Online Appendix to
Globalization and the Environment

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Appendix A Choosing Relevant Data

Appendix A.1 Which Environmental Goods?

One could separate most environmental goods that research analyzes into three categories—local pollution, greenhouse gases, and natural resources. We focus on explaining properties of each that are most relevant to research.

Local pollution

Air and water pollution are sometimes called "local" pollutants since they primarily affect health and well-being in the country or region where they are emitted. Local pollutants also primarily affect well-being in the time period when they are released, though in specific settings some toxic pollutants can be absorbed in soil or groundwater and cause environmental damage over longer time periods. A large share of local air pollution comes from fossil fuel combustion. A large share of water pollution comes from fossil fuels, organic materials, and chemicals. Environmental policies have strictly regulated local pollutants for decades in most high-income and many middle-income countries by using policy tools like pollution standards, cap-and-trade markets, or pollution taxes. End-of-pipe pollution control technologies like scrubbers can decrease emissions of many local pollutants by 90 percent or more even without changing inputs or other aspects of production technology.

In addition to end-of-pipe control technologies, local pollution emissions depend on a plant's industry and outputs, its inputs, and its production technology. For example, steel is widely traded in many countries. Steel can be produced by using electricity to melt scrap steel and reform it, a technology usually called electric arc furnaces or mini-mills. Alternatively, steel can be produced in a vertically integrated plant, which burns fossil fuels to heat coke, iron ore, and limestone together to produce pig iron and then steel from raw materials. Mini mills and vertically integrated steel plants can produce the same outputs, but use different technologies and inputs (Collard-Wexler and Loecker 2015), and thus may have different environmental impacts.

Air pollution is sometimes estimated to have the largest monetized damages among most environmental goods. For example, a third to a half of all estimated benefits of major recent US regulations in all domains (defense, education, immigration, etc.) in a recent ten-year period came from just one type of air pollution, particulate matter (Dominici et al. 2014). Research suggests that air pollution causes about 5 million premature deaths globally each year (Global Burden of Disease 2018, p. 1940). Air pollution damages are large in part because particulate matter and to a lesser extent ozone pollution are estimated to increase adult mortality substantially. Air pollution also creates other external costs like morbidity, decreased worker productivity, capital depreciation, and defensive costs like air filters and asthma medications.

The external costs of water pollution are more complex. In industrialized countries, pollution of surface waters, which include rivers, lakes, wetlands, and oceans, is primarily believed to affect social welfare through decreasing recreational activity (Keiser and Shapiro 2019). In these countries, drinking water treatment plants typically remove pollution before water is piped to households. While the effectiveness of that treatment varies, and there are specific episodes where polluted rivers decrease health (Austin 2020; Flynn and Marcus 2020), water pollution in industrialized countries is often assumed to have limited effects on health. In developing countries, where drinking water treatment is less effective and many people consume or contact untreated water, economic activity can damage human health through water pollution. Water pollution can decrease firm productivity in heavily water-dependent industries like agriculture, and water pollution regulations can decrease productivity in most industries.

Research uses a range of approaches to quantify these damages. One is a direct estimate of how changes in trade exposure affect environmental quality and welfare outcomes like health (e.g., Keskin 2009; Bombardini and Li 2020). Another is to use existing estimates of these relationships as parameters in a model (e.g., Muller et al. 2011).

Greenhouse gases and climate

Greenhouse gases are a transboundary pollutant that differ from local pollution in many ways. Although climate change damages differ by country, greenhouse gases create the same global climate change externality regardless of where they are emitted. Engineers have not developed economically viable end-of-pipe abatement technologies for greenhouse gases. Thus, the amount of carbon dioxide (CO_2) emitted from fossil fuel combustion depends only on the quantity and quality of fossil fuels burned.[1] This makes it easier to measure CO_2 emissions, though also means that changing incomes may have less scope to decrease CO_2 emissions through end-of-pipe abatement technology (Cole and Elliott 2003). Many countries have had gasoline taxes for decades, but industrial policies targeting greenhouse gases are more recent and less common or stringent. The external costs of greenhouse gases occur in future decades and centuries, not only in the time period when they are emitted. Greenhouse gases are sometimes categorized as a natural resource, though we discuss them separately given their importance and distinct characteristics.

[1]Carbon capture and sequestration technology exists but is prohibitively expensive.

About three-fourths of global greenhouse gas emissions come from energy, another 5 to 8 percent from industrial processes and landfills, and nearly 20 percent from agriculture, forestry, and land use (Roser 2021). Another relevant breakdown is by greenhouse gas. CO_2 emissions account for three-fourths of global greenhouse gas emissions. Methane (CH_4) accounts for another 17 percent and nitrous oxide (N_2O) for 6 percent (Ritchie and Roser 2021).[2]

Greenhouse gas emissions accelerate climate change, which decreases social welfare through a range of channels. Climate change can increase premature mortality, decrease agricultural yields, cause civil conflict and crime, decrease labor supply, increase extreme weather, and increase energy demands for cooling. Emerging evidence suggests that human health accounts for a large share of monetized climate damages (Burgess et al. 2017; Hsiang et al. 2017; Carleton et al. 2020).

Trade research uses two general approaches to quantify the damages from greenhouse gas emissions. Economists studying climate change often build "integrated assessment models" that incorporate detailed economic, environmental, and biophysical components. Some trade research combines integrated assessment models with spatial equilibrium models. For example, Krusell and Smith (2017) build a model of 19,000 regions across the Earth's surface that experience climate change and interact, and Conte et al. (2020) build a two-sector dynamic model at the same level of geographic detail, and Nordhaus (2015) combines a classic integrated assessment model with a structural gravity model of trade. Economists have a range of views on how to interpret the numbers from integrated assessment models given their complexity (Pindyck 2013; IWG 2016).

The "social cost of carbon" is an important quantity calculated from integrated assessment models. It represents the global social cost of emitting one additional ton of greenhouse gas emissions. Specifically, it accounts for how increasing current greenhouse gas emissions by one ton would affect atmospheric greenhouse gas concentrations over future centuries; how those concentrations affect the global climate; how that change in global climate affects mortality, crop yields, conflict, and other channels in future centuries; and then it monetizes these damages, sums them around the globe, and discounts them back to total present value.

The second general approach to quantifying the damages from greenhouse gas emissions takes estimates of the social cost of carbon from integrated assessment models, then multiplies a change in greenhouse gas emissions by this cost. This approach tends to be better suited to research focused on a specific domain or setting that does not change the trajectory of global greenhouse gas emissions enough to meaningfully change the social cost of carbon.

[2] We do not discuss fluorinated gases like chlorofluorocarbons (CFCs), which account for the last 2 percent of greenhouse gases.

Natural resources

Natural resources differ from local pollutants and greenhouse gases along several dimensions. Some resources, like forests or groundwater, are renewable and have both a stock and a natural rate of regeneration. Others, like copper or iron, are nonrenewable, though innovation may increase the share of nonrenewable resources that are technologically or economically feasible to extract. The costs of extracting resources can be local or global—forests, for example, may improve water quality (local benefit) and provide a biodiversity reservoir (local and global benefit). Policies around resources vary widely, including policies like excise taxes on mineral extraction, quotas on fisheries, and inflexible standards on timber harvesting.

Natural resource depletion creates a range of social costs. An important cost of extracting resources is the decreased future stock. Future public or private owners bear this cost. Many natural resources create ecosystem services that generate amenity, productivity, or other values. Healthy forests, for example, can purify groundwater, prevent catastrophic wildfires, decrease air pollution, and prevent floods (Druckenmiller 2020). Healthy animal ecosystems can provide crop pollination, pest management, and food sources (Frank 2018).

Appendix A.2 Ambient Versus Emissions Data

Research faces tradeoffs in deciding whether to analyze the level of environmental quality or how economic activity changes environmental quality. For pollution, this is a decision between measuring ambient pollution or pollution emissions. Many studies analyze both.

Ground-based monitoring of ambient data can measure air or water pollution from automated or manual monitors, and so describe the quality of the environment that people in specific locations experience. Ambient monitoring is less often used in research on greenhouse gases, since greenhouse gases mix uniformly in the atmosphere, and so ambient CO_2 concentrations are largely a global time series without regional variation. Ground-based monitoring can record environmental quality in hundreds or thousands of locations in high-income countries, often with hourly, daily, or weekly frequency. In developing countries, ground-based monitoring is more limited, and often focuses on one or a few major urban areas.

Remote sensing (satellite) measures of pollution have provided a recent alternative data source on ambient pollution. Remote sensing measures are available for a range of air pollutants and to a limit extent water pollution, though are most widely available for particulate matter (Di et al. 2016; Van Donkelaar et al. 2019). Remote sensing data products have different geographic resolution; some represent a one degree by one degree grid; others capture pollution of individual neighborhoods. These data also have different temporal resolution, from daily to annual. These data are especially useful in developing countries where ground-based monitoring is limited (e.g., Gutierrez and Teshima 2018). Remote sensing can also be useful for measuring levels and changes in some natural resources like timber and fish.

Ambient environmental quality data do not directly identify the pollution source. Other research uses emissions data which identify the industry, location, or firm producing the pollution. This can allow closer links to economic models than ambient data allow, since firm choices like investment, production, pricing, abatement, and compliance; firm attributes like productivity, location, industry, and age; and regulator choices like inspections, standards, and stringency all affect emissions of the affected source more directly than they affect quality of the regional environment.

Data quality is an important consideration for emissions data. The highest-quality data typically come from continuous emissions monitoring systems, which are required for many air pollution cap-and-trade markets. These systems include a device connected to a source's smokestack and a machine which analyzes the pollution concentration from emissions in real time. Regulators typically mandate the monitoring methodology, and they are believed to be extremely accurate. Measurements with this high quality are available for the largest sources and the most common air pollutants. Reasonable quality data come from a sampling of a plant's smokestack or discharge pipe, measure the concentration of pollution, and multiplying it by the observed or estimated air or water flow rate. Many emissions data come from engineering calculations, where firms use laboratory or design calculations to assess how specific technologies are supposed to affect emissions. Engineering estimates are common, but their accuracy is less certain than is the quality of direct measures. Regional, national, or global emissions measures sometimes take the ratio of emissions to output from direct observation or engineering estimates, then multiply this "emissions factor" by data on output from other sources.

Firms also self-report data in most emissions data sets. Since emissions data can be used to assess compliance with some environmental regulations, this can produce incentives for misreporting. Some empirical tests of data quality, such as for toxic pollution emissions from U.S. firms, underscore caution about the quality of emissions data (Currie et al. 2015).

Carbon dioxide (CO_2) emissions from fossil fuel combustion are easier to measure accurately. As discussed earlier, knowing the physical quantity of fossil fuels burned (e.g., the barrels of oil, cubic feet of natural gas, and tons of coal) provides a reasonably accurate measure of CO_2 emissions. No knowledge of abatement technologies, combustion temperature, industrial technology, or other details are needed to know how much CO_2 is emitted from a given quantity of fossil fuel combustion. This corresponds to what the United Nations Intergovernmental Panel on Climate Change calls the "Tier 1" method of measuring greenhouse gas emissions, in which a researcher observes physical units of fossil fuel combustion and multiplies them by an emissions coefficient representing the tons of greenhouse gas emitted per physical unit of fossil fuel burned.[3] This is useful because many industrial surveys ask firms about their energy consumption, and firms can measure fossil fuel consumption from accounting data without relying on environmental estimates of abatement technologies. In cap-and-trade markets like the European Union's Emissions Trading System, firms operate continuous emissions monitoring systems for CO_2.

Appendix A.3 National Versus Global Analysis

Most industrialized countries and many developing countries collect data on ambient levels of air and water quality and on natural resources. A smaller number measure pollution emissions. Many studies use one country's data on environmental quality. Researchers often combine independent economic data like industrial surveys or policies with environmental data, which can make it difficult to analyze more than one country at a time, particularly when the industrial surveys are confidential and accessed in secure and isolated computer facilities. Research has been able to pool data from several European countries (Wagner et al. 2020). Research on trade and the environment uses several types of environmental data covering large numbers of firms or countries. Some studies use ground-based monitoring data from one country, such as Bombardini and Li (2020)'s study of how the growth in trade due to China's World Trade Organization accession affected Chinese air quality. Most industrialized and many developing countries have networks of air quality monitoring data with measurements readily available to researchers. Ambient water quality monitoring data are less readily available but still widely used in research (e.g., Ebenstein (2012); Lipscomb and Mobarak (2016)).

An alternative approach is to use environmental quality data from a large number of countries. The most common multi-country ground-based monitoring dataset is the United Nations' Global Environmental Monitoring System (GEMS), which has data beginning in 1978, covering 80 countries and 11,000 monitoring sites. The GEMS data were used in early research on the Environmental Kuznets Curve (Grossman and Krueger 1993) and many subsequent studies. Other research uses remote sensing data for many countries.

One useful alternative is to use emissions data for many industries and countries from global multi-region input-output tables. Most of these global datasets include industry-level measures of emissions of several pollutants, and in some cases natural resources.

Researchers have created at least five distinct multi-region input output tables, each

[3] Scientists distinguish this from the "Tier 2" method, which uses country- or setting-specific emissions coefficients.

with a different focus, and all with some environmental data. The World Input Output Dataset is commonly used in recent academic research on international trade (e.g., Costinot and Rodriguez-Clare 2014; Antràs and de Gortari 2020). The Global Trade and Analysis Project (GTAP) has more detail on agriculture and a pre-programmed computable general equilibrium model. Exiobase has the most (160) distinct industries, and Eora has more (190) distinct countries. The OECD Input-Output Database has more detail on OECD countries. Some published comparisons of these datasets focused on their measures of CO_2 suggest they are broadly similar though have nontrivial differences (Moran and Wood 2014).

Input-output tables report the emissions of each pollutant directly from each industry. An important calculation asks what change in emissions is required to produce a dollar of output in each industry and country, including emissions from the entire value chain. This is sometimes called measurement of a good's environmental footprint, or the "total" emissions from a good. Total emissions from an industry includes emissions from the own industry and also emissions from the industry's entire value chain.

Total emissions are typically calculated from combining the Leontief Inverse with direct emissions coefficients. Let x denote an $S \times 1$ column vector of gross output from each industry in a single closed economy. Let A be an $S \times S$ input-output matrix. Each entry in A represents the dollars of input from the industry in a given row to product output for the industry in a given column. For example, a coefficient of 0.02 for row=natural gas and column=vehicles would indicate that two cents of natural gas are needed to produce a dollar of vehicles. Let d denote an $S \times 1$ column vector of final demand for each industry in the economy.

A basic accounting identity states that each industry's gross output is sold either to other firms as intermediate goods or to final demand:

$$x = Ax + d$$

Subtracting Ax from both sides then premultiplying both sides by $(I - A)^{-1}$ gives

$$\begin{aligned} (I - A)x &= d \\ x &= (I - A)^{-1}d \end{aligned}$$

The $S \times S$ matrix $(I - A)^{-1}$ is known either as the Leontief Inverse or the matrix of total requirements. It describes the gross output from each industry needed to produce a dollar of final demand in each industry, including the direct inputs, the inputs to the direct inputs, and so on all the way through the entire value chain. For example, a coefficient of 0.04 for row=natural gas and column=vehicles would mean that producing a dollar of vehicles requires four cents of natural gas in vehicle assembly factories, and also in factories that supply vehicle assembly factories, and in the factories supplying those, etc.

To measure emissions along the entire value chain, we multiply the gross output of each industry by the direct emissions rate e of that industry:

$$E = e(I - A)^{-1}d$$

Here E is a column vector representing the total emissions rate of each industry, including emissions from directly producing goods in the industry and from the entire value chain.

Measuring total emissions from many open countries rather than a single closed economy is straightforward. Simply interpret each observation in the relevant vectors as a country×industry rather than an industry. For example, an observation in A might represent natural gas from the U.S. (the row) used to produce vehicles in Mexico (the column).

Appendix B Supplemental Tables and Figures

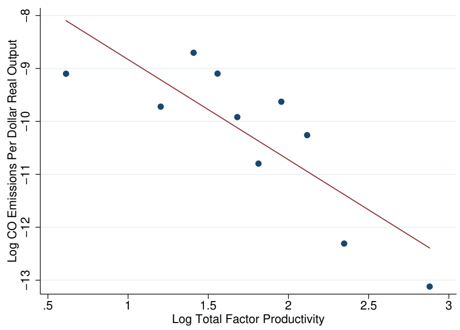
Table B1: Cleanest and Dirtiest Industries in Global Data: Other Pollutants, Total Emission Rates

	CH_4 (1)	N_2O (2)	CO (3)	NH_3 (4)	NMVOC (5)	SO_x (6)
Panel A. Cleanest industries						
Real estate activities	0.501	0.009	0.987	0.021	0.270	0.240
Financial intermediation	0.682	0.015	1.410	0.036	0.374	0.290
Equipment & machine rentals	1.149	0.027	2.643	0.069	0.694	0.523
Wholesale trade	1.461	0.036	3.282	0.093	0.821	0.623
Retail fuel; vehicle repair, sales	0.919	0.019	2.852	0.041	0.825	0.439
Mean of cleanest 5 industries	*0.942*	*0.021*	*2.235*	*0.052*	*0.597*	*0.423*
Panel B. Dirtiest industries						
Coke, oil refining, nuclear fuel	12.903	0.061	65.406	0.232	18.365	3.215
Air transport	3.471	0.083	32.876	0.112	4.268	1.475
Water transport	3.508	0.086	33.826	0.132	6.181	6.682
Other non-metallic mineral	7.930	0.098	19.306	0.223	5.475	6.967
Electricity, gas, water supply	8.829	0.108	15.100	0.126	2.645	16.926
Mean of dirtiest 5 industries	*7.328*	*0.087*	*33.303*	*0.165*	*7.387*	*7.053*

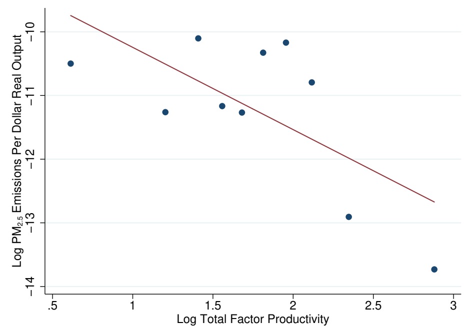
NOTES: Data represent the year 2009. Emission rates are in metric tons per million dollars of output. Total rates are calculated by inverting a global multi-region input-output table. Values refer to the mean value across countries, weighted by the value of output; industries are ordered based on mean emission rate across all listed pollutants. Output traded (%) equals total international trade divided by total gross output for the indicated industry. All dollars are in 2018 USD, deflated using the U.S. GDP deflator. CO_2 is carbon dioxide, NO_x is nitrogen oxides, and SO_x is sulfur oxides.

Figure B1: Emission Rates and Firm Productivity, Other Pollutants

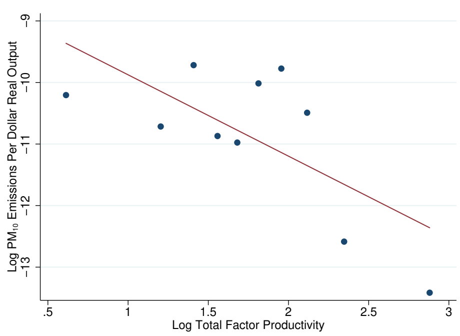
(a) Carbon monoxide (CO)



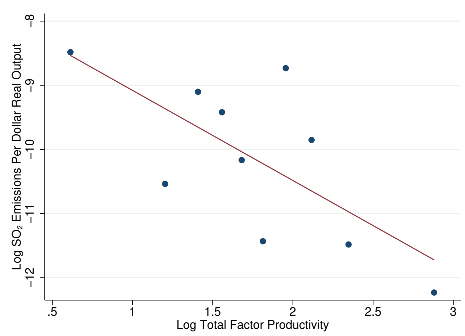
(b) Particulate matter smaller than 2.5 micrometers ($PM_{2.5}$)



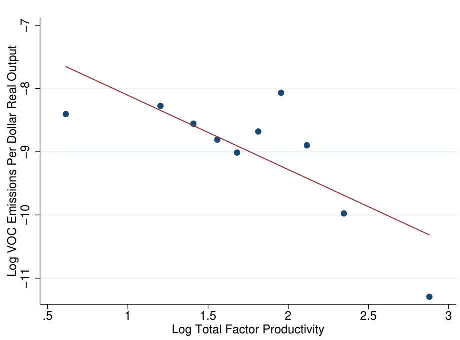
(c) Particulate matter smaller than 10 micrometers (PM_{10})



(d) Sulfur dioxide (SO_2)



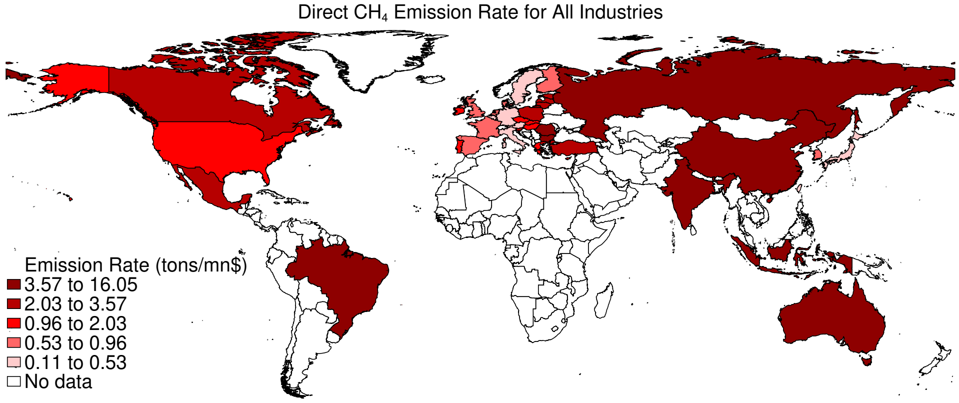
(e) Volatile organic compounds (VOC)



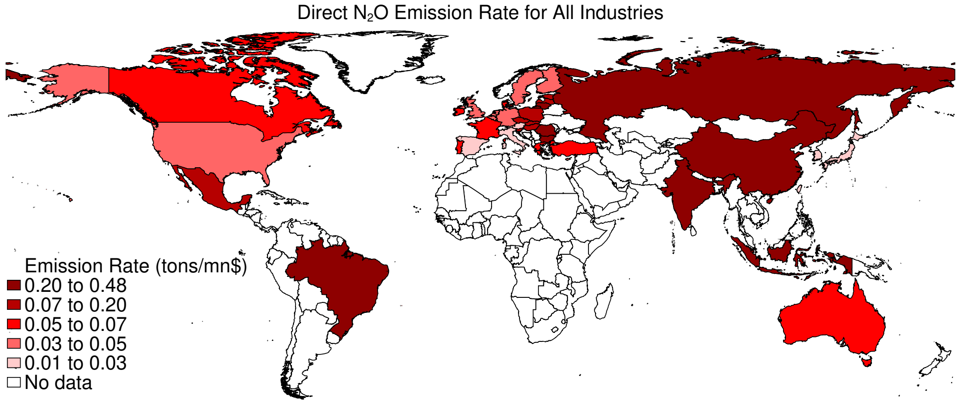
NOTES: Figure adapted from Shapiro and Walker (2018). See notes to Figure 1 in main text for details.

Figure B2: Direct Emission Rate, by Country and Pollutant, Other Pollutants

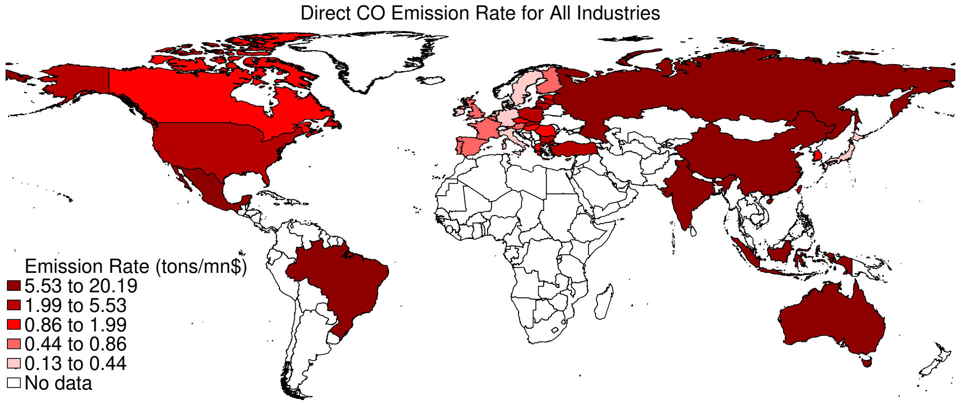
(a) Methane (CH_4)



(b) Nitrous oxide (N_2O)



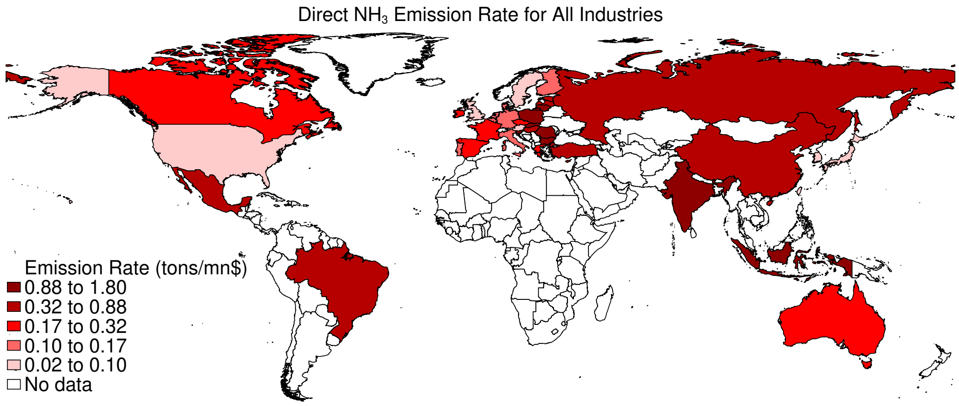
(c) Carbon monoxide (CO)



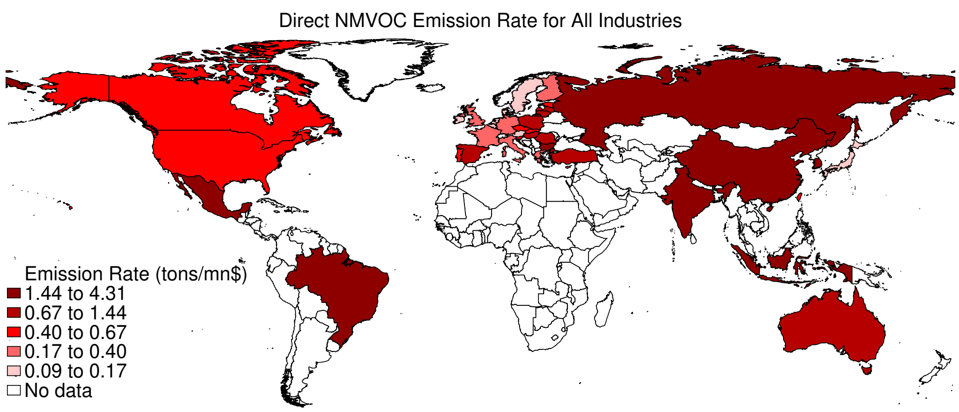
NOTES: Data for the year 2009 from WIOD. See text for details.

Figure B2: Direct Emission Rate, by Country and Pollutant, Other Pollutants

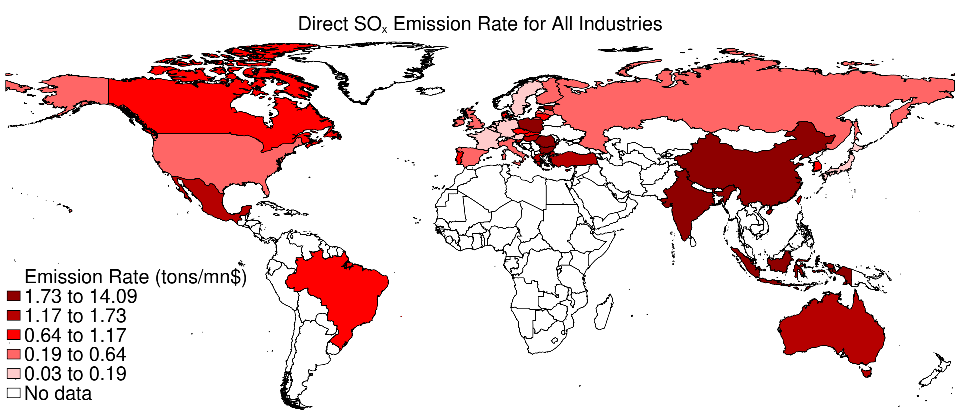
(d) Ammonia (NH_3)



(e) Non-methane volatile organic compounds (NMVOC)



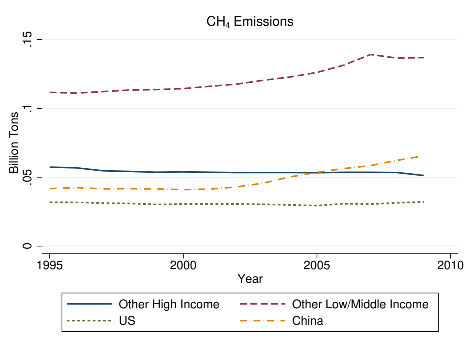
(f) Sulfur oxides (SO_x)



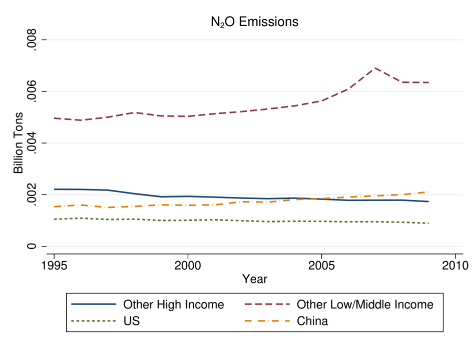
NOTES: Data for the year 2009 from WIOD. See text for details.

Figure B3: Direct Emissions, by Group of Countries and Year, Other Pollutants

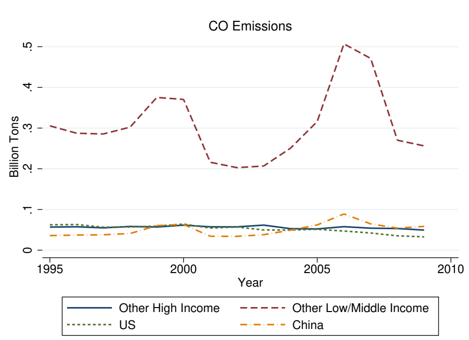
(a) Methane (CH_4)



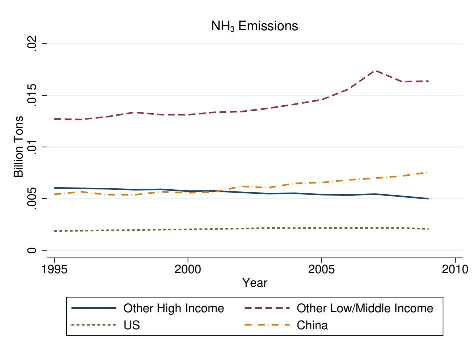
(b) Nitrous oxide (N_2O)



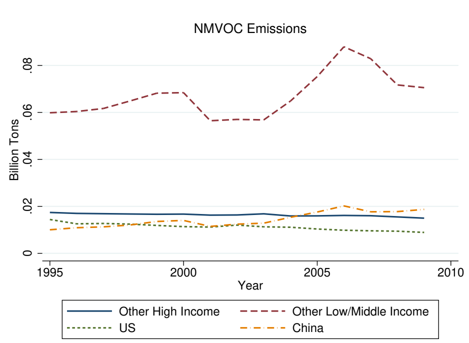
(c) Carbon monoxide (CO)



(d) Ammonia (NH_3)



(e) Non-methane volatile organic compounds (NMVOC)



(f) Sulfur oxides (SO_x)

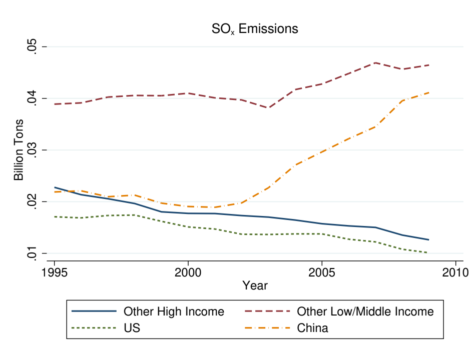
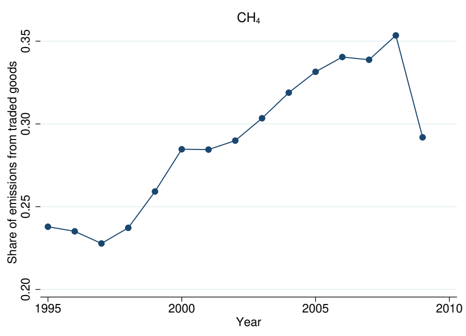
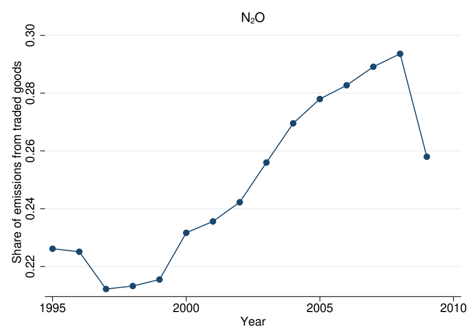


Figure B4: Share of Global Pollution Embodied in Traded Goods, by Year, Total Emissions, Other Pollutants

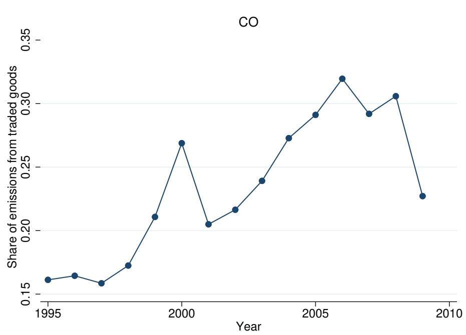
(a) Methane (CH_4)



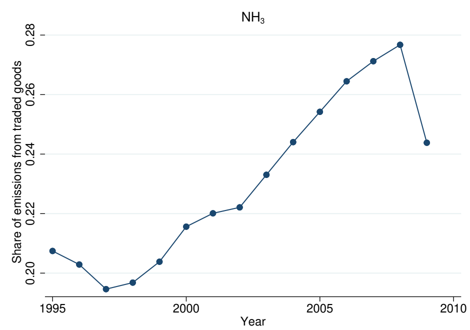
(b) Nitrous oxide (N_2O)



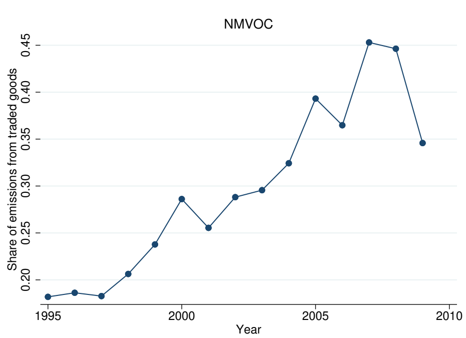
(c) Carbon monoxide (CO)



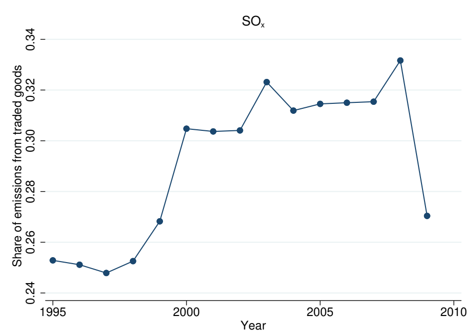
(d) Ammonia (NH_3)



(e) Non-methane volatile organic compounds (NMVOC)



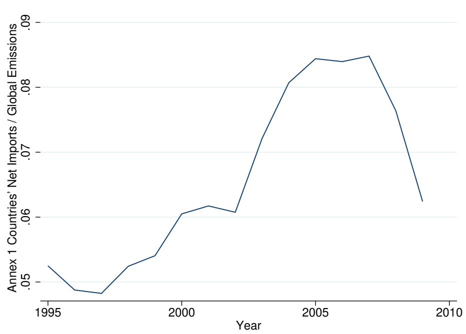
(f) Sulfur oxides (SO_x)



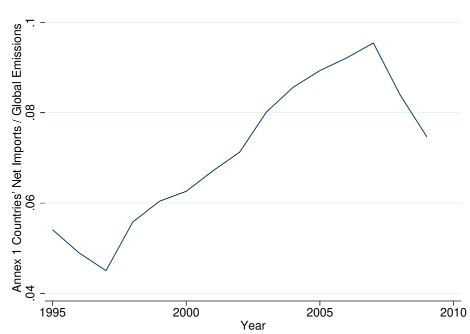
NOTES: the numerator (total emissions from traded goods) includes emissions from the entire value chain of traded goods.

Figure B5: Emissions Embodied in Net Imports of High-Income Countries, Other Pollutants

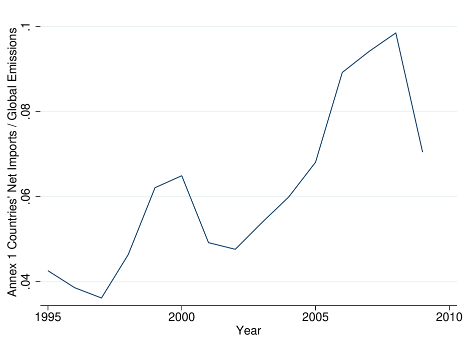
(a) Methane (CH_4)



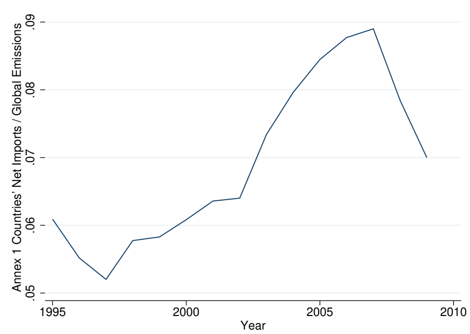
(b) Nitrous oxide (N_2O)



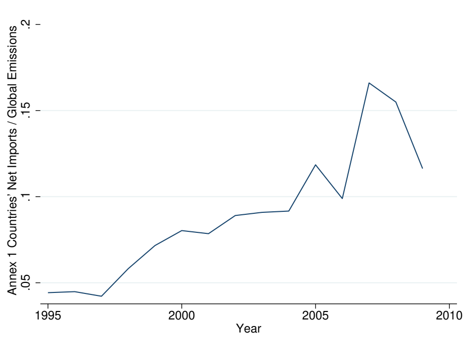
(c) Carbon monoxide (CO)



(d) Ammonia (NH_3)



(e) Non-methane volatile organic compounds (NMVOC)



(f) Sulfur oxides (SO_x)

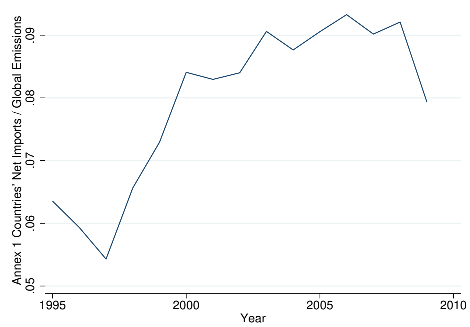
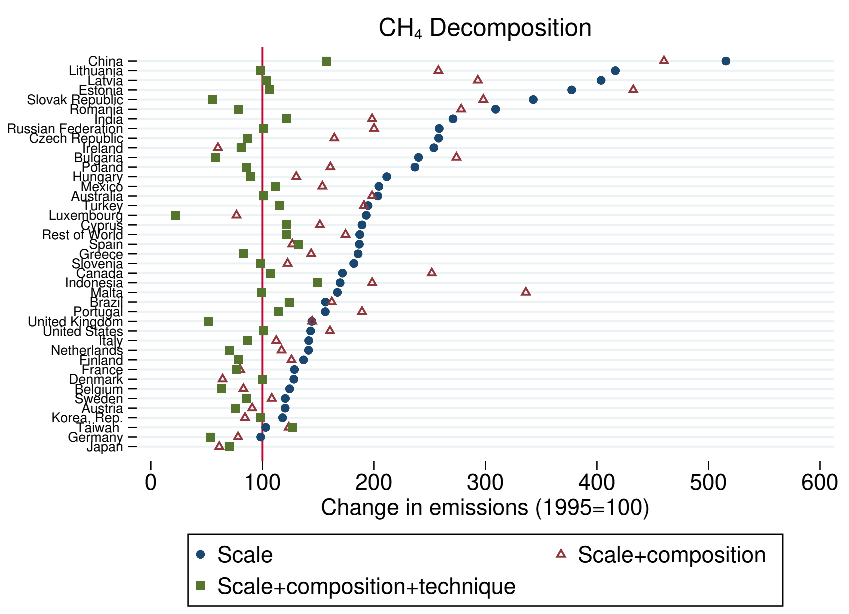
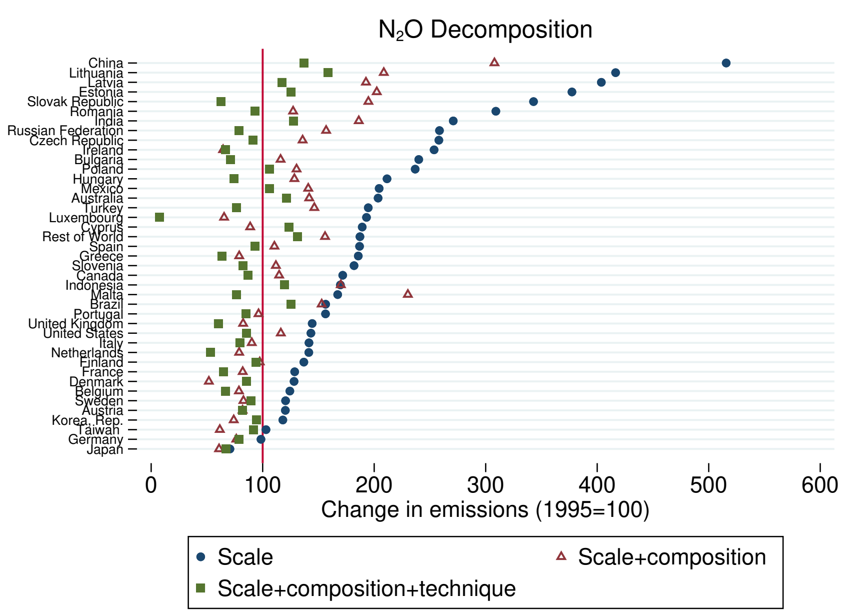


Figure B6: Decomposition of Scale, Composition, and Technique, Other Pollutants

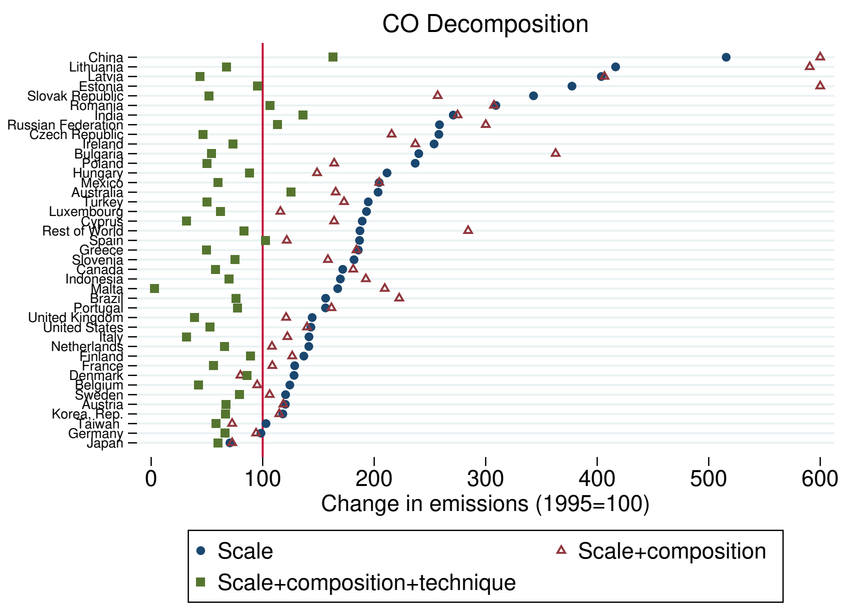
(a) Methane (CH_4) Decomposition



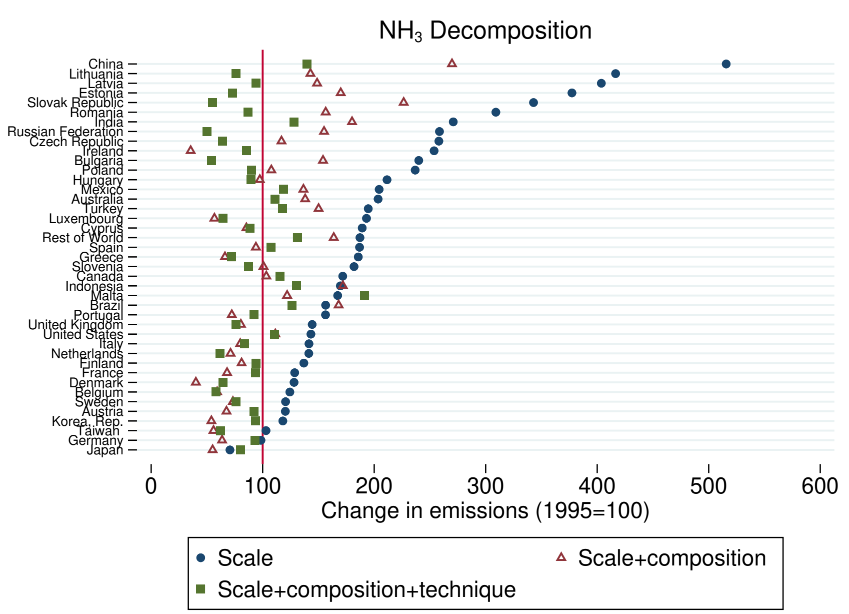
(b) Nitrous Oxide (N_2O) Decomposition



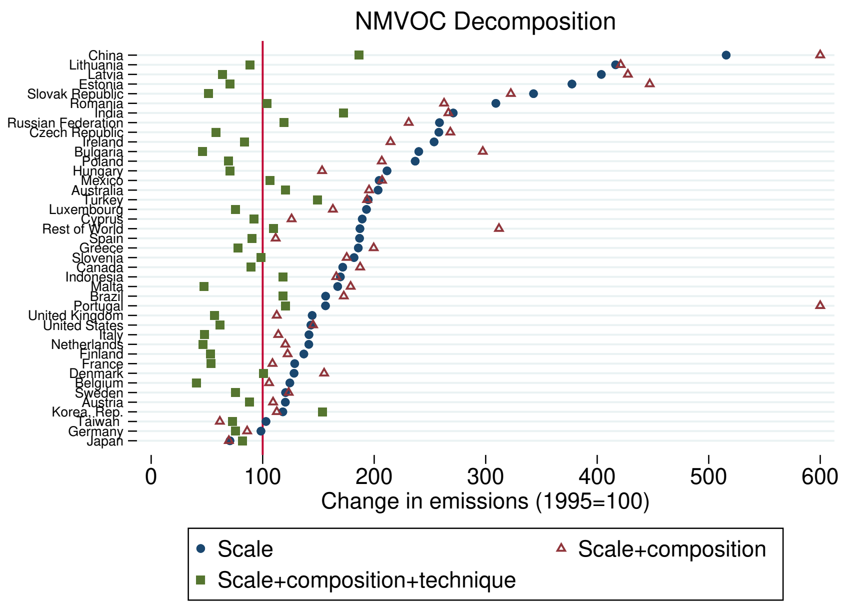
(c) Carbon monoxide (CO) Decomposition



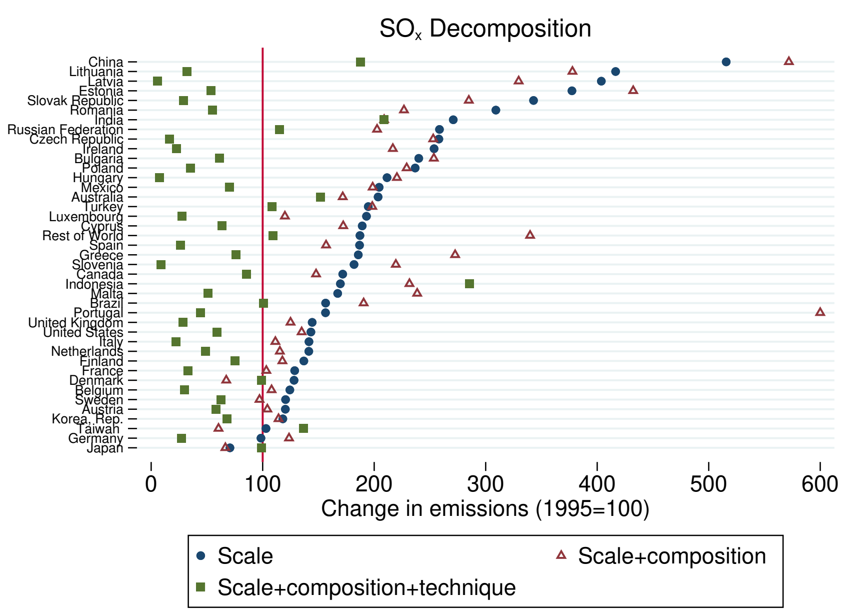
(d) Ammonia (NH_3) Decomposition



(e) Non-methane volatile organic compounds (NMVOC) Decomposition



(f) Sulfur oxides (SO_x) Decomposition



NOTES: scale represents 100 times national value added (GDP) in 2009, divided by national value added in 1995. Scale+composition modifies the scale value to keep emission rates (technique) the same for each country*sector in 2009 as it was in 1995. Emission rates are measured as tons directly emitted per dollar of value added. Scale+composition+technique represents 100 times emissions in 2009, divided by emissions in 1995. Vertical red line at "Change in emissions "=100 represents the value for no change in emissions between 1995 and 2009.

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