

# Technology, International Trade, and Carbon Emissions from U.S. Industry

Tao Wang<sup>\*†</sup>

September, 2019

## Abstract

This paper investigates the driving forces behind the decreasing trend of carbon dioxide (CO<sub>2</sub>) emissions from the U.S. industrial sector. From 1998 to 2007, real gross output grew by 7.9%, while CO<sub>2</sub> emissions decreased by 4.6%. Using CO<sub>2</sub> emissions intensities data compiled for year 1998 and subsequent emissions and production data, I decompose the technology, composition and scale effects for the changes over the period. The main contributing factor for the clean-up of U.S. industry was the technology effects, i.e., the decrease in emissions intensities across the sector, which accounted for almost all of the reduction in emissions. Furthermore, fuel switching accounted for one fourth of these effects, with the rest attributed to efficiency improvements. Increasing net imports amounted to about one third of the size of the technology effects.

*JEL Classification:* F18, Q54, Q56

*Keywords:* CO<sub>2</sub> emissions, decomposition, international trade.

---

<sup>\*</sup>I am very grateful to Gene Grossman, Michael Oppenheimer and Stephen Redding for their continual support and encouragement. I also have benefited from insightful comments made by seminar participants at Princeton University, the Environmental Defense Fund and Swarthmore College. I thank the International Economics Section (IES), the Princeton Environmental Institute (PEI) and the Pace Center for Civic Engagement at Princeton University for their generous financial support.

<sup>†</sup>Department of Economics, Swarthmore College. Email: twang1@swarthmore.edu.

# 1 Introduction

The overall greenhouse gas (GHG) emissions in the United States have been on a slowing growth path in the past two decades. As depicted in Figure 1, the average growth rate dropped from about two percent per year in the 1990s to about half a percent in the mid-2000s. In particular, carbon dioxide (CO<sub>2</sub>) emissions, the most important GHG accounting for about five sixths of total emissions,<sup>1</sup> seemed to have reached a plateau before the Great Recession of 2008 and 2009. In the meantime, U.S. Gross Domestic Product (GDP) averaged about three percent annual growth in real terms (U.S. Bureau of Economic Analysis (BEA), 2012) from 1990 to 2007. These differential growth rates imply that the U.S. economy has become “greener” with its emissions intensity<sup>2</sup> on a downward trend. Common explanations include a general shift from a manufacturing-based economy to a service-based economy,<sup>3</sup> as well as an overall increases in energy efficiency (U.S. Environmental Protection Agency (EPA), 2012).

While most of the decomposition studies on U.S. CO<sub>2</sub> emissions have been conducted for the aggregate economy, this paper takes a closer look at one particular sector, industry, which appears to have contributed the most to the overall clean-up process. Industry, or the industrial sector, which includes activities in manufacturing, mining, construction and agriculture,<sup>4</sup> is responsible for a significant portion of CO<sub>2</sub> emissions in the United States. As shown in Figure 2, while CO<sub>2</sub> emissions from the transportation, commercial and residential sectors were all on the rise until the financial crisis hit, industrial CO<sub>2</sub> emissions have been on a steady decline after reaching a peak in 1997. The emissions displayed a 4.6% drop from 1998 to 2007 despite a 7.9% increase in real gross output.<sup>5</sup> During this period, industry’s share of total CO<sub>2</sub> emissions decreased from 35% to 31%, double the two percentage point drop in the sector’s share of total economic activity (BEA, 2012). As a result, the industrial sector has become less emission intensive at a substantially faster pace than the overall U.S. economy.

What drives this greening trend of U.S. industry? There are two major potential sources, advances in production or abatement processes, i.e., the technique or technology effect, and changes in the composition of goods produced, i.e., the composition effect. Most of the CO<sub>2</sub> emissions in industry, as well as in other sectors, are related to energy, and come from fossil fuel use either directly in the production process or indirectly

---

<sup>1</sup>From 1990 to 2010, CO<sub>2</sub> emissions, excluding land use, land-use change, and forestry (sinks), represent on average 83.5% of total US GHG emissions measured in terms of Global Warming Potential using weights from the IPCC Second Assessment Report (EPA, 2012).

<sup>2</sup>The emissions intensity is defined as the amount of emissions per unit of GDP or gross output, typically measured in metric tons of CO<sub>2</sub>-equivalent per \$1,000 of real GDP or gross output.

<sup>3</sup>In 1990, private goods-producing industries accounted for about 24% of US GDP, and this share was in steady decline, reaching below 20% by mid-2000s. Meanwhile, the service industries’ share increased from 62% in 1990 to about 68% in the mid-2000s (BEA, 2012).

<sup>4</sup>The classification adopted in this paper is consistent with energy consumption data from the US Energy Information Administration (EIA).

<sup>5</sup>The increase in real GDP, or value added, is even larger at 16.7% from 1998 to 2007 (BEA, 2012).

through electricity consumption.<sup>6</sup> Hence, technological advances can come in two ways, improvements in energy efficiency, or substitution in the energy mix, in both direct energy use and electricity generation. On the other hand, the compositional changes in production can also be further distinguished into two sources, a decrease in the final demand for carbon-intensive goods, or an increase in the share of such goods that are imported.<sup>7</sup> The latter scenario is often the basis for such concerns that the United States and other high-income countries have reduced their GHG emissions intensity by shipping “dirty” industries to the developing countries.

It is important to allocate credit for the clean-up of U.S. industry among the various trends in technology, product mix, and international trade. If it is simply a result of importing more carbon-intensive products and producing less of them domestically, then the U.S. experience cannot be replicated globally. The least developed countries will not be able to find even poorer countries from which to import the carbon-intensive products. The world will run out of “pollution havens” as all countries strive to become greener. On the other hand, if it has resulted from technological advances, particularly efficiency improvements, the clean-up can be replicable, and will provide promising opportunities to address climate change. In addition, alternative perspectives on the greening process can have significant implications for the potential of energy policy to influence future energy efficiency trends. Energy-efficiency programs are more likely to influence energy trends within specific industries, while changes due to shifts in the overall economic structure are less likely to be swayed by energy policy mandates.

It needs to be kept in mind that industrial activities are not the only source of GHG emissions in the United States. By the late 2000s, industrial CO<sub>2</sub> emissions represent just about 30% of all CO<sub>2</sub> emissions and 25% of total GHG emissions. Nonetheless, industry, and manufacturing in particular, accounts for a large share of the rhetoric in the public and political debate on the economic and environmental consequences of climate change regulations in the context of global trade, centering on issues like carbon leakage and competitiveness concerns.<sup>8</sup> Meanwhile, the transportation, commercial and residential sectors are not subject to such concerns about pollution havens or international competition. This paper therefore focuses on the industrial sector. It is also noted that although data through 2010 are presented whenever possible, most of the analysis focuses on the period from 1998 to 2007, between the peak of industrial CO<sub>2</sub> emissions and the onset of the Great Recession.

The rest of the paper is organized as follows, the next section of the paper briefly reviews the recent literature on decomposition analysis applied to related issues. Section 3 describes the data used for the analyses. Section 4 shows that technology accounted

---

<sup>6</sup>From 1990 to 2010, emissions from fossil fuel combustion represent on average 93.6% of overall US CO<sub>2</sub> emissions, excluding land use, land-use change, and forestry (sinks). Other sources include non-energy use of fuels, natural gas systems and process emissions, mostly in metal and lime and cement production (EPA, 2012).

<sup>7</sup>The final demand for U.S. goods includes domestic consumption and exports. In the decomposition presented later in this paper, I separate the effects of the changes in domestic consumption, which is termed the composition effect, and that of the net imports.

<sup>8</sup>See Onder (2012) for a review on key issues on trade and climate change.

for the majority of the clean-up from 1998 to 2007, while changes in the composition of industries had a negligible effect. Section 5 looks at the fossil fuel consumption of the industrial sector and illustrates that most of the technique effect was manifested in reduced energy use, while fuel switching and improved efficiency in the power sector did not make much of a contribution. Section 6 shows that over the same period, emissions embodied in the increased net imports of the United States amounted to less than one third of the clean-up due to the technique effect. Therefore, shifting carbon-intensive production overseas contributed at most a minor share, less than one fourth, of the overall clean-up of U.S. industry. The last section concludes.

## 2 Related Literature

Decomposition analysis has deep roots in economics, dating back to Leontief's (1970) analysis with an extended input-output framework. A large number of studies have applied the decomposition methodology to analyze pollution, energy use, as well as other issues to understand trends over time or differences across regions.<sup>9</sup> It provides an intuitive tool to attribute the changes in a variable of interest to a number of different factors, for instance, the previously mentioned composition and technique effects. Generally, the decomposition exercise is viewed as a preliminary step for the analysis of fundamental determinants of the movement in the variable of interest. The next step involves relating the decomposed effects to elements such as government policies or market forces, using an equilibrium model of the economy. The decomposition exercise can be particularly useful if the fundamental determinants that matter for structural change are substantially independent from those that matter for technological change. In the case of carbon emissions, the compositional shift is typically driven by product market considerations, namely the demand-side factors in both domestic and international markets; while the changes in emissions intensities are usually due to factor market or supply-side reasons such as fuel switching or innovations in the production and abatement technologies. While these factors are not completely independent, as they may all be tied to the relative prices of the goods from different industries, decomposition analysis does offer valuable information on the nature of the movement in overall emissions levels.

The usefulness of the methodology as an analytical tool for policy making on national energy and environmental issues has been widely acknowledged, though there is yet to be a consensus on which decomposition method is the best. Most of the decomposition

---

<sup>9</sup>Decomposition analysis has also been widely used in labor economics (see Fortin, Lemieux & Firpo, 2011, for an overview). A key difference between the application in that literature and the application to emissions or energy use is that the former case lacks a clear structure unlike the latter. As to be shown in the paper, the overall emissions can be written as a deterministic function of the emissions intensities and industry outputs, which are then related to the decomposed effects. There can be interactions between these effects, and hence the decomposition can include a residual term. However, this is different from the unexplained component of a decomposition without a clear structural form and the structural coefficients need to be estimated. Because of this difference, there is less concern for identifying causality in the current application. The causes that lead to the decomposed effects are beyond the scope of the decomposition analysis itself.

studies fall into one of two categories, index decomposition analysis (IDA) or structural decomposition analysis (SDA). The IDA, sometimes referred to as “index number analysis,” adopts methodologies based on economic indices such as the Divisia or the Laspeyres indices. Over the years researchers have proposed various improvements (for a summary, see Ang, 2004), and a selection of the IDA formulations are presented in the appendix to this paper. The IDA has always been a popular tool with its relatively low data requirements. It only needs industry-level data within the disaggregated industries, i.e., it uses output per industry for the economic decomposition. Not surprisingly it has been applied to a large number of time periods and countries (for reviews, see Ang and Zhang (2000) and Liu and Ang (2007)). On the other hand, the SDA, also referred to as the “input-output decomposition analysis,” combines industry-level data with input-output tables. The decomposition is therefore based on the input–output coefficients (matrix) in addition to the final demand of each industry. Thus, the SDA is capable of distinguishing between a range of technological effects and final demand effects that are not possible in the IDA framework (Hoekstra and Van der Bergh, 2003). With increased availability of input-output tables and further methodological improvements, the SDA has become more widely adopted in recent years (for reviews, see Rose (1999), Liu (2004) and Su (2011)).

The literatures on the IDA and the SDA have been developed largely independently of each other. However, despite their differences, the techniques employed in the analyses, particularly the various weighting methods, can be transferred from IDA to SDA, and vice versa (Hoekstra and Van der Bergh, 2003).<sup>10</sup> In the current paper, elements from both the IDA and the SDA approaches are utilized. The main analytical tool is an IDA method similar to a Laspeyres index, following Levinson (2009). When analyzing the emissions embodied in international trade, the emissions intensities used are derived from an input-output framework akin to SDA.

With the popularity of decomposition analysis, there have been quite a few applications to U.S. CO<sub>2</sub> emissions. Studies published prior to 2004 cover various periods spanning the 1960s through the 1990s. Studies focusing on specific sectors found that a decline in energy intensity contributed the most to reducing carbon intensity of U.S. manufacturing, while structural change had a smaller but significant impact (Torvanger, 1991; Golove and Schipper, 1996; Greening, Davis & Schipper, 1997; Schipper, et al., 2001). In the transportation sector, similar conclusions were reached (Scholl, Schipper & Kiang, 1996; Lakshmanan and Han, 1997) except for freight (Greening, Ting & Davis, 1999). The story is no different in the residential sector (Schipper, Hass, & Sheinbaum, 1996; Greening, Ting & Krackler, 2001). Therefore, it is not surprising that, at the level of the aggregate economy, energy intensity was identified as the most important driver behind the downward trend of emissions intensity (Golove and Schipper, 1997; Schipper, Ting, Khrushch & Golove, 1997; Sun and Malaska, 1998; Hamilton and Turton, 2001). All the aforementioned studies used IDA methods. Casler and Rose (1998) provides a rare study using SDA applied to U.S. CO<sub>2</sub> emissions and shows that substitution within the

---

<sup>10</sup>For example, Lenzen (2006) shows the similarity, in additive form, between the Shapley/Sun method in IDA (Ang, Liu & Chew., 2003) and the Dietzenbacher-Los (1998) method in SDA. In multiplicative decomposition, de Boer (2009) shows that the generalized Fisher Index (Ang, Liu & Chung, 2004) in IDA is identical to the multiplicative form of Dietzenbacher-Los in SDA.

energy sector and between energy and other inputs were the leading causes of the decline in emissions from 1972 to 1982.

More recent studies of CO<sub>2</sub> emissions have provided alternative perspectives to the issue. Vinuya, DiFurio & Sandoval (2010) decomposes CO<sub>2</sub> emissions by each state in the United States and shows that efficiency gains, a lower share of fossil fuels in total energy consumption, and lower emissions intensities of fuels, all contributed to decelerating emissions growth in the United States from 1990 to 2004. Malla and Im (2011) decomposes CO<sub>2</sub> emissions from power generation in the United States from 1990 to 2005 and attempts to forecast future emissions with estimates of component factors. Unlike older studies, neither includes an effect of structural change in economic activities.

Since most of CO<sub>2</sub> emissions are energy related, studies on energy use and energy intensity should shed light on the evolution of emissions as well. Earlier research has shown that the changes in the energy mix and the emissions factors of fuels are not important drivers for emissions trends for the United States largely from the 1960s to the 1990s. Therefore, the forces behind the trends in energy use or energy intensity should translate into factors affecting CO<sub>2</sub> emissions and carbon intensity. Among the large number of decomposition studies of U.S. energy use or energy intensity covering similar periods, the majority agree that declining sector-specific energy intensities were the most important factor contributing to lowering the overall energy intensity of the U.S. economy, with structural change taking a secondary role (Liu and Ang, 2007).

Interestingly, since the mid-2000s, there have not been as many published decomposition studies of U.S. energy use, despite its continued popularity in applications to other economies. A number of recent studies of the aggregate U.S. economy seem to suggest that structural change has become more important since the 1990s. A study by the Office of Energy Efficiency and Renewable Energy of the U.S. Department of Energy (2012) analyzes the U.S. energy intensity trend from 1985 to 2004 and concludes that, out of a 27% decrease in energy to GDP ratio during the period, a shift in the composition of the economy caused a 17% decline, while the remaining 10% was achieved by improving energy intensity within individual subsectors or industries. Huntington (2010) finds that shifts between 65 industries in the commercial, industrial and transportation sectors accounted for almost 40% of the reduction in the U.S. economy's aggregate energy intensity from 1997 to 2006, with the figure rising to 54% when transportation is excluded. Weber (2009) uses both IDA and SDA methods to analyze the changes in U.S. energy use from 1997 to 2002 and concludes that changes in the structure of the economy explain the 12% drop in energy intensity more than increased energy efficiency. On the other hand, Metcalf (2008) suggests that roughly 75% of the decline in U.S. energy intensity from 1970 to 2003 resulted from efficiency improvements.

There are several potential reasons that empirical results from different studies may not agree. First, since the authors may use data from different sources, adopt different measures of economic activities, or cover different time periods and/or different sectors of the economy, some differences are natural. Though it may well be the case that, for the overall economy, structural shifts between the major sectors have become more important, efficiency improvements may still be the driving force in reducing sector-level energy or emissions intensity. This paper attempts to determine whether this is the case in the

industrial sector. The analysis also employs the most recently available emissions and production data, which may reveal patterns different from earlier data.

Second, the relative importance of technology, or energy efficiency, and industrial structure, or product mix, often depends on the level of aggregation in the decomposition analysis (Weber, 2009; Su, Huang, Ang & Zhou, 2010). Some studies conduct the analysis at a more aggregated level lacking detailed industry classification due to data limitations. Since most studies can only assess technology indirectly as a residual, after accounting for composition effects, analyses at more aggregated levels inevitably misclassify some within-sector compositional variations as technique changes. The finer industry disaggregation used in this study makes it less likely to exaggerate the role of technology in emissions abatement.

A recently developed literature, closely related to the decomposition and input-output analysis is the one on emissions embodied in international trade (for reviews, see Wiedmann, Lenzen, Turner & Barrett (2007) and Wiedmann (2009)). Adopting the methods used to analyze the traditional factor content of trade, these studies try to assess the emissions content of goods traded between economies and calculate a balance of emissions traded for certain individual economies, as well as pairs or groups of countries. The results are used to assess the impacts of trade on countries' carbon footprint and potential carbon leakage of climate change policies. The United States and other industrialized countries have been found to be large net importers of embedded carbon (see, for instance, Peters and Hertwich (2008)). Naturally, this observation and the increase in global trade have been linked to the structural change of the United States and other high-income economies and it has been suggested that rich countries have become cleaner by relocating production of pollution-intensive products elsewhere.

Interestingly, despite such broad claims, few studies have directly addressed the role of international trade in reducing the emissions intensity of developed economies. This paper attempts to fill this gap by assessing the importance of international trade on the clean-up of U.S. industry. One recent study that offered particular insights used in this paper is Levinson's (2009) analysis on air pollution from U.S. manufacturing. Using data on disaggregated industries, he shows that the technique effect dominates in the clean-up of U.S. manufacturing in the past several decades. Increased international trade explains less than one third of the reduction in pollution from composition changes, and only one-tenth of the overall pollution reduction of the sector. This paper draws on Levinson's method of presenting time trends and provides a more complete picture of the evolution of CO<sub>2</sub> emissions from U.S. industry, in addition to decomposition results between end years. The SDA approach for analyzing embodied emissions in international trade is also adopted.

### 3 Data

This section describes the data used in the analysis. Data on total industrial CO<sub>2</sub> emissions are obtained from the U.S. Greenhouse Gas Inventory Report by the EPA (2012). To conform to the definition of industry adopted in this study as well as the energy use data

from the EIA, the sum of the reported CO<sub>2</sub> emissions from the industrial and agricultural sectors is used as the total for industry. Emissions from power generating industries are distributed to end-use sectors. Hence, the overall industrial CO<sub>2</sub> emissions used here include direct emissions from agriculture, mining, construction and manufacturing, as well as indirect emissions embodied in purchased electricity used in those activities. The majority of CO<sub>2</sub> emissions from this aggregated sector come from manufacturing, accounting for just about 80%.<sup>11</sup>

CO<sub>2</sub> emissions intensities of disaggregated industries are drawn from a report by the Economics and Statistics Administration (ESA) (2010). The underlying data are those from the Manufacturing Energy Consumption Survey (MECS) by the EIA for the years 1998, 2002 and 2006 as well as the EIA and the EPA's emissions inventory data for the relevant years. Direct emissions are estimated by distributing the reported emissions of more aggregated sectors to disaggregated Iliad<sup>12</sup> industries based on energy use data. As with the case of overall emissions, emissions from power generating industries are distributed to end-use industries. In addition to energy-related emissions, major process emissions and emissions from non-energy use are also accounted for. Total embodied emissions in the output of each industry, taking into consideration the emissions content of intermediate inputs, are estimated using an input-output framework similar to SDA. Emissions embodied in imported inputs are assumed to be the same as their domestic counterparts. The emissions data are combined with real gross output data from the BEA (2012) to estimate the emissions intensities of respective industries. Gross output is chosen as the unit of economic activity rather than value added for two reasons. First, value added or GDP data are only available for disaggregated industries in manufacturing, but not for those in agriculture, mining or construction. Second, international trade data are typically reported as the value of shipments, which corresponds more closely to gross output rather than value added.

International trade data are taken from the U.S. Census Bureau.<sup>13</sup> The raw data in the 8-digit Harmonized System (HS) classification are then aggregated to the 6-digit North American Industry Classification System (NAICS), using concordances provided by the Census Bureau and Pierce and Schott (2009).

Sectoral energy use by fuel type, the CO<sub>2</sub> emissions conversion factors of the various energy sources, and the related CO<sub>2</sub> emissions are obtained from the Annual Energy Review of the EIA (2012). Note that these emissions are less than those reported by the EPA, since they only include CO<sub>2</sub> emissions from energy use, and not process emissions, etc.

---

<sup>11</sup>The percentage is calculated using data from the Economics and Statistics Administration (ESA) for the years 1998, 2002 and 2006.

<sup>12</sup>Iliad stands for *Interindustry Large-scale Integrated And Dynamic model of the US*. It is a detailed input-output model developed by the Interindustry Forecasting Project at the University of Maryland (Inforum). Based on the 2002 North American Industry Classification System (NAICS), it has 360 input-output sectors, out of which 265 are in agriculture, mining, construction and manufacturing.

<sup>13</sup>The data for years 1990 to 2005 are obtained from Schott (2008), and those for years 2006 to 2010 are from data disks published by the Census Bureau (2007-2011).



The units of analysis are the BEA's input-output industries, based on NAICS. With 237 industries, it is the most detailed common disaggregation of the data assembled for this study. All data are converted using appropriate concordances. This level of disaggregation provides far more detail than recent decomposition analysis of U.S. CO<sub>2</sub> emissions or energy use. Although there were studies using more than 480 industries in the 1980s, more recent studies typically use fewer than 50 industries in the aggregate economy and fewer than 30 industries in the industrial sector (Liu and Ang, 2007). More importantly, this approach helps to mitigate the aggregation issue discussed in section 2 and allows a clearer interpretation of the result.

It is worth noting that there are a few potential issues with the data. The first is the limited availability of emissions data by disaggregated industries, which limits the analysis to a short time span. The greening process of U.S. industry has been ongoing since the 1970s. According to the EIA's emissions data, industrial CO<sub>2</sub> emissions from energy use hit its highest level in 1979. From then until 2007, emissions have decreased by more than 12%, while real GDP of private goods producing industries has almost doubled. The EPA's earliest emission data go back to 1990. From then until 2007, industrial emissions increased by two percent while real GDP grew 55%. Nonetheless, the available period from 1998 to 2006 coincides with the time between the most recent peak of industrial emissions in 1997 and the Great Recession. It should provide valuable information without having to worry about the economy in a severe crisis, and may reveal new patterns different from those previously discovered. In addition, following Levinson (2009), the scale and composition effects can be projected using only the base-year (1998) emissions intensities, and a series of yearly decompositions can be presented for a more complete illustration of the process.

A second issue is the discrepancies between the emissions data provided by the various sources. CO<sub>2</sub> emissions from energy use, directly from the EIA, are only used in decomposing the fuel mix. The emissions data from the EPA and the ESA are reasonably similar. Overall CO<sub>2</sub> emissions attributed to the industrial sector by the ESA are larger than those reported by the EPA in 1998 and 2002, by about two percent and three percent respectively. The figures for 2006 are almost the same, with the ESA number exceeding that from the EPA by less than one tenth of a percent. Since the ESA used emissions reported by the EIA and the EPA as basis for their calculations, the discrepancies should have been relatively small. One possible explanation for the ESA figures being larger could be that the ESA assigns some of the emissions from the transportation sector, namely those from light-duty vehicles, to the industrial sector (as well as households and public sectors). In this case, the similarity of the 2006 numbers is puzzling. However, this could be explained by the fact that the ESA used the initial release of the MECS for 2006, while the EPA figures have been revised later on. Fortunately, for the main analysis based on the Laspeyres index, only the emissions intensities of the base year and relative changes in emissions are needed, with units being irrelevant. Any mismatches between the ESA and the EPA figures will not be a problem as long as the ratio of the true industrial emissions to the EPA estimates remains constant over time.

A third data issue arises from the need to choose an appropriate price index to deflate the nominal measures of economic activity. In certain emissions-intensive industries,

prices may have changed faster than the overall producer price index (PPI) due to factors unrelated to the nature of the products. Therefore, using the PPI can exaggerate changes in predicted emissions based on the scale and composition of the industrial sector as revenues rather than actual quantities are used to measure output. For instance, since energy-intensive industries are also carbon-intensive, when energy prices rise faster than the PPI, using the PPI will exaggerate the role of technology in the clean-up. This is indeed a problem, because the period from 1998 to 2006 has witnessed fast increases in fossil fuel prices. Therefore, industry-specific price indices are used in the analysis. However, by doing so, the composition of the industries is sensitive to the choice of base year. Fortunately, this does not have any significant effect on the results.

## 4 Technology: An Indirect Assessment of the Technique Effect

In environmental economics, it is now conventional to think about changes in total pollution as coming from three sources, the overall size of the economy (“scale”), the mix of sectors and industries comprising the economy (“composition”), and the technologies employed in production and abatement (“technique”). Mathematically, total industrial CO<sub>2</sub> emissions,  $V$ , can be written as the sum of emissions from each of its component industries,  $V_i$ . This in turn can be written as the gross output of industry,  $Y$ , multiplied by the sum of each industry’s share of total output,  $\theta_i = Y_i/Y$ , times an emissions coefficient that reflects the amount of emissions per dollar of real gross output in that industry  $z_i = V_i/Y_i$ ,

$$V = \sum_i V_i = \sum_i Y_i z_i = Y \sum_i \theta_i z_i \quad (1)$$

or, in vector notation,

$$V = Y \boldsymbol{\theta}' \mathbf{z} \quad (2)$$

where  $\boldsymbol{\theta}$  and  $\mathbf{z}$  are  $n \times 1$  vectors comprising the market shares of each of the  $n$  industries and their emissions intensities, respectively.

Totally differentiating equation (2) yields

$$dV = \boldsymbol{\theta}' \mathbf{z} dY + Y \mathbf{z}' d\boldsymbol{\theta} + Y \boldsymbol{\theta}' d\mathbf{z} \quad (3)$$

The first term in equation (3) is the scale effect, which explains what happens to total emissions as the overall size of the industrial sector increases, holding fixed the composition of disaggregated industries and their emissions intensities; the second term is the composition effect, which accounts for the changing mix of industries, holding constant the overall scale and the emissions intensities; and the third term is the technique effect, which captures changes in emissions levels resulting from varying the emissions intensities, holding fixed scale and composition.<sup>14</sup>

---

<sup>14</sup>This formulation in total differentials is based on infinitesimal changes. As pointed out by Levinson (2009), using it for decomposition of discrete-time changes assumes that there are no interaction terms.

Estimating how much of the historical emissions reduction can be attributed to each of the three effects in equation (3) requires time series data on total emissions  $V$ , total output  $Y$ , and each industry's share of total output  $\theta$ . The one variable in equation (3) that is not available by year is  $\mathbf{z}$ , each industry's emissions intensity. Therefore, I calculate the first term and a modified version of the second term in equation (3), and construct the third term as the remainder. In discrete-time notation,

$$\begin{aligned}
\Delta V &= V^t - V^0 \\
&= \Delta V_Y + \Delta V_\theta + \Delta V_z \\
\Delta V_Y &= Y^t \theta^{0'} \mathbf{z}^0 - V^0 \\
\Delta V_\theta &= Y^t \theta^{t'} \mathbf{z}^0 - Y^t \theta^{0'} \mathbf{z}^0 \\
\Delta V_z &= V^t - Y^t \theta^{t'} \mathbf{z}^0
\end{aligned} \tag{4}$$

where the superscripts 0 and  $t$  denote the base and the current periods respectively, and  $\Delta V_Y$ ,  $\Delta V_\theta$  and  $\Delta V_z$  are the scale, composition and technique effects. This is effectively a modified Laspeyres index decomposition in additive form with the following interpretation.  $\Delta V_Y$  is the change in overall emissions resulting from a scaling of the economy, holding composition and the emissions intensities fixed;  $\Delta V_Y + \Delta V_\theta$  gives the changes in emissions resulting from changes in economic activities including both the scale and composition aspects, holding emission intensities fixed;  $\Delta V_z$  captures the residual changes, resulting from changes in the emissions intensities and their interactions with scale and compositional changes. Compared to a conventional Laspeyres index decomposition,<sup>15</sup> the scale effect remains the same, while the residual term in the Laspeyres decomposition is spread over the composition and technique effects in equation (4). The changes in percentage terms relative to the base-year emissions are then reported. This formulation uses the base-year, or start-year, emissions intensities,  $\mathbf{z}^0$ . The results may differ from what they would be if end-year intensities,  $\mathbf{z}^t$ , were used.<sup>16</sup> In particular, if over this time period the dirty industries were cleaned up more, proportionally, than the clean industries, then using the base-year emissions intensities will underestimate the technique

---

For instance, changing the scale of industry does not affect the industry composition or the emissions intensities. Alternatively, we can think of equation (3) as assuming that all of those interaction terms are combined into the third term, the technique effect, which will be a remainder of changes after accounting for the first and second terms. This is equivalent to a Laspeyres index decomposition with the residual term added to the third term.

<sup>15</sup>See the method (a) in the appendix for a description of the Laspeyres index methods. A Laspeyres index decomposition of equation (2) in the additive form is

$$\begin{aligned}
\Delta V &= \Delta V_Y + \Delta V_\theta + \Delta V_z + \Delta V_R \\
\Delta V_Y &= Y^t \theta^{0'} \mathbf{z}^0 - V^0 \\
\Delta V_\theta &= Y^0 \theta^{t'} \mathbf{z}^0 - V^0 \\
\Delta V_z &= Y^0 \theta^{0'} \mathbf{z}^t - V^0
\end{aligned}$$

and  $\Delta V_R$  is a residual term consisting of the interaction terms of the scale ( $\Delta V_Y$ ), composition ( $\Delta V_\theta$ ) and technique ( $\Delta V_z$ ) effects.

<sup>16</sup>In this case, the scale, composition and technique effects are formulated as follows.

effect (in percentage terms). Hence, by using the base-year intensities, it gives a conservative estimate of the role of technology. On the contrary, if over this time period the emissions-intensive industries cleaned up less relatively, the role of technology will be overstated. Based on the available data on the emissions intensities in years 1998, 2002 and 2006, it appears that neither scenario is a concern, as the correlations between the initial-period intensities and the percentage changes in the four or eight years afterwards are very weak.

Figure 3 illustrates the analysis for industrial CO<sub>2</sub> emissions. Line (1) plots the trend for CO<sub>2</sub> emissions from U.S. industry, as reported by the EPA and scaled so that the 1998 emissions equal 100. The emissions in 2007 are 4.6% below the 1998 level. This represents the combined scale, composition, and technique effects, or  $\Delta V$  in equation (4), relative to base-year emissions,  $V^0$ . Line (2) depicts the total real gross output of the U.S. industrial sector, deflated using sectoral price indices and scaled so that the 1998 value equals 100. If the mix of industries making up the industrial sector had remained constant, i.e.,  $d\theta = 0$ , and the technology of production and abatement had remained constant, i.e.,  $dz = 0$ , line (2) represents how emissions would have changed over time. This 7.9% increase from 1998 to 2007 is the scale effect, or  $\Delta V_Y$ . Line (3) in the figure is the result of multiplying each industry's real gross output in each year ( $Y_i^t$ ) by the CO<sub>2</sub> emissions coefficient in 1998 ( $\mathbf{z}_i^0$ ) and aggregating across industries to obtain  $Y^t \theta^{t'} \mathbf{z}^0$ . It represents what CO<sub>2</sub> emissions would have been in each year if each industry had produced its concurrent output, but used the production and abatement technology from 1998. This combines the scale and composition effects,  $\Delta V_Y + \Delta V_\theta$ , which added up to 8.5% from 1998 to 2007. Line (3) lies slightly above line (2), indicating that the composition of the U.S. industrial sector had shifted slightly toward industries that emit CO<sub>2</sub> more heavily. The difference between line (3) and line (2) suggests that the composition effect,  $\Delta V_\theta$ , had led to an increase in emissions of about 0.6%. This effect is small and not consistent over time. As can be seen in the figure, in 2006, the composition effect suggests a slight move toward cleaner industries relative to 1998. Lastly, the technique effect,  $\Delta V_z$ , is the difference between lines (1) and (3). From 1998 to 2007, the scale, composition, and technique effects together accounted for a reduction of CO<sub>2</sub> emissions by 4.6%, while the scale and composition effects alone would have implied an increase in emissions of 8.5%. Therefore, the technique effect must account residually for a 13.1% decline in emissions, offsetting the opposite forces of the scale and composition effects.

It is not surprising that improvements in technology turn out to be the most important factor contributing to the clean-up. What is interesting, however, is that changes in industry composition had little effect. If anything, U.S. industry seems to have shifted

---


$$\begin{aligned}\Delta V_Y &= V^T - Y^t \theta^{T'} \mathbf{z}^T \\ \Delta V_\theta &= Y^t \theta^{T'} \mathbf{z}^T - Y^t \theta^{t'} \mathbf{z}^T \\ \Delta V_z &= Y^t \theta^{t'} \mathbf{z}^T - V^t\end{aligned}$$

Compared to a conventional Paasche index decomposition (See the method (b) in the appendix), the technique effect remains the same, with the residual term spread over the other two terms.

toward more emissions-intensive industries over the period. Previous studies have generally found the composition effect to be of the other direction, i.e., toward a cleaner mixture of industries, and of a large magnitude (Weber, 2009; Huntington, 2010). There are two plausible explanations for the different findings here. First, this study covers only the industrial sector, while the other studies apply to the overall economy. Therefore, broader structural changes between aggregate sectors, such as a shift from manufacturing to service, will not be captured in the current analysis. Rather, this will be reflected as a smaller scale effect, i.e., the industrial output had grown more slowly than it would have had it maintained the same share of GDP. Second, this may indeed be a new pattern revealed by more recent data. Looking closely at lines (2) and (3) in Figure 3, one can see that indeed the composition shift was toward cleaner industries in the late 1990s. However, the trend has been reversed in the 2000s, generating a net composition effect that is negligible. This can potentially be attributed to the lack of a national climate change policy in the United States. While other industrialized countries committed to quantitative GHG emissions targets under the Kyoto Protocol, the United States had not and did not plan to ratify the protocol which went into effect in mid-2000s. This unique position, absent of carbon taxes or cap-and-trade systems, has contributed a U.S. comparative advantage in producing more carbon-intensive goods. Though these compositional shifts are small and could be affected by a number of factors

As mentioned in Section 2, there have been a multitude of decomposition methods proposed and utilized in empirical research. Each index has its advantages and shortcomings. Generally, alternative decomposition methods provide similar results, though differences could be significant at times. To provide a robustness check for the analysis, I calculate a variety of decomposition indices for comparison and present the results in the appendix. In all cases, the results are qualitatively similar to those presented above.

## 5 Energy Demand and Fuel Switching: Decomposing the Technique Effect

The previous section shows that the technique effect is responsible for the clean-up of the U.S. industrial sector. This section takes a closer look at this effect and attempts to allocate credit to different types of technique changes, using a different set of data. Two main technological advances are directly related to energy use, which is the largest source of CO<sub>2</sub> and of overall GHG emissions. One of these is the improvement in energy efficiency or energy productivity. If an industry uses less energy to produce the same amount of goods, the industrial CO<sub>2</sub> emissions need not grow as the economy expands. The other is the change in the fuel mix that the industries employ. Since the different types of fossil fuels have substantially different conversion factors between their energy content and carbon content, switching from using a dirtier fossil fuel, such as coal, to a cleaner one, like natural gas, may significantly reduce CO<sub>2</sub> emissions.

Potentially, the conversion factors may also vary over time. Nonetheless, in the case of primary energy sources such as coal, oil and natural gas, the conversion factors are mainly determined by the chemical makeup of the fuel. Hence, such variations, while

they do exist across location and time, are very small in magnitude. The lone exception is electricity, whose conversion factor is in turn largely affected the mix of primary energy sources used for its generation. Therefore, changing conversion factors is not considered a major explanation for the technique effect.

This section focuses on energy-related CO<sub>2</sub> emissions and leaves out process emissions from the analysis. CO<sub>2</sub> emissions from fossil fuels and biomass use, including those directly by the industrial sector and those indirectly through the use of retail electricity, account for more than 80% of all industrial CO<sub>2</sub> emissions. Similar to equation (1), total energy-related emissions from industry,  $V^E$ , can be written as the sum of emissions from each of its energy sources,  $V_j^E$ . This in turn can be written as total energy demand from industry,  $E$ , multiplied by the sum of each fuel's share of total energy,  $\sigma_j = E_j/E$ , times a conversion factor that reflects the amount of emissions per unit of energy content for that energy source,  $c_j = V_j^E/E_j$ . Further, the total energy demand,  $E$ , can be expressed by the real gross output of the industrial sector,  $Y$ , times the average energy intensity of the sector,  $e$ .

$$V^E = \sum_j V_j^E = \sum_j V_j^E c_j = E \sum_j \sigma_j c_j = eY \sum_j \sigma_j c_j \quad (5)$$

or in vector notation,

$$V^E = E\boldsymbol{\sigma}'\mathbf{c} = eY\boldsymbol{\sigma}'\mathbf{c} \quad (6)$$

where  $\boldsymbol{\sigma}$  and  $\mathbf{c}$  are  $m \times 1$  vectors comprising the shares of each of the  $m$  fuels and their emissions conversion factors, respectively.

Totally differentiating equation (6) yields

$$dV^E = \boldsymbol{\sigma}'cdE + E\mathbf{c}'d\boldsymbol{\sigma} + E\boldsymbol{\sigma}'d\mathbf{c} \quad (7)$$

$$= e\boldsymbol{\sigma}'cdY + Y\boldsymbol{\sigma}'cde + eY\mathbf{c}'d\boldsymbol{\sigma} + eY\boldsymbol{\sigma}'d\mathbf{c} \quad (8)$$

Equation (7) closely mirrors equation (3). The first term is the scale effect, relating to the level of total energy use. The second term is the composition effect, which accounts for the effect of the changing mix of energy sources. The third term is the technique effect, which captures the effect of the changes in the carbon intensity of various fuel sources. As discussed earlier, the only major energy source whose carbon intensity may have substantial moves in the time frame of the analysis is electricity. If the mixture of the primary sources used in electricity generation changes significantly, electricity can become more or less emissions intensive. Additionally, if the power stations and the electric grid become more efficient, hence requiring less raw energy to provide a unit of retail electricity, the conversion factor for electricity will also become smaller.

Equation (8) further decomposes the energy scale effect into contributions from the size of the industrial sector and its energy intensity. One may be tempted to label the change in energy intensity as purely technological; however, it does include the compositional effects resulting from a restructuring of the industries with varying energy intensities within the industrial sector.

Figure 4 shows the result of the decomposition following equation (7) in a similar way to equation (4). From 1998 to 2007, CO<sub>2</sub> emissions from energy use by the industrial

sector were reduced by about 7.6%, as shown by line (1). The main contributing factor is a reduction in energy use, represented by line (2), which dropped by about seven percent during the period. The composition effect, i.e., the difference between line (3) and line (2), is small and has actually contributed to more emissions, by 0.4%, over the same period, as much of the shift was from relatively less carbon intensive natural gas to more carbon intensive petroleum prior to the shale gas boom in the late 2000s. In the meantime, reduced carbon intensities of the energy sources contributed to a reduction of CO<sub>2</sub> emissions of about one percent. In fact, this technique effect comes predominantly from a reduced carbon conversion factor for retail electricity. This in turn comes from two sources. The first is the improved efficiency in the power sector and its delivery system, resulting in less primary energy use for the same amount of electricity provided for retail use. The second factor is the mix of primary energy sources for the power sector. In more recent years, the technique effect has become more pronounced as the emissions intensity of electricity drops further with gas-powered plants replacing coal generation, with the shale gas boom providing cheap natural gas on the U.S. market.

The observation that most of the energy-related CO<sub>2</sub> emissions reduction comes from lower energy demand despite output growth supports the idea that improved energy efficiency is an important factor in the greening of U.S. industry. However, there remains to be determined what exactly drives this reduced energy intensity of the industrial sector. It can come from adopting new technologies or practice innovations that saves energy, or from substitution of the energy input with other factors in production, such as labor or raw materials. After all, the period of 1998-2007 was one that saw crude oil prices rise from \$20 to \$80. The increasingly expensive fossil fuels could have potentially induced firms to engage in more energy-saving arrangements in one way or another. From a policy perspective, the two possibilities have different implications. If the change was driven by improved energy efficiency or technological breakthroughs, a policy aiming to replicate the clean-up may emphasize innovation and technology diffusion. On the other hand, if most of the changes are a result of input substitution, then market based policies that affect the relative prices of inputs might be more effective. This is the idea of directed technological change in the framework of Acemoglu, Aghion, Bursztyn & Hemous. (2012). Of course, the two aspects are not independent of one another. Both could be responses to increasing energy prices and both serve to optimize production. The substitution of production factors is in fact an important component of production technology.

A number of studies have attempted to further pin down the potential causes of the aforementioned improvement in energy productivity. Casler and Rose (1998) uses SDA to show that substitution within the energy sector and between energy and other inputs was the leading cause of the decline in carbon dioxide emissions in the United States over the period from 1972 to 1982. Sue Wing (2008) uses econometric methods to show that price-induced substitution of variable inputs generated transitory energy savings, while innovation induced by energy prices had only a minor impact. Due to data limitations further analysis is beyond the scope of the current paper.

## 6 International Trade: Measuring Displaced Emissions

The previous sections have documented the declining trends in the carbon emissions and energy use of U.S. industry. In recent years, one focal point of the discussion on climate change policies has been carbon leakage, i.e., such clean-ups by the developed economies have simply come from shifting the production of emissions-intensive goods elsewhere. To analyze whether the experience of U.S. industry in the late 1990s to the mid-2000s is subject to the same concern, I apply a similar approach to analyze emissions related to goods traded internationally. Let  $V^M$  be the extra CO<sub>2</sub> that would have been emitted in the United States had imported goods been produced domestically. This can be written as the sum of the extra emissions from each imported industry,  $Y_i^M$ , which in turn can be expressed as the total value of imports,  $Y^M$ , multiplied by the sum of each industry's share in that total imports,  $\theta_i^M = Y_i^M/Y^M$ , times each industry's emissions per dollar of shipments in the United States,  $z_i = V_i/Y_i$ ,

$$V^M = \sum_i V_i^M = \sum_i Y_i^M z_i = Y^M \sum_i \theta_i^M z_i \quad (9)$$

or, in vector notation,

$$V^M = Y^M \boldsymbol{\theta}^M \mathbf{z} \quad (10)$$

where  $\boldsymbol{\theta}^M$  and  $\mathbf{z}$  are  $n \times 1$  vectors comprising the import shares of each of the  $n$  industries and their emissions intensities, respectively.

Note that  $V^M$  does not measure the emissions occurring overseas as a consequence of producing the goods for the United States, because other countries could have different emissions intensities from the United States. In addition, neither does it measure the exact additional U.S. industrial emissions had those imported goods been produced domestically, because producing all imports domestically would almost surely alter the relative prices and affect the domestic emission intensities. Rather,  $V^M$  estimates the amount of CO<sub>2</sub> emissions “displaced” by imports, assuming that domestic emissions intensities were not affected.

Another important issue that needs to be addressed before proceeding with the analysis is to choose the appropriate measure of emissions intensities. In the previous analysis of domestic emissions, direct emissions intensities have been used, accounting for only emissions that are generated directly by the industry making the output.<sup>17</sup> The fact that the emissions generated by intermediate products are not separately calculated does not matter. The intermediate input of one industry must be the output of another. Therefore, the emissions embodied in intermediate products are accounted for as long as they are produced domestically. In the case of international trade, however, ignoring the emissions embodied in intermediate inputs can significantly underestimate the emissions embodied in the entire production process of traded goods (Levinson, 2009). To address this issue, I use total emissions intensities derived through an input-output framework, which takes

---

<sup>17</sup>Except for emissions in the electricity generating industry, which are distributed to end-use industries.



into account emissions throughout the production chain. Analysis using direct emissions intensities is also presented for comparison.

A similar decomposition analysis to equation (4) can be performed on the displaced emissions. Totally differentiating equation (10) yields

$$dV^M = \boldsymbol{\theta}^{M'} \mathbf{z} dY^M + Y \mathbf{z}' d\boldsymbol{\theta} + Y \boldsymbol{\theta}' d\mathbf{z} \quad (11)$$

where the three terms in the decomposition are the scale, composition and technique effects respectively. Unlike in previous sections, since the displaced emissions are not directly measured, but only estimated using current-period trade data and base-year emissions intensities data, only the scale and composition effects can be estimated.

Figure 5 shows the evolution of emissions embodied in U.S. imports from 1998 to 2010. Total value of U.S. imports, represented by line (1), grew by more than 75% in real terms from 1998 to 2007. This is the scale effect in equation (11). Line (2) plots the displaced emissions calculated following equation (10), taking into account emissions from intermediate inputs while assuming that the emissions intensities stayed constant as in 1998. It closely tracks the path of the volume growth. This suggests that overall the mix of U.S. imports did not become more emissions intensive since the late 1990s, as the difference between line (2) and line (1) represents the composition effect. In fact, the average imports appeared to have become slightly less emissions intensive in recent years. Note that an analysis using the direct emissions intensities would suggest a much stronger clean-up trend in the composition of U.S. imports. The emissions embodied in U.S. exports are also calculated in a similar fashion, and are presented in Figure 6. The U.S. exports also grew rapidly, up by 60% from 1998 to 2007. Unlike the imports, the embodied emissions of the U.S. exports seem to have slightly outpaced their volume growth. Using the direct emissions intensities would again lower the emissions path, but not by much this time.

It is also interesting to further disaggregate trade with different partner countries. U.S. trade was traditionally dominated by its exchange with other industrialized countries, but imports from emerging markets have been rising rapidly during the time period under consideration. In 1998, imports from high-income OECD countries represented 52% of all U.S. imports; exports to these countries accounted for 57% of total U.S. exports. By 2007, the shares had dropped to 41% and 51% respectively, and further to 35% and 45% by the end of the decade as the developed economies were slow to recover from the global financial crisis. Concerns about carbon leakage and competitiveness often surface in debates about domestic regulations of carbon emissions. Such worries, similar to the pollution haven theories, focus on trade with the developing nations. Figure 7 shows the decomposition of the trade-embodied emissions disaggregated to trade with Annex I countries,<sup>18</sup> or the industrialized countries, and the others. Indeed, different patterns can be observed for the two groups. Apart from the striking difference in growth rates, it is notable that the

---

<sup>18</sup>Annex I countries are those that are parties to the Annex I of the Kyoto Protocol. These include high-income OECD countries, which are traditionally important trade partners of US, and Eastern European and some former Soviet states, whose share in US trade is small (less than two percent of imports or exports throughout the analysis period). Annex I countries committed to quantitative GHG emissions caps under the Kyoto Protocol.

composition of the U.S. imports from Annex I countries have become cleaner over time, while that from non-Annex I economies have become more carbon-intensive. The average U.S. exports to non-Annex I countries have also become more emissions intensive, though the exports to Annex I countries have not shown much change in terms of emissions intensity. These facts are consistent with the findings of Wang (2012) that the United States is importing more emissions-intensive products from countries with less stringent climate change policies. The differential paths in the trading patterns suggest that such concerns about carbon leakage are not completely off base.

The strong growth in international trade, particularly in imports, led to more than a doubling of net imports for the United States, as shown by line (1) in Figure 8. Though the net imports do not appear to have become more emissions intensive, the rise in its scale has sizable implication for the emissions picture of U.S. industry. Figure 3 illustrates the last step in the analysis, estimating the fraction of the U.S. emissions reduction that can be explained by changes in the combined scale and compositional variations of international trade. Using emission intensities of 1998 and replacing the imports in equation (10) with the changes in net imports from 1998, I obtain an estimate of CO<sub>2</sub> emissions displaced by the changes in net trade from 1998 had technology remained unchanged since then. By 2007, this would imply a four percent increase in emission relative to the 1998 level. Line (4) in Figure 3 uses this series. Holding technology fixed as of 1998, line (4) plots what U.S. industrial CO<sub>2</sub> emissions would have been if the all increased net imports since 1998 had instead been produced domestically in the United States. The difference between line (3) and line (4) therefore represents the contribution of net trade changes to the clean-up of U.S. industry. From 1998 to 2007, this net trade change effect of negative four percent amounts to about one third of the scale effect and a little less than one fourth of the total clean-up from the combined scale, composition effects and no-net-trade-change scenario, i.e., the difference between line (1) and line (4). The remaining three quarters are attributed to the technique effect.

It should be noted that this no-net-trade-change scenario, similar to all the displaced emissions calculations, represents a purely partial-equilibrium analysis. In no sense does line (4) in Figure 3 represent what the level of U.S. industrial emissions would actually have been absent trade growth even if technology stayed constant. It is merely an accounting exercise, asking what fraction of the clean-up of U.S. industry can be matched to increased imports. In fact, if the United States imports the carbon-intensive goods because they are less expensive when produced abroad, then in the absence of trade growth the U.S. economy would likely produce and consume fewer such carbon-intensive goods.

## 7 Conclusion

The analysis suggests that recently most of the carbon emissions reduction in the U.S. industrial sector has come from changes in technology, rather than from increases in net imports or changes in the types of goods produced domestically. From 1998 to 2007, industrial CO<sub>2</sub> emissions decreased by 4.6%. The technique effect is by far the most important driving force, which accounts for almost all of the reduction in emissions. With

respect to international trade, the effect of increased net imports amounts to less than one third of the technique effect, or less than one fourth of the total clean-up of U.S. industry. Furthermore, most of the technique effect can be attributed to improved energy efficiency in the industrial sector, with fuel switching playing a minor role.

The decomposition exercises are rather mechanical, and they are meant to serve as a first step in identifying the forces driving carbon emissions as well as opportunities for further environmental improvement. A useful accompanying exercise would be to decompose the changes in carbon emissions of the aggregate economy and find out if the findings on the industrial sector generalize to the wider economy. An interesting follow-up study would be to assess the drivers behind the downward trend in energy demand, as mentioned in section 5. Despite a lack of CO<sub>2</sub> emissions regulations at the federal level, there have been plenty of state and regional policies attempting to address climate change in the United States. Did any of these or other environmental regulations have an impact on energy uses? Was it caused by innovation and improvements in technology or do energy prices play a more important role? Further analysis should provide more insight into the evolution of U.S. GHG emissions as well as the impacts of potential policies.

## References

- Acemoglu, D., Aghion, P., Bursztyn, L., & Hémous, D. (2012). "The environment and directed technical change," *American Economic Review*, 102, 131-166.
- Ang, B.W. (2004) "Decomposition analysis for policymaking in energy: Which is the preferred method?" *Energy Policy*, 32, 1131-1139.
- Ang, B.W., Liu, F.L., & Chew, E.P. (2003). "Perfect decomposition techniques in energy and environmental analysis,". *Energy Policy*, 31, 1561-1566.
- Ang, B.W., Liu, F.L., & Chung, H.S. (2004). "A generalized Fisher index approach to energy decomposition analysis,". *Energy Economics*, 26, 757-763.
- Ang, B.W. & Zhang, F.Q. (2000). "A survey of index decomposition analysis in energy and environmental studies," *Energy*, 25, 1149-1176.
- Boyd, G.A., Hanson, D.A., & Sterner, T. (1988). "Decomposition of changes in energy intensity: A comparison of the Divisia index and other methods," *Energy Economics*, 10, 309-312.
- Casler, S.D., & Rose, A. (1998). "Carbon dioxide emissions in the US economy: A structural decomposition analysis," *Environmental and Resource Economics*, 11, 349-363.
- de Boer, P. (2009). "Generalized Fisher index or Siegel-Shapley decomposition?" *Energy Economics*, 31, 810-814.
- Dietzenbacher, E. & Los, B. (1998). "Structural decomposition techniques: Sense and sensitivity," *Economic Systems Research*, 10, 307-324.
- Economics and Statistics Administration (ESA), U.S. Department of Commerce (DOC). (2010). "US carbon dioxide emissions and intensities over time: A detailed accounting of industries, government and households." Available at: <http://www.esa.doc.gov/Reports/u.s.-carbon-dioxide>.
- Fortin, N., Lemieux, T., & Firpo, S. 2011. "Decomposition methods in economics," in Card, D., & Ashenfelter, O., eds., *Handbook of Labor Economics*, 4th Edition, Elsevier North Holland, 1-102.
- Golove, W.H. & Schipper, L.J. (1996). "Long-term trends in US manufacturing energy consumption and carbon dioxide emissions," *Energy*, 21, 683-692.
- Golove, W.H., & Schipper, L.J. (1997). "Restraining carbon emissions: Measuring energy use and efficiency in the USA," *Energy Policy*, 25, 803-812.
- Greening, L.A., Davis, W.B., & Schipper, L. (1998). "Decomposition of aggregate carbon intensity for the manufacturing sector: Comparison of declining trends from 10 OECD countries for the period 1971-1991," *Energy Economics*, 20, 43-65.

- Greening, L.A., Ting, M., & Davis, W.L. (1999). "Decomposition of aggregate carbon intensity for freight: Trends from 10 OECD countries for the period 1991-1993," *Energy Economics*, 21, 331-361.
- Greening, L.A., Ting, M., & Krackler, T.J. (2001). "Effects of changes in residential end-uses and behavior on aggregate carbon intensity: Comparison of 10 OECD countries for the period 1970 through 1993. *Energy Economics*, 23(2), 153-178.
- Hamilton, C. & Turton, H. (2002). "Determinants of emissions growth in OECD countries," *Energy Policy*, 30, 63-71.
- Hoekstra, R. & Van den Bergh, J.C. (2003). "Comparing structural decomposition analysis and index," *Energy Economics*, 25, 39-64.
- Huntington, H.G. (1989). "The impact of sectoral shifts in industry on US energy demands," *Energy*, 14, 363-372.
- Huntington, H.G. (2010). "Structural change and US energy use: Recent patterns," *Energy Journal*, 31, 25-39.
- Intergovernmental Panel on Climate Change (IPCC). (2007). "Summary for policymakers," in Metz, B., Davidson, O.R., Bosch, P.R., Dave, R., & Meyer, L.A. (eds.), *Climate Change 2007: Mitigation. Contribution of Working Group III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.
- Kim, Y. & Worrell, E. (2002). "International comparison of CO<sub>2</sub> emission trends in the iron and steel industry," *Energy policy*, 30, 827-838.
- Leontief, W. (1970). "Environmental repercussions and the economic structure: An input-output approach," *Review of Economics and Statistics*, 52, 262-271.
- Lescaroux, F. (2008). "Decomposition of US manufacturing energy intensity and elasticities of components with respect to energy prices," *Energy Economics*, 30, 1068-1080.
- Levinson, A. (2009). "Technology, international trade, and pollution from US manufacturing," *American Economic Review*, 99, 2177-2192.
- Liu, F. (2004). "Decomposition analysis applied to energy: Some methodological issues," Dissertation. Available at <http://scholarbank.nus.sg/handle/10635/14741>.
- Liu, H., Polenske, K.R., Guilhoto, J.J.M., & Xi, Y. (2011). "Direct and indirect energy consumption in China and the United States," MRPA Paper No. 37960. Available at <http://mpra.ub.uni-muenchen.de/37960/>.
- Liu, N. & Ang, B.W. (2007). "Factors shaping aggregate energy intensity trend for industry: Energy intensity versus product mix," *Energy Economics*, 29, 609-635.

- Malla, S. & Im, E.I. (2011) "Assessment of factors affecting carbon dioxide emission from power generation in the united states: A decomposition analysis," *Asia-Pacific Journal of Social Sciences, Special Issue No. 2*, 97-113.
- Metcalf, G.E. (2008), "An empirical analysis of energy intensity and its determinants at the state level," *Energy Journal*, 29, 1-26.
- Mulder, P. & de Groot, H.L.F. (2012). "Structural change and convergence of energy intensity across OECD countries, 1970-2005," *Energy Economics*, 34, 1910-1921.
- Office of Energy Efficiency and Renewable Energy, U.S. Department of Energy. (2012). "Energy intensity indicators." Available at [http://www1.eere.energy.gov/analysis/eii\\_index.html](http://www1.eere.energy.gov/analysis/eii_index.html).
- Onder, H. (2012). "Trade and climate change: An analytical review of key issues," *Economic Premise*, 86, the World Bank, Washington, DC.
- Peters, G.P. & Hertwich, E.G. (2008). "CO<sub>2</sub> embodied in international trade with implications for global climate," *Environmental Science and Technology*, 42, 1401-1407.
- Pierce, J.R. & Schott, P.K. (2010). "Concording US Harmonized System codes over time." Available at: [http://faculty.som.yale.edu/peterschott/sub\\_international.htm](http://faculty.som.yale.edu/peterschott/sub_international.htm).
- Rose, A. (1999). "Input-output structural decomposition analysis of the energy and environment," *Handbook of Environmental and Resource Economics*, Cheltenham: Elgar, 1104-1179.
- Schipper, L.J., Haas, R., & Sheinbaum, C. (1996). "Recent trends in residential energy use in OECD countries and their impact on carbon dioxide emissions: A comparative analysis of the period 1973–1992," *Mitigation and Adaptation Strategies for Global Change*, 1, 167-196.
- Schipper, L., Murtishaw, S., Khrushch, M., Ting, M., Karbuz, S., & Unander, F. (2001). Carbon emissions from manufacturing energy use in 13 IEA countries: long-term trends through 1995. *Energy Policy*, 29(9), 667-688.
- Schipper, L., Ting, M., Khrushch, M., & Golove, W. (1997). "The evolution of carbon dioxide emissions from energy use in industrialized countries: An end-use analysis," *Energy Policy*, 25, 651-672.
- Scholl, L., Schipper, L., & Kiang, N. (1996). "CO<sub>2</sub> emissions from passenger transport: A comparison of international trends from 1973 to 1992," *Energy Policy*, 24, 17-30.
- Schott, P.K. (2008). "The relative sophistication of Chinese exports," *Economic Policy*, 23, 5-49.
- Su, B. (2011). "Environmental input-output analysis: Emissions embodied in trade and structural decomposition analysis," Dissertation. Available at <http://scholarbank.nus.sg/handle/10635/30258>.

- Su, B., Huang, H.C., Ang, B.W., and Zhou, P. (2010). "Input-output analysis of CO<sub>2</sub> emissions embodied in trade: The effects of sector aggregation," *Energy Economics*, 32, 166-175.
- Sue Wing, I. (2008). "Explaining the declining energy intensity of the US economy," *Resource and Energy Economics*, 30, 21-49.
- Sun, J.W. (1998). "Changes in energy consumption and energy intensity: A complete decomposition model," *Energy Economics*, 20, 85-100.
- Sun, J.W. and Malaska, P. (1998). "CO<sub>2</sub> emission intensity in developed countries 1980-1994," *Energy*, 23, 105-112.
- Torvanger, A. (1991) "Manufacturing sector carbon dioxide emissions in nine OECD countries, 1973-87: A Divisia index decomposition to changes in fuel mix, emission coefficients, industry structure, energy intensities and international structure," *Energy Economics*, 13, 168-186.
- U.S. Bureau of Economic Analysis (BEA) (2012). *GDP by Industry Data*. Available at [http://www.bea.gov/industry/gdpbyind\\_data.htm](http://www.bea.gov/industry/gdpbyind_data.htm).
- U.S. Census Bureau. (2007-2011). *US Imports Merchandise Trade, 2006-2010*, Washington, DC: U.S. Census Bureau.
- U.S. Census Bureau. (2007, 2009-2010). *Annual Survey of Manufactures (ASM), 2006, 2008-2009*. Available at: [http://factfinder.census.gov/servlet/DatasetMainPageServlet?\\_program=EAS](http://factfinder.census.gov/servlet/DatasetMainPageServlet?_program=EAS).
- U.S. Census Bureau. (2008). *2007 Economic Census and Surveys*. Available at: [http://factfinder.census.gov/servlet/DatasetMainPageServlet?\\_program=ECN](http://factfinder.census.gov/servlet/DatasetMainPageServlet?_program=ECN).
- U.S. Energy Information Administration (EIA). (2012). *Annual Energy Review*. Available at <http://www.eia.gov/totalenergy/data/annual/index.cfm>.
- U.S. Environmental Protection Agency (EPA). (2012). *Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990-2010*. Available at <http://www.epa.gov/climatechange/ghgemissions/usinventoryreport.html>.
- Vinuya, F., DiFurio, F., & Sandoval, E. (2010). "A decomposition analysis of CO<sub>2</sub> emissions in the United States," *Applied Economics Letters*, 17, 925-931.
- Weber, C.L. (2009). "Measuring structural change and energy use: Decomposition of the US economy from 1997 to 2002," *Energy Policy*, 37, 1561-1570.
- Wiedmann, T. (2009) "A review of recent multi-region input-output models used for consumption-based emission and resource accounting," *Ecological Economics*, 69, 211-222.

Wiedmann, T., Lenzen, M., Turner, K. & Barrett, J. (2007). "Examining the global environmental impact of regional consumption activities – Part 2: Review of input-output models for the assessment of environmental impacts embodied in trade," *Ecological Economics*, 61, 15-26.



## Appendix: Alternative Decomposition Analysis

As explained previously, the decomposition analysis featured in the main text largely amounts to an additive version of the Laspeyres index. To provide a robustness check for the analysis, I present in this appendix alternative IDA results for comparison.

A couple of data related issues are noted here. First, since calculating the indices, other than the modified Laspeyres used in the main text, requires detailed emissions coefficients at both the start and end periods, the indices reported are for changes between years 1998, 2002 and 2006, the years for which data are available. Second, the overall industrial emissions data utilized in the indices are also different from the series used in the main analysis. While the yearly emissions levels used before come from EIA, the emissions data in the IDA are from ESA, which conform with the emissions intensities data available. This results in different estimates of the changes in industrial CO<sub>2</sub> emissions over the years.

The indices are presented in Tables 1 through 2. The methods included are some of the widely adopted and recommended in decomposition analysis and related research (Ang, 2004). The traditional Laspeyres and Paasche methods produce sizable residues, sometimes larger than certain component effects. This can be attributed to weighting solely based on the starting or ending period. When the analyzed period is longer and changes are larger, the interaction effects of the different main components can become more pronounced and it results in large residue changes unaccounted. Nonetheless, these two methods still yield decomposition results in line with the other methods. The results suggest a similar story to the analysis in the main text. The technique effect has been the main driving force behind the reduction in the U.S. industrial CO<sub>2</sub> emission since late 1990s. It accounts for about four fifths of the clean-up (after accounting for the increase in scale), which the rest one fifth coming from the composition effect. The composition effect appears to be larger than claimed in the main text. This is partly due to the difference in end year. It can be seen in Figure 3 that by 2006, the composition effect does give a small contribution to the clean-up, but it vanishes after that.

Table 4 provides a similar presentation of IDA of industrial CO<sub>2</sub> emissions from energy use, offering a comparison to section 5. Since the emissions intensities data by fuel is available for all years, I provide the result for the period between 1998 and 2007, the focal period in the main text. This time, all methods provide remarkably similar decomposition results. They confirm the story that reduced energy use, or the scale effect, is by far the most important factor in the decline of energy-related CO<sub>2</sub> emissions from U.S. industry, accounting for more than 88% of the changes. The composition effect, or the changing energy mix, has a very small impact increasing emissions. The magnitude of the technique effect, mainly due to improved efficiency in the electricity sector, accounts for about one seventh of the decline of industrial energy intensity.

A summary of the decomposition methods used follows.

## Summary of Index Decomposition Formulae

Assume that  $V$  is an aggregate, there are  $n$  factors,  $V = \sum_i x_{1,i}x_{2,i}\dots x_{n,i}$  and  $V_i = x_{1,i}x_{2,i}\dots x_{n,i}$ , where  $i$  denotes an attribute of the aggregate such as an industry or fuel type. Further assume that from period 0 to period  $T$  the aggregate changes from  $V^0 = \sum_i x_{1,i}^0x_{2,i}^0\dots x_{n,i}^0$  to  $V^T = \sum_i x_{1,i}^Tx_{2,i}^T\dots x_{n,i}^T$ . Then a multiplicative decompositions is

$$D_{total} = V^T/V^0 = D_{x_1}D_{x_2}\dots D_{x_n}D_{residue}$$

and an additive decomposition is

$$\Delta V_{total} = V^T - V^0 = \Delta V_{x_1} + \Delta V_{x_2} + \dots + \Delta V_{x_n} + \Delta V_{residue}$$

where  $D_{residue}$  and  $\Delta V_{residue}$  are residual terms. Some methods do not have a residual term by design and are called perfect decomposition. Hence, calculations following equation (4) yield perfect decomposition. Note also that the additive decompositions in the tables are presented as a fraction of base period aggregate.

The relevant formulae for the methods are summarized below.

(a) Laspeyres index methods

The conventional Laspeyres index uses base period weights. The formulae of the effect of the  $k$ th factor are:

Multiplicative:

$$D_{x_k}^L = \frac{\sum_i x_{1,i}^0 \dots x_{k,i}^T \dots x_{n,i}^0}{\sum_i x_{1,i}^0 \dots x_{k,i}^0 \dots x_{n,i}^0}$$

Additive:

$$\Delta V_{x_k}^L = \sum_i x_{1,i}^0 \dots x_{k,i}^T \dots x_{n,i}^0 - \sum_i x_{1,i}^0 \dots x_{k,i}^0 \dots x_{n,i}^0$$

(b) Paasche index methods

The other basic index, Paasche, uses end period weights.

Multiplicative:

$$D_{x_k}^P = \frac{\sum_i x_{1,i}^T \dots x_{k,i}^T \dots x_{n,i}^T}{\sum_i x_{1,i}^T \dots x_{k,i}^0 \dots x_{n,i}^T}$$

Additive:

$$\Delta V_{x_k}^P = \sum_i x_{1,i}^T \dots x_{k,i}^T \dots x_{n,i}^T - \sum_i x_{1,i}^T \dots x_{k,i}^0 \dots x_{n,i}^T$$

(c) Fisher index method

The Fisher “ideal” index is calculated as the geometric mean of the Laspeyres and Paasche indices.

Multiplicative:

$$D_{x_k}^F = \sqrt{D_{x_k}^L D_{x_k}^P}$$

The Fisher index gives perfect decomposition.

(d) Log mean Divisia index methods (LMDI I)

The LMDI I methods take a rather simple form and give perfect decomposition.

Multiplicative:

$$D_{x_k} = \exp \left( \sum_i \frac{L(V_i^T, V_i^0)}{L(V^T, V^0)} \ln \left( \frac{x_{k,i}^T}{x_{k,i}^0} \right) \right)$$

Additive:

$$\Delta V_{x_k} = \sum_i L(V_i^T, V_i^0) \ln \left( \frac{x_{k,i}^T}{x_{k,i}^0} \right)$$

where function  $L(a, b)$  is the logarithmic average of two positive numbers  $a$  and  $b$  given by

$$\begin{aligned} L(a, b) &= \frac{a - b}{\ln a - \ln b} \quad \text{for } a \neq b \\ &= a \quad \text{for } a = b. \end{aligned}$$

(e) Arithmetic mean Divisia index methods (AMDI)

The AMDI methods employ an arithmetic mean weight function instead of the log mean weight function used in LMDI I methods. Their formulae are therefore slightly simpler. The decomposition results they give are often close to those from the LMDI I, though they do not give perfect decomposition.

Multiplicative:

$$D_{x_k} = \exp \left( \sum_i \frac{1}{2} \left( \frac{V_i^T}{V^T} + \frac{V_i^0}{V^0} \right) \ln \left( \frac{x_{k,i}^T}{x_{k,i}^0} \right) \right)$$

Additive:

$$\Delta V_{x_k} = \sum_i \frac{1}{2} (V_i^T + V_i^0) \ln \left( \frac{x_{k,i}^T}{x_{k,i}^0} \right)$$

(f) Generalized Fisher index method

The modified Fisher ideal index method gives a perfect multiplicative decomposition. The general formulae are a little complicated (see Ang et. al. (2004) for detail) When decomposition involves only two factors, it is identical to the Fisher ideal index. In the case of the analysis performed here, there are three factors and the formulae are given below (subscript  $i$  in all variables are omitted for conciseness):

$$\begin{aligned} D_{x_1} &= \left[ \frac{\sum x_1^T x_2^0 x_3^0}{\sum x_1^0 x_2^0 x_3^0} \left( \frac{\sum x_1^T x_2^T x_3^0}{\sum x_1^0 x_2^T x_3^0} \frac{\sum x_1^T x_2^0 x_3^T}{\sum x_1^0 x_2^0 x_3^T} \right)^{\frac{1}{2}} \frac{\sum x_1^T x_2^T x_3^T}{\sum x_1^0 x_2^T x_3^T} \right]^{\frac{1}{3}} \\ D_{x_2} &= \left[ \frac{\sum x_1^0 x_2^T x_3^0}{\sum x_1^0 x_2^0 x_3^0} \left( \frac{\sum x_1^T x_2^T x_3^0}{\sum x_1^T x_2^0 x_3^0} \frac{\sum x_1^0 x_2^T x_3^T}{\sum x_1^0 x_2^0 x_3^T} \right)^{\frac{1}{2}} \frac{\sum x_1^T x_2^T x_3^T}{\sum x_1^T x_2^0 x_3^T} \right]^{\frac{1}{3}} \\ D_{x_3} &= \left[ \frac{\sum x_1^0 x_2^0 x_3^T}{\sum x_1^0 x_2^0 x_3^0} \left( \frac{\sum x_1^T x_2^0 x_3^T}{\sum x_1^T x_2^0 x_3^0} \frac{\sum x_1^0 x_2^T x_3^T}{\sum x_1^0 x_2^T x_3^0} \right)^{\frac{1}{2}} \frac{\sum x_1^T x_2^T x_3^T}{\sum x_1^T x_2^T x_3^0} \right]^{\frac{1}{3}} \end{aligned}$$

(g) Shapley/Sun method

Sun (1998) proposed an additive decomposition method which is identical to the Shapley decomposition used by researchers in cost allocation problems. This method creates perfect decomposition by distributing the interaction terms in the conventional Laspeyres index method to the main effects. It has therefore been referred to as the refined Laspeyres index method. The formulae for the three factor case are:

$$\begin{aligned}\Delta V_{x_1} &= \sum \Delta x_1 x_2^0 x_3^0 + \frac{1}{2} \sum \Delta x_1 (\Delta x_2 x_3^0 - x_2^0 \Delta x_3) + \frac{1}{3} \sum \Delta x_1 \Delta x_2 \Delta x_3 \\ \Delta V_{x_2} &= \sum x_1^0 \Delta x_2 x_3^0 + \frac{1}{2} \sum \Delta x_2 (\Delta x_1 x_3^0 - x_1^0 \Delta x_3) + \frac{1}{3} \sum \Delta x_1 \Delta x_2 \Delta x_3 \\ \Delta V_{x_3} &= \sum x_1^0 x_2^0 \Delta x_3 + \frac{1}{2} \sum \Delta x_3 (\Delta x_1 x_2^0 - x_1^0 \Delta x_2) + \frac{1}{3} \sum \Delta x_1 \Delta x_2 \Delta x_3\end{aligned}$$

where  $\Delta x_k = x_k^T - x_k^0$ .

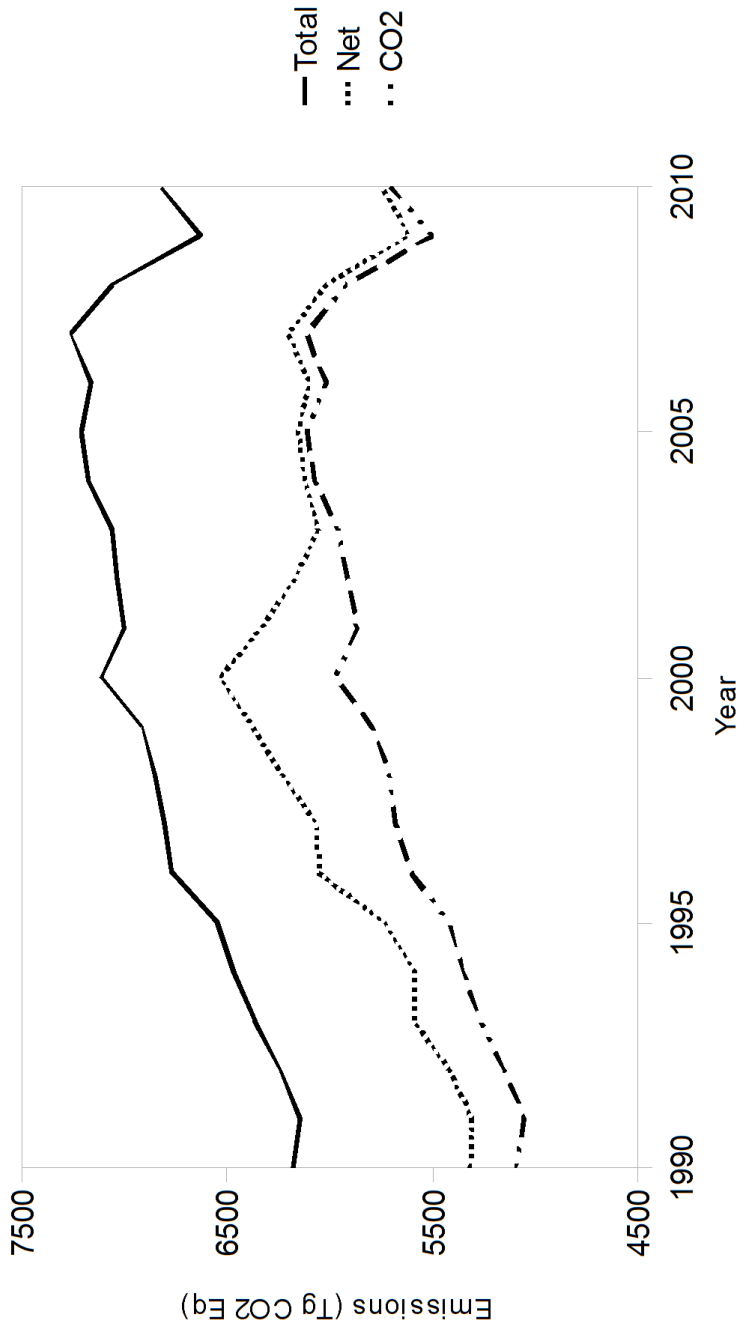


Figure 1: U.S. Greenhouse Gas Emissions

*Note:* Emissions are measured in teragrams (million metric tons) of CO<sub>2</sub>-equivalent. Net GHG emissions include emissions from land use, land-use change, and forestry (sinks). Both total GHG and CO<sub>2</sub> emissions exclude emissions from land use, land-use change, and forestry (sinks).  
 Data Source: EPA (2012).

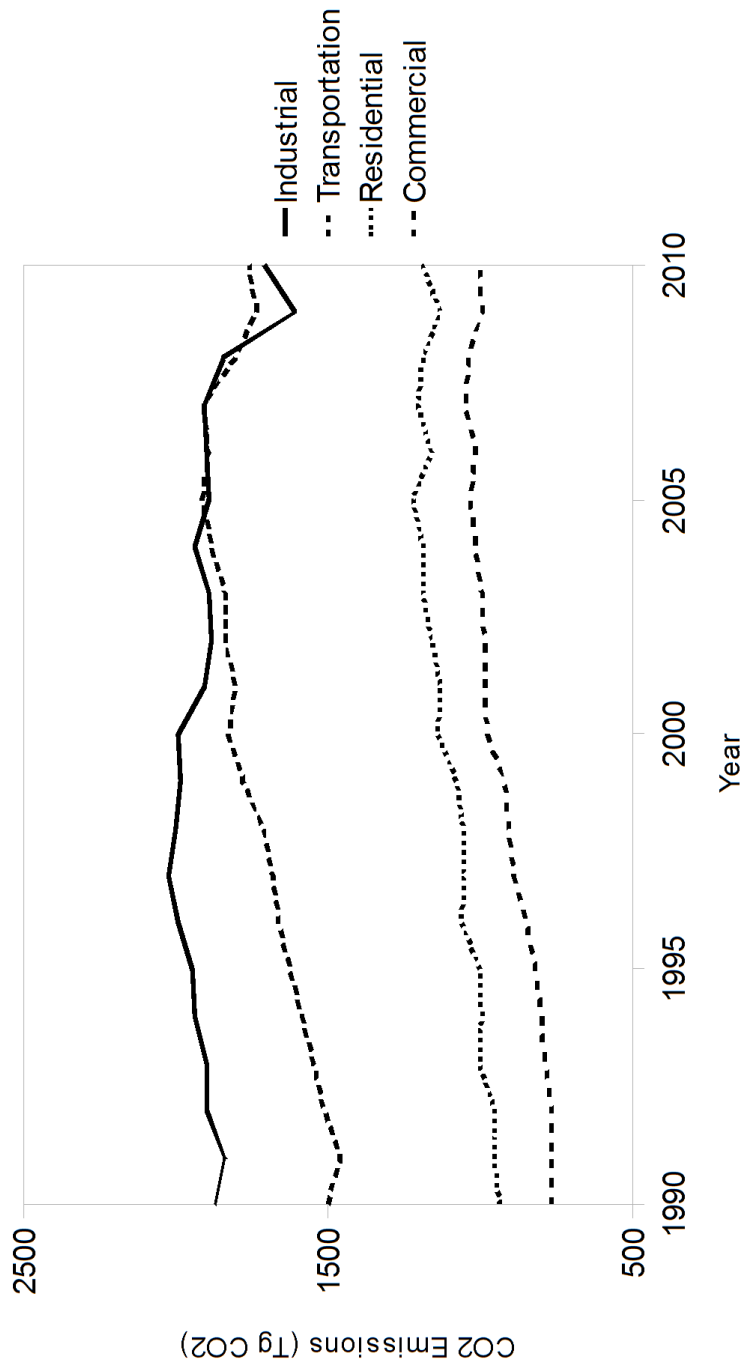


Figure 2: U.S. CO<sub>2</sub> Emissions Allocated to Economic Sectors

*Note:* Emissions are measured in teragrams (million metric tons) of CO<sub>2</sub>.  
Data Source: EPA (2012).

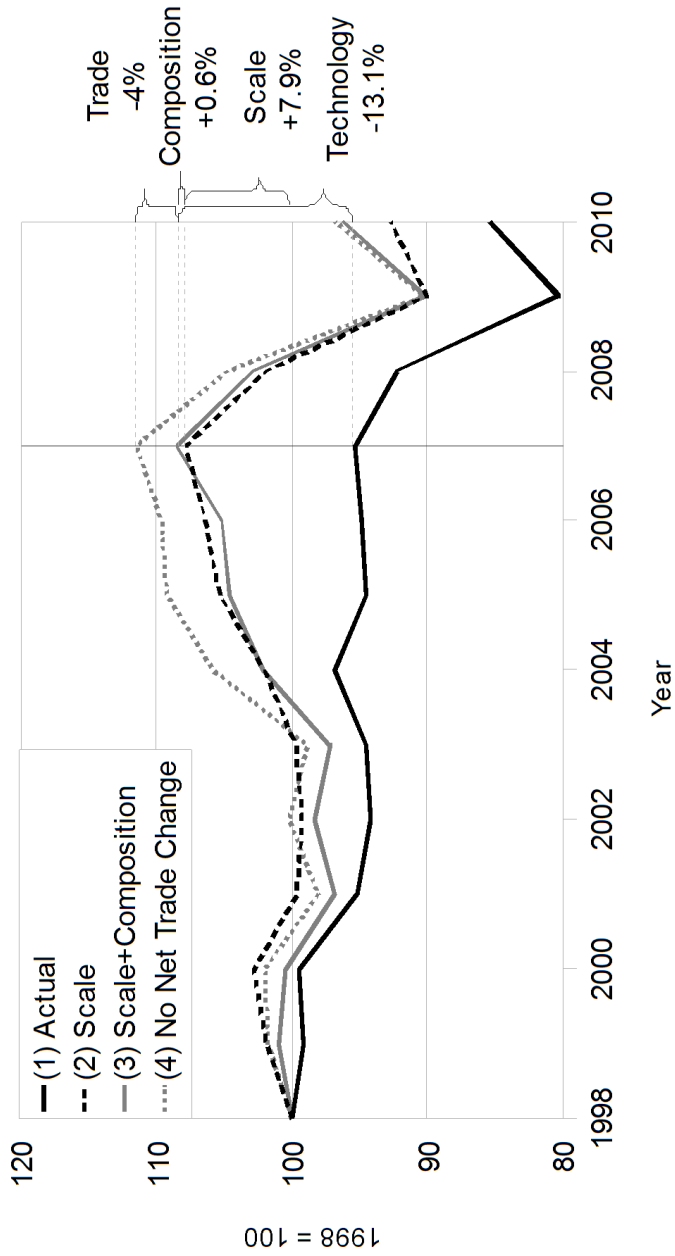


Figure 3: CO<sub>2</sub> Emissions from U.S. Industry

Note: CO<sub>2</sub> emissions are shown in relative terms, with industrial CO<sub>2</sub> emissions in 1998 equal to 100. The decomposition follows equation (4): scale, line (2) relative to 100; composition, line (3) - line (2); technique, line (1) - line (3).

Taking into account of international trade effect: scale + composition, line (4) relative to 100; net trade change, line (3) - line (4).  
Data Source: Author's calculation.

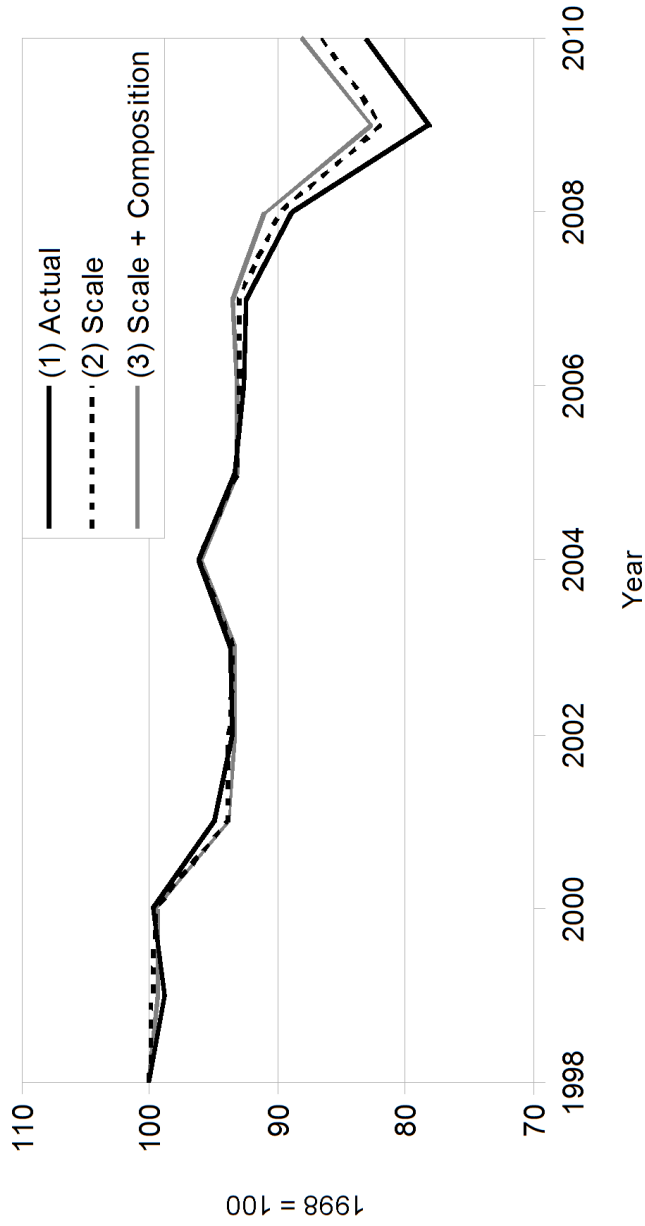


Figure 4: U.S. Industrial CO<sub>2</sub> Emissions from Energy Consumption

*Note:* CO<sub>2</sub> emissions are shown in relative terms, with energy-related industrial CO<sub>2</sub> emissions in 1998 equal to 100. The decomposition follows equation (7): scale (energy demand), line (2) relative to 100; composition (fuel mix), line (3) - line (2); technique (conversion factors), line (1) - line (3).

Data Source: Author's calculation.



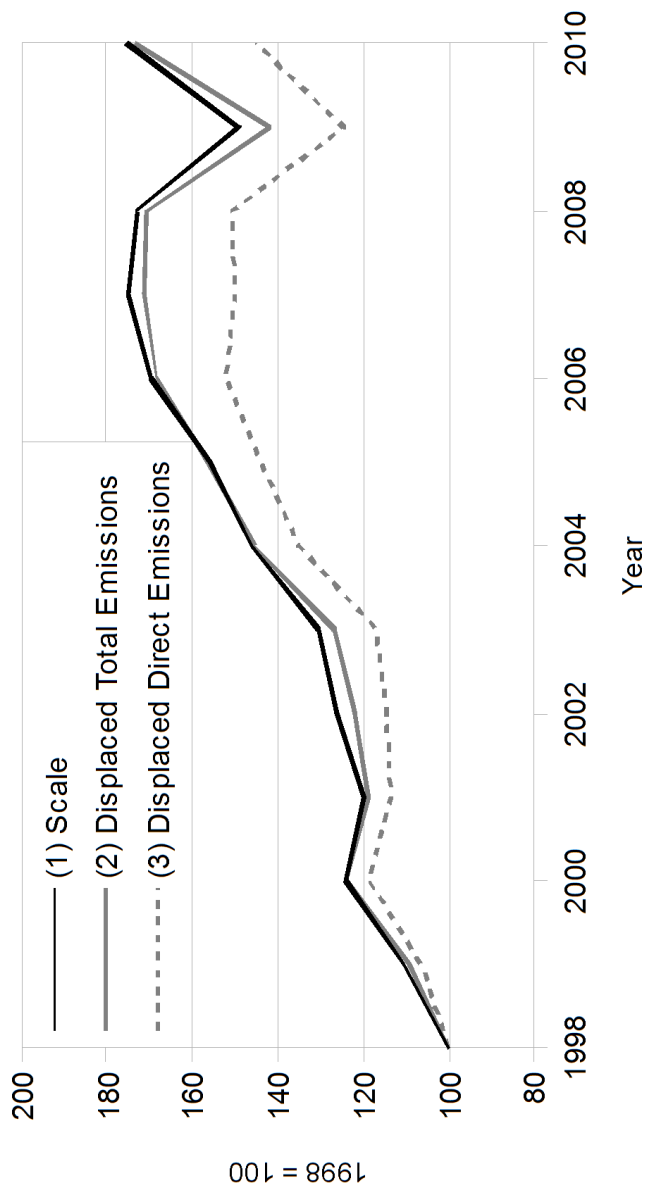


Figure 5: “Displaced” CO<sub>2</sub> Emissions by U.S. Imports

*Note:* CO<sub>2</sub> emissions are shown in relative terms, with CO<sub>2</sub> emissions displaced by the U.S. imports in 1998 equal to 100. The decomposition follows equation (11): scale, line (1) relative to 100; composition, line (2) - line (1).

Data Source: Author’s calculation.

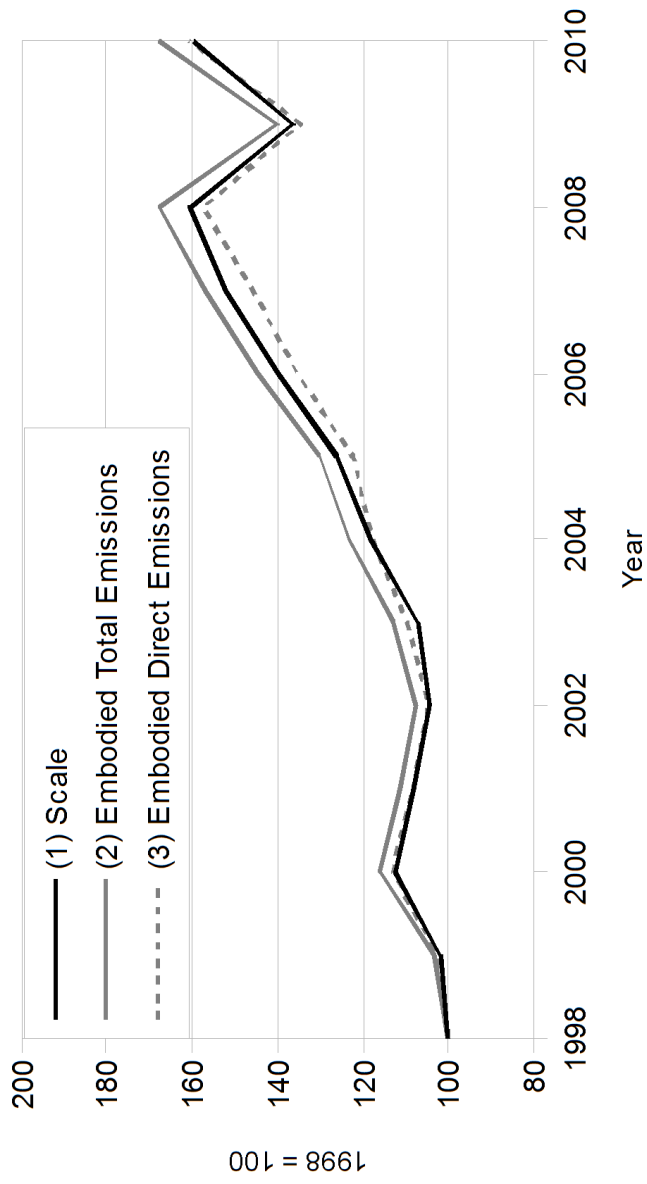


Figure 6: Embodied CO<sub>2</sub> Emissions of U.S. Exports

*Note:* CO<sub>2</sub> emissions are shown in relative terms, with CO<sub>2</sub> emissions embodied in the U.S. exports in 1998 equal to 100. The decomposition follows equation (11): scale, line (1) relative to 100; composition, line (2) - line (1).

Data Source: Author's calculation.

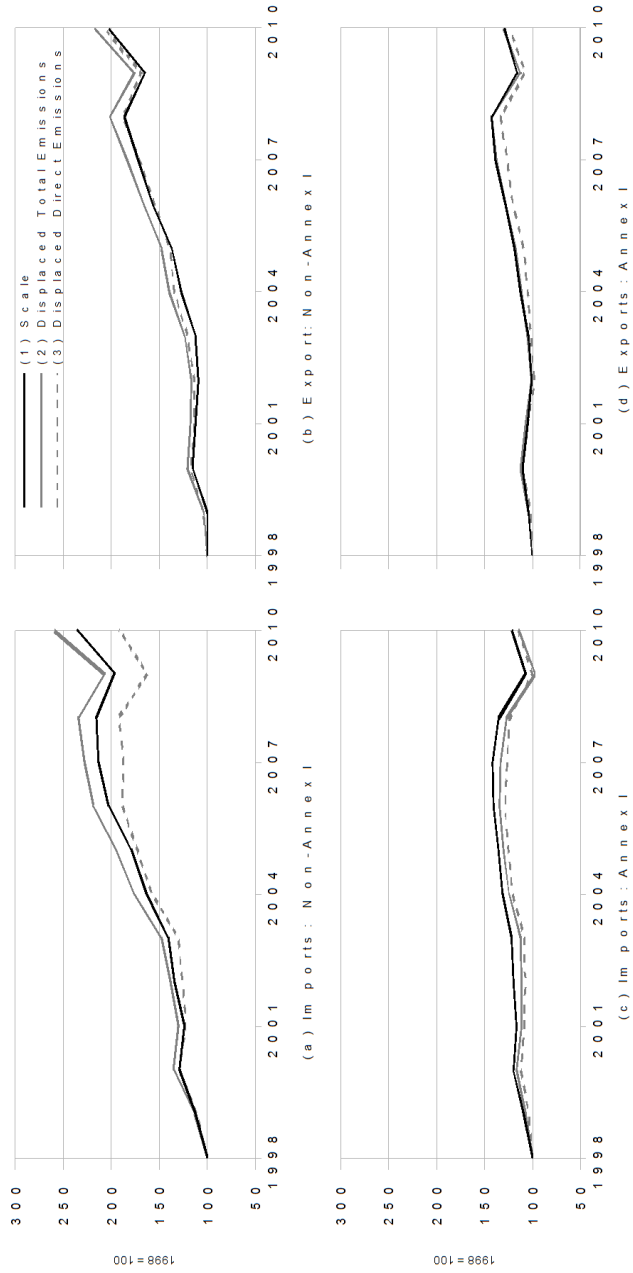


Figure 7: CO<sub>2</sub> Emissions Embodied in U.S. Trade by Country Groups

Note: CO<sub>2</sub> emissions are shown in relative terms, with those in 1998 equal to 100. The decomposition follows equation (11): scale, line (1) relative to 100; composition, line (2) - line (1).

Data Source: Author's calculation.

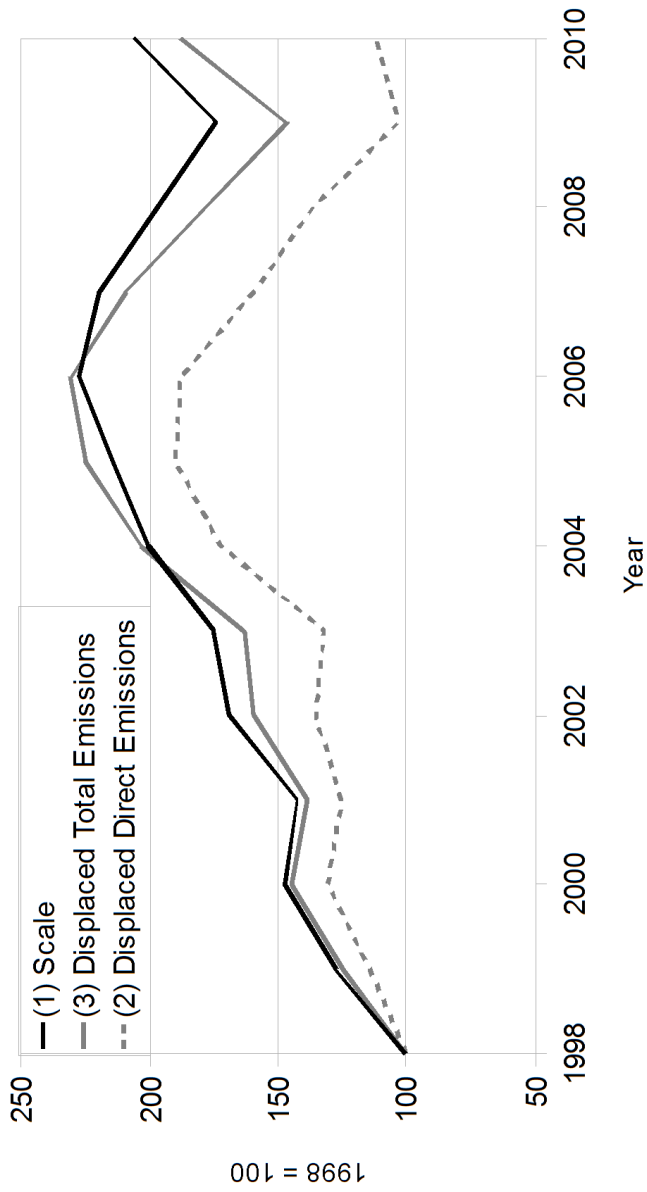


Figure 8: “Displaced” CO<sub>2</sub> Emissions by U.S. Net Imports

*Note:* CO<sub>2</sub> emissions are shown in relative terms, with CO<sub>2</sub> emissions displaced by the U.S. net imports in 1998 equal to 100. The decomposition follows equation (11): scale, line (2) relative to 100; composition, line (3) - line (2); technique, line (1) - line (3).

Data Source: Author’s calculation.

Table 1: Index Decomposition of US Industrial CO2 Emissions: 1998 - 2002

Decomposition	Laspeyres (a)	Paasche (b)	Fisher (c)	LMDI I (d)	AMDI (e)	Gen. Fisher (f)	Shapley/Sun (g)
<b>Multiplicative</b>							
Scale	.9925	.9926	.9926	.9926	.9926	.9926	
Composition	.9914	.9789	.9851	.9843	.9840	.9851	
Technology	.9754	.9631	.9692	.9701	.9710	.9692	
Residue	.9875	1.0127	1	1	.9993	1	
<b>Additive</b>							
Scale	-.0075	-.0071		-.0072	-.0073		-.0073
Composition	-.0086	-.0204		-.0155	-.0158		-.0145
Technology	-.0246	-.0363		-.0296	-.0294		-.0305
Residue	-.0116	.0115		0	.0002		0

Note: Industrial CO2 emissions fell by 5.23% from 1998 to 2002. The components of a multiplicative decomposition multiply to .9477. The components of an additive decomposition add up to -.0523.

Table 2: Index Decomposition of US Industrial CO2 Emissions: 2002 - 2006

Decomposition	Laspeyres (a)	Paasche (b)	Fisher (c)	LMDI I (d)	AMDI (e)	Gen. Fisher (f)	Shapley/Sun (g)
<b>Multiplicative</b>							
Scale	1.0721	1.0721	1.0721	1.0697	1.0721	1.0721	
Composition	.9899	.9825	.9862	.9859	.9860	.9862	
Technology	.9302	.9233	.9267	.9274	.9272	.9267	
Residue	.9925	1.0076	1	1	.9997	1	
<b>Additive</b>							
Scale	.0721	.0659		.0685	.0689		.0690
Composition	-.0101	-.0174		-.0141	-.0139		-.0137
Technology	-.0698	-.0814		-.0746	-.0745		-.0755
Residue	-.0124	.0129		0	-.0006		0

Note: Industrial CO2 emissions fell by 2.02% from 2002 to 2006. The components of a multiplicative decomposition multiply to .9798. The components of an additive decomposition add up to -.0202.

Table 3: Index Decomposition of US Industrial CO2 Emissions: 1998 - 2006

Decomposition	Laspeyres (a)	Paasche (b)	Fisher (c)	LMDI I (d)	AMDI (e)	Gen. Fisher (f)	Shapley/Sun (g)
<b>Multiplicative</b>							
Scale	1.0641	1.0641	1.0641	1.0635	1.0641	1.0641	
Composition	.9886	.9611	.9747	.9717	.9719	.9747	
Technology	.9080	.8828	.8953	.8986	.8986	.8953	
Residue	.9722	1.0286	1	1	.9992	1	
<b>Additive</b>							
Scale	.0641	.0559		.0594	.0599		.0603
Composition	-.0114	-.0376		-.0277	-.0281		-.0242
Technology	-.0920	-.1233		-.1031	-.1043		-.1074
Residue	-.0321	.0336		0	.0011		0

Note: Industrial CO2 emissions fell by 7.14% from 1998 to 2006. The components of a multiplicative decomposition multiply to .9286. The components of an additive decomposition add up to -.0714.

Table 4: Index Decomposition of US Industrial CO<sub>2</sub> Emissions from Energy Use: 1998 - 2007

Decomposition	Laspeyres (a)	Paasche (b)	Fisher (c)	LMDI I (d)	AMDI (e)	Gen. Fisher (f)	Shapley/Sun (g)
<b>Multiplicative</b>							
Scale	.9317	.9317	.9317	.9318	.9317	.9317	
Composition	1.0028	1.0031	1.0029	1.0028	1.0028	1.0029	
Technology	.9885	.9888	.9887	.9887	.9887	.9887	
Residue	1.0003	.9997	1	1	1.0001	1	
<b>Additive</b>							
Scale	-.0683	-.0677		-.0679	-.0681		-.0680
Composition	.0028	.0028		.0027	.0024		.0028
Technology	-.0115	-.0105		-.0110	-.0110		-.0110
Residue	.0008	-.0008		0	.0004		0

Note: Industrial CO<sub>2</sub> emissions from energy use fell by 7.62% from 1998 to 2007. The components of a multiplicative decomposition multiply to .9238. The components of an additive decomposition add up to -.0762.