollars, we align each year with the 2002 pollution intensity data to maintain constant production technology. This process is repeated for every household across all relevant years in the CEX, resulting in a single value for each household representing the total pollution associated with its consumption. This pollution amount reflects the environmental impact created using the 2002 production technology. It allows for estimating EECs

across households and over time about household income and other demographics.

The primary aim of our study is to discern the sources of pollution associated with the production of goods consumed by U.S. households, with a specific focus on the diverse countries contributing to this environmental impact. We initially employed the consumption value by household i, industry j and country c ($C_{ijc}$) relative to the U.S.'s GDP in 2002 (amounting to $ 10,900,000,000,000) to calculate the consumption to GDP ratio by country and industry ($CG_{jc}$). In expression (2.4) below, the consumption-to-GDP ratio represents the percentage of economic activity in the country attributed to consumption.

$$CG_{jc} = \sum_{i} \frac{C_{ijc}}{GDP} \tag{3.2}$$

Next, we utilize the ratio of the value of imports (amounting to $ 1,150,000,000,000) to GDP amounting to $ 10,900,000,000,000 as a measure to signify the percentage of consumption expenditure allocated to imports. This ratio, which is 10.6%, indicates the portion of the country's economic activity (GDP) represented by the value of imported goods.

Hence, the share of imported goods by country and industry ($SI_{jc}$) is calculated by multiplying the consumption to GDP ratio ($CG_{jc}$) by the percentage of consumption spent on imports.

$$SI_{jc} = CG_{jc} \times 0.106 \tag{3.3}$$

With the calculated ratio of imported goods consumed by U.S. households, we can now dissect the various sources of pollution emissions from different countries and industries. For example, if a U.S. household consumes 100 units of domestically produced goods in Industry AtB, generating 100 pounds of pollution emissions, and their consumption of imported goods in the same industry is doubled, then the household is responsible for generating 200 pounds of emissions by consuming imported goods. Further, considering the EPS to be 10% more stringent in the U.S., the household would be responsible for an estimated 220 pounds of emissions from other countries.

Furthermore, we categorize foreign countries into two groups, namely developed and developing countries, to conduct a more detailed analysis of the sources of pollution for which U.S. households are responsible when consuming goods. In order to enhance the precision and facilitate

a comparative analysis of the average per-household values for the emission of five pollutants, we have categorized them into two distinct groups: global pollutants, which include carbon monoxide (CO), nitrogen oxides (NOx), and volatile organic compounds (VOC); and local pollutants, comprising particulate matter with a diameter of 10 micrometers or less (PM10) and sulfur dioxide (SO2). This classification allows for a more nuanced examination of their respective characteristics and impacts on air quality.

In light of the findings presented by Leibensperger et al. (2011), the categorization of pollutants into global and local dimensions is substantiated by their transport characteristics and consequential impacts on air quality. Unger et al. (2006), employing global models, has demonstrated that alterations in worldwide anthropogenic emissions of oxidant precursors, encompassing NOx, CO, VOCs, exert an impact on concentrations of particulate matter at the Earth's surface. The enhancement of aerosol formation by CO, NOx, and VOCs emissions underscores their ability to influence PM levels on a broader scale. Conversely, local pollutants encompass PM10 and SO2. Amann et al. (2013) shows that developed countries implement stringent regulations to manage these local pollutants, emphasizing their commitment to achieving air quality objectives to safeguard public health and visibility within their territories. Heald et al. (2006) demonstrates that the direct intercontinental transport of anthropogenic organic and nitrate aerosols contributing to the presence of PM10 has a diminished significance.

Table 3.1 displays the average per-household pollution emission levels for 1995 and 2011, originating from regions such as the Rest of the World (ROW), developed countries, and developing countries. The emissions are classified into two discernible categories: global and local. Between 1995 and 2011, emissions embedded in household consumption exhibited a decrease. The more significant reduction in emissions for global pollutants is particularly noteworthy compared to their local counterparts during this period. This discrepancy emphasizes the heightened global awareness and concerted efforts to address pollutants with transboundary impacts. The overarching commitment to global environmental sustainability has likely contributed to the more substantial decline in emissions from substances recognized for their widespread influence on air quality and climate. This trend underscores the effectiveness of collaborative international initiatives in mitigating these pollutants' environmental impact.

**Table 3.1**: *Average Values for the Five Pollutants*

| | ROW | | | Developed Countries | | | Developing Countries | | |
|---|---|---|---|---|---|---|---|---|---|
| | 1995 | 2011 | Difference | 1995 | 2011 | Difference | 1995 | 2011 | Difference |
| Variable | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Goabal Pollutant(pounds, 2002 technology) | | | | | | | | | |
| NOx | 3.453 | 3.232 | -0.221 | 1.166 | 1.128 | -0.038 | 2.287 | 2.104 | -0.183 |
| | (0.062) | (0.036) | (0.20) | (0.021) | (0.014) | (0.025) | (0.042) | (0.023) | (0.048) |
| CO | 3.104 | 2.848 | -0.256 | 1.397 | 1.295 | -0.102 | 1.708 | 1.553 | -0.155 |
| | (0.073) | (0.045) | (0.086) | (0.037) | (0.024) | (0.044) | (0.038) | (0.022) | (0.044) |
| VOC | 1.538 | 1.409 | -0.129 | 0.586 | 0.545 | -0.041 | 0.952 | 0.863 | -0.089 |
| | (0.029) | (0.017) | (0.034) | (0.012) | (0.008) | (0.014) | (0.018) | (0.010) | (0.021) |
| Local Pollutant(pounds, 2002 technology) | | | | | | | | | |
| PM10 | 0.773 | 0.720 | -0.053 | 0.288 | 0.275 | -0.013 | 0.485 | 0.444 | -0.041 |
| | (0.015) | (0.009) | (0.017) | (0.006) | (0.004) | (0.007) | (0.009) | (0.005) | (0.010) |
| SO2 | 2.502 | 2.433 | -0.069 | 1.194 | 1.188 | -0.006 | 1.308 | 1.245 | -0.063 |
| | (0.047) | (0.030) | (0.056) | (0.024) | (0.016) | (0.030) | (0.024) | (0.015) | (0.028) |
| Observations | 1,896 | 3,623 | | 1,896 | 3,623 | | 1,896 | 3,623 | |

Notes: Values calculated using sample weights. Standard errors in parentheses. Nominal incomes adjusted using the CPI for all items; nominal expenditures adjusted using the corresponding price series for food and beverages, gasoline, electricity, fuel oil, and core expenditure.

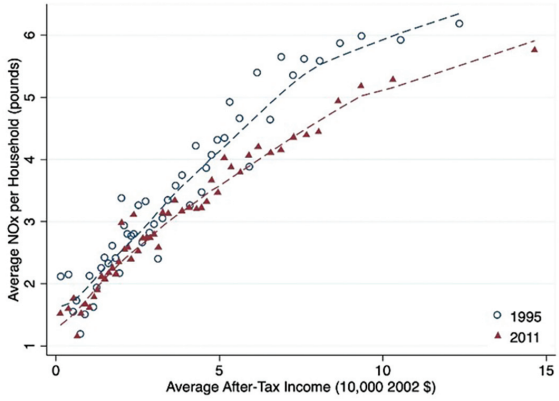
Furthermore, our analysis reveals a noteworthy trend regarding the pollution embedded in the consumption of U.S. households, indicating that emissions originating from developing countries outweigh those from developed nations. Despite the substantial share of developing nations in global trade flows, accounting for 61.13%, the predominant source of pollution in U.S. household consumption emanates from these developing countries, ranging from 60.55% to 91.3%. This finding underscores the significant environmental impact associated with the consumption patterns of developing nations. It emphasizes the need for targeted strategies to address and mitigate pollution hotspots within these regions.

## 3.3 Environmental Engel Curves for the ROW

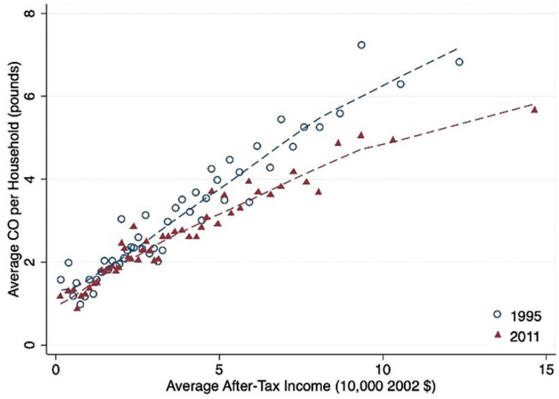
### 3.3.1 Nonparametric Estimates

Initially, we construct Environmental Engel Curves (EECs) to illustrate the connection between pollution embedded in consumption and income levels, without accounting for other household characteristics, for the Rest of the World (ROW). We first categorize households within the 1995 cross-sectional data of the CEX into fifty groups, each representing 2% of the total income distribution for 1995. After-tax income is employed for this classification to mitigate potential distortions in the Engel curve between 1995 and 2011 that might arise from alterations in the progressivity of income tax policy. Next, we compute the mean pollution linked to consumption within each of the fifty income groups. In Fig. D.1, we depict the distribution of households across income bins for 1995 and 2011. Graphing these fifty data points, with income on the horizontal axis and pollution on the vertical axis, results in a nonparametric EEC for 1995, illustrated as the upper line in Fig. 3.4. To illustrate the temporal evolution of the EEC, Fig. 3.4 presents a second EEC estimated using the 2011 CEX. The same income bin cutoff values employed in the 1995 EEC are applied to construct the 2011 EEC for direct comparability.

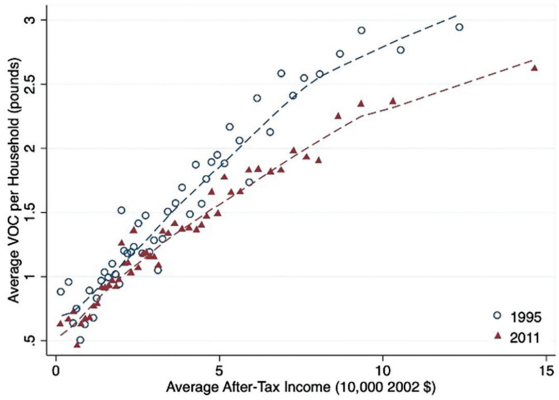
The EECs presented in Fig. 3.4 reveal three key observations. Firstly, the upward slope of the EECs indicates that wealthier households contribute more significantly to overall pollution, consistent with their higher consumption of goods and services. Secondly, the income elastici-




(a) Nitrogen Oxides (NOx)




(b) Carbon Monoxide (CO)




(c) Volatile Organic Compounds (VOCs)

Notes: Income is adjusted for inflation using the all-items CPI. Consumption expenditure is adjusted using the core CPI with food, fuel, gasoline, and electricity adjusted separately using the corresponding CPI. Each pair of dots represents an income level corresponding to 2% of the 1995 CEX sample, with the highest and lowest 1% of households trimmed based on after-tax income.

**Figure 3.4**: *Nonparametric EECs for Global Pollutants*

ties of the EECs are less than 1, implying that pollution is deemed a necessity according to these curves. While concavity is more pronounced at the higher end of the income distribution, affluent households play a substantial role in total pollution. This interplay between slope and concavity has considerable implications for overall pollution, as demonstrated later. Thirdly, a noticeable downward shift in EECs over time is evident, indicating that households in the 2011 EEC contributed less to pollution than their 1995 counterparts with comparable incomes. This shift is not attributed to technological advancements or abatement measures, as both curves share the same 2002 emissions intensities. Instead, it signifies a change in consumption patterns influenced by evolving factors such as prices, regulations, or societal norms.

In Fig. D.2, we graph nonparametric EECs for two additional local air pollutants, PM10 and SO2. The patterns observed for these pollutants mirror those of the previously discussed pollutants (NOx, CO, and VOCs), displaying an upward trend, concavity, and a downward shift over time.

We assess the robustness of the nonparametric estimates presented in Fig. 3.4 through various methods. Fig. D.3 and Fig. 3.4 display panels illustrating Engel curves based on total household expenditure and household pre-tax income, respectively. Notably, the Engel curves in these figures exhibit the same characteristics and properties as those discussed for the panels in Fig. 3.4, affirming the consistency of the results across different measures of household economic indicators.

A pertinent issue with the methodology illustrated in Fig. 3.4 is the potential violation of the law of one price. This concern arises if certain regions in the country exhibit both higher household incomes and elevated relative prices for goods that entail more significant pollution in their production. To further elaborate on this concern, consider a scenario where two regions within the country, Region A and Region B, have different household income levels and distinct relative prices for goods. If Region A experiences higher household incomes and simultaneously faces higher relative prices for goods that involve more pollution in their production, the resulting Engel curve could conflate the influence of income elasticity with the impact of these price differences. This could lead to a misleading interpretation of the pollution-income relationship. Moreover, suppose that over time, incomes and relative prices change at different rates in these regions. In that case, the analysis may be biased due to the influence of price effects on the observed shifts and movements along the Engel curves. Therefore, the potential non-uniformity in income and price

dynamics across regions necessitates careful consideration when interpreting the analysis results.

Table 3.2 presents relevant household characteristics during the period from 1995 to 2011. Notably, NOx emissions exhibited a marginal decrease from 3.45 pounds to 3.23 pounds, while average after-tax income increased by 17.9%, rising from $38,350 to $45,220 (Table 3.1). Concurrently, there were discernible shifts in household demographics, including aging, smaller household sizes, higher educational attainment, increased urbanization, and a lower likelihood of marriage. We employ parametric estimations for further analysis to ascertain how these demographic changes contribute to the observed patterns in EECs.

**Table 3.2**: *Data Summarization for Demographics*

| | 1995 | 2011 |
|---|---|---|
| Variable | (1) | (2) |
| After-tax income | 3.835 | 4.522 |
| ($10,000 in 2002 dollars) | (0.086) | (0.066) |
| Household size | 2.558 | 2.546 |
| | (0.046) | (0.027) |
| Age of household head | 48.11 | 50.03 |
| | (0.544) | (0.331) |
| Head is married (share of population) | 0.545 | 0.523 |
| Race of head is black | 0.104 | 0.111 |
| Education of head (share of population) | | |
| Elementary only | 0.208 | 0.135 |
| High school | 0.351 | 0.252 |
| Some college | 0.222 | 0.301 |
| College | 0.132 | 0.204 |
| More than college | 0.0866 | 0.108 |
| Region (share of population) | | |
| Northeast | 0.184 | 0.185 |
| Midwest | 0.209 | 0.218 |
| South | 0.275 | 0.354 |
| West | 0.189 | 0.234 |
| Rural | 0.143 | 0.0786 |

Notes: See notes in Table 3.1.

### 3.3.2 Parametric Estimate

In order to consider factors beyond income that may influence the composition and volume of goods and services consumed within households, our approach involves estimating a set of regressions. In these regressions, the dependent variable is household pollution, while the independent variables encompass after-tax income, the square of income, and additional covariates.

$$P_{it} = \alpha_t Y_{it} + \beta_t Y_{it}^2 + \delta_t X_{it} + \varepsilon_{it} \tag{3.4}$$

The pollution variable, $P_{it}$, is regressed against after-tax income ($Y_{it}$) and a vector of other covariates ($X_{it}$). The coefficients in the regression equations are indicated by the subscript t, signifying that separate regressions are conducted yearly, allowing for a year-specific analysis of the relationship between pollution, income, and other covariates. This approach enables a nuanced examination of the dynamics over time and the impact of various factors on pollution levels.

Table 3.3 presents the regression estimates derived from expression (3.4). In the first column, we conduct a regression analysis of NOx pollution emissions using the 1995 CEX. The findings reveal that 1995 a one-unit increase in after-tax income ($10,000) corresponds to a 0.45-pound increase in NOx pollution originating from other countries. Conversely, a one-unit increase in the squared term of after-tax income is associated with a 0.01-pound decrease in NOx pollution emissions. The opposing effects of these two variables indicate a concave shape of the EEC in 1995. Notably, both results exhibit statistical significance.

Moreover, demographic shifts significantly influence the pollution embedded in US household consumption. Specifically, when the head of the household is married, there is an additional 0.53-pound increase in NOx emissions. Similarly, residing in a rural area corresponds to a substantial 0.76-pound increase in NOx emissions. In summary, the outcomes indicate that households characterized by larger size, older age, marital status, higher education levels, non-black ethnicity, and rural residence indirectly contribute to a higher pollution level. Columns (2) and (3) present the regression estimates for two other global pollutants, CO and VOCs, revealing similar result patterns.

**Table 3.3**: *Parametric EECs for Global Pollutants*

| | ROW | | | | | |
|---|---|---|---|---|---|---|
| | 1995 | | | 2011 | | |
| | NOx | CO | VOC | NOx | CO | VOC |
| Dependent Variable (pounds): | (1) | (2) | (3) | (4) | (5) | (6) |
| After-tax income ($10,000 in 2002 d0llars) | 0.453*** | 0.413*** | 0.212*** | 0.335*** | 0.318*** | 0.152*** |
| | (0.06) | (0.076) | (0.0275) | (0.027) | (0.038) | (0.0130) |
| After-tax income squared | -0.011* | 0.001 | -0.00372 | -0.007*** | -0.004 | -0.00263** |
| | (0.005) | (0.008) | (0.00245) | (0.0016) | (0.002) | (0.000775) |
| Household size | 0.427** | 0.275* | 0.162** | 0.554*** | 0.388*** | 0.224*** |
| | (0.122) | (0.137) | (0.0592) | (0.06) | (0.073) | (0.0270) |
| Household size squared | -0.024 | -0.014 | -0.00861 | -0.037*** | -0.024* | -0.0150*** |
| | (0.016) | (0.016) | (0.00772) | (0.008) | (0.010) | (0.00343) |
| Age | 0.063*** | 0.044* | 0.0253*** | 0.065*** | 0.043*** | 0.0252*** |
| | (0.015) | (0.019) | (0.00721) | (0.008) | (0.012) | (0.00403) |
| Age squared | -0.0006*** | -0.0005** | -0.000256*** | -0.0005*** | -0.0003* | -0.000202*** |
| | (0.0001) | (0.0002) | (6.58e-05) | (8.04e-05) | (0.0001) | (3.90e-05) |
| Married | 0.531*** | 0.407* | 0.229*** | 0.435*** | 0.419*** | 0.195*** |
| | (0.130) | (0.160) | (0.0607) | (0.076) | (0.102) | (0.0362) |
| Race: Black | -0.498*** | -0.385* | -0.205** | -0.243** | -0.255* | -0.111*** |
| | (0.141) | (0.166) | (0.0651) | (0.07) | (0.093) | (0.0314) |
| Race: Asian | -0.601* | -0.708* | -0.299* | -0.704*** | -0.677*** | -0.329*** |
| | (0.273) | (0.296) | (0.129) | (0.133) | (0.166) | (0.0603) |
| Race: Other | 0.026 | 0.113 | 0.0206 | 0.017 | 0.219 | 0.0329 |
| | (0.460) | (0.418) | (0.192) | (0.166) | (0.261) | (0.0861) |
| Education: High school | 0.204 | 0.160 | 0.0923 | 0.468*** | 0.456*** | 0.209*** |
| | (0.127) | (0.142) | (0.0576) | (0.072) | (0.075) | (0.0316) |
| Education: Some college | 0.496** | 0.416* | 0.223** | 0.628*** | 0.738*** | 0.307*** |
| | (0.149) | (0.170) | (0.0675) | (0.076) | (0.086) | (0.0343) |
| Education: College | 0.244 | 0.520* | 0.172* | 0.499*** | 0.725*** | 0.273*** |
| | (0.159) | (0.212) | (0.0766) | (0.094) | (0.127) | (0.0452) |
| Education: Graduate | 0.369 | 0.538 | 0.186 | 0.583** | 0.991*** | 0.329*** |
| | (0.245) | (0.308) | (0.115) | (0.175) | (0.261) | (0.0872) |
| Region: Midwest | 0.106 | -0.175 | 0.0151 | -0.180 | -0.286 | -0.103* |
| | (0.129) | (0.177) | (0.0622) | (0.105) | (0.153) | (0.0519) |
| Region: South | 0.212 | -0.037 | 0.0693 | 0.110 | -0.106 | 0.00235 |
| | (0.128) | (0.185) | (0.0628) | (0.103) | (0.151) | (0.0516) |
| Region: West | 0.085 | -0.200 | 0.0259 | -0.150 | -0.282* | -0.0860 |
| | (0.153) | (0.204) | (0.0772) | (0.096) | (0.140) | (0.0476) |
| Rural | 0.760*** | 0.566* | 0.318*** | 0.241 | 0.313 | 0.125 |
| | (0.168) | (0.245) | (0.0792) | (0.186) | (0.268) | (0.0929) |
| Constant | -1.019 | -0.421 | -0.370 | -1.504 | -1.163 | -0.608 |
| | (0.434) | (0.534) | (0.203) | (0.214) | (0.272) | (0.0978) |
| Income elasticity at median | 0.367 | 0.462 | 0.408 | 0.331 | 0.386 | 0.355 |
| | (0.031) | (0.040) | (0.032) | (0.021) | (0.036) | (0.024) |
| F-test of income coefficients | 107.7 | 84.27 | 114.2 | 181.1 | 97.14 | 168 |
| Observations | 1,313 | 1,313 | 1,313 | 3,623 | 3,623 | 3,623 |
| R-squared | 0.513 | 0.401 | 0.506 | 0.434 | 0.275 | 0.402 |

Notes: Robust standard errors in parentheses. Household pollution calculated by multiplying itemized household consumption with 2002 pollution intensity of production for each type of good and summing for each household. Includes upstream pollution based on a Leontief input-output calculation. Nominal incomes adjusted using the CPI for all items; nominal expenditures are adjusted using the corresponding core, food and beverage, gasoline, electricity, and fuel oil CPIs.
*** for 1%, ** for 5%, * for 10%

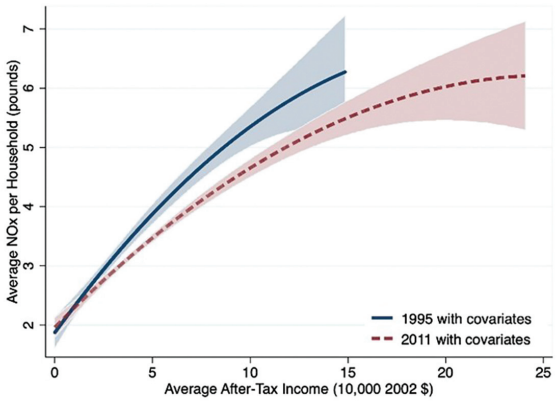
To compare the parametrically estimated EECs over time, columns (4) through (6) of Table 3.3 replicate the regression using the 2011 CEX. In column (4), a one-unit increase in after-tax income raises NOx emissions by 0.34 pounds, while a one-unit increase in after-tax income squared decreases pollution by 0.01 pounds. The statistically significant results indicate a similar shape of the EEC compared to 1995. Additionally, the table reveals that over time, household size and age had more significant effects on pollution in 2011 than in 1995, while the marital status of the head of the household and residence in rural areas had more minor effects[8]. EECs of local pollutants are presented in Table D.1. The results exhibit a similar pattern compared to the global pollutants.

Fig. 3.5 visually represents the expected relationship between income and global pollutant emission, as inferred from the EECs derived in Table 3.3. Panel (a) in Fig. 3.5 corresponds to columns 1 and 4 of Table 3.3, in which EECs illustrate income expansion paths. Similar to the nonparametric EECs in Fig. 3.4, these curves demonstrate an upward trajectory, income elasticities below 1, and a discernible downward trend over time. Of significance is that the curves manifest an augmented concavity in recent years. This graphical depiction enhances our understanding of the intricate dynamics between income levels and global pollutants' environmental impact.[9]

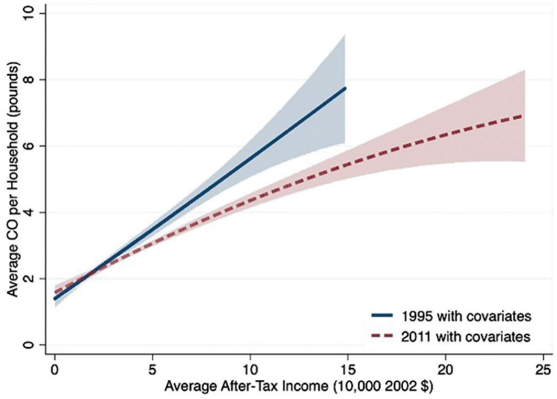
In Fig. 3.5, the conspicuous trend indicates that wealthier households considerably impact the elevation of pollution emissions in other countries. This phenomenon is attributed to the consumption patterns of affluent households, which involve a higher demand for goods and services that, in turn, lead to increased pollution emissions (Lundberg and Lundberg, 2012). Additionally, de Groot (2003) demonstrates that as consumers experience an increase in wealth, their consumption patterns transform. In the initial phases of income growth, there is a discernible shift towards the consumption of manufacturing products characterized by a higher emission intensity. However, consumers tend to favor services recognized for their relatively smaller environmental footprint as income rises. Consequently, this implies that although affluent households with higher demand

[8]Drawing inspiration from Sager (2019), we compared expression (3.4) with more flexible semiparametric models. Adhering to the methodology proposed byHardle and Mammen (1993), we subjected each polynomial degree to a test evaluating the null hypothesis concerning the appropriateness of the adjustment of degree n+1. Our objective was to identify the minimum polynomial degree where the null hypothesis consistently withstood scrutiny (remained unchallenged or failed to be rejected). The results confirm that, for 2011, the quadratic model stands out as the optimal selection.

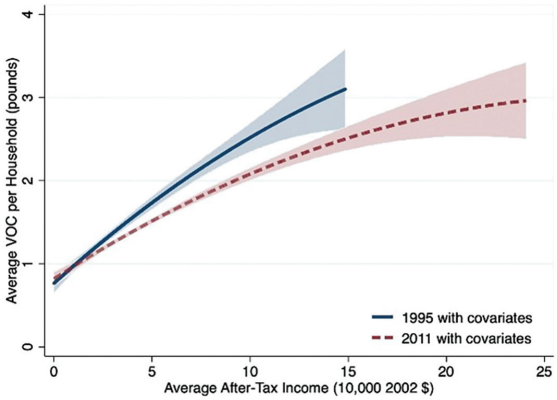
[9]Parametric EECs for local pollutants are presented in Fig. D.5.




(a) Nitrogen Oxides (NOx)




(b) Carbon Monoxide (CO)




(c) Volatile Organic Compounds (VOCs)

Notes: All other covariates are fixed at their mean values. Inflation adjustments are in Fig. 3.4. Standard errors for pollution intensity of production are not estimated, so 95% confidence intervals (shaded) reflect variation in household spending.

**Figure 3.5**: *Parametric EECs for Global Pollutants*

contribute more to pollution, the marginal change diminishes as income increases, reflecting the changing composition of the consumption bundle.

We also note a decline in pollution embedded in U.S. household consumption from 1995 to 2011, primarily driven by affluent households. This reduction aligns with the escalating environmental challenges and increasing pressures to consider the repercussions of human activities on the natural ecosystem. Globally, businesses have responded by adopting more sustainable practices in both their operations and marketing strategies (Kotler, 2011). According to Cronin et al. (2011), a prevalent marketing approach to this evolving market landscape involves adjusting existing or introducing new products and production methods to mitigate ecological impact and enhance environmental performance.[10] Moreover, affluent households significantly contribute to reducing pollution emissions over time, driven by evolving market trends and heightened environmental awareness. Based on Lorek (2015), the higher purchasing power allows wealthier households to invest in eco-friendly products and embrace sustainable practices. A notable segment of these affluent consumers, often called LOHAS (Lifestyles of Health and Sustainability) or LOVOS (Lifestyles of Voluntary Simplicity), actively seek a healthy and sustainable lifestyle.[11]

The two methodologies employed thus far signify contrasting extremes in parameterization. Fig. 3.4 illustrates mean pollution across income groups, adopting a nonparametric approach with no assumed functional form. In contrast, considering other household characteristics, Fig. 3.5 assumes a quadratic relationship between pollution and income. As a middle-ground alternative, we have conducted estimations for all EECs using restricted cubic splines, incorporating five spline knots instead of the income quadratic (Fig. D.6).[12] The graphical representations of

[10] Since eco-friendly products allow firms to meet environmental mandates, establish a competitive edge, and drive future growth (Nidumolu et al., 2009), sustainable product development activities are anticipated to gain even greater significance in the future (Varadarajan, 2017).

[11] This group represents a growing green product and service market, especially in countries such as Australia, Germany, France, Italy, Japan, Canada, and the USA. Approximately 20% of the population in these countries is willing to pay extra for environmentally friendly offerings, encompassing ecological foods, energy-saving solutions, green energy sources, eco-friendly homes, and sustainable clothing and furniture (Frank-Martin and Peattie, 2009).

[12] According to Harrell (2001), a recommended practice is to place knots at equally spaced percentiles of the original variable's (after-tax income) marginal distribution. In our application, we opted for knots at the 5th, 27.5th, 50th, 72.5th, and 95th percentiles. When utilizing a restricted cubic spline, the result is a continuous smooth function characterized by linearity before the first knot, a piecewise cubic polynomial between adjacent knots, and linearity again after the last knot. By estimating Engel curves using restricted cubic splines over income, we can visualize the relationship between income and pollution emission as a piecewise cubic polynomial.

the splines share similarities with both the nonparametric and quadratic specifications, depicting upward-sloping curves with elasticities of less than one and a downward shift over time.

### 3.3.3 Decomposing the Composition Effects

The movements along EECs are contingent upon the intrinsic preferences of wealthier households compared to their less affluent counterparts, assuming no changes in other variables. Notably, these movements are not influenced by specific environmental policy interventions. This implies that movements along an EEC might offer predictive insights into future pollution levels, especially under existing environmental regulations, if household incomes increase without any accompanying alterations in other factors. For instance, consider a scenario where the incomes of wealthier households increase significantly over the next decade. However, their preferences for goods and services remain the same with varying pollution intensities and the prevailing environmental policies. In such a case, the movements along the EEC could indicate the potential trajectory of pollution levels in the absence of new regulatory measures. This underscores the importance of understanding the role of household income dynamics in shaping pollution trends within the framework of existing environmental regulations.

On the contrary, shifts in EECs result from evolving collective preferences or shifts in environmental policies that impact the relative dynamics of supply and demand for goods with varying pollution intensities. When EECs shift downward, indicating a reduction in pollution, the environmental benefits associated with such changes are contingent upon corresponding shifts in preferences or the implementation of more stringent environmental policies. The persistence of environmental gains from downward-shifting EECs is possible with concurrent preference adjustments or the reinforcement of environmental regulations. For example, suppose a country experiences a shift in aggregate consumer preferences towards eco-friendly products, leading to a downward shift in the EECs. In that case, the environmental benefits will be realized if this shift is sustained over time. Similarly, if regulatory interventions aim to reduce the demand for pollution-intensive goods, the downward shift in EECs can contribute to positive environmental outcomes. The long-term effectiveness of such shifts in reducing pollution levels hinges on the continuity of

these preference changes or the durability of environmental policy measures.

The Oaxaca-Blinder decomposition offers a methodology to disentangle these components while maintaining demographic variables constant. In the context of our analysis, we establish the average pollution level for a specific year by referencing the regression outcomes presented in Table 3.3.

$$\overline{P}_t = \alpha_t \bar{Y}_t + \beta_t \bar{Y}_t^2 + \delta_t \bar{X}_t \tag{3.5}$$

In expression (3.5), $P_{it}$ represents the average indirect pollution, $\bar{Y}_t$ and $\bar{Y}_t^2$ denotes the average income and income squared, respectively, and $\bar{X}_t$ corresponds to the average of other included covariates. The error term is omitted as the average OLS error is inherently constructed to be 0.

The change in average pollution between 1995 and 2011 can be expressed in expression (3.6).

$$\begin{aligned} \overline{P}_{11} - \overline{P}_{95} = {} & \alpha_{95}(\bar{Y}_{11} - \bar{Y}_{95}) + \beta_{95}(\bar{Y}_{11}^2 - \bar{Y}_{95}^2) && \text{(Term 1)} \\ & + (\alpha_{11} - \alpha_{95})\bar{Y}_{11} + (\beta_{11} - \beta_{95})\bar{Y}_{11}^2 && \text{(Term 2)} \\ & + \bar{X}_{11}(\delta_{11} - \delta_{95}) + (\bar{X}_{11} - \bar{X}_{95})\delta_{95} && \text{(Term 3)} \end{aligned} \tag{3.6}$$

In expression (3.6), term 1 captures the impact of changing income on total air pollution emissions while holding the 1995 OLS coefficients constant. This represents a movement along the 1995 EEC. On the other hand, the term 2 accounts for the effect of changing coefficients on income and income squared, indicating a shift or alteration in the shape of the EEC. Lastly, term 3 accommodates changes in all other covariates, encompassing demographics, household size, and their respective changing coefficients. It is essential to recognize that these components collectively contribute to explaining the observed variations in average pollution levels over the specified period.

Table 3.4 provides a detailed breakdown of the outcomes derived from expression (3.6). Focusing on NOx and examining column 1, each value is computed by multiplying the change in average values of the variable (referenced from Tables 3.1 and 3.2) by the 1995 OLS coefficients (column 1 of Table 3.3).[13] These entries signify the expected alteration in pollution resulting from

[13]For example, in Table 3.2, the average income increased by 0.69 ($10,000 in 2002 dollars), and the coefficient of income in the 1995 OLS is 0.453. The change due to after-tax income (the first element of term 1) equals 0.3

specific modifications in the variable while keeping all other factors constant, including technological influences. At the bottom of Table 3.4, these effects are categorized into those influenced by changes in income (or movements along the EEC) and those influenced by alterations in other covariates. Remarkably, the NOx content embedded in the average household's consumption witnessed a marginal decrease of 0.221 pounds between 1995 and 2011. Changes in average after-tax income and income squared contributed to a theoretical increase of 0.18 pounds (comprising a 0.31 increase from after-tax income and a 0.13 decrease from after-tax income squared). Simultaneously, demographic shifts would have led to an additional reduction of 0.007 pounds. The residual difference, amounting to 0.4 pounds (-0.221-0.18+0.007), is attributed to shifts in the EEC.

The rise in emissions attributed to variations in household income, exemplified by the 0.18-pound upsurge in NOx, can be dissected into distinct components at the household level, namely scale and composition. Within an EEC framework, affluent households tend to consume more goods and services. However, the composition of their consumption exhibits a less pollution-intensive mix. The interplay between these two factors hinges on the specific characteristics of the EEC. In cases where EECs exhibit inelasticity, the compositional component gains prominence, resulting in higher-income households being proportionally less responsible for pollution. This effect becomes more pronounced when EECs take on an increasingly concave shape.

Drawing inspiration from the works of Levinson (2009a), Shapiro and Walker (2018), and Levinson and O'Brien (2019), we present an extended decomposition model aimed at elucidating the variations in pollution emissions attributed to the overall change in income (term 1 of expression (3.6)), distinguishing between the scale effect ($SC_t$) and composition effect ($CC_t$). Aligning with these prior investigations, we calculate the growth rate by dividing the income in each year by the income in 1995. Following this, the scale effect ($SC_t$) is determined by multiplying the volume of pollution discharge in 1995 by the income growth rate. The scale effect ($SC_t$) for the year t relative to 1995 is articulated as follows:

$$SC_t = \overline{P}_{95} \times [(\bar{Y}_t - \bar{Y}_{95})/\overline{Y}_{95}] \tag{3.7}$$

$(0.69 \times 0.453)$.

**Table 3.4**: *Movement Along Parametric EECs for Global Pollutants*

| | ROW | | |
|---|---|---|---|
| | NOx | CO | VOC |
| Dependent Variable: | (1) | (2) | (3) |
| after-tax income ($10,000 in 2002 dollars) | 0.311 | 0.283 | 0.146 |
| | (0.064) | (0.069) | (0.03) |
| After-tax income squared | -0.128 | 0.012 | -0.045 |
| | (0.064) | (0.092) | (0.030) |
| Household size | -0.005 | -0.0033 | -0.002 |
| | (0.023) | (0.015) | (0.009) |
| Household size squared | 0.0026 | 0.0015 | 0.0009 |
| | (0.01) | (0.006) | (0.003) |
| Age | 0.122 | 0.084 | 0.049 |
| | (0.05) | (0.046) | (0.021) |
| Age squared | -0.121 | -0.089 | -0.05 |
| | (0.049) | (0.045) | (0.021) |
| Married | -0.012 | -0.009 | -0.005 |
| | (0.010) | (0.008) | (0.004) |
| Race dummies | -0.0100 | -0.010 | -0.005 |
| Education dummies | 0.044 | 0.066 | 0.025 |
| Regional dummies | -0.028 | -0.050 | -0.014 |
| **Total change due to income (movement along EEC)** | 0.183 | 0.295 | 0.101 |
| **Scale Effect** | 0.618 | 0.556 | 0.276 |
| **Composition Effect** | -0.435 | -0.261 | -0.175 |
| **Total change due to other demographics** | -0.007 | -0.009 | 0.006 |
| **Unexplained difference (shift in EEC)** | -0.397 | -0.542 | -0.236 |

Notes: Estimates based on Oaxaca-Blinder decompositions. Robust standard errors in parentheses. Movements along each Engel curves described in expression (3.6)) Term 1. Total change due to other demographics described in expression (3.6)) Term 3. Shifts in Engel curves described in expression (3.6)) Term 2. The value of index based on 2002 production technology for all years. Ater-tax income measured in $10,000.
*** for 1%, ** for 5%, * for 10%

Subsequently, recognizing that Term 1 in expression (3.6) signifies a movement along the curve, encompassing the summation of the scale effect ($SC_t$) and the composition effect ($CC_t$), we can delineate the composition effect at year t relative to 1995, utilizing expression (3.7), as follows:

$$\begin{aligned} CC_t &= \text{Term } 1_t - SC_t \\ &= \alpha_{95}(\bar{Y}_t - \bar{Y}_{95}) + \beta_{95}(\bar{Y}_t^2 - \bar{Y}_{95}^2) \\ &\quad -\overline{P}_{95} \times [(\bar{Y}_t - \bar{Y}_{95})/\overline{Y}_{95}] \end{aligned} \tag{3.8}$$

Based on the information presented in Table 3.2, it is observed that the average after-tax income increased by 17.9% between 1995 and 2011. Simultaneously, the average pollution embedded in household consumption of NOx in 1995 (refer to Table 3.1, column 1) is 3.453. Consequently, the scale effect is calculated as 0.618 ($3.453 \times 0.179$). The composition effect, which contributes to the reduction of NOx emissions, is strongly negative at -0.44. In summary, the relationship can be expressed in the form of an equation encompassing the summarized terms from expressions (3.6) to (3.8) as follows:

$$\begin{aligned} \overline{NOx}_{11} - \overline{NOx}_{95} &= \text{Term } 1_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \\ \overline{NOx}_{11} - \overline{NOx}_{95} &= SC_{11} + CC_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \\ -0.221 &= 0.618 - 0.435 - 0.397 - 0.007 \end{aligned} \tag{3.9}$$

As per expression (3.9), it is discerned that the environmental improvement, signifying a reduction in pollution emissions, is primarily ascribed to the composition effect and shifts in the EECs. Conversely, demographic changes play a minor role in this context.

$$\begin{aligned} \overline{CO}_{11} - \overline{CO}_{95} &= \text{Term } 1_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \\ \overline{CO}_{11} - \overline{CO}_{95} &= SC_{11} + CC_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \\ -0.256 &= 0.556 - 0.261 - 0.542 - 0.009 \end{aligned} \tag{3.10}$$

$$\begin{aligned}
\overline{VOC}_{11} - \overline{VOC}_{95} &= \text{Term } 1_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \qquad (3.11)\\
\overline{VOC}_{11} - \overline{VOC}_{95} &= SC_{11} + CC_{11} + \text{Term } 2_{11} + \text{Term } 3_{11}\\
-0.129 &= 0.276 - 0.175 - 0.236 + 0.006
\end{aligned}$$

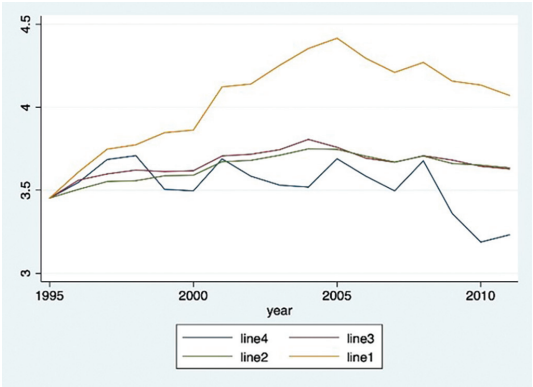
Similar patterns have been observed in expressions (3.10) and (3.11) for the other two global pollutants, CO and VOCs. However, there is a notable distinction in the magnitudes of contribution from the two effects. The shifts in EECs account for more than half, contributing approximately 65% to the changes in the two global pollutants, while NOx's shift contributes 47%.[14]

Fig. 3.6 delineates the temporal evolution of the relative magnitudes of various effects on global pollutants, employing the same decomposition methodology annually from 1995 to 2011. The upper line illustrates the pollution level that would ensue if the proportions of goods and services consumed by households remained constant while household incomes increased—representing the scale effect at the household level. Conversely, the lower line (Line 4) portrays the anticipated pollution in each year, calculated by pairing the 2002 emissions intensity coefficients with the respective year's CEX expenditures. This accounts for the actual mix of household goods and services while keeping technology fixed based on 2002 emissions intensities.

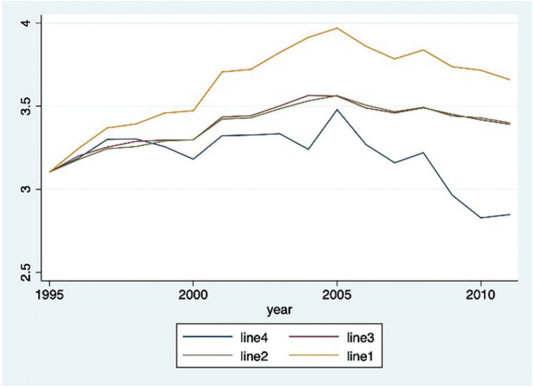
The discrepancy between the scale effect (line 1) and the change in pollution emissions (line 4) can be decomposed into three distinct components, as per expression (3.9): the composition effect, shifts in EECs (term 2), and demographic changes (term 3). Line 2 illustrates the hypothetical impact of movements along the 1995 EEC. The gap between Lines 1 and 2 signifies the counterbalancing compositional effect, reflecting the inelastic shape of EECs. Line 3 delineates the contribution of changing demographics in addition to changing income, slightly dipping below line 2 due to other factors like household size, education, and geography, which collectively resulted in a marginal net decrease in the pollution intensity of consumption. The remaining gap between line 3 and line 4 represents the shift in EECs. This figure more distinctly illustrates the magnitude of the reduction contribution among the three effects.[15]

[14] Movements along the parametric EECs for local pollutants are depicted in Table D.2, showcasing similar patterns where the composition effect and shifts contribute significantly to environmental improvement.

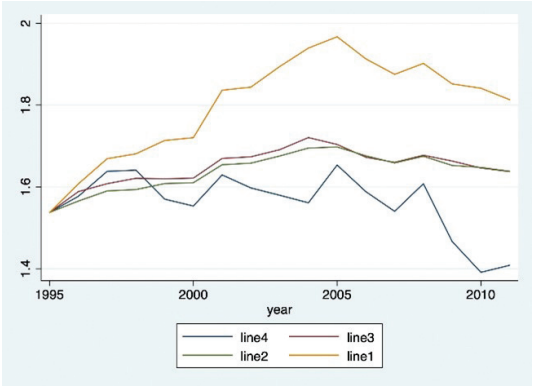
[15] Fig. D.7, illustrating the decomposition of the composition effect for local pollutants, consistently demonstrates discernible patterns.




(a) Nitrogen Oxides (NOx)




(b) Carbon Monoxide (CO)




(c) Volatile Organic Compounds (VOCs)

Line (1) Scale Effect; Line (2) Movement Along Engel Curve;
Line (3) Movement Along Engel Curve and Demographic Changes; Line (4) Index Predicted

Notes: The changing index calculates the scale effect in proportion to real after-tax income growth. Movements are long, and shifts in the Engel curve are calculated by estimating the value of indexes each year using the 1995 Engel curve coefficients. Pollution predicted using NEI-based pollution coefficients is estimated by matching itemized consumption expenditure in each year with the corresponding industry's 2002 pollution intensity

**Figure 3.6**: *Decomposition of Predicted Pollution from Household Consumption*

## 3.4 Environmental Engel Curves Across Regions

### 3.4.1 Parametric Estimate

Environmental pollution is the cost of economic growth resulting from increased industrialization, urbanization, mechanization, agricultural use of fertilizers and pesticides, and mismanagement of human waste (Nazeer et al., 2016). This issue is particularly prominent in developing countries with less stringent environmental regulations.[16] Understanding the sources of pollution embedded in U.S. household consumption becomes imperative as it unravels the intricate dynamics between economic activities and environmental consequences. In this section, we analyze discernments between developed and developing countries, highlighting the disparities in their contributions to pollution. Doing so contributes to the broader discourse on sustainable development, emphasizing the need to address environmental challenges associated with economic growth for the long-term well-being of societies.

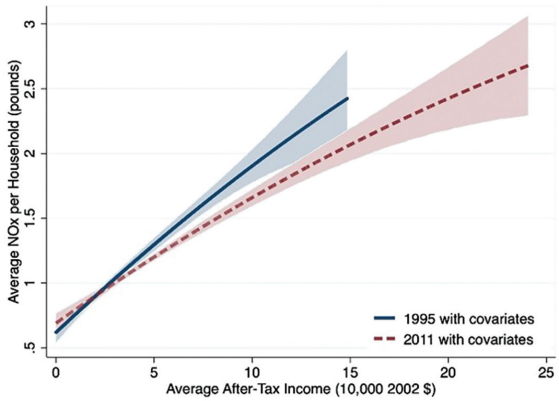
Fig. 3.7 presents the parametric EECs for NOx, distinguishing between developed and developing countries.[17] The figure clearly illustrates that NOx emissions embedded in U.S. household consumption predominantly originate from developing countries. In contrast, developed countries contribute significantly to overall trade flows. Data from the World Integrated Trade Solution (WITS) for 2002 indicates that developed countries constituted 79% of total trade flows while developing countries accounted for the remaining share.

The observed disparity critically examines the intricate environmental and economic dynamics between developed and developing nations, necessitating further exploration and analysis. Several contributing factors underpin this phenomenon. Firstly, the regulatory landscape in developing countries, while often resembling that of developed countries, is frequently fraught with challenges related to implementation and enforcement. This leads to a weak first stage in the regulatory process (Arceo et al., 2016).[18] Secondly, the Pollution Haven Hypothesis posits that industries

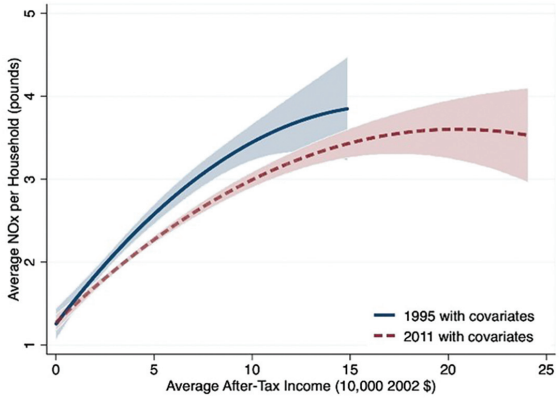
[16] According to Greenstone and Hanna (2014), in developing countries, the impact of environmental pollution is particularly severe, leading to adverse health effects, increased disabilities, and higher mortality rates annually.

[17] EECs for the other two global pollutants are depicted in Fig. D.8 and Fig. D.9, revealing consistent patterns comparable to the Engel curves estimated in Section 3.2. These patterns exhibit an upward-sloping, concave shape and a downward shift over time.

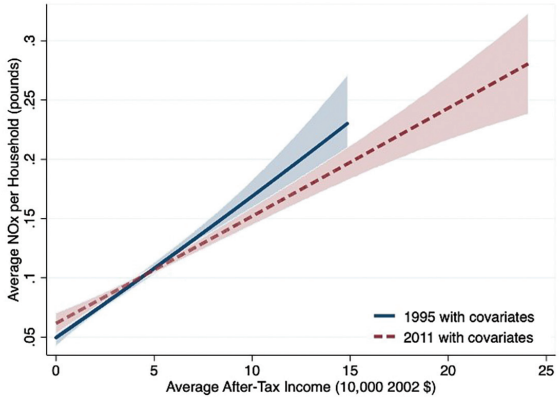
[18] For instance, studies by Greenstone and Hanna (2014) in India and Davis (2008) on driving restrictions reveal




(a) Developed Countries




(b) Developing Countries




(c) China

Notes: See notes in Fig. 3.5

**Figure 3.7**: *Parametric EECs for NOx*

with high pollution intensity, colloquially termed "dirty industries," have migrated from developed to developing economies.[19] To substantiate this hypothesis,the pollution haven hypothesis. Akbostanci et al. (2007) conducted a study focusing on Turkey during the 1994–1997 period.[20] The findings indicated that exports increased with the degree of industry pollution intensity, providing empirical support for the pollution haven hypothesis.

Additionally, we conducted a specific analysis focusing on China, which constitutes 21% of trade flows in developing countries. However, our findings revealed that only a tiny fraction of pollution sourced in developing countries can be attributed to China. This observation may caused by China's growth trajectory, particularly its slower growth in the 1990s compared to the rapid expansion in the 2000s. Although China generated substantial pollution during this period, its trade volume was relatively small. Notably, China's emissions of NOx were around 4% among developing countries in 1995, reflecting its relative size at that time. China's significance in trade grew substantially after joining the WTO, leading to the elimination of specific trade policies.

Examining trade flows in China, we observed that the growth in trade flows surpassed the growth in value-added trade flows, with the majority of trade originating from developed countries. When considering value-added trade, the exports from China significantly diminish due to the inclusion of imported inputs in the goods exported by China.[21] Analyzing growth trade flows indicates that most pollution originates from developed countries. However, a substantial portion of goods exported by China comprises value added from other countries. Consequently, when evaluating the value-added in China, it may appear much smaller than its exports, especially considering factors such as the prevalence of free trade zones, where 40% of Chinese exports emanate.[22]

implementation issues and, in the latter case, no discernible impact on air pollution.

[19] Stringent environmental regulations in developed nations, driven by environmental concerns, have increased domestic production costs for these industries. In contrast, developing countries, with lower wages and less stringent environmental regulations, become attractive alternative producers for such sectors. Consequently, these developing nations serve as pollution havens for industries with significant environmental impacts.

[20] The research examined the pollution haven argument from a trade perspective, utilizing manufacturing industry data at the four-digit ISIC level through a panel data approach.

[21] As highlighted by Xing and Detert (2010), only about 4% of the value of an iPhone assembled in China and exported to the United States is attributed to Chinese value added. Johnson and Noguera (2017) observed a decline in the ratio of world value-added exports to world exports from 87% to 79% between 1970 and 2009. This metric is an inverse indicator, reflecting the extent of reciprocal trade within the value chain during the specified period.

[22] Koopman et al. (2012) initially documented this notable increase in the Domestic Value Added (DVA) ratio, emphasizing the differential Input-Output structure of firms in China's export-processing zones. Subsequently, Kee and Tang (2016) revealed that declining tariffs enhanced the competitiveness of China's upstream producers outside

Table 3.5 presents parametric estimates for global pollutants using expression (3.4) across regions.[23] The results indicate that the coefficient estimates for after-tax income are positive and statistically significant, suggesting upward-sloping EECs. The elasticity values being less than 1 imply concave Engel curves. Furthermore, a comparison of the estimates between 1995 and 2011 reveals a downward shift. Focusing on Panel (a), Column (1) for developed countries, a one-unit increase in after-tax income in 1995 corresponds to a 0.143-pound increase in NOx emissions. In Panel (b), the increase is approximately double, with a one-unit increase in after-tax income causing a 0.311-pound rise in NOx emissions. For China, the increase is 0.11 pounds. These findings align with the insights from Fig. 3.7, indicating that pollution emissions embedded in U.S. household consumption primarily originate from developing countries.

### 3.4.2 Decomposing the Composition Effects

Table 3.6 presents the outcomes of the decomposition analysis for global pollutants originating from different sources, including developed countries (Panel A), developing countries (Panel B), and China (Panel C). The table delineates the contributions of the four effects outlined in expression (3.9) – namely, the scale effect, composition effect, shift in the EECs, and demographic changes – to the alterations in pollution embedded in U.S. household consumption. Notably, for NOx emissions originating from developed countries, the reduction in emissions is roughly equally attributed to the composition effect and shifts in the EECs, as shown in expression (3.12). Conversely, in developing countries (Panel B), the composition effect emerges as a slightly more substantial contributor to the reduction in NOx emissions (expression (3.13)).

$$\begin{aligned} \overline{NOx}_{11} - \overline{NOx}_{95} &= \text{Term } 1_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \qquad (3.12) \\ \overline{NOx}_{11} - \overline{NOx}_{95} &= SC_{11} + CC_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \\ -0.038 &= 0.209 - 0.128 - 0.128 + 0.001 \end{aligned}$$

the processing zones, making them more appealing as suppliers for the processing segment.

[23] The estimates for local pollutants can be found in Table D.3.

**Table 3.5**: *Parametric EECs for Global Pollutants*

Panel A: Parametric Environmental Engel Curves for developed countries

| | Developed Countries | | | | | |
|---|---|---|---|---|---|---|
| | 1995 | | | 2011 | | |
| | NOx | CO | VOC | NOx | CO | VOC |
| Dependent Variable (pounds): | (1) | (2) | (3) | (4) | (5) | (6) |
| after-tax income ($10,000 in 2002 dollars) | 0.143*** | 0.179* | 0.078*** | 0.107*** | 0.140* | 0.056*** |
| | (0.02) | (0.0392) | (0.011) | (0.012) | (0.0208) | (0.007) |
| After-tax income squared | -0.0014 | 0.00267 | -0.0004 | -0.001 | -0.000839 | -0.0005 |
| | (0.002) | (0.00405) | (0.001) | (0.0007) | (0.00123) | (0.0004) |
| Other regressors | Yes | Yes | Yes | Yes | Yes | Yes |
| Income elasticity at median | 0.382 | 0.490 | 0.436 | 0.333 | 0.397 | 0.364 |
| | (0.029) | (0.046) | (0.034) | (.029) | (0.044) | (0.033) |
| F-test of income coefficients | 124.3 | 72.93 | 107.4 | 124.1 | 76.01 | 109.6 |
| Observations | 1,313 | 1,313 | 1,313 | 3,623 | 3,623 | 3,623 |
| R-squared | 0.532 | 0.359 | 0.470 | 0.369 | 0.234 | 0.323 |

Panel B: Parametric Environmental Engel Curves for developing countries

| | Developing Countries | | | | | |
|---|---|---|---|---|---|---|
| | 1995 | | | 2011 | | |
| | NOx | CO | VOC | NOx | CO | VOC |
| Dependent Variable (pounds): | (1) | (2) | (3) | (4) | (5) | (6) |
| after-tax income ($10,000 in 2002 dollars) | 0.311*** | 0.233*** | 0.135*** | 0.228*** | 0.178*** | 0.097*** |
| | (0.042) | (0.038) | (0.017) | (0.016) | (0.018) | (0.007) |
| After-tax income squared | -0.009** | -0.002 | -0.003* | -0.0056*** | -0.003** | -0.002*** |
| | (0.004) | (0.004) | (0.0015) | (0.001) | (0.001) | (0.0004) |
| Other regressors | Yes | Yes | Yes | Yes | Yes | Yes |
| Income elasticity at median | 0.360 | 0.441 | 0.392 | 0.329 | 0.377 | 0.35 |
| | (0.033) | (0.038) | (0.033) | (0.019) | (0.03) | (.0204) |
| F-test of income coefficients | 88.27 | 90.63 | 103.5 | 201.8 | 122.5 | 210.9 |
| Observations | 1,313 | 1,313 | 1,313 | 3,623 | 3,623 | 3,623 |
| R-squared | 0.478 | 0.429 | 0.494 | 0.443 | 0.316 | 0.437 |

Panel C: Parametric Environmental Engel Curves for China

| | China | | | | | |
|---|---|---|---|---|---|---|
| | 1995 | | | 2011 | | |
| | NOx | CO | VOC | NOx | CO | VOC |
| Dependent Variable (pounds): | (1) | (2) | (3) | (4) | (5) | (6) |
| after-tax income ($10,000 in 2002 dollars) | 0.011*** | 0.016*** | 0.008*** | 0.009*** | 0.012*** | 0.005*** |
| | (0.002) | (0.004) | (0.0012) | (0.001) | (0.002) | (0.0006) |
| After-tax income squared | 4.93e-05 | 0.0004 | 4.64e-06 | 4.21e-06 | -3.01e-05 | -5.65e-06 |
| | (0.0002) | (0.0004) | (0.0001) | (7.17e-05) | (0.0001) | (3.97e-05) |
| Other regressors | Yes | Yes | Yes | Yes | Yes | Yes |
| Income elasticity at median | 0.408 | 0.539 | 0.515 | 0.342 | 0.416 | 0.412 |
| | (0.032) | (0.054) | (0.042) | (0.037) | (0.058) | (0.038) |
| F-test of income coefficients | 113.8 | 61.93 | 94.36 | 95.78 | 53.20 | 119.2 |
| Observations | 1,313 | 1,313 | 1,313 | 3,623 | 3,623 | 3,623 |
| R-squared | 0.495 | 0.307 | 0.429 | 0.317 | 0.186 | 0.315 |

Notes: See notes in Table 3.3.

$$\begin{aligned} \overline{NOx}_{11} - \overline{NOx}_{95} &= \text{Term } 1_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \\ \overline{NOx}_{11} - \overline{NOx}_{95} &= SC_{11} + CC_{11} + \text{Term } 2_{11} + \text{Term } 3_{11} \\ -0.183 &= 0.410 - 0.308 - 0.268 - 0.017 \end{aligned} \tag{3.13}$$

In contrast, reducing pollution emissions embedded into U.S. household consumption, specifically for CO and VOCs, manifests a nuanced pattern. The shifts observed in the EECs contribute marginally more substantially than the composition effect to the reduction of pollution emissions, with the magnitude of this disparity exhibiting a degree of significance that is not particularly pronounced. Overall, the contribution of both the composition effect and shifts in EECs is roughly equal in effecting the reduction of emissions ingrained in U.S. household consumption, aligning with the findings of Levinson and O'Brien (2019). We have additionally conducted a separate analysis to decompose the composition effect for China in Panel C. The outcomes reveal a similar pattern compared to developed and developing countries. The estimations for local pollutants can be found in Table D.4.

## 3.5 Conclusion

In conclusion, our focus on the sources of pollution in both developing and developed countries stems from the urgency and significance of addressing environmental challenges on a global scale. The environmental concerns in developing nations have reached critical levels due to the rapid pace of globalization, urbanization, and industrialization. This acceleration has depleted natural resources and led to severe pollution associated with economic activities. The environmental degradation in these countries poses a serious threat to sustainable development and long-term economic growth.

Our study has thoroughly examined the environmental ramifications stemming from trade dynamics, with a specific focus on the pollution embedded in U.S. household consumption. By estimating both nonparametric and parametric EECs, we have unveiled a noteworthy revelation: while developed nations account for the majority of trade flows, the pollution contributing to U.S.

**Table 3.6**: *Movement Along Parametric EECs for Global Pollutants*

Panel A: Movement along parametric EECs for developed countries

| | Developed Countries | | |
|---|---|---|---|
| | NOx | CO | VOC |
| Dependent Variable: | (1) | (2) | (3) |
| **Total change due to income (movement along EEC)** | 0.081 | 0.156 | 0.049 |
| **Scale Effect** | 0.209 | 0.250 | 0.105 |
| **Composition Effect** | -0.128 | -0.095 | -0.056 |
| **Total change due to other demographics** | 0.010 | 0.004 | 0.006 |
| **Unexplained difference (shift in EEC)** | -0.128 | -0.262 | -0.096 |

Panel B: Movement along parametric EECs for developing countries

| | Developing Countries | | |
|---|---|---|---|
| | NOx | CO | VOC |
| Dependent Variable: | (1) | (2) | (3) |
| **Total change due to income (movement along EEC)** | 0.102 | 0.139 | 0.052 |
| **Scale Effect** | 0.410 | 0.306 | 0.171 |
| **Composition Effect** | -0.308 | -0.167 | -0.119 |
| **Total change due to other demographics** | -0.017 | -0.013 | 0.000 |
| **Unexplained difference (shift in EEC)** | -0.268 | -0.281 | -0.141 |

Panel C: Movement along parametric EECs for China

| | China | | |
|---|---|---|---|
| | NOx | CO | VOC |
| Dependent Variable: | (1) | (2) | (3) |
| **Total change due to income (movement along EEC)** | 0.0084 | 0.0150 | 0.0052 |
| **Scale Effect** | 0.017 | 0.021 | 0.009 |
| **Composition Effect** | -0.0090 | -0.0061 | -0.0039 |
| **Total change due to other demographics** | 0.0019 | 0.0005 | 0.0006 |
| **Unexplained difference (shift in EEC)** | -0.007 | -0.021 | -0.011 |

Notes: See notes in Table 3.4.

household consumption predominantly originates from developing countries. The observed disparity between developed and developing nations regarding pollution emissions raises complex questions about regulatory effectiveness and the global distribution of environmentally intensive industries.

Furthermore, employing a decomposition model designed to identify the origins of pollution emissions, we dissected the roles played by various factors, including the scale effect, composition effect, shifts in EECs, and demographic changes. Our nuanced findings illuminate distinct patterns in the contributions of these factors across different pollutants and regions. Significantly, the composition effect and shifts in EECs emerged as pivotal contributors to the reduction in emissions embedded in U.S. household consumption, exhibiting a consistent pattern of approximately equal significance. These insights deepen our understanding of the intricate interplay between trade, consumption behaviors, and environmental outcomes.

As we navigate the intricate global trade landscape, our findings underscore the critical importance of considering both structural changes in consumption behavior and evolving production network patterns in addressing environmental challenges associated with international trade. This research lays the groundwork for future inquiries, facilitating targeted policy interventions and industry-level analyses to promote sustainable trade practices and mitigate environmental impact.

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# Appendix A

# Supplemental Appendix to Engel Curves on Outsourcing and Foreign Environmental Taxes: A Valued-Added Approach

## A.1 Matching CEX with the WIOD code and Environmentally Related Taxes data.

### A.1.1 CEX to WIOD code

The Consumer Expenditure Surveys (CEX) serve as a valuable resource for gathering comprehensive data pertaining to household consumption expenditures, particularly those related to specific goods. Within the framework of the CEX, both consumption and income data are meticulously categorized using Universal Classification Codes (UCC), collectively representing a substantial portion, approximately 80% to 90%, of total household expenditures.

The Consumer Expenditure Survey (CEX) comprises two distinct surveys, namely, the Interview Survey and the Diary Survey. The Interview Survey is meticulously designed by the Bureau of Labor Statistics (BLS) to elicit data regarding substantial and recurring expenditures that respondents can reasonably recollect over at least three months. Typically, expenditures reported

in the Interview Survey pertain to categories such as property, automobiles, major appliances, and regular recurring expenses like rent, utilities, and insurance (Battistin, 2003). Conversely, the Diary Survey is specifically designed to capture data related to frequently purchased items, which tend to be challenging for respondents to recall, even after a few weeks. These frequently purchased items encompass expenditures on food, beverages (both at home and in eating establishments), housekeeping supplies, nonprescription drugs, and various personal care products and services (Attanasio et al., 2004). Collectively, the data obtained from both surveys comprehensively cover the entire spectrum of consumer unit expenditures. It is essential to note that the U.S. Census Bureau is responsible for collecting CEX data on behalf of the BLS. The distinctive nature of CEX data empowers researchers to investigate the relationship between consumer expenditures, income, and the characteristics of consumer units.

Levinson and O'Brien (2019) conducted a research study in which they undertook the meticulous task of aligning consumption expenditure data extracted from the Consumer Expenditure Surveys (CEX) with Input-Output (IO) codes. This alignment process was accomplished through a manual comparison of the descriptions of consumption categories and production industries. By scrutinizing the textual descriptions of these categories and industries, they were able to establish meaningful connections between them, facilitating a deeper understanding of the relationships between consumer spending patterns and specific economic sectors.

Expanding upon the pioneering work of Levinson and O'Brien (2019), our study further broadens the horizon by rigorously crafting a manual concordance, bridging Input-Output (IO) codes with those found in the World Input-Output Database (WIOD). Numerous IO codes may correspond to the same WIOD code owing to the restricted number of sectors (35 sectors and 40 countries). This concordance is established through an exhaustive examination of the descriptive attributes associated with consumption categories and production industries.[1]

In the matching conducted by Levinson and O'Brien, UCC codes related to food expenditures were linked to IO codes starting with 311 and 312, which typically relate to the manufacturing of food products such as Breakfast Cereal Manufacturing. This distinction arises from the specific definition of "Food, Beverages, and Tobacco," which primarily covers the manufacturing of these

[1]Please refer to Figure A1 for the integration process of WIOD, CEX, and EPS data.

products. Conversely, "Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods" focuses on the retail sale of various finished goods, including food products when sold through retail channels. This differentiation in focus justifies the allocation of consumption to these separate categories. A similar rationale applies to other categories like "Textiles and Textile Products," "Leather," "Leather and Footwear," and others. This clarifies why most consumption is not attributed to “Retail Trade.”

For quick reference, the complete concordance details can be accessed within the codebook, specifically located in the "IO-WIOD" sheet of the accompanying Excel file.

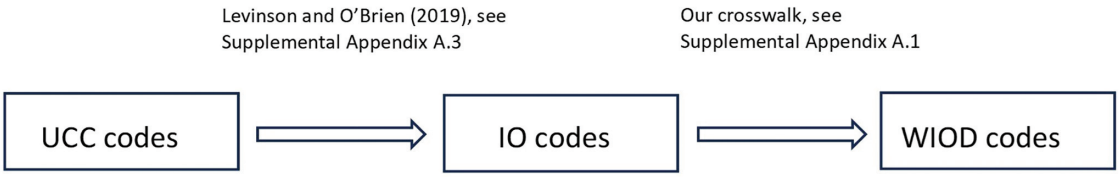



**Figure A.1**: *Components of the Consumer Price Index, 1982-2014*

### A.1.2 Environmentally Related Taxes to WIOD code

The OECD maintains an extensive database known as Policy Instruments for the Environment (PINE), which was initially developed in collaboration with the European Environment Agency (EEA). This comprehensive database serves as a repository of both qualitative and quantitative information pertaining to a wide array of environmentally related policy instruments (OECD, 2023). These instruments encompass environmentally motivated taxes, fees, and charges, as well as tradable permits, deposit-refund systems, subsidies with environmental objectives, and voluntary approaches that governments employ to address environmental concerns. It is noteworthy that this database is readily accessible to the public at the following web address: oe.cd/pine.

In the codebook’s Excel file, specifically within the "TaxRevenue" sheet, you will find a comprehensive listing of environmentally related taxes and their corresponding revenue figures for the year 2002. These entries encompass countries that are encompassed within the World Input-Output Table. It’s important to note that the recorded revenue values are denominated in US dollars for

consistency and ease of comparison.

Additionally, within the same codebook, the "RevenueSector" sheet offers valuable insights into the alignment between the names of these taxes and the specific economic sectors to which they are associated. This concordance allows for a more granular understanding of how tax revenues are distributed among different sectors.

Furthermore, as part of our meticulous efforts, we have manually established associations between the sector names and the corresponding codes used within the World Input-Output Database (WIOD). This strategic matching of sector names with WIOD codes enhances our ability to link tax revenues with various industry classifications as outlined in the WIOD. This alignment facilitates a more nuanced analysis of tax revenue distribution across different sectors and industries, contributing to a comprehensive understanding of the economic dynamics associated with environmentally related taxes.

Please be aware that a single tax instrument may pertain to several distinct industry sectors. Therefore, in order to distribute the tax revenue among these industries, a weighted average was computed, taking into consideration the value added by each sector. Furthermore, the environmentally related tax, often referred to as tax ratios, is determined by the ratio of tax revenue to value added.

The absence of the implementation of environmentally related taxes across all 35 sectors in 2002 can be attributed to a multifaceted interplay of factors encompassing policy considerations, regulatory frameworks, economic assessments, political influences, and the unique environmental circumstances and focal points characteristic of individual countries or regions during that period. Additionally, the dearth of data concerning environmentally related tax revenue across all nations in the year 2002 can be ascribed to a multifaceted interplay of factors encompassing data accessibility, divergent national tax frameworks, reporting methodologies, temporal discrepancies, policy idiosyncrasies, and the operational capacity for data compilation.

In order to compute the environmentally related tax revenues for countries and industries where data was missing, we utilized the Country Similarity Index (CSI), available at https://objectivelists.com/. The Country Similarity Index is designed to quantitatively assess the degree of similarity between countries in comparison to other nations. This index is based on statistical methodologies and as-

signs equal weighting to five fundamental dimensions of countries: their demographic characteristics, cultural attributes, political structures, technological advancement, and geographic attributes.

In instances where data for a particular industry was absent in Country A, we employed a weighted averaging approach. This involved calculating the average tax rate for the same industry across the following categories: countries that ranked among the top 5 most similar to Country A based on the Country Similarity Index (CSI) and countries covered in the World Input-Output Database (WIOD). In cases where the top 5 similar countries lacked revenue information for the required industry, we expanded our scope to include a broader range of countries, particularly those categorized as developed/developing nations. If the necessary information remained unavailable, we proceeded to calculate a weighted average of tax revenues for the same industry across all available countries. The information regarding country similarity can be located in the "Similarity" sheet of the codebook.

### A.1.3 Assign consumption categories to industries

In accordance with the approach employed by Levinson and O'Brien (2019), we adopt their methodology for associating consumption categories with industries. The UCC codes encompass a range of data categories, such as "men's suits" or "wigs, hairpieces, or toupees" collectively representing a substantial portion, approximately 60% to 70%, of household expenditures. Furthermore, the UCC codes encompass broader categories, including "the total purchases made at grocery stores", which contribute an additional 20% to 25% of spending. However, it's important to note that the Consumer Expenditure (CEX) interviews do not gather information pertaining to housekeeping supplies, personal care products, or non-prescription drugs, which collectively account for approximately 5% to 15% of the overall expenditures (U.S. Bureau of Labor Statistics, 2015).

In line with the findings of Levinson and O'Brien (2019), it is evident that numerous consumption categories exhibit a straightforward correspondence with specific IO industries. For instance, the UCC code 339992, encompassing music instruments and accessories, evidently aligns with IO industries categorized under 339992, primarily engaged in musical instrument manufacturing.

Nevertheless, it is worth highlighting that not all consumption items present clear correspondences. Many instances necessitate a subjective judgment in determining which production industry most aptly aligns with the given consumption category. For instance, they establish a connection between the UCC code 680904, representing dating services, and the IO industry 511180, which pertains to database, directory, and other publishers.

The Consumer Expenditure Surveys (CEX) encompass a considerably greater number of consumption categories compared to the available Input-Output (IO) industries within the input-output tables. Consequently, a single IO industry frequently encompasses multiple UCC items. It's important to note that not all UCC codes are pertinent to household consumption. In such instances, UCC assignments are not designated for the respective IO industries. The Consumer Expenditure Survey (CEX) encompasses a comprehensive total of 858 distinct Universal Classification Code (UCC) categories, spanning the years from 1984 to 2014. Notably, only 142 of these UCC categories align with corresponding Input-Output (IO) codes. In contrast, the Bureau of Economic Analysis (BEA) employs 417 production-related IO codes within their benchmark input-output tables.

Please note that mortgage-related UCC codes that start with 2203 were matched to the IO code 522A00, specifically categorized as "Nondepository credit intermediation and related activities." This IO code is further linked to sector J, "Financial Intermediation," within the WIOD industry classification. rental payments, categorized under UCC code 800700, have been matched to the IO code 531000, which represents "Real Estate" and is further classified under the WIOD code 70, specifically as "Real Estate Activities." In the CEX, the number of consumption categories significantly exceeds the count of IO industries found within the input-output tables. Consequently, a singular IO industry typically encompasses multiple UCC items. As a consequence of this disparity, it becomes challenging to precisely analyze mortgage and rental payments within the corresponding WIOD industries.

For a detailed exploration of this mapping between UCC and IO codes, we kindly refer you to our supplementary "UCC-IO" spreadsheet, conveniently available in Excel format.

### A.1.4 WIOD code with corresponding sectors

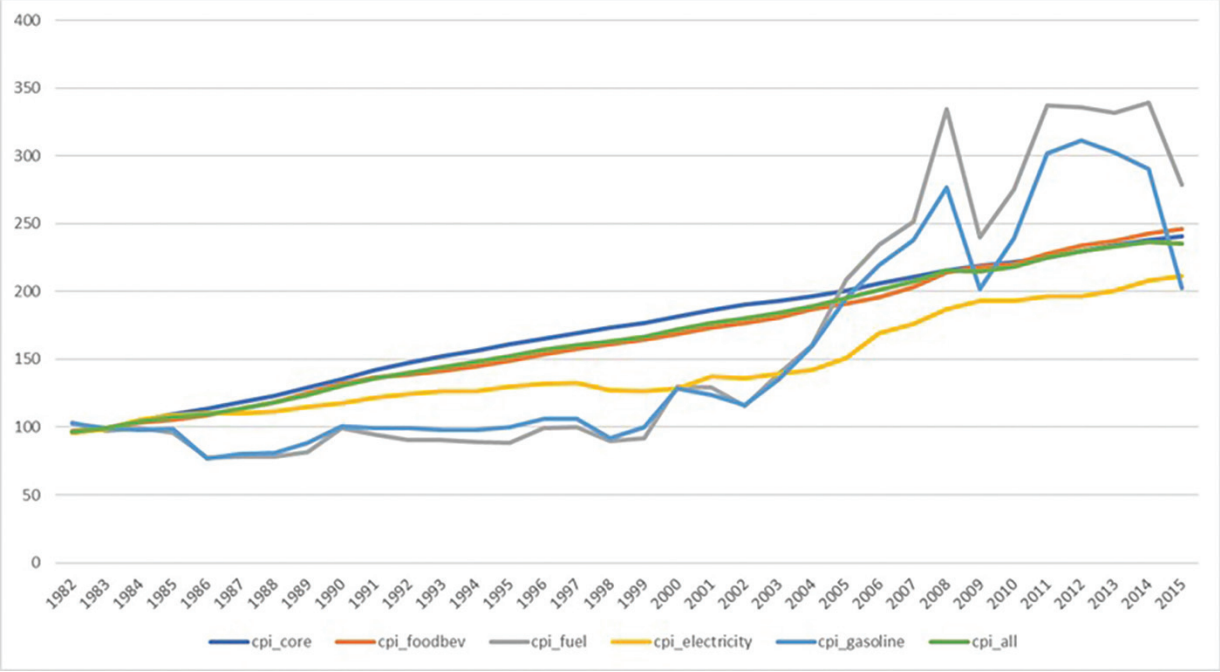
The World Input-Output Database (WIOD) encompass comprehensive data from 40 countries across 35 distinct industries, providing a broader level of aggregation compared to individual Input-Output (IO) codes (Timmer et al., 2015b). Additionally, it's worth noting that mortgage and rental payments have been categorized under the "Financial Intermediation" industry (coded as J) within the WIOD system. This classification has been made based on the overarching characteristics and aggregate nature of WIOD codes. Specific details regarding the categories represented by the WIOD codes can be found in Fig. A.1.

**Table A.1**: *WIOD Code*

| WIOD code | Sectors |
|---|---|
| 15t16 | Food, Beverages and Tobacco |
| 17t18 | Textiles and Textile Products |
| 19 | Leather, Leather and Footwear |
| 20 | Wood and Products of Wood and Cork |
| 21t22 | Pulp, Paper, Paper , Printing and Publishing |
| 23 | Coke, Refined Petroleum and Nuclear Fuel |
| 24 | Chemicals and Chemical Products |
| 25 | Rubber and Plastics |
| 26 | Other Non-Metallic Mineral |
| 27t28 | Basic Metals and Fabricated Metal |
| 29 | Machinery, Nec |
| 30t33 | Electrical and Optical Equipment |
| 34t35 | Transport Equipment |
| 36t37 | Manufacturing, Nec; Recycling |
| 50 | Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel |
| 51 | Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles |
| 52 | Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods |
| 60 | Inland Transport |
| 61 | Water Transport |
| 62 | Air Transport |
| 63 | Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies |
| 64 | Post and Telecommunications |
| 70 | Real Estate Activities |
| 71t74 | Renting of M&Eq and Other Business Activities |
| AtB | Agriculture, Hunting, Forestry and Fishing |
| C | Mining and Quarrying |
| E | Electricity, Gas and Water Supply |
| F | Construction |
| H | Hotels and Restaurants |
| J | Financial Intermediation |
| L | Public Admin and Defence; Compulsory Social Security |
| M | Education |
| N | Health and Social Work |
| O | Other Community, Social and Personal Services |
| P | Private Households with Employed Persons |

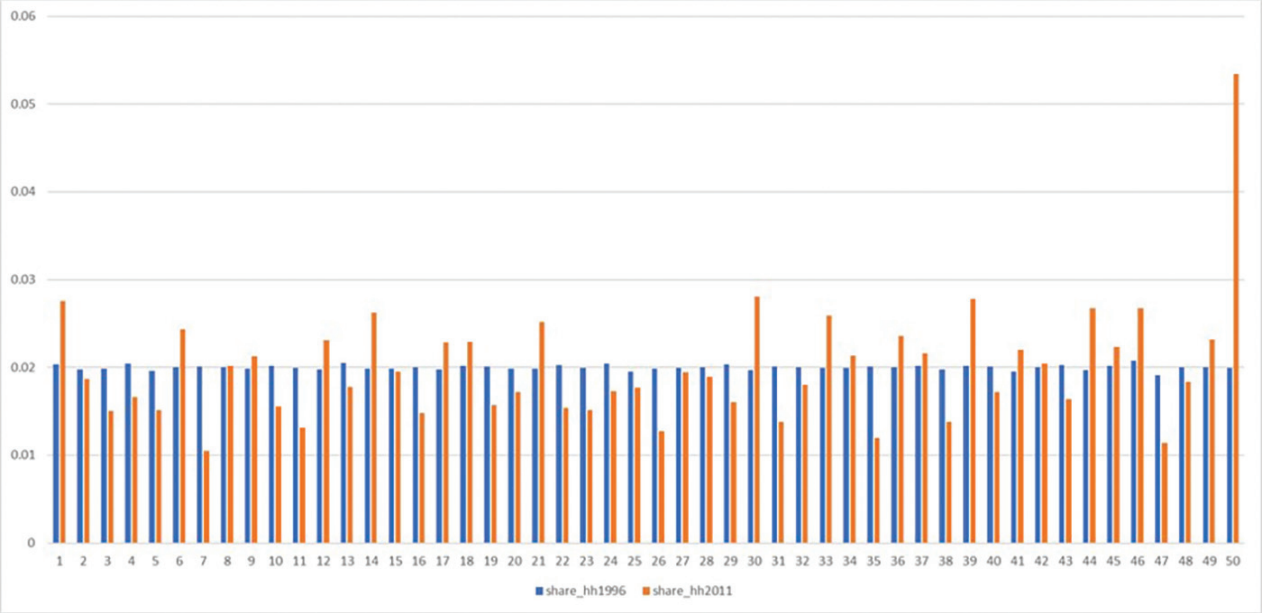
# Appendix B

# Appendix: Chapter 1



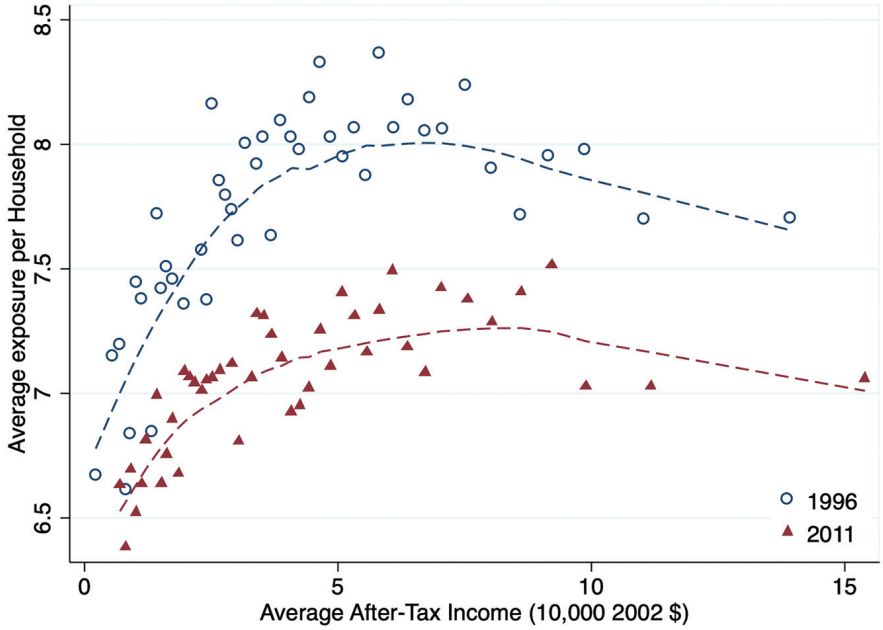

Note: Core CPI includes all items, less food and energy.
Source: Bureau of Labor statistics, Consumer Price Index (available at http:// www.bls.gov/icpi/)

**Figure B.1**: *Components of the Consumer Price Index, 1982-2014*

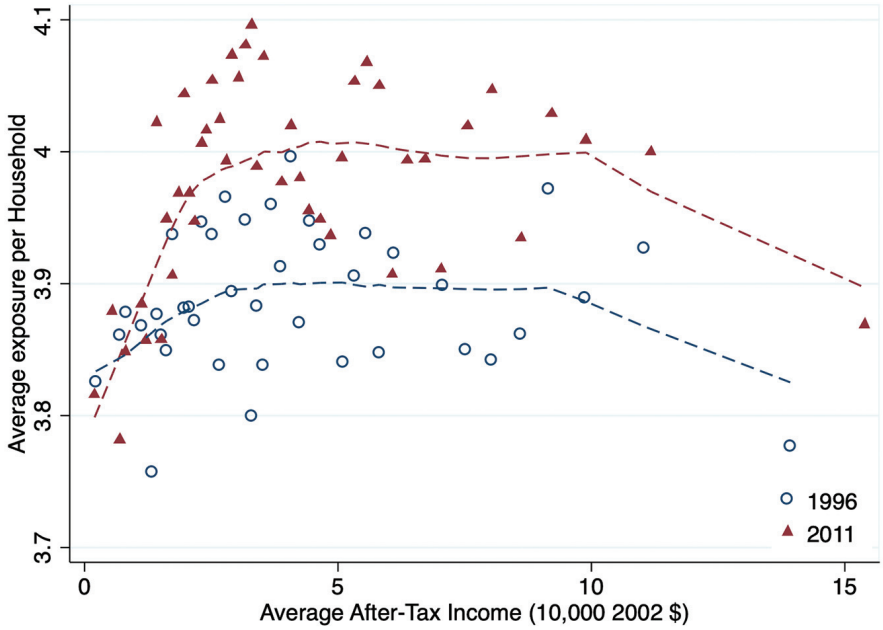



Notes: The 1996 CEX is split into 50 groups based on after-tax income.
Source: Bureau of Labor statistics, Consumer Expenditure Surveys (available at https://www.bls.gov/cex/)

**Figure B.2**: *Share of Households in Each Income Bin*



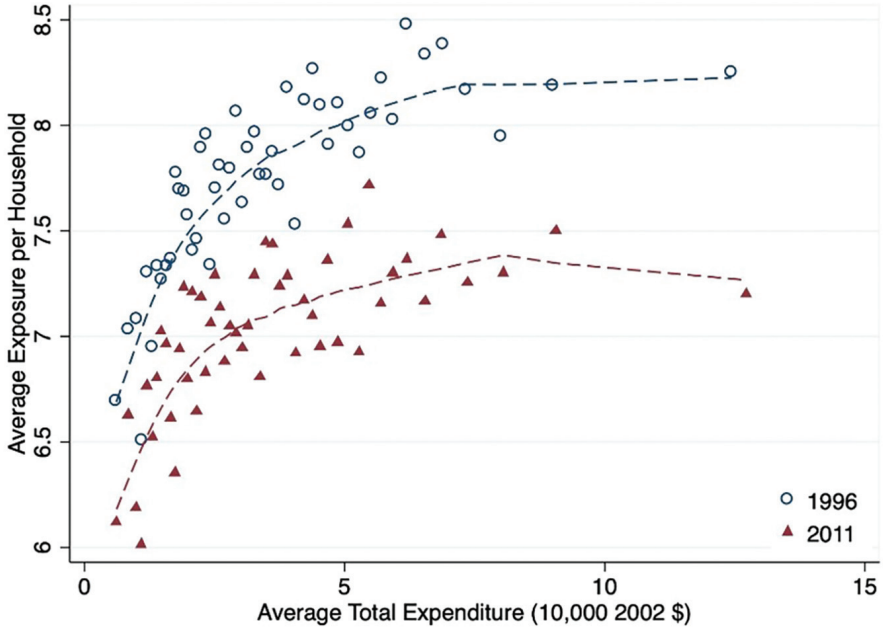

(a) Exposure to Outsourcing Index



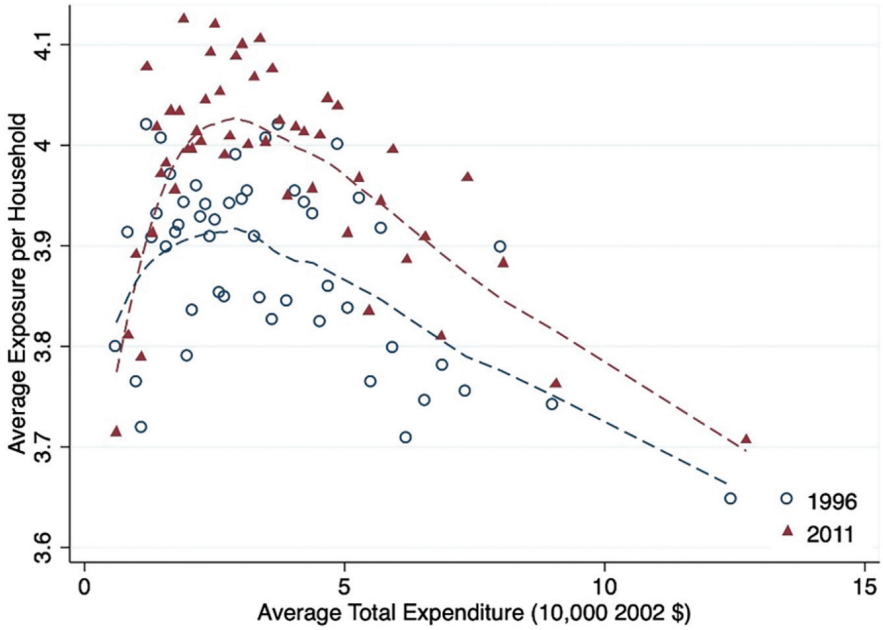

(b) Exposure to Foreign Environmental Taxes Index

Notes: Income is adjusted for inflation using the all-items CPI. Consumption expenditure is adjusted using the core CPI with food, fuel, gasoline, and electricity adjusted separately using the corresponding CPI. Each pair of dots represents an income level corresponding to 2% of the 1996 CEX sample, with the highest and lowest 1% of households trimmed based on after-tax income.

**Figure B.3**: *Outsourcing Embodied in Household Consumption*



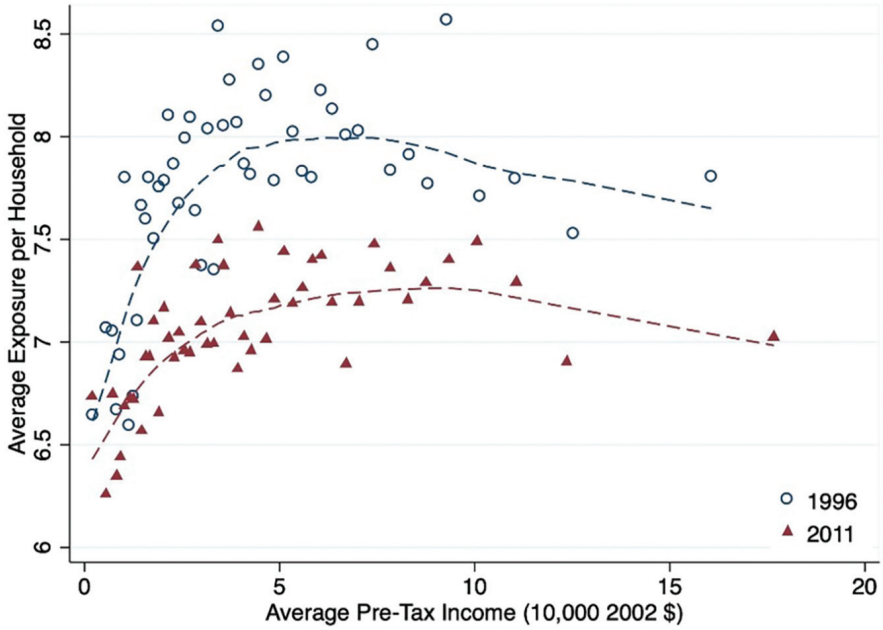

(a) Exposure to Outsourcing Index



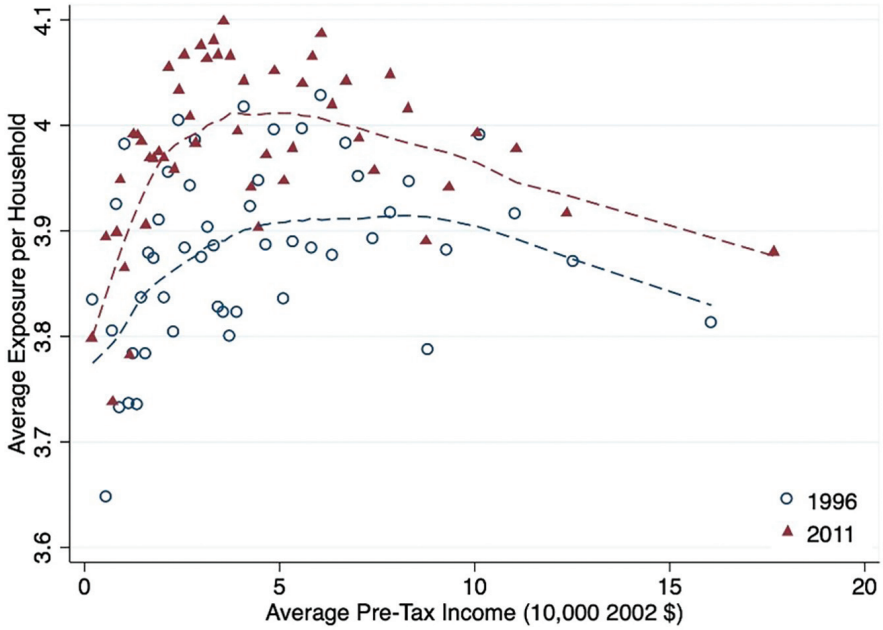

(b) Exposure to Foreign Environmental Taxes Index

Notes: Income is adjusted for inflation using the all-items CPI. Consumption expenditure is adjusted using the core CPI with food, fuel, gasoline, and electricity adjusted separately using the corresponding CPI. Each pair of dots represents an income level corresponding to 2% of the 1996 CEX sample, with the highest and lowest 1% of households trimmed based on after-tax income.

**Figure B.4**: *Engel Curves based on Total Expenditure*



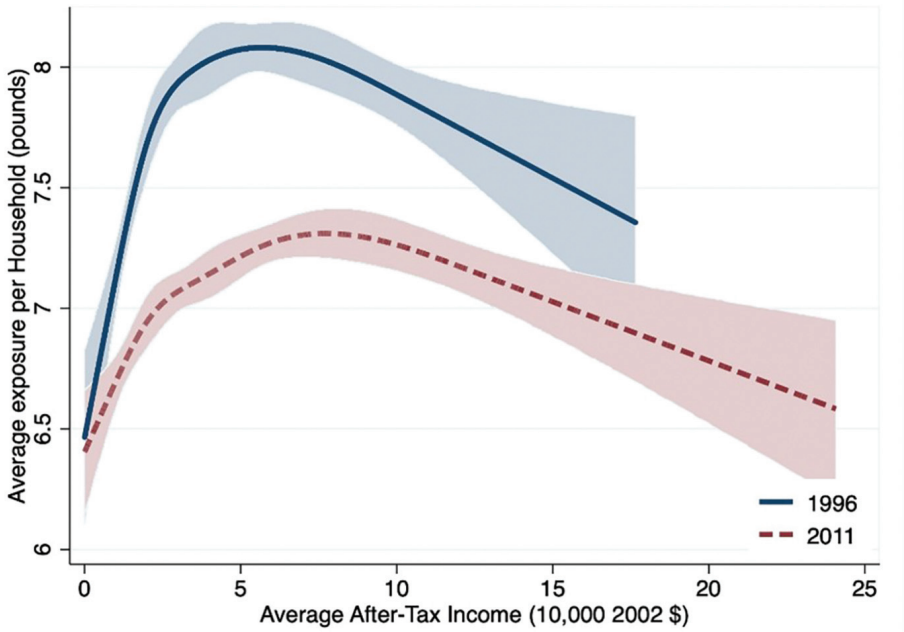

(a) Exposure to Outsourcing Index



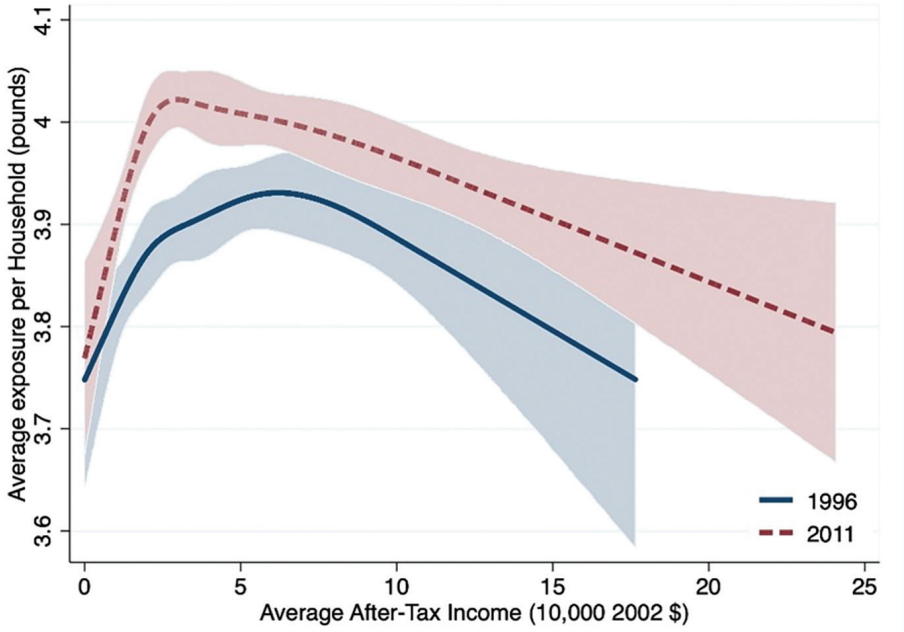

(b) Exposure to Foreign Environmental Taxes Index

Notes: Income is adjusted for inflation using the all-items CPI. Consumption expenditure is adjusted using the core CPI with food, fuel, gasoline, and electricity adjusted separately using the corresponding CPI. Each pair of dots represents an income level corresponding to 2% of the 1996 CEX sample, with the highest and lowest 1% of households trimmed based on after-tax income.

**Figure B.5**: *Engel Curves based on Pre-Tax Income*




(a) Exposure to Outsourcing Index




(b) Exposure to Foreign Environmental Taxes Index

Notes: Inflation adjustments as in Fig. 1.5. All other covariates are fixed at their mean values. Estimation is based on five knots placed at percentiles as suggested in Harrell (2001). Standard errors for index values are not estimated, so 95 percent confidence intervals (shaded) reflect variation in household spending.

**Figure B.6**: *Engel Curves Using a Restricted Cubie Spline*

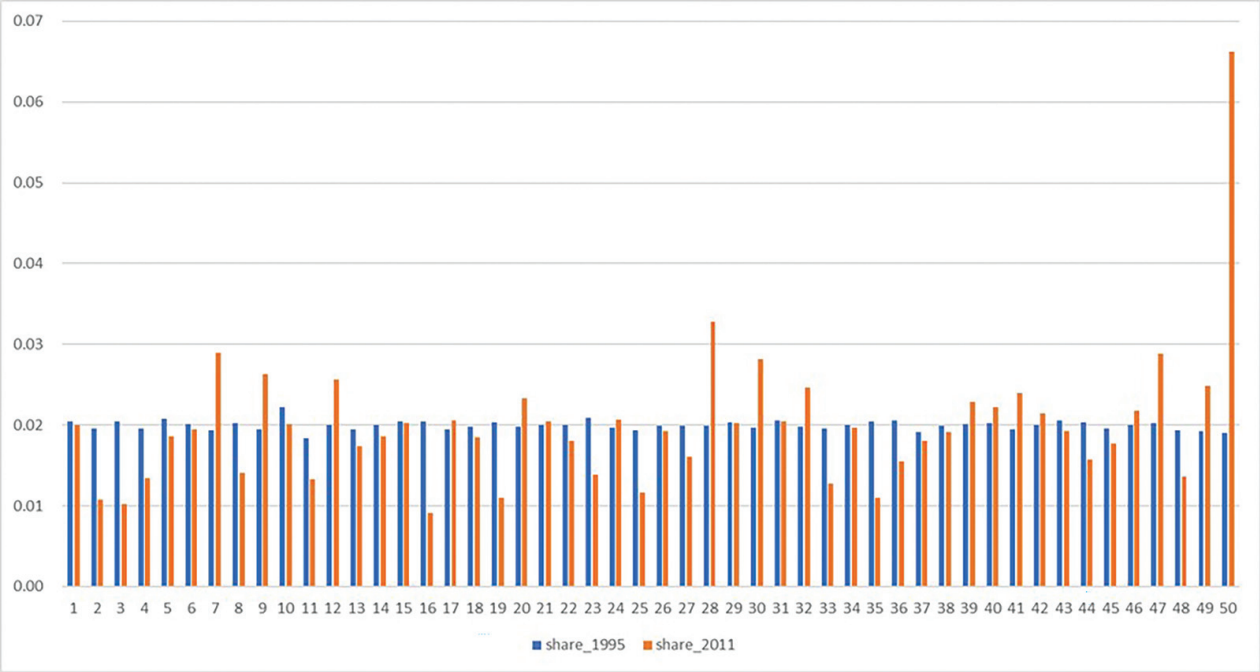
**Table B.1**: *Parametric Engel Cuves*

| | EO | | EFET | |
|---|---|---|---|---|
| Dependent vairable: | 1996 | 2011 | 1996 | 2011 |
| Exposure per Household | (1) | (2) | (3) | (4) |
| After-tax income | 0.215*** | 0.097*** | 0.046*** | 0.0280*** |
| | (0.035) | (0.021) | (0.012) | (0.00722) |
| After-tax income squared | -0.014*** | -0.005*** | -0.003*** | -0.00161*** |
| | (0.002) | (0.001) | (0.001) | (0.000366) |
| Household size | 0.259*** | 0.255*** | -0.043 | -0.0163 |
| | (0.075) | (0.063) | (0.027) | (0.0227) |
| Household size squared | -0.021** | -0.018* | 0.004 | 0.000284 |
| | (0.008) | (0.007) | (0.003) | (0.00276) |
| Age | 0.059*** | 0.059*** | 0.010** | 0.0104*** |
| | (0.013) | (0.009) | (0.004) | (0.00319) |
| Age squared | -0.0005*** | -0.0005*** | -0.0001** | -8.33e-05*** |
| | (0.0001) | (0.00008) | (0.00004) | (2.95e-05) |
| Married | 0.283*** | 0.149* | 0.015 | 0.0422* |
| | (0.089) | (0.066) | (0.029) | (0.0231) |
| Race: Black | -0.563*** | -0.327*** | -0.002 | 0.0155 |
| | (0.103) | (0.086) | (0.035) | (0.0326) |
| Race: Asian | -0.382* | -0.599*** | 0.055 | 0.0677 |
| | (0.206) | (0.125) | (0.070) | (0.0428) |
| Race: Other | 0.644 | 0.111 | -0.008 | -0.0147 |
| | (0.485) | (0.237) | (0.195) | (0.0611) |
| Education: High school | 0.182* | 0.350*** | -0.040 | 0.0703** |
| | (0.107) | (0.092) | (0.032) | (0.0313) |
| Education: Some college | 0.102 | 0.342*** | -0.077** | 0.00591 |
| | (0.112) | (0.092) | (0.032) | (0.0312) |
| Education: College | -0.166 | 0.007 | -0.046 | -0.0229 |
| | (0.119) | (0.104) | (0.037) | (0.0347) |
| Education: Graduate | -0.436*** | -0.084 | -0.059 | -0.0359 |
| | (0.134) | (0.114) | (0.042) | (0.0395) |
| Region: Midwest | 0.427*** | 0.344** | 0.087*** | 0.106*** |
| | (0.098) | (0.076) | (0.030) | (0.0259) |
| Region: South | 0.720*** | 0.505*** | 0.032 | 0.161*** |
| | (0.094) | (0.074) | (0.029) | (0.0237) |
| Region: West | -0.058 | -0.159 | 0.101*** | 0.142*** |
| | (0.101) | (0.079) | (0.032) | (0.0261) |
| Rural | 0.820*** | 0.454*** | 0.138*** | 0.0254 |
| | (0.093) | (0.110) | (0.035) | (0.0471) |
| Constant | 4.630*** | 4.229 | 3.548*** | 3.497*** |
| | (0.319) | (0.259) | (0.101) | (0.0899) |
| F-test of income coefficients | 18.53 | 11.38 | 7.248 | 9.880 |
| Observations | 2,419 | 3,447 | 2,420 | 3,306 |
| R-squared | 0.209 | 0.139 | 0.035 | 0.038 |

Notes: See the note to Table 1.2

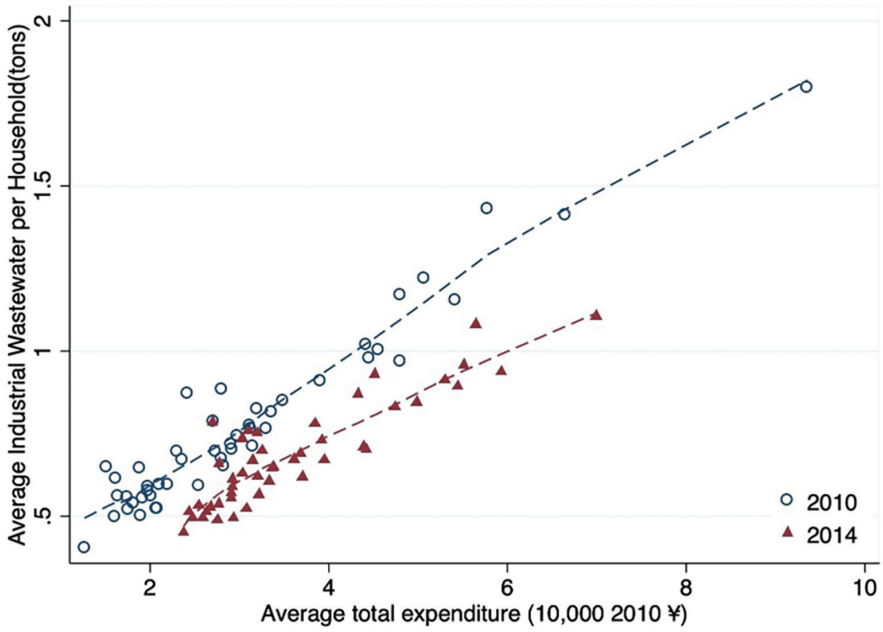
# Appendix C

# Appendix: Chapter 2



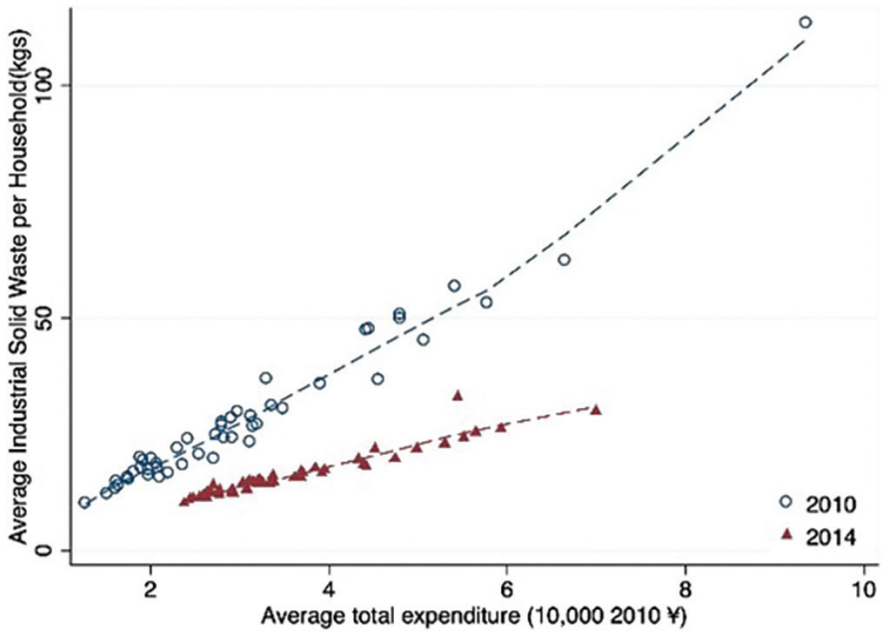

Notes: Core CPI includes all items, less food and energy.
Source: Bureau of Labor statistics, Consumer Price Index (available at http:// www.bls.gov/icpi/)

**Figure C.1**: *Components of the Consumer Price Index, 1982-2014*

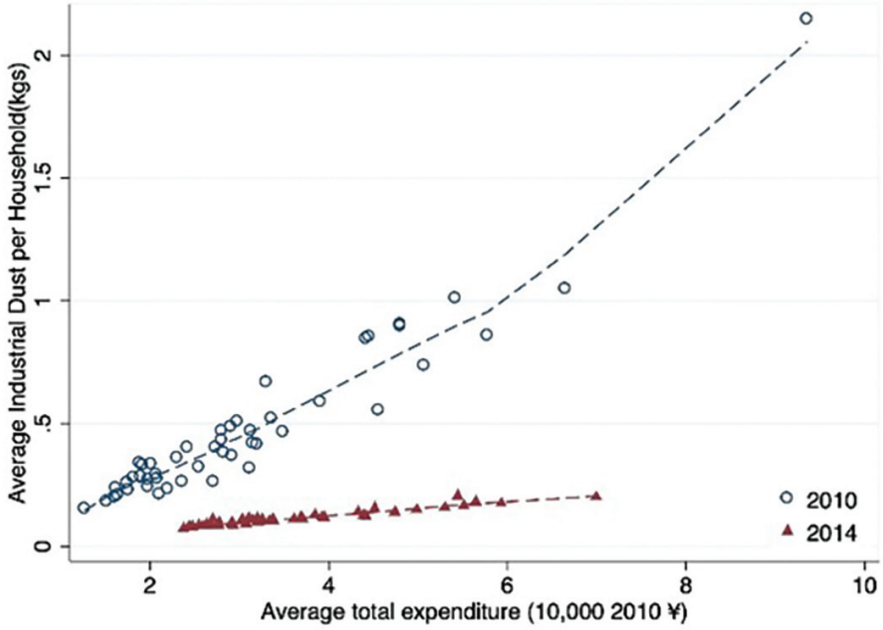



Notes: Total expenditure is adjusted for inflation using the all-items CPI. Each pair of dots represents an income level corresponding to 2% of the 2010 CFPS sample, with the highest and lowest 1% of households trimmed based on after-tax income.

**Figure C.2**: *Engel Curves Based on Total Expenditure: Industrial Wastewater (IW)*



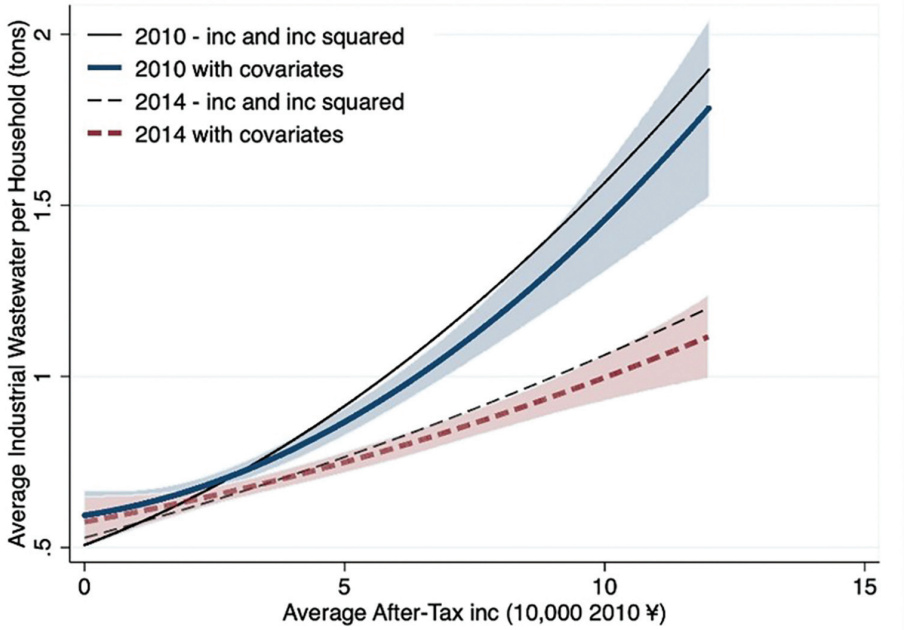

(a) Industrial Solid Waste (ISW)




(b) Industrial Dust (ID)

Notes: Total expenditure is adjusted for inflation using the all-items CPI. Each pair of dots represents an income level corresponding to 2% of the 2010 CFPS sample, with the highest and lowest 1% of households trimmed based on after-tax income.

**Figure C.3**: *Engel Curves Based on Total Expenditure*




Notes: All other covariates are fixed at their mean values. Inflation adjustments as in Fig. 2.3 Standard errors for pollution intensity of production are not estimated. So, 5% confidence intervals (shaded) reflect variations in household spending.

**Figure C.4**: *Engel Curves Based on Parametric Estimates: Industrial Wastewater (IW)*

**Table C.1**: *List of WIOD Codes and Descriptions*

| WIOD | Name and description |
|---|---|
| B | Mining and quarrying |
| C1012 | Manufacture of food products, beverages and tobacco products |
| C1315 | Manufacture of textiles, wearing apparel and leather products |
| C16 | Manufacture of wood and of products of wood and cork, except furniture; etc. |
| C17 | Manufacture of paper and paper products |
| C18 | Printing and reproduction of recorded media |
| C19 | Manufacture of coke and refined petroleum products |
| C20 | Manufacture of chemicals and chemical products |
| C21 | Manufacture of basic pharmaceutical products and pharmaceutical preparations |
| C22 | Manufacture of rubber and plastic products |
| C23 | Manufacture of other non-metallic mineral products |
| C24 | Manufacture of basic metals |
| C25 | Manufacture of fabricated metal products, except machinery and equipment |
| C26 | Manufacture of computer, electronic and optical products |
| C27 | Manufacture of electrical equipment |
| C28 | Manufacture of machinery and equipment n.e.c. |
| C29 | Manufacture of motor vehicles, trailers and semi-trailers |
| C30 | Manufacture of other transport equipment |
| C3132 | Manufacture of furniture; other manufacturing |
| D35 | Electricity, gas, steam and air conditioning supply |
| E36 | Water collection, treatment and supply |
| E3739 | Sewerage; waste collection, treatment and disposal activities; materials recovery; etc. |
| G47 | Retail trade, except of motor vehicles and motorcycles |
| F | Construction |
| K65 | Insurance, reinsurance and pension funding, except compulsory social security |
| P | Education |
| Q | Human health and social work activities |
| RS | Creative, Arts, Sports, Recreation and entertainment activities and all other personal service activities |

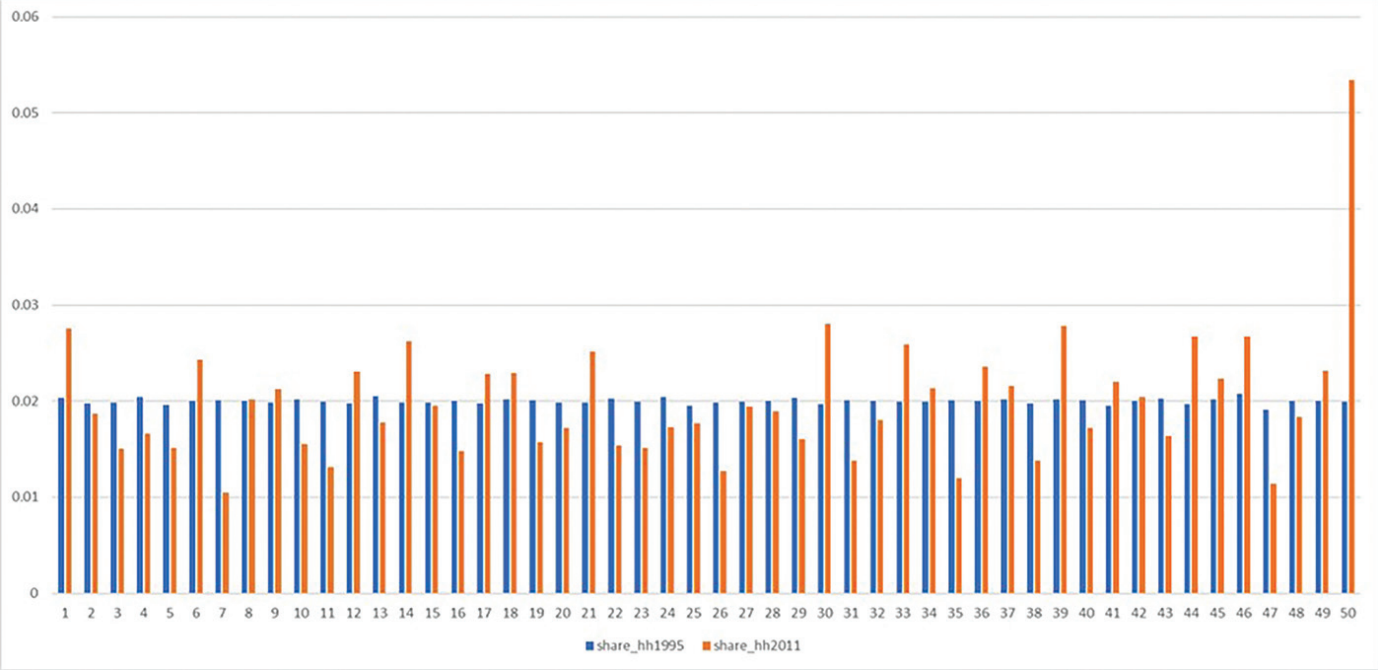
**Table C.2**: *Parametric Environmental Engel Curves for IW*

| Dependent vairable: | 2010 | | 2012 | 2014 | Coefficient change. 2010-2014 |
|---|---|---|---|---|---|
| Exposure per Household | (1) | (2) | (3) | (4) | (5) |
| After-tax income | 0.057** | 0.006 | 0.038*** | 0.023 | 0.016 |
| (¥10,000 in 2010 yuan) | (0.019) | (0.020) | (0.011) | (0.016) | (0.026) |
| After-tax income squared | 0.005* | 0.007** | -0.0004 | 0.001 | -0.006** |
| | (0.002) | (0.002) | (0.001) | (0.001) | (0.003) |
| Household size | | 0.099** | 0.087*** | 0.157*** | 0.059 |
| | | (0.034) | (0.023) | (0.035) | (0.049) |
| Household size squared | | -0.005 | -0.005 | -0.010 | -0.006 |
| | | (0.005) | (0.003) | (0.004) | (0.006) |
| Age | | -0.0003 | -0.003 | -0.0086** | -0.0084 |
| | | (0.006) | (0.005) | (0.007) | (0.009) |
| Age squared | | 3.73e-06 | 6.19e-05 | 9.34e-05 | 0.00009 |
| | | (5.70e-05) | (4.55e-05) | (6.57e-05) | (0.00009) |
| Married | | -0.009 | 0.110** | -0.085 | -0.076 |
| | | (0.054) | (0.034) | (0.078) | (0.10) |
| Education: High school | | 0.089** | 0.139*** | 0.047 | -0.042 |
| | | (0.034) | (0.024) | (0.028) | (0.044) |
| Education: Some college | | 0.229*** | 0.481*** | 0.216*** | -0.013 |
| | | (0.064) | (0.068) | (0.062) | (0.089) |
| Education: College | | 0.370*** | 0.402*** | 0.364*** | -0.006 |
| | | (0.083) | (0.057) | (0.079) | (0.114) |
| Education: Graduate | | 0.625 | 0.719** | 0.225 | -0.4 |
| | | (0.387) | (0.259) | (0.179) | (0.426) |
| Region: Northeast | | 0.049 | 0.159*** | 0.011 | -0.038 |
| | | (0.035) | (0.031) | (0.034) | (0.049) |
| Region: NorthMunicipalities | | 0.320 | 0.306*** | 0.244* | -0.076 |
| | | (0.180) | (0.0732) | (0.123) | (0.218) |
| Region: North Coast | | 0.074 | 0.035 | 0.033 | -0.041 |
| | | (0.059) | (0.030) | (0.042) | (0.072) |
| Region: Central Coast | | 0.215*** | 0.372*** | 0.356*** | 0.141 |
| | | (0.058) | (0.051) | (0.082) | (0.100) |
| Region: South Coast | | 0.087 | 0.231*** | 0.035 | -0.052 |
| | | (0.046) | (0.050) | (0.044) | (0.064) |
| Region: Central | | 0.062* | 0.083** | 0.096* | 0.035 |
| | | (0.030) | (0.026) | (0.042) | (0.051) |
| Region: Northwest | | 0.137** | 0.092** | 0.049 | -0.088 |
| | | (0.041) | (0.034) | (0.039) | (0.057) |
| Urban | | 0.107*** | 0.004 | 0.035*** | -0.072*** |
| | | (0.026) | (0.016) | (0.009) | (0.027) |
| Constant | 0.507 | 0.235 | 0.0190 | 0.373 | 0.138 |
| | (0.036) | (0.122) | (0.133) | (0.155) | (0.197) |
| F-test of income coefficients | 109.4 | 46.03 | 32.50 | 21.17 | |
| Observations | 112,536 | 112,536 | 130,380 | 76,836 | |
| R-squared | 0.004 | 0.005 | 0.004 | 0.004 | |

Notes: Robust standard errors in parentheses. Household pollution calculated by multiplying itemized household consumption with t he 2010 WIOD pollution intnesity for each type of good and summing for each household. Includes upstream pollution based on a Leontief input-output calculation. Nominal incomes adjusted using the CPI for all items.
**** for 1%, ** for 5%, * for 10%*

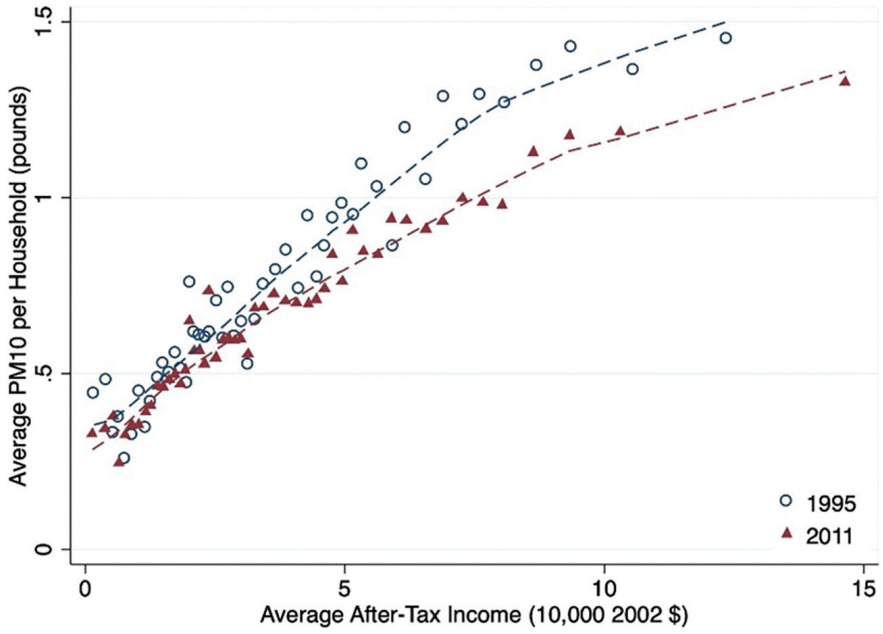
# Appendix D

# Appendix: Chapter 3

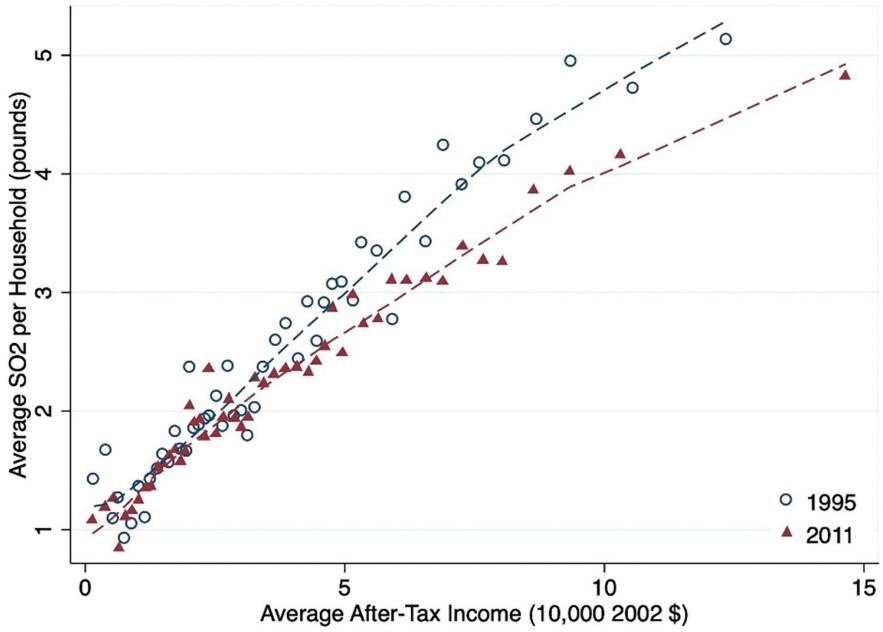



Notes: The 1995 CEX is split into 50 groups based on after-tax income.
Source: Bureau of Labor statistics, Consumer Expenditure Surveys (available at https://www.bls.gov/cex/)

**Figure D.1**: *Share of Households in Each Income Bin*



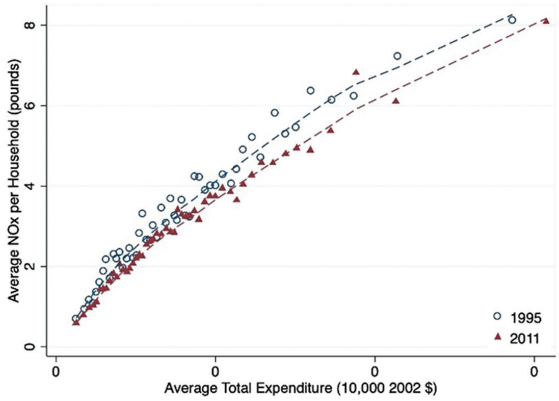

(a) Particulate Matter with a diameter of 10 micrometers or less (PM10)



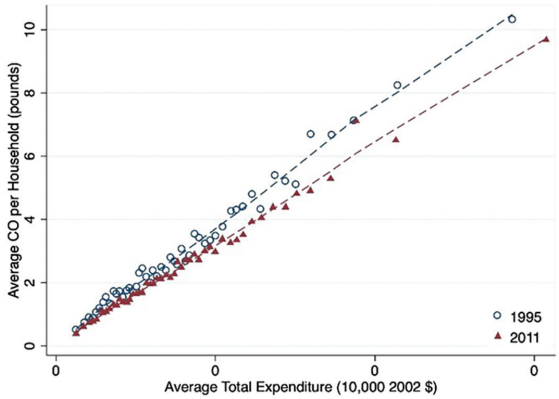

(b) Sulfur Dioxide (SO2)

Notes: See notes in Fig. 3.4.

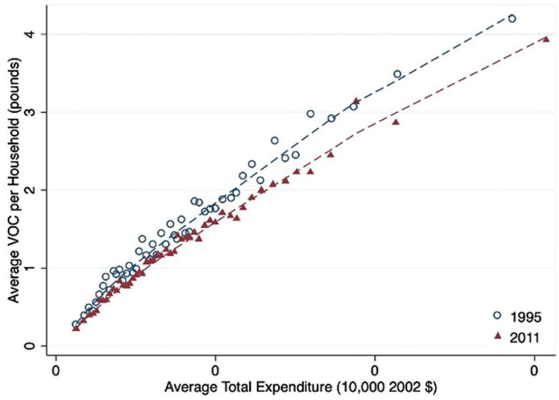
**Figure D.2**: *Nonparametric EECs for Local Pollutants*




(a) Nitrogen Oxides (NOx)



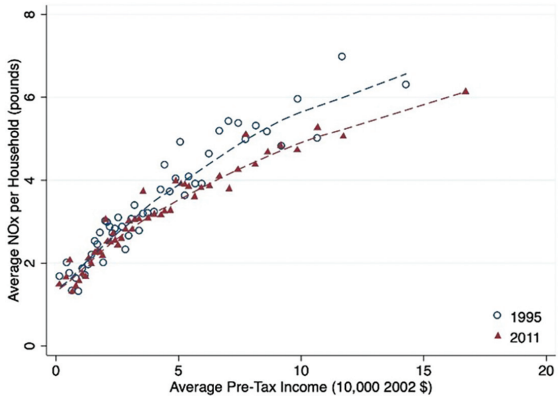

(b) Carbon Monoxide (CO)



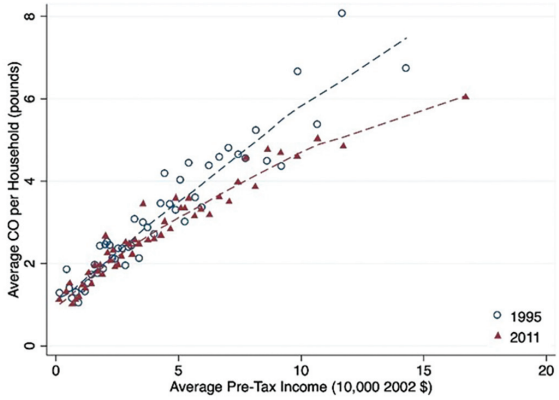

(c) Volatile Organic Compounds (VOCs)

Notes: Total expenditure is adjusted for inflation using the all-items CPI. Itemized consumption expenditure is adjusted using the core CPI with food, fuel, gasoline, and electricity adjusted separately using the corresponding CPI. Each pair of dots represents an income level corresponding to 2% of the 1995 CEX example, with the highest and the lowest 1% of households trimmed based on after-tax income.

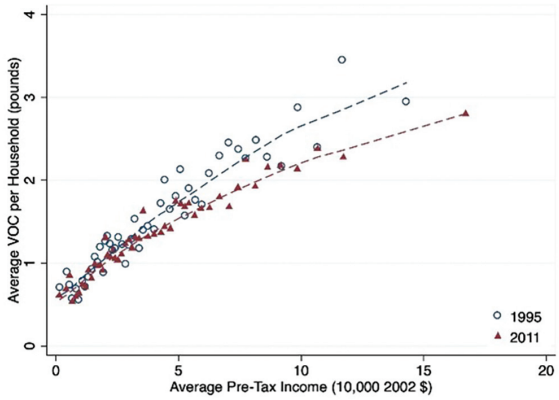
**Figure D.3**: *Engel Curves based on Total Expenditure*




(a) Nitrogen Oxides (NOx)



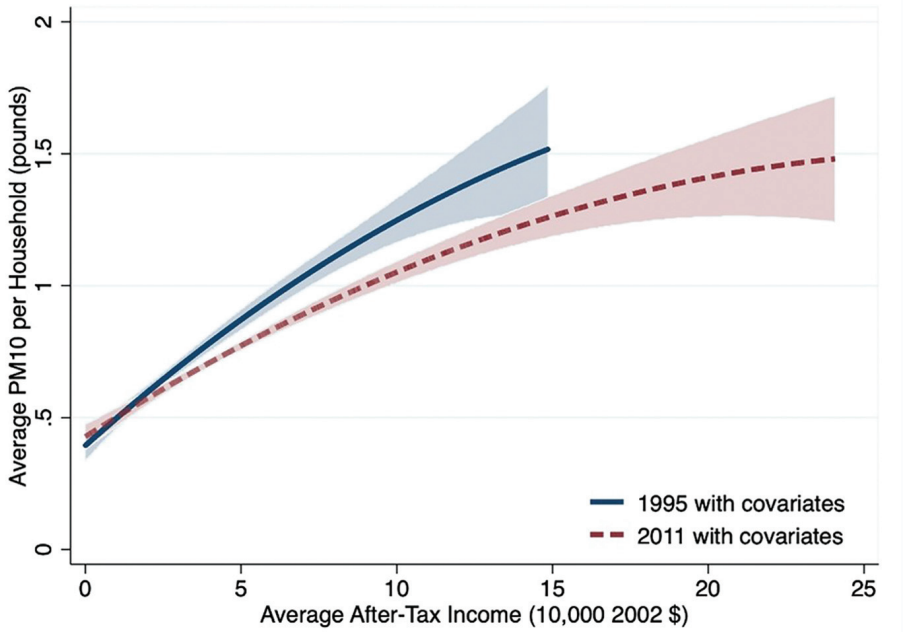

(b) Carbon Monoxide (CO)



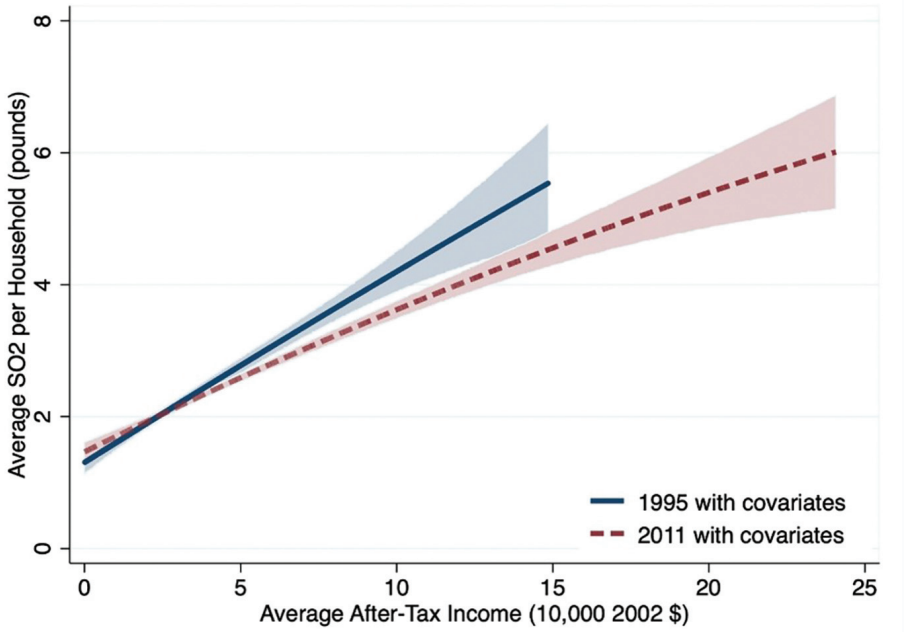

(c) Volatile Organic Compounds (VOCs)

Notes: See notes in Fig. 3.4

**Figure D.4**: *Engel Curves based on Pre-Tax Income*



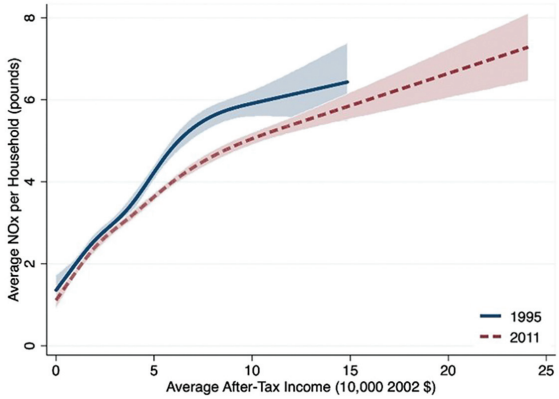

(a) Particulate Matter with a diameter of 10 micrometers or less (PM10)



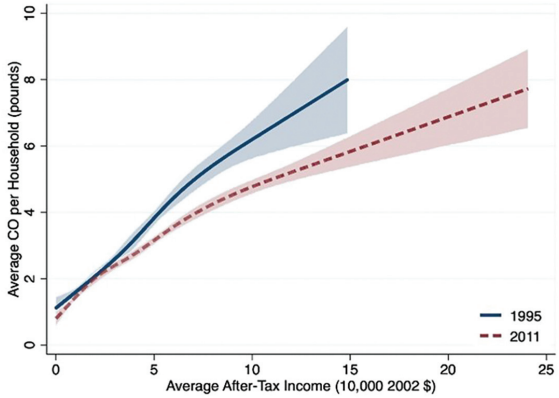

(b) Sulfur Dioxide (SO2)

Notes: See notes in Fig. 3.4.

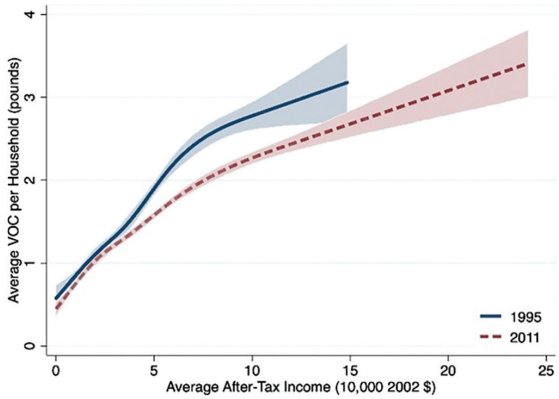
**Figure D.5**: *Parametric EECs for Local Pollutants*




(a) Nitrogen Oxides (NOx)



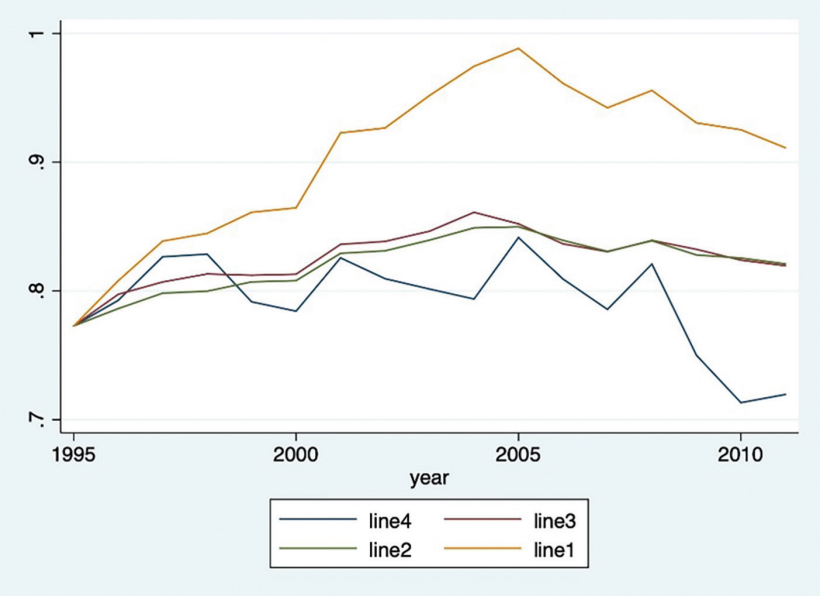

(b) Carbon Monoxide (CO)



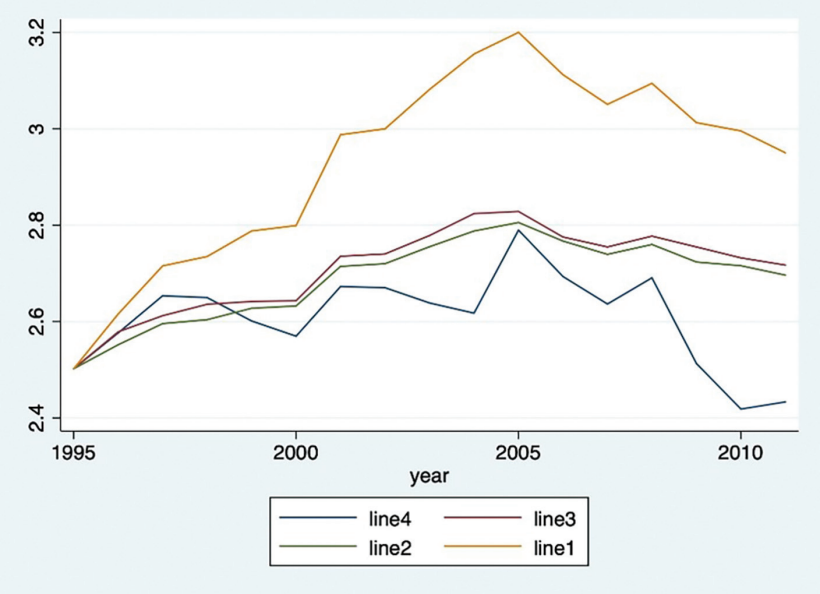

(c) Volatile Organic Compounds (VOCs)

Notes: Inflation adjustments as in Fig. 3.4. All other covariates are fixed at their mean values. Estimation is based on five knots placed at percentiles, as Harrell (2001) suggested. Standard errors for index values are not estimated, so 95 percent confidence intervals (shaded) reflect variation in household spending.

**Figure D.6**: *Engel Curves Using a Restricted Cubie Spline*




(a) Particulate Matter with a diameter of 10 micrometers or less (PM10)

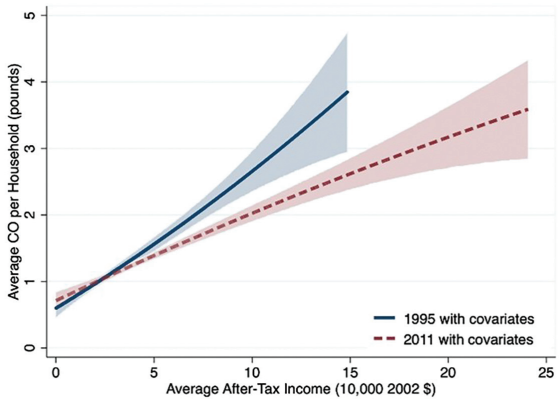



(b) Sulfur Dioxide (SO2)

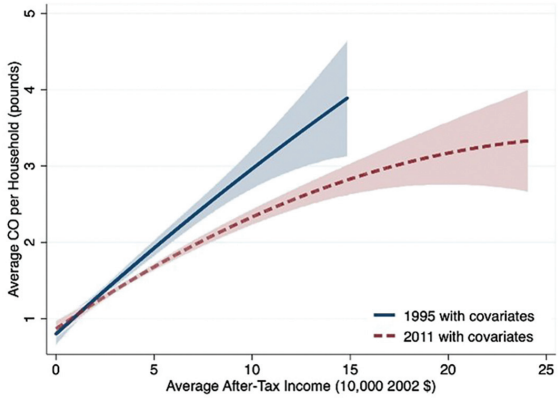
Line (1) Scale Effect; Line (2) Movement Along Engel Curve;
Line (3) Movement Along Engel Curve and Demographic Changes; Line (4) Index Predicted

Notes: See notes in Fig. 3.6

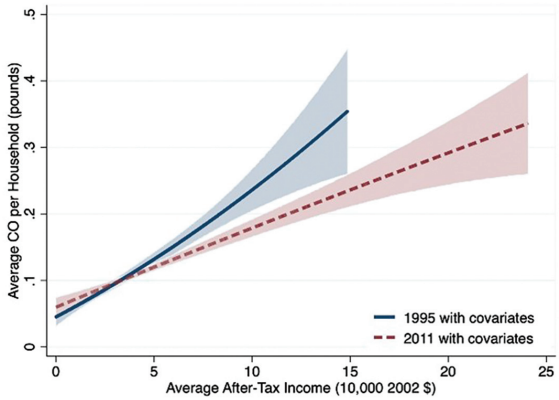
**Figure D.7**: *Decomposition of Predicted Pollution from Household Consumption*




(a) Developed Countries



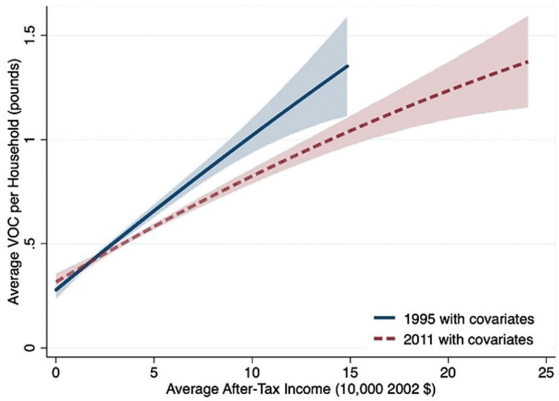

(b) Developing Countries



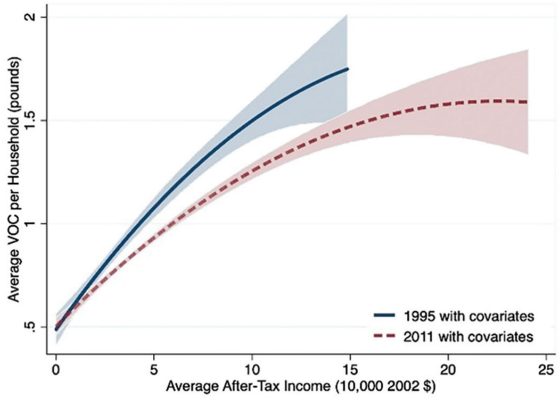

(c) China

Notes: See notes in Fig. 3.5

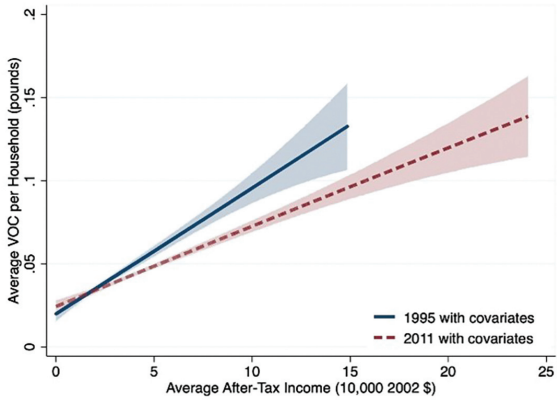
**Figure D.8**: *Parametric EECs for CO*




(a) Developed Countries




(b) Developing Countries




(c) China

Notes: See notes in Fig. 3.5

**Figure D.9**: *Parametric EECs for VOCs*

**Table D.1**: *Parametric EECs for Local Pollutants*

| | ROW | | | |
|---|---|---|---|---|
| | 1995 | | 2011 | |
| | PM10 | SO2 | PM10 | SO2 |
| Dependent Variable (pounds): | (1) | (2) | (3) | (4) |
| After-tax income ($10,000 in 2002 d0llars) | 0.106*** | 0.299*** | 0.076*** | 0.234*** |
| | (0.014) | (0.045) | (0.007) | (0.024) |
| After-tax income squared | -0.002 | -0.0009 | -0.0013** | -0.0019 |
| | (0.0012) | (0.004) | (0.0004) | (0.0014) |
| Household size | 0.087** | 0.268** | 0.114*** | 0.373*** |
| | (0.029) | (0.088) | (0.014) | (0.046) |
| Household size squared | -0.005 | -0.014 | -0.007*** | -0.026*** |
| | (0.004) | (0.011) | (0.0018) | (0.006) |
| Age | 0.013*** | 0.032** | 0.014*** | 0.035*** |
| | (0.004) | (0.011) | (0.002) | (0.007) |
| Age squared | -0.0001*** | -0.0003** | -0.0001*** | -0.0002** |
| | (3.21e-05) | (0.0001) | (2.12e-05) | (7.16e-05) |
| Married | 0.114*** | 0.318** | 0.1*** | 0.314*** |
| | (0.031) | (0.095) | (0.020) | (0.064) |
| Race: Black | -0.110** | -0.268** | -0.056*** | -0.178** |
| | (0.032) | (0.1) | (0.016) | (0.053) |
| Race: Asian | -0.139* | -0.433** | -0.168*** | -0.491*** |
| | (0.067) | (0.199) | (0.031) | (0.104) |
| Race: Other | 0.008 | 0.010 | 0.016 | 0.032 |
| | (0.098) | (0.273) | (0.042) | (0.135) |
| Education: High school | 0.043 | 0.189* | 0.104*** | 0.330*** |
| | (0.029) | (0.084) | (0.016) | (0.049) |
| Education: Some college | 0.108** | 0.405*** | 0.150*** | 0.528*** |
| | (0.034) | (0.1) | (0.018) | (0.056) |
| Education: College | 0.075* | 0.421*** | 0.130*** | 0.602*** |
| | (0.038) | (0.120) | (0.024) | (0.078) |
| Education: Graduate | 0.091 | 0.562** | 0.174** | 0.775*** |
| | (0.058) | (0.184) | (0.053) | (0.164) |
| Region: Midwest | 0.012 | -0.095 | -0.054 | -0.239* |
| | (0.031) | (0.097) | (0.030) | (0.096) |
| Region: South | 0.034 | -0.017 | 0.003 | -0.077 |
| | (0.031) | (0.101) | (0.031) | (0.095) |
| Region: West | 0.011 | -0.06 | -0.049 | -0.153 |
| | (0.037) | (0.121) | (0.027) | (0.088) |
| Rural | 0.164*** | 0.257* | 0.071 | 0.113 |
| | -0.04 | (0.126) | -0.056 | (0.170) |
| Constant | -0.190 | -0.331 | -0.313 | -0.835 |
| | -0.1 | (0.312) | -0.05 | (0.168) |
| Income elasticity at median | 0.398 | 0.393 | 0.343 | 0.344 |
| | (0.032) | (0.030) | (0.0275) | (0.026) |
| F-test of income coefficients | 113.1 | 120.5 | 125 | 162.3 |
| Observations | 1,313 | 1,313 | 3,623 | 3,623 |
| R-squared | 0.504 | 0.524 | 0.368 | 0.397 |

Notes: See notes in Table 3.3.

**Table D.2**: *Movement Along Parametric EECs for Local Pollutants*

| | ROW | |
|---|---|---|
| | PM10 | SO2 |
| Dependent Variable: | (1) | (2) |
| after-tax income ($10,000 in 2002 dollars) | 0.073 | 0.205 |
| | (0.015) | (0.044) |
| After-tax income squared | -0.025 | -0.011 |
| | (0.015) | (0.052) |
| Household size | -0.0011 | -0.003 |
| | (0.005) | (0.014) |
| Household size squared | 0.0005 | 0.0015 |
| | (0.002) | (0.006) |
| Age | 0.025 | 0.062 |
| | (0.011) | (0.030) |
| Age squared | -0.026 | -0.056 |
| | (0.011) | (0.028) |
| Married | -0.003 | -0.007 |
| | (0.002) | (0.006) |
| Race dummies | -0.002 | -0.007 |
| Education dummies | 0.012 | 0.056 |
| Regional dummies | -0.007 | -0.021 |
| **Total change due to income (movement along EEC)** | 0.048 | 0.194 |
| **Scale Effect** | 0.138 | 0.448 |
| **Composition Effect** | -0.090 | -0.254 |
| **Total change due to other demographics** | -0.002 | 0.021 |
| **Unexplained difference (shift in EEC)** | -0.099 | -0.284 |

Notes: See notes in Table 3.4.

**Table D.3**: *Parametric EECs for Local Pollutants*

Panel A: Parametric Environmental Engel Curves for developed countries

| | Developed Countries | | | |
|---|---|---|---|---|
| | 1995 | | 2011 | |
| | PM10 | SO2 | PM10 | SO2 |
| Dependent Variable (pounds): | (1) | (2) | (3) | (4) |
| after-tax income ($10,000 in 2002 dollars) | 0.038*** | 0.134*** | 0.027*** | 0.108*** |
| | (0.005) | (0.023) | (0.004) | (0.013) |
| After-tax income squared | -0.0003 | 0.0012 | -0.0002 | -9.18e-05 |
| | (0.0005) | (0.002) | (0.0002) | (0.0008) |
| Other regressors | Yes | Yes | Yes | Yes |
| Income elasticity at median | 0.427 | 0.401 | 0.350 | 0.347 |
| | (0.033) | (.032) | (0.04) | (0.029) |
| F-test of income coefficients | 109.9 | 109.8 | 76.01 | 142.2 |
| Observations | 1,313 | 1,313 | 3,623 | 3,623 |
| R-squared | 0.474 | 0.497 | 0.276 | 0.365 |

Panel B: Parametric Environmental Engel Curves for developing countries

| | Developing Countries | | | |
|---|---|---|---|---|
| | 1995 | | 2011 | |
| | PM10 | SO2 | PM10 | SO2 |
| Dependent Variable (pounds): | (1) | (2) | (3) | (4) |
| after-tax income ($10,000 in 2002 dollars) | 0.067*** | 0.165*** | 0.049*** | 0.126*** |
| | (0.009) | (0.023) | (0.004) | (0.011) |
| After-tax income squared | -0.0018* | -0.0021 | -0.001*** | -0.0018** |
| | (0.0007) | (0.002) | (0.0002) | (0.0007) |
| Other regressors | Yes | Yes | Yes | Yes |
| Income elasticity at median | 0.381 | 0.386 | 0.340 | 0.341 |
| | (0.033) | (0.030) | (0.022) | (.023) |
| F-test of income coefficients | 99.12 | 119.7 | 173.3 | 179.7 |
| Observations | 1,313 | 1,313 | 3,623 | 3,623 |
| R-squared | 0.487 | 0.526 | 0.418 | 0.422 |

Panel C: Parametric Environmental Engel Curves for China

| | China | | | |
|---|---|---|---|---|
| | 1995 | | 2011 | |
| | PM10 | SO2 | PM10 | SO2 |
| Dependent Variable (pounds): | (1) | (2) | (3) | (4) |
| after-tax income ($10,000 in 2002 dollars) | 0.003*** | 0.015*** | 0.002*** | 0.013*** |
| | (0.0005) | (0.003) | (0.0004) | (0.002) |
| After-tax income squared | 9.74e-06 | 0.0002 | 4.52e-07 | 1.19e-05 |
| | (5.40e-05) | (0.0003) | (2.00e-05) | (0.0001) |
| Other regressors | Yes | Yes | Yes | Yes |
| Income elasticity at median | 0.471 | 0.404 | 0.368 | 0.343 |
| | (0.038) | (0.034) | (0.049) | (0.030) |
| F-test of income coefficients | 98.05 | 101.4 | 65.47 | 135.5 |
| Observations | 1,313 | 1,313 | 3,623 | 3,623 |
| R-squared | 0.429 | 0.480 | 0.243 | 0.359 |

See notes in Table 3.3.

**Table D.4**: *Movement Along Parametric EECs for Local Pollutants*

Panel A: Movement along parametric EECs for developed countries

| | Developed Countries | |
|---|---|---|
| | PM10 | SO2 |
| Dependent Variable: | (1) | (2) |
| **Total change due to income (movement along EEC)** | 0.023 | 0.106 |
| **Scale Effect** | 0.052 | 0.214 |
| **Composition Effect** | -0.029 | -0.108 |
| **Total change due to other demographics** | 0.002 | 0.019 |
| **Unexplained difference (shift in EEC)** | -0.038 | -0.131 |

Panel B: Movement along parametric EECs for developing countries

| | Developing Countries | |
|---|---|---|
| | PM10 | SO2 |
| Dependent Variable: | (1) | (2) |
| **Total change due to income (movement along EEC)** | 0.025 | 0.088 |
| **Scale Effect** | 0.087 | 0.234 |
| **Composition Effect** | -0.062 | -0.146 |
| **Total change due to other demographics** | -0.004 | 0.002 |
| **Unexplained difference (shift in EEC)** | -0.062 | -0.153 |

Panel C: Movement along parametric EECs for China

| | China | |
|---|---|---|
| | PM10 | SO2 |
| Dependent Variable: | (1) | (2) |
| **Total change due to income (movement along EEC)** | 0.0023 | 0.0128 |
| **Scale Effect** | 0.004 | 0.025 |
| **Composition Effect** | -0.0019 | -0.0118 |
| **Total change due to other demographics** | 0.0004 | 0.0030 |
| **Unexplained difference (shift in EEC)** | -0.003 | -0.002 |

Notes: See notes in Table 3.4.