# ESSAYS ON TRADE LIBERALIZATION AND THE ENVIRONMENT IN CHINA

The University of Nottingham

By

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# ABSTRACT

This thesis is concerned with understanding the relationship between trade liberalization and the environment in the context of China. Four empirical essays are conducted to investigate different aspects of the nexus. We first look at the changing patterns of revealed comparative advantage in manufacturing industries for China and other countries to examine whether dirty industries have 'migrated' from developed countries to China as a result of an environmental regulatory gap. The attention is then turned to the determinants of trade specialization and the role played by environmental stringency using cross-industry regressions within a Heckscher-Ohlin framework. The environmental consequences of trade liberalization are evaluated at both the industrial and provincial level. Next, Environmental Input-Output Analysis (EIOA) is used to measure the 'potential' and 'actual' pollution content (for three air pollutants, $CO_2$, $SO_2$, $NO_x$) in imports and exports by industry and overall. In the last essay, we evaluate different and countervailing effects (scale, income and trade-induced composition effects) of trade's impact on the environment using Chinese provincial data.

Some generalizations can be made from the studies. Firstly, little evidence is found to support the feared 'Dirty Industry Migration' phenomenon from North (developed countries) to South (e.g. China) at ISIC 3 digit level for the past three decades. Secondly, environmental stringency seems to be a negative effect on trade performance at cross-industry level in China. Thirdly, China 'saves' in environmental terms through trade and its exports structure is cleaner than that of imports; however, these two conclusions are completely overturned when technology heterogeneity across countries is allowed for. Finally, the channels through which trade liberalization can affect the environment are conflicting and there is no clear cut answer to the question 'is freer trade good or bad to the environment'.

# CHAPTER ONE

# INTRODUCTION

## 1.1 CONTEXT AND BACKGROUND

The worldwide concern over the interaction between trade liberalization and the environment started as early as the beginning of 1970s. For example, the United Nations Conference on the Human Environment in Stockholm in 1972 was the first global conference on environmental issues. In 1980s, the Montreal Protocol on the Substances that Deplete the Ozone Layers set a good example for the subsequent international agreements such as the Kyoto Protocol. Along with the creation of free trade promoting agreements and organizations such as North America Free Trade Agreement (NAFTA) and World Trade Organization (WTO) in the 1990s, fears of competitiveness loss[1] for the developed world and fears of environmental disaster for the less developed countries made the links between trade liberalization and the environment hotly debated.

With three decades of economic reforms and opening-up, China now has a very large economy, indeed larger than most developed countries in terms of GDP[2]; however, it

[1]It is argued that stricter environmental regulations will lower the international competitiveness of the firms in the developed countries.

[2] China is estimated to be the third largest economy in terms of nominal GDP in 2008 with 3.86 trillion dollars and China's ranking as the second largest economy in terms of GDP adjusted by purchasing power parity (PPP) remains (World Bank, 2009).

also has a grave risk of being nominated as one of the most polluted countries in the world[3].

Rapid trade growth, especially export growth encouraged by the export-oriented policies, and capital inflows have been accredited for their contribution to China's rapid economic growth. In the beginning of the Economic Reform in late 1970s, China only enjoyed about 1% of total world trade (sum of exports and imports) but recent data (WTO, 2008) show that Chinese export share of the world's total exports is approaching 9% and the import share is close to 7% in 2007. Attracted by low labour cost and preferential policies for foreign enterprises along coastal regions, foreign investment flows have also increased dramatically in China. Between 1979 and 2007, the actually utilised value of foreign investment is about 955 billion US dollars and that of foreign direct investment (FDI) is about 760 billion US dollars, respectively 3.12% and 2.88% of total GDP in China during this period. In 2007, the actually utilised value of foreign investment and that of FDI are respectively 23.87% and 22.78% of GDP in 2007 (China Statistical Yearbook, 2008).

Environmental degradation in China is certainly not a recent phenomenon that only stems from its opening-up process.[4] However, it is evident that the environment in China has been deteriorating at an unprecedented speed during the period of the trade liberalization process. In the early stage of the Economic Reform and opening up, environment protection in China was blatantly ignored and sacrificed for economic growth. By the early 1990s, the environmental situation was so notoriously worsened

[3] China has 20 of the world's 30 most polluted cities according to World Bank data. State Environmental Protection Agency (SEPA, China) reported in 2006 that China is the world's No.1 emitter of $SO_2$ emissions. The Netherlands Environmental Assessment Agency was the first to report that China overtook the US and became No.1 in $CO_2$ emissions in 2007.

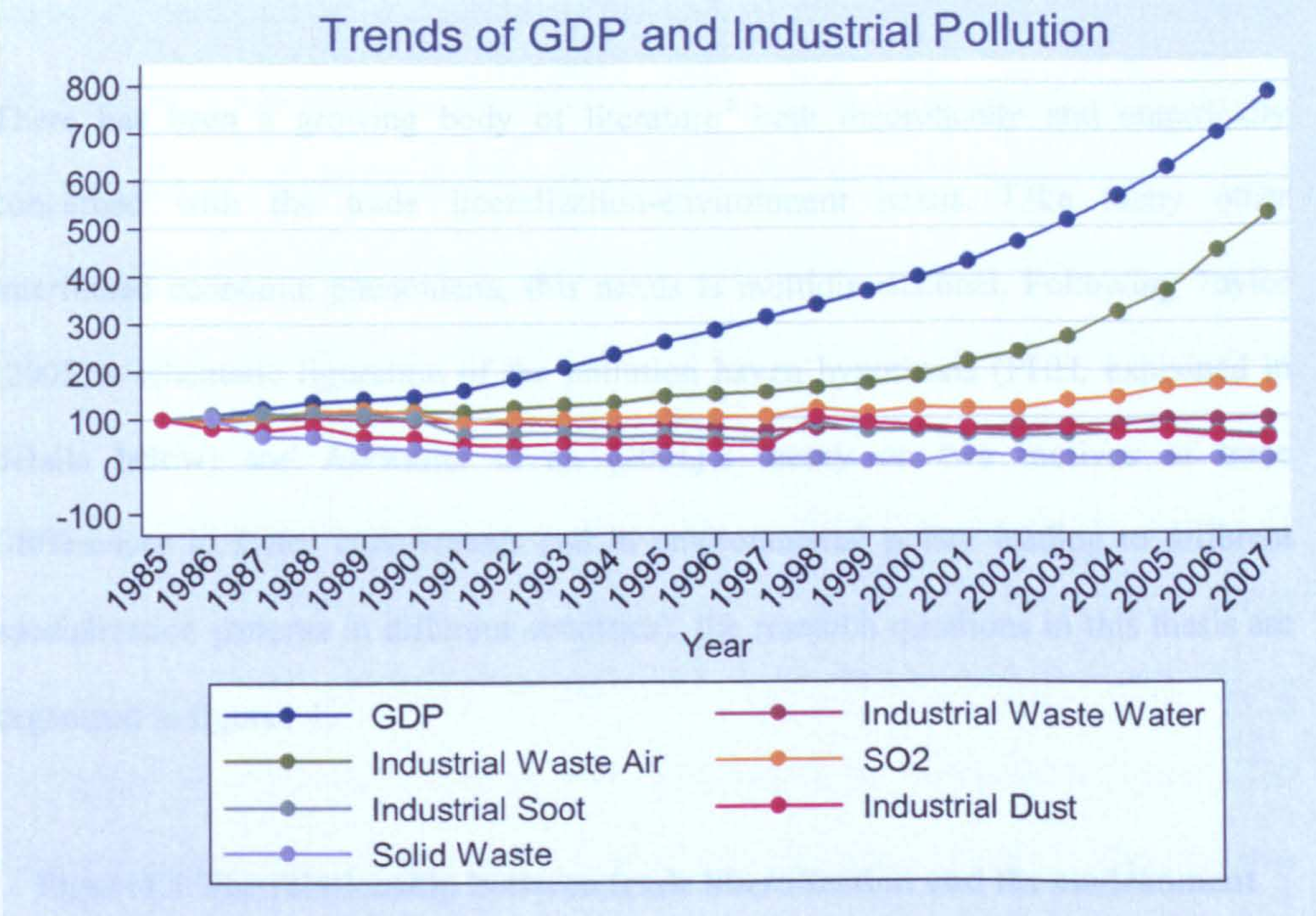
[4] As a matter of fact, it is seen as a century long, even millennium-old course by many researchers (Smil, 1984; Elvin, 1993, 2004; Edmonds, 1994; Shapiro, 2001; Economy, 2004).

that China's Environmental Action Plan for 1991-2000[5] highlighted seven priority problems to tackle: water pollution, especially contamination by organic waste; urban air pollution, as measured by particulates and sulphur dioxide; hazardous and toxic solid waste in urban areas; water shortages, particularly in northern China; soil erosion; loss of forests and grasslands. Accumulated pollution, however, has been causing great damage in various ways: acid rain falls on one third of the land; one-third to one fourth of Chinese people lack access to clean drinking water; hundreds of thousands Chinese people die of respiratory diseases caused by poor air quality. Some international observers have been very pessimistic about China's huge environmental problem. Smil (1993:192) claims that 'there are no solutions within China's economic, technical, and manpower reach that could halt and reverse these degradative trends-- not only during the 1990s but also during the first decade of the new century'.

China's environment protection network has been developing quickly and has been accredited for its sophistication. Although the enforcement of environmental protection laws has been questioned, the laws and standards are showing effectiveness which is evidenced by the statistics of pollution indicators. As industrial pollution is a primary contributor to China's environmental degradation, we provide in table 1.1 the trends of GDP and different indicators of industrial pollution between 1985 and 2007. While GDP has increased to eight fold in 2007 compared to 1985, the industrial pollution has not risen in such a dramatic manner. Solid waste disposal seems to have the largest decrease scaled by initial level. Industrial waste water, industrial dust and industrial soot have remained relatively steady with variations across the years. Industrial waste air has increased to five fold while $SO_2$ has almost increased to the double of 1985.

[5] It was prepared jointly by the then National Environmental Protection Agency (NEPA) and the State Planning Commission (SPC) in 1994.

**Table 1.1 Trends of GDP and Industrial Pollution 1985-2007**



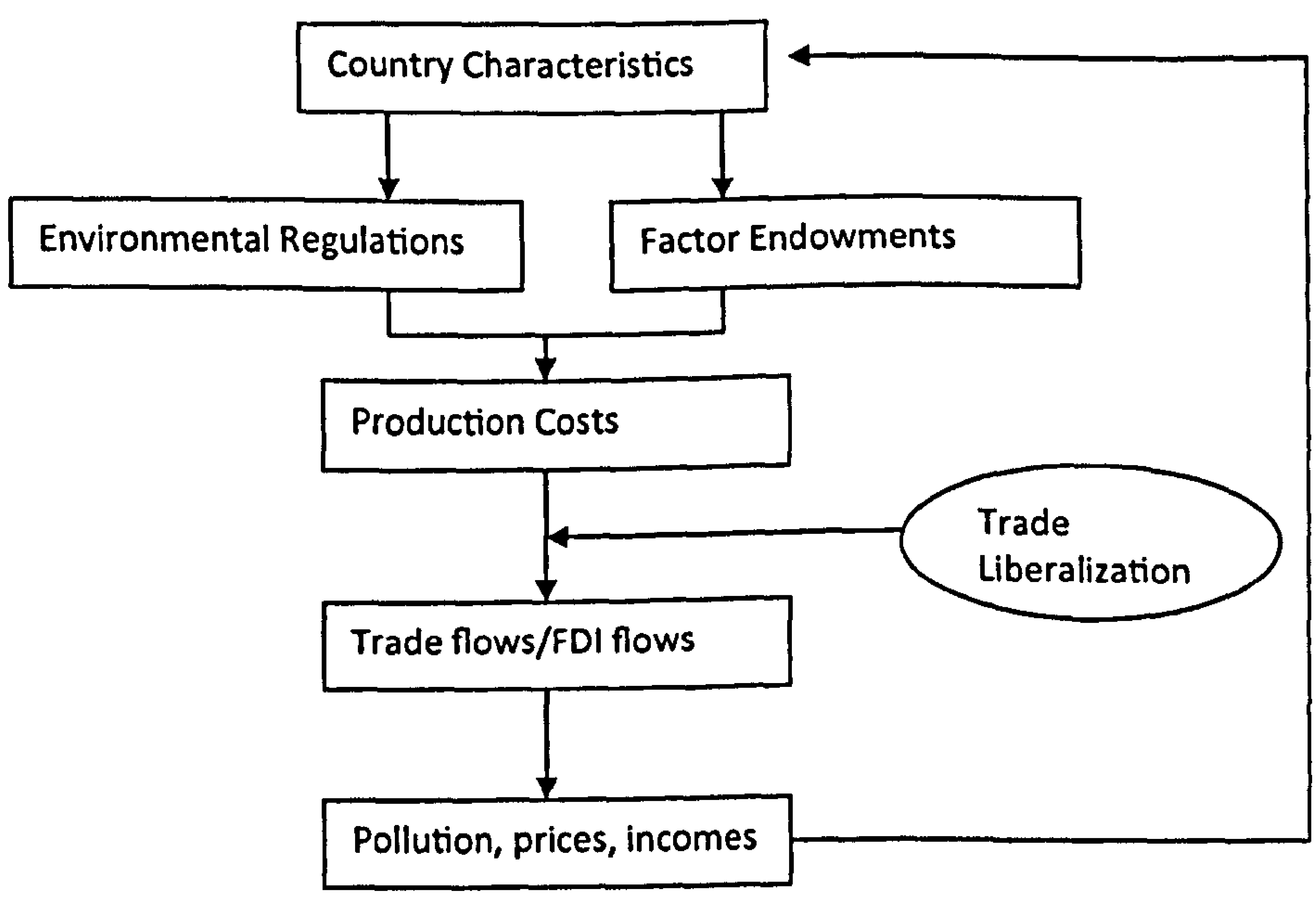

Note: values are adjusted to 1985=100 (for solid waste, 1986=100); GDP is gross domestic product measured in constant price and adjusted to 1985=100; Data from China Statistical Yearbook (various years).

As trade liberalization is an indispensable part of China's growth miracle while the issue of pollution is a bottleneck for China's future economic growth, the linkage between trade liberalization and the environment in China is receiving growing attention. This project is hence motivated by the need to understand and quantify the various aspects in the relationship between trade liberalization and the environment in China.

## 1.2 RESEARCH AIMS

There has been a growing body of literature[6] both theoretically and empirically concerned with the trade liberalization-environment nexus. Like many other interlinked economic phenomena, this nexus is multidimensional. Following Taylor (2005)'s schematic figuration of the pollution haven hypothesis (PHH, explained in details below) and Antweiler et al. (2001)'s theory on two motives of trade (differences in factor endowments and in environmental policy leading to different specialization patterns in different countries), the research questions in this thesis are organized in figure1.1.

**Figure1.1 The relationship between trade liberalization and the environment**




The line from country characteristics to environmental regulations, then to production costs, to trade/FDI flows, and finally to pollution emissions, is embedded in the

[6] For extensive surveys of this literature, see Dean, 1992; Ferrantino, 1997; Beghin et al., 1999; Levinson, 1996; Savas, 1999; Tisdell, 2000.

pollution haven argument. The PHH stresses the importance of environmental stringency as a source of production cost and hence comparative price advantage which affects trade patterns. The theoretical side of the PHH hypothesis is broadly explored and it is predicted that North (the group of developed countries) specializes in clean good while South (the group of less developed countries) specializes in dirty good; however, the empirical methodology and evidence are mixed. Detailed literature review is provided in chapter two. Similarly, the line from country characteristics and factor endowments to trade flows and pollution emissions follows the traditional Heckscher-Ohlin (H-O) framework and the factor endowments hypothesis (FEH) predicts that North specializes in dirty good (also capital intensive) while South specializes in clean good due to their differences in capital-labour ratio. The theoretical predictions of the PHH and the FEH seem to be in strong contrast to each other but the effects of the two may coexist as they work through different mechanisms. Examining the time-series data of trade flows of different industries may reflect some of the truth. If the environmental regulatory gap between North and South is sufficiently large to cause deviations in H-O predictions, we shall see increasing comparative advantage in dirtier industries in developing countries like China and the opposite shall be true for developed countries especially those with higher environmental standards than other countries. Our first objective is then to examine the PHH argument by looking at the changing patterns of comparative advantage in China and its major trading partners at industrial level.

Due to the coexistence of other factors (capital, labour, etc), the role of environmental stringency is likely to be masked if we look at the ex post trade flows only. The impact of environmental stringency on export performance shall not be ignored even if we do not find any evidence to support the PHH from investigation of trade pattern changes. Empirical studies have also attempted to quantify the weight of environmental stringency on the international competitiveness of the domestic firms as well as on firm/FDI location choice. Due to data limitation, most studies are confined to examine the impact of increasing environmental standards on US imports at industrial level. After decades of development in environment protection laws and rules, China has applied a 'polluter pays' principle[7] in environmental regulations: charges must be levied for excessive pollution emissions of enterprises and the levy income must be used in environmental protection related activities. Since pollution abatement costs and trade statistics are available at industrial level, our second question is thus "does environmental stringency matter to trade specialization (export performance) at industrial level in the context of China?"

Another line of research focuses on the impact of trade liberalization on the environment. According to the Heckscher-Ohlin-Vanek theory, trade can be conceived as the exchange of the services of production factors. Given that the environment is often seen as a production factor in related theoretical models, the service of the environment in producing exportable and importable can also be measured. The environmental consequences of international trade can be evaluated by calculating the embodiment of environmental services in net trade. We are interested in two related questions: first, whether China is indeed a net exporter of environmental services (in terms of volume) due to its huge trade surplus; second, which is dirtier (in terms of intensity), China's exports structure or imports structure?

[7] A 'polluter pays' principle has various definitions which have a common element that the party responsible for producing pollution is held responsible by environmental laws for reducing the pollution. In China, enterprises are only levied for excessive pollution emissions.

The impact of trade liberalization on the environment has distinctive and sometimes countervailing effects. With greater market access and technology spillovers, trade liberalization serves as a source of economic and income growth which in turn encourages better environmental protection. In the mean time, it can hasten natural resource depletion and cause specialization in dirty goods which are harmful to the environment. In the case of China, trade growth has boosted economic growth and technological advance. However this impact is not balanced across China's vast geography: coastal provinces have benefited more than inland provinces in GDP growth and technological advance. Given the great variations in pollution emissions in Chinese provinces, it is our interest to evaluate the different channels of trade's impact on the environment and to draw some policy implications. The last question is then "what are the mechanisms of trade liberalization's impact on the environment, using provincial level analysis?"

## 1.3 ROAD MAP

In order to refine the understanding of the relationship between trade liberalization and the environment in China, we look at different aspects of this broad topic. The thesis firstly examines the export performance/trade specialization consequences of environmental policy heterogeneity across countries, and then investigates the role of environmental stringency on trade performance/specialization within a cross-industry H-O framework for China. The second half of the thesis focuses on the environmental consequences of trade liberalization by investigating the pollution content in trade within an Input-Output framework and by decomposing trade's impact into different mechanisms using Antweiler et al. (2001)'s theoretical models.

Chapter two is the scene-setting part of the thesis. Using trade information of manufacturing industries between 1976 and 2004 in 100 countries, we attempt to examine the changes in trade patterns which may provide information for the PHH. We critically review alternative revealed comparative advantage (RCA) indices before adopting two specific indices to investigate the changing trade pattern of industries according to their 'dirtiness'. The findings suggest that China has revealed increasing comparative advantage in cleaner industries and increasing comparative disadvantage in dirtier industries, which argue against the pollution haven hypothesis on the developing country side. In addition, little evidence is found for the PHH on the developed country side.

Chapter three then investigates the determinants of trade specialization in a cross-industry regression analysis for China. The role of environmental policy is especially looked at. We find some sensitivity in the empirical results according to how trade specialization is measured. Controlling for unobserved heterogeneity in industries and time specific effects, we do find evidence for the hypothesis that stringent environmental policy has negative impact on export performance. Moreover, the export performance of dirtier industries seems to be more adversely affected by increasing environmental stringency.

Chapter four addresses the issue of environmental consequence of trade openness by looking at the overall pollution content (i.e. environmental services) embodied in exports and imports using Environmental Input-Output analysis. To address the weaknesses in the existing literature, we distinguish the 'actual' and 'potential' pollution content of trade by using alternative assumptions of production technologies for the imported goods. It turns out that China 'saves' in environmental terms by producing and exporting cleaner goods than the importable; however, China is exporting more pollution content than actually embodied in the imported goods due to China's less energy efficient production technologies compared to the advanced industrialized economies.

Chapter five decomposes the impact of trade liberalization on the environment into distinctive channels: the scale effect, the income effect and the trade-induced composition effect. Using Chinese provincial data between 1985 and 2007, we carry out the econometric analysis for the determination of provincial pollution levels. The results provide evidence that an increase in economic activities brings increase in pollution emissions while an increase in income level tends to reduce pollution. We find that factor endowments and environmental stringency tend to offset each other and result in a small trade-induced composition effect which has mixed sign under different modelling and estimation. We also find that capital intensity is associated with dirtier production and more emissions.

Chapter six summarizes the main empirical findings of the thesis upon which policy implications are also considered. Moreover, it highlights the limitations of the empirical techniques used, the contributions of the thesis made to the literature. Finally, it points to possible research areas for further work.

# CHAPTER TWO

# POLLUTION HAVENS AND REVEALED COMPARATIVE ADVANTAGE

## 2.1 INTRODUCTION

Over the past three decades, the Chinese economy as a whole and its trade regime specifically has undergone significant reforms. The characteristics of Chinese trade flows--their remarkable growth, the structure of sectoral trade, the geographical distribution, together with their underlying causes--have been explored. One aspect of trade specialization research links to the weaker environmental regulations in China. It is feared that dirty industries facing higher environmental controls in the industrialized countries may have found 'pollution havens' in developing countries like China where environmental protection is taken less seriously. Research has been undertaken to address whether such fear is supported empirically by examining changes in trade patterns.

The main research question investigated in this chapter is whether China has specialized in line with a comparative advantage in pollution intensive industries. As mentioned in the introduction chapter, the Pollution Haven Hypothesis suggests that a developing country with relatively lax environmental regulations will be made dirtier as a result of trade liberalization and become pollution havens for the world's pollution intensive industries. Given less stringent environmental regulations than its major trading partners, China is predicted to have a comparative price advantage in producing dirty goods. The traditional H-O framework, however, predicts that China become more specialized, as it opens up, in relatively clean (usually labour intensive) goods given its large endowment of labour and its relative scarcity in physical capital and human capital, and as a result can become less specialized in the production of pollution intensive goods. In practice, of course, the two effects may be simultaneously influencing different sectors in China and the net impact on specialization depends on the relative importance of the two effects. As suggested by Balassa (1965: 103), "for purposes of indicating the possible consequences of trade liberalization, it appears sufficient to provide information on revealed comparative advantage." In this chapter, we explore what the actual trade flows reveal about the relative strengths of the two forces (or possibly of other forces).

By investigating the sectoral trade flows of manufacturing industries for China as well as its major trading partners during the period 1976-2004, we aim to find out the dynamics of Chinese revealed comparative advantages in different industries which are categorized according to their 'dirtiness'. The main findings suggest that although China has undergone significant structural change in sectoral trade, China has shown little or no revealed comparative advantage in pollution intensive industries. Rather, China has increased revealed comparative disadvantage in the most polluting industries, while most of the cleanest industries in China have increased revealed comparative advantage over time. There is also little evidence that the pollution intensive industries have decreased comparative advantage in the selected high income countries.

The remainder of the chapter is organized as follows: section 2.2 describes the theoretical framework of the pollution haven hypothesis, while section 2.3 provides a summary of empirical evidence in this branch of research. A definition of 'dirtiness' will be provided in section 2.4. Section 2.5 compares China's trade structure and performance with selected developed countries. Section 2.6 discusses the concept of revealed comparative advantage and its concomitant indices. Section 2.7 summarises the revealed comparative advantage patterns against sectoral pollution intensities for China as well as for five selected high income economies. Finally, section 2.8 provides some concluding remarks.

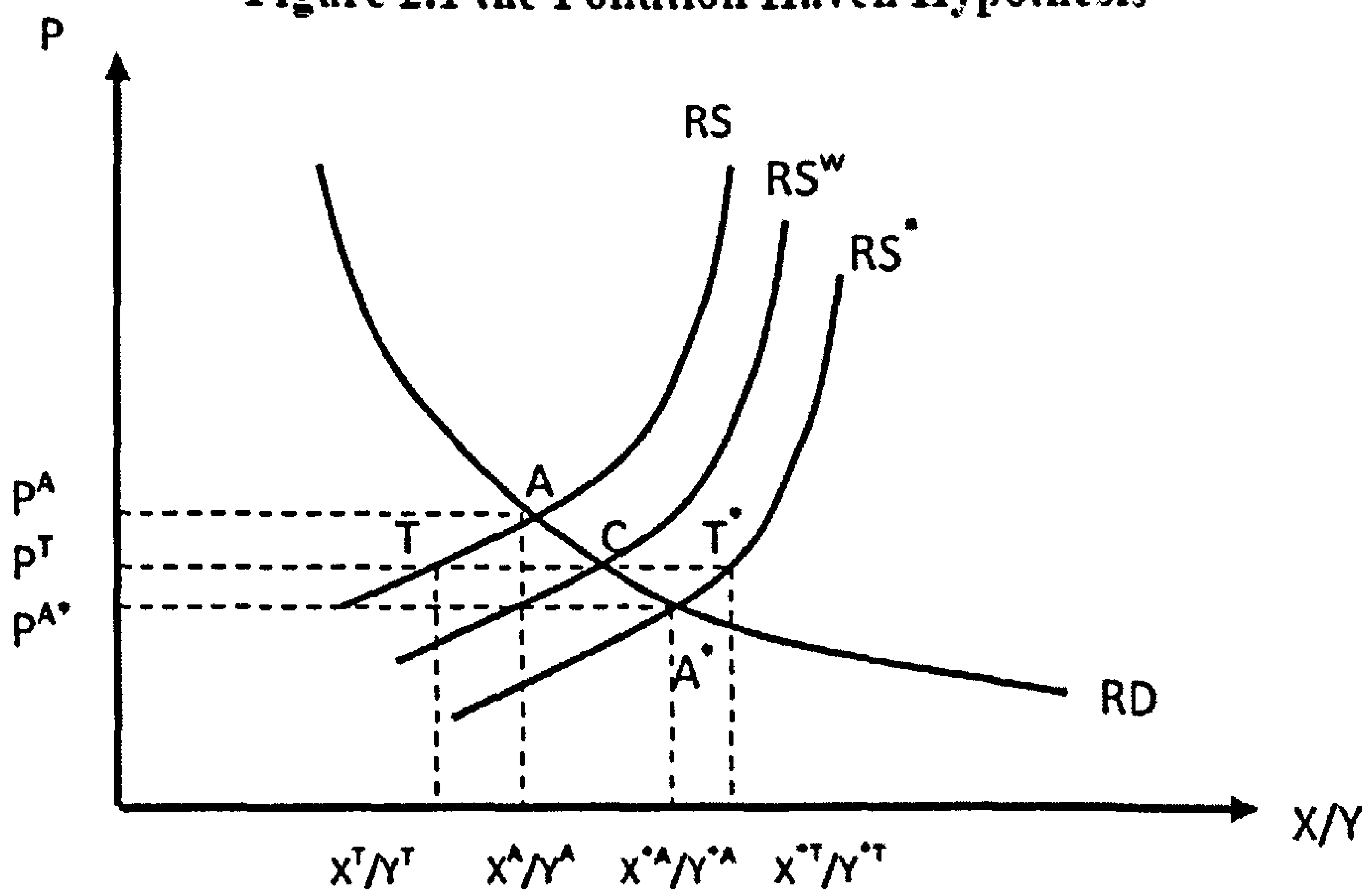
## 2.2 THE POLLUTION HAVEN HYPOTHESIS

Traditional comparative advantage theories state that changes in trade performance should reflect changes in factor endowments such as capital, labour and land; but increasingly, new theories claim that environmental regulations are potentially playing an important role in influencing domestic firms' international competitiveness and shaping up a country's comparative advantage.

There are two main schools of thought on the impact of environmental regulation differentials on competitiveness. One school votes for the negative effect of environmental regulations on competitiveness and comparative advantage. The theoretical works can be found in Siebert (1974, 1977), Pethig (1976), McGuire (1981), Baumol and Oates (1988:257-283), Krutilla (1991), Carrao and Siniscalco (1992), Chichilnisky (1994), Copeland and Taylor (1994, 2003), Palmer, Oates and Portney (1995), Simpson and Bradford (1996), Antweiler, Copeland and Taylor (2001). The main argument is that: by pricing environmental factors, environmental regulations can form part of production costs. As a result of heterogeneous environmental pricing, other things equal, countries with lax environmental standards can become relatively competitive in producing and exporting pollution intensive goods while countries with stringent environmental standards lose comparative advantage in dirty industries. If capital is freely mobile, pollution intensive industries will be driven out of an area with stringent environmental regulations and relocating to an area with laxer environmental regulations. Pethig (1976) extends several propositions of the neoclassical trade theories to pollution generating industries and derives different versions of the theorem of comparative advantage with respect to environmental scarcity. McGuire (1981) shows that, environmental regulations can be, under specific conditions, equivalent to negative neutral technical progress. McGuire also investigates FDI (foreign direct investment) flows and dirty industries relocation due to stricter environmental standards in the regulated area. Baumol and Oates (1988: 257-283) demonstrate in a two-country (rich and poor) two-good (dirty and clean) setting that the rich country which adopts an environmental control programme will specialize in the clean good while the poor country will specialize in the dirty good. This school of thought can be summarized by the Pollution Haven Hypothesis: countries with laxer environmental regulations (developing countries) will be made dirtier as a result of trade liberalization and become pollution havens for the world's pollution intensive industries.

We adopt Copeland and Taylor (2003)'s pollution haven model to illustrate the PHH. The basics of the model: two goods, $X$ is dirty with price p and $Y$ is the clean numeraire good; two factors, $K$ refers to capital and $L$ is labour. $e$ is the emission intensity which is the result of environmental taxes and the equilibrium output of $X$. Let an asterisk denote Southern variables. North and South have the same capital to labour ratio, although North has absolute larger stocks of factors and hence richer than South. To investigate the pollution haven mechanism, the authors adopt the comparative advantage approach which is common in the traditional international trade literature. Basically, this approach employs a relative demand and supply analysis for the two goods, as shown in figure 2.1.

**Figure 2.1 the Pollution Haven Hypothesis**




Note: diagram adopted from Copeland and Taylor (2003). A and $A^*$ denote autarkic equilibriums while T and $T^*$ denote production points in trading equilibriums. C denotes consumption in trading equilibrium.

Because preferences are assumed identical and homothetic and demand decreases as price goes up, there is only one common downward-sloping demand curve in the figure (denoted as RD). Relative supply curve is denoted as RS, which is upward sloping, i.e. RS'(p)>0.

Since an increase in the emissions intensity ($e$) would stimulate the $X$ industry and contract the $Y$ industry, $\partial RS/\partial e>0$. The relative supply curve for South lies to the right of that for North since emission intensity is higher in South than in North[8]. The world supply curve $RS^w$ is a weighted average of the RS and $RS^*$ curves and lies in between of the two. If trade opens, North's equilibrium would move from A to T and that of South would move from $A^*$ to $T^*$. Thus, the autarky relative price of $X$ is higher in

[8] It could be the result of either a rigid emission scheme (exogenous) in North or an income gap driven regulatory gap between North and South. Copeland and Taylor (2003) explore income difference as the root of regulatory differences in which case the pollution supply and demand curves are shifted upwards because of higher income in North and hence pollution taxes are higher in North. Consequently, emission intensities are lower in North than in South.

North than in South, which implies that the South has a comparative price advantage in producing $X$ (the dirty good). On this basis, international trade leads to South specializing in dirty good production and North specializing in clean good production. To make up the gap between consumption and production, southern production of the dirty good rises while that of clean good falls (from $X^{*A}/Y^{*A}$ to $X^{*T}/Y^{*T}$) and the contrary applies to North (from $X^{A}/Y^{A}$ to $X^{T}/Y^{*T}$). A pollution haven pattern of production and trade thus happens in South.

The other school of thought on the impact of environmental regulations argues that stricter environmental regulation can have little or even positive impact on international competitiveness (brought to attention by Porter, 1991). On the one hand, to counteract the negative effect of rising environmental standards, developed countries may either erect high trade barriers (especially non-tariff barriers) on dirty goods imports from the countries that have laxer environmental standards, or subsidize the threatened domestic producers. On the other hand, technology innovation triggered by stringent environmental standards and government intervention could, to some extent, offsets or even overcomes the negative effect of stringent environmental regulations. Porter and Van der Linde (1995) argue that a country with relatively stringent environmental regulations can benefit from the improvement in environmental quality and is likely to develop new comparative advantages in the environmentally more sensitive industries. These advantages, in the long run, might more than offset the short-term losses. This proposition is often referred to as the 'Porter Hypothesis'. However, Palmer et al. (1995) argue that the Porter hypothesis is too optimistic in the sense that it sees tightening environmental standards as a cost-free paradigm.

# 2.3 EMPIRICAL EVIDENCE

In the literature of environmental regulation and competitiveness, several approaches have been used to empirically examine the role of environmental regulations in shaping a country's trade pattern and/or firms' competitiveness. They include the analyses on trade pattern changes, on the role of environmental stringency on the determination of specialization using the Heckscher-Ohlin framework and Gravity-type models, and on the role of environmental regulations on FDI location. We group and discuss the empirical literature according to their methodological framework.

## 2.3.1 Descriptive analysis

In this section we review the empirical studies that attempt to examine the role of environmental regulations using descriptive statistics on production and trade. Comparison is generally made between trade performance in developed countries (North) and in less developed countries (South), with the definition of 'dirty' industries and 'clean' industries invariably based on US data, either on pollution abatement costs and expenditures (PACE) or on emissions of pollutants (from Industrial Pollution Projection System (IPPS), see Hettige et al., 1995).

The previous studies fall into two groups, those analysing trade and production shares of dirty industries and those using revealed comparative advantage indices. In the first group, research work has focused mainly on the time-series production share, growth rate and net exports of dirty goods compared to other goods or total (manufacturing) output. Low (1992) finds out that the growth rate of 'dirty' industry exports in Mexico exceeded that of total exports between 1981 and 1989. It is questionable, however, if this finding applies to other developing countries. Jänike et al. (1997) find the general tendency of net exports between 1960 and 1991 has not involved the general relocation of 'dirty' basic industries from developed to developing countries. In fact, the high-income market economies have remained net exporters of major dirty industries, with the net export share in some of the dirty industries becoming even higher at the end of the period. Decreases in net exports of the high income group could only be found in a few dirty industries such as copper, nickel and tin.

To the contrary, Mani and Wheeler (1999) find supportive evidence for pollution havens in poor countries by exploring the trends of pollution intensive industries in different economic groups between 1960 and 1995. Their results show that pollution-intensive output (grouping of five dirty industries) as a percentage of total manufacturing has fallen consistently in the OECD countries and risen steadily in the developing world. Moreover, the periods of rapid increase in net exports of pollution-intensive products from developing countries coincided with periods of rapid increase in the cost of pollution abatement in the OECD countries. But the authors also argue that the tendency towards formation of a pollution haven seems to have been self-limiting and transient because economic growth brings countervailing effects through regulation and technical expertise, which is evidenced by the 'cascading' pattern of production and import/export ratio of dirty industries in the Newly Industrialized Countries, Developing East Asia and South Asia.

Other studies investigate the issue of pollution havens using a revealed comparative advantage framework. Using measures of trade flows and revealed comparative advantage as indicators of shifts of patterns of international industrial location, Low and Yeats (1992) find that between 1965 and 1988 more developing countries gained comparative advantage in dirty industries. However, the significance of this discovery is muted by the finding that industrialized countries were still the major exporters of "dirty" good: 17 OECD countries accounting for 72.5% of world exports of such goods.

These findings receive supportive evidence from other studies, such as Sorsa (1994) who examines the trade patterns of environmentally sensitive goods (ESGs)[9] in industrial economies as well as developing countries as a whole. It is found that 'the bulk of world exports of environmentally sensitive goods continue to originate in industrial countries -over 70%'. Nevertheless, there are differences between countries. While the U.S, Japan, Norway, and Sweden lost market share in environmentally sensitive goods, Austria, Finland and Germany gained market share in these goods. In addition, industrialized countries as a whole have also been found to have maintained their comparative advantage (based on Balassa's revealed comparative advantage index) in these goods at the aggregate level over developing countries, although product level analysis gives some indication of a shift in comparative advantage towards developing countries.

Following Mani and Wheeler (1997)'s definition of five dirtiest industries, Grether and de Melo (2003) examine the patterns of production and trade for 52 countries during the period 1981-1998. Their results show that the second richest and the richest quintile have experienced decreasing trends in output and export share of some of the dirty industries. The RCA-based evidence on delocalization of dirty industries towards the South is rather mixed. As a group, developing countries exhibit increasing revealed comparative disadvantage in pollution intensive products. Within the dirty industries and within countries, there is, however, some evidence for pollution havens in poor countries: developing countries have experienced an increase in RCA in pollution intensive products.

[9] Environmental sensitive goods (ESG) are defined in Sorsa (1994) as those that incurred the highest pollution control expenditure in the US in 1988.

To sum up, existing studies provide mixed results for the PHH despite of the simplicity of the methods used. While production share of dirty industries in developing countries seems to have grown faster to be larger than earlier decades, this piece of evidence, however, is not rigorously convincing since we do not know the changes in trade patterns and whether such a change is indeed caused by North-South regulatory differences. In addition, it is shown that industrialized countries were still the major exporters of dirty goods in the 1990s, accounting for more than 70% of world's total. At disaggregated level, RCA-based findings show dirty industries in developed countries seem to have a decreasing revealed comparative advantage in dirty goods while developing countries seem to export more dirty goods. When the countries are lumped together as North or South, the reverse seems to be true: as a group, developing countries exhibit increasing revealed comparative disadvantage in polluting products while developed countries maintain their comparative advantage.

The divergence in findings may result from both methodology and data differences. Regulatory differential is only one possible determinant of specialization along with trade liberalization. Traditional production factors also could play important roles in affecting specialization. By lumping together countries into North or South, factor endowment differentials and regulatory gaps are masked. A developing country with presumably lower environmental stringency could be relatively labour abundant as China, or relatively natural resource abundant such as Arabian countries. These two types of developing countries are likely to respond quite differently in specialization terms to trade liberalization. Similarly, by lumping together pollution intensive goods, we may lose sight of the unobserved heterogeneity in industries. Some polluting industries (higher transportation cost or heavily protected) may be less footloose than others. Consequently, the footloose industries have a greater capacity to seek locations in South while the less footloose ones may have to expand in North. Thirdly, there is no consensus on the choice of trade performance index. While comparative price advantage of lax environmental regulations is theoretically pinned down, it is often difficult to use a price formulation of the principle of comparative advantage. Not all trade performance indices used may be correctly representing the changing pattern of comparative advantage.

### 2.3.2 Heckscher-Ohlin framework

A conventionally used framework in this subject is Heckscher-Ohlin (H-O) modelling, where comparative advantage is determined by the environmental regulatory gap as well as factor endowment differentials. In this methodology, trade performance indices are often expressed as a function of factor endowments and environmental stringency. However, data on environmental stringency are either unavailable across time or incompatible among countries. Hence, early studies have either adopted a qualitative measure of environmental stringency or employed pollution abatement costs based on the US data.

An early attempt at investigating the impact of environmental stringency on trade patterns is made by Tobey (1990), who uses trade flows data on five pollution-intensive industries in 23 countries in 1975. Based on two alternative approaches, i.e. including a qualitative variable for regulatory stringency[10], and performing an omitted variable (regulatory stringency) test, Tobey tests the hypothesis that "stringent environmental policy has caused trade patterns to deviate in commodities produced by the world's 'dirty' industries". No empirical evidence is found from either approach that the introduction of environmental control measures has caused trade patterns to deviate from the traditional Heckscher-Ohlin-Vanek (HOV) predictions.

[10] It is adopted from Walter and Ugelow (1979).

By extending Tobey's estimations, a number of studies have examined the link between environmental stringency and competitiveness by incorporating heterogeneity across regions and industries as well as endogeneity of environmental regulations. The results are at best mixed.

Cole and Elliott (2003) provide an HOV type test of the link between environmental stringency and net exports for 4 pollution intensive industries in 60 countries in 1995. According to their results, environmental stringency is not a statistically significant determinant of net exports, regardless of, which alternative measures of environmental stringency used, whether environmental regulations treated as exogenous or endogenous, or whether the industries are pooled together or regressed individually.

On the contrary, Wilson et al. (2002) regress net exports in five pollution-intensive industries (individually) on factor endowments and environmental stringency. They use pooled cross-section data (time dummies included) for 24 countries between 1994 and 1998. It is found that environmental stringency is negatively related to net exports of most pollution intensive industries, once country heterogeneity such as enforcement of environmental regulations is controlled for. To control for unobserved differences in the effectiveness of environmental legislation, they use a slope dummy for developed (or developing) countries. Their results show that environmental legislation has a more dramatic effect on net exports in OECD countries than in non-OECD countries.

Quite a few studies of environmental stringency and trade specialization are performed using Heckscher-Ohlin-Samuelson (H-O-S) [11] framework, with factor

[11] There is difference between Heckscher-Ohlin-Samuelson modelling and Heckscher-Ohlin-Vanek modelling as the latter is the 'factor content' version of the HOS model. Although the cross-section HOV

intensities and a measure of environmental stringency collectively explaining trade patterns. A number of studies focus on industries in the US or in other OECD countries, since developed countries generally have better data records on environmental regulations and pollution abatement costs than developing countries.

Kalt (1988) is probably the earliest H-O study on the relationship between the US environmental stringency and industrial competitiveness. He regresses changes in net exports between 1967 and 1977 across 78 industries on changes in environmental compliance costs and other control variables. Although the effect of environmental stringency on trade patterns is insignificant when 78 industries are pooled together, he does find significant and negative effect from environmental stringency for manufacturing industries, and especially so when chemical industries are excluded[12].

Grossman and Krueger (1992) use the ratio of US pollution abatement costs to industry value added as a measure of environmental stringency. They investigate whether the pattern of US imports from Mexico and the pattern of US foreign investment in Mexico in 1987 have been affected by the higher costs of pollution abatement in the US. Their findings suggest no significant effect on import penetration from Mexico due to higher US environmental standards.

The usage of cross-section data often makes it difficult to control for unobserved characteristics of countries or industries that may be correlated with the key explanatory variables. As Levinson and Taylor (2004: 24) put it "the first, and simplest, implication of our discussion so far is that cross-section regressions of net imports on pollution abatement costs may be biased by unobserved heterogeneity."

allows to consider multiple factor multi-commodity case, Bowen et al. (1987) show that it is only a weak version of H-O hypothesis.

[12] Jaffe et al. (1995) point out that this result is puzzling given the fact that chemical industries are subject to relatively high environmental compliance costs.

Another impossible mission for cross-section analysis is to tackle endogeneity. A few recent studies have employed panel data to address both the endogeneity of environmental regulation and unobserved heterogeneity of the industries. A significant negative effect of environmental regulation on competitiveness has been found in these studies.

Ederington and Minier (2001) argue that the reason why previous research has only found a negligible impact of environmental regulations on trade flows is because these studies treat the level of environmental regulation as exogenously determined (implicitly assuming away the possibility that trade considerations may play a role in the setting of environmental policy). To address this weakness, they estimate a system of simultaneous equations: an equation modelling the determination of environmental protection, and an equation modelling the determination of imports. Following Grossman and Krueger (1992), they regress import penetration on the level of environmental stringency and trade barriers for US manufacturing industries between 1978 and 1992. Their fixed effects estimates find a small predicted effect of environmental regulations on import penetration. After taking endogeneity into account, they use three-stage least squares (3SLS) estimation and find a much larger effect of environmental regulation on trade flows. Although the sensitivity of the results to the choice of instruments is a concern, their results suggest that countries tend to endogenously under-tax import competing industries and over-tax export industries.

Levinson and Taylor (2004) develop an econometric model to demonstrate how unobserved heterogeneity, endogeneity and aggregation issues bias measurement of the relationship between regulatory costs and trade. Using data from the US, Canada, and Mexico for 130 manufacturing industries from 1977 to 1986, they conduct both fixed effects estimation and two stage least squares (2SLS) estimation. Fixed-effects estimates provide evidence that import penetration from Canada and Mexico into the US is positively correlated with pollution abatement costs. Their 2SLS estimates are consistently and robustly larger than the FE estimates.

A recent study by Cole et al. (2005) investigates the competing effects of factor intensities and environmental regulations to explain why US specialization in dirty industries does not seem to decrease. Using US two and three-digit SIC levels of industry aggregation between 1978 and 1994, they find that environmental stringency does have a negative effect on U.S specialization indices but this effect has been overcome, in terms of elasticity magnitude, by significantly positive effects of human capital intensity and physical capital intensity. By using an instrumental variable approach, they also find pollution abatement cost actually has a larger effect (in terms of elasticity) on trade specialization once endogeneity is addressed.

Ederington et al. (2005) propose and test several common explanations for why the effect of environmental regulations on trade may be difficult to detect. They propose that: 1) environmental regulations have stronger effects on trade between industrialized and developing countries (while most trade occurs among industrialized economies); 2) footlooseness [13] also affects the sensitivity of industries towards regulatory differences; 3) for most industries pollution abatement costs are a small component of total costs, and the effects of the differences in these small costs are overwhelmed by other more important factors. They show that industries with the largest pollution abatement costs also happen to be the least geographically mobile, or "footloose". After accounting for these distinctions, they find a significant effect of pollution costs on US imports (between 1978 and 2002 at 4-digit industry level) from developing countries, and in pollution-intensive, footloose industries.

[13] Footlooseness refers to geographical mobility of an industry and is usually measured as transport cost, fixed plant cost as well as the extent of agglomeration economy.

Mulatu et al. (2004) examine the impact of environmental regulation on net exports of 2-digit ISIC manufacturing industries during the period 1977-1992 in Germany, the Netherlands and the US. They also distinguish pollution-intensive from non pollution-intensive industries, resource-based from non resource-based industries, to test unobserved heterogeneity in industries. Their empirical results show that the estimated effects of stringency of environmental regulation on export competitiveness differ across the three countries: a negative impact in the US, a negative impact in Germany only when pollution intensive industries are distinguished from other industries; for the Netherlands, the country with laxest environmental regulations among the three according to PACE data, the negative link is not existent and sometimes a positive significant effect is obtained.

### 2.3.3 Gravity models: bilateral trade flows

The gravity model of trade resembles Issac Newton's law of gravity and predicts bilateral trade flows based on the sizes of and distance between trading partners. The model has also been used to test hypotheses rooted in theories of trade such as H-O theory. This type of modelling has become popular in empirical studies of environmental regulation and bilateral trade flows in recent years.

As van Beers and van den Bergh (1997: 30) argue "a disadvantage of this approach [the H-O-V approach], which is based on multilateral trade flows, is that the effects of differences in strict environmental regulations on trade flows between countries may cancel out as multilateral trade is an aggregate of bilateral trade flows."

By repeating the empirical test of Tobey (1990) with a gravity model using two output-oriented environmental policy strictness indicators (namely a broad and a narrow energy-based one), van Beers and van den Bergh (1997) find a significant negative effect of stricter domestic environmental regulations on exports in 1992. However, the effect is insignificant for dirty trade flows, which may be due to the possibility that most dirty industries are resource based and thus less mobile. Contrary to the prediction, they find a significant negative effect of trading partner's environmental regulation on domestic exports, pointing to the existence of import barriers that go together with relatively strict environmental regulations.

To examine the reliability of the results, van Beers and van den Berg (2000) re-test the analysis in Tobey (1990), replacing the focus on multilateral trade flows by one on bilateral trade flows. This is actually an update of van Beers and van den Berg (1997) in terms of country sample and sectors coverage. The results provide partial support for Tobey, namely no significant effects for dirty goods trade flows. Moreover, results for total exports show a positive (albeit counterintuitive) effect of relatively strict environmental policy on exports which is consistent with an omitted variable test in Tobey. Analysis of sector specific trade data provided no significant export effects of a relatively stringent environmental policy for chemicals and steel, which is in line with Tobey. The export effects are significantly negative for mining and non-ferrous metals but significantly positive for paper. They conclude that the results for 1992 show more significant effects than those for 1975, which may be due to the longer gestation period of environmental policy implementation and impacts.

Motivated by the gravity models in van Beers and van den Bergh (1997), Harris et al. (2002) examine the relationship between environmental regulation and foreign trade in a three-dimensional panel data framework for a panel of 24 OECD countries over a sample period of 1990-1996. They find that environmental costs do not have a real impact on foreign trade, once country specific effects as well as time effects are taken into consideration. They conclude that a simple cross-sectional or naive panel-data model is mis-specified when the stringency measures, and probably also the other quantitative explanatory variables, absorb the influence of the missing specific effects.

Grether and de Melo (2003) also search for evidence of changes of imports in response to regulatory gap. Using a gravity model, they examine the determinants of import flows in five heavily polluting industries for 52 countries between 1981 and 1998. Estimations for total imports versus dirty imports, as well as footloose (non-resource-based) imports versus non-footloose imports, are performed. They find support for the pollution haven hypothesis in the case of footloose imports. However, when endogeneity is controlled, this relationship is not robust. It is noteworthy that they measure the regulatory gap between countries by difference in GDP per capita (which may be only partially related to the stringency of environmental regulations).

Jug and Mirza (2005) investigate the role of environmental regulations in structural gravity equations based on monopolistic competition. Using a panel of 9 ISIC industries in European countries between 1996 and 1999, they find that environmental expenditure data (cost-based) is negatively influencing trade flows, even when unobserved heterogeneity in countries and industries as well as endogeneity of environmental regulation is taken into account. A robustness check shows that this finding is not due to adoption of the environmental stringency proxy.

## 2.3.4 Summary of previous studies

We have seen so far a wide diversity of approaches and data adopted by the studies on the relationship between environmental stringency and trade performance (competitiveness), for example, a Heckscher-Ohlin model vs. Gravity framework, cross-section vs. panel data, as well as different measurement of environmental standards. Quite a few empirical studies have also examined the influence of environmental regulations on FDI location choice. The methodologies and empirical results are mixed. Detailed summaries can be found in Eskeland and Harrison (2003), Dean et al. (2005) and Smarzynska-Javorcik and Wei (2005). The examination of intra-country FDI location choice in China can be found in empirical papers such as Dean et al. (2005), Amiti and Javorcik (2008), Zhang and Fu (2008).

Early studies usually find an insignificant effect of regulatory stringency on industrial competitiveness. On this account, 'small environmental cost' is often being used as an explanation. For example, Pearson (1987) claims that the effect on trade will be correspondingly low since environmental control costs are a small fraction of production costs in virtually every industry. Tobey (1990: 206) also makes similar comments: "as already noted, a reasonable explanation for these empirical results may simply be that the magnitude of environmental expenditures in countries with stringent environmental policies are not sufficiently large to cause a noticeable effect." Lucas et al. (1992) also point out that "these studies conclude that direct investment does not appear to be stimulated by such regulations, partly because the cost of emission controls is generally a tiny fraction of operating costs."

However, as Levinson and Taylor (2004:1) argue 'while it is possible that more stringent environmental regulations have a small effect on firms' costs and international competitiveness, it seems unlikely that more stringent regulations would have no effect whatsoever'.

Recent studies have made improvements in methodology to isolate the effect of environmental stringency. Quite a few weaknesses in early studies are identified and addressed. For example, endogeneity of environmental stringency, certain industrial characteristics (such as pollution intensity and footlooseness) and unobserved heterogeneity are addressed in panel data.

With regard to measuring environmental stringency, it is still difficult to have internationally comparable indicators. Hence most studies are confined to single country (normally a developed country such as the US) data or OECD data.

Finally and importantly, we have to bear in mind that the complicated adjustment mechanisms (real wages, real exchange rates) that operate when regulations are imposed are not accounted for in existing studies (Jaffe et al., 1995).

The following sections focus on examining the changes in trade patterns over past decades before we turn into econometric analysis on the effect of environmental stringency on the competitiveness in chapter three.

## 2.4 DEFINING 'DIRTINESS' OF INDUSTRIES

The existing commodity categorization standards such as International Standard Industrial Categorization of All Economic Activities (ISIC) and Standard International Trade Classification (SITC) mainly focus on production processes. Studies in the literature have adopted different categorization principles (according to product attributes) in order to suit their research, for example in the context of revealed comparative advantage, Hufbauer (1970), Lim (1997), Hinloopen and van Marrewijk (2004). To examine the changing patterns of trade flows in dirty industries as well as in relatively clean ones, we need to define the 'dirtiness' of an industry. Various definitions exist such as: (1) intensity of energy use per unit of output; (2) intensity of emissions per unit of output (per employee or per unit of value added); (3) associated socioeconomic costs, e.g., illness (especially respiratory diseases); (4) pollution abatement operating costs or pollution control expenditures (Low and Yeats, 1992; Sorsa, 1994). A direct approach is to identify pollution intensive sectors as those with high emissions intensity per unit of output. Based on detailed firm level data, Hettige et al. (1995) estimate the industrial emissions by merging U.S manufacturing data and emission data at the firm level (over 200,000 factories) for detailed product categories (1,500 categories) for the late 1980s. They also construct toxic pollution risk-intensity indices for more aggregate level. Important questions arise, however, about the use of such measures. Firstly, how applicable are these US-based estimates to other countries? Country specific factors such as resource abundance and technologies affect the production process of a product and may also incur different emission intensities. However, the ranking of an aggregate sector may be more similar across countries than the ranking of a specific product.[14] That is one reason why we focus on the industries at ISIC 3-digit level rather than on more disaggregated product categories. Secondly, even within this data source, correlations of different pollutant intensities are low cross classes of pollutants. This means that an industry defined as highly pollution intensive in terms of water pollutants may be relatively clean in terms of air pollutants. Hettige et al. (1995) find that a few industries are highly intensive in all pollutants. Thirdly, these estimates do not allow for variations of pollution intensity over the years. We have to question whether or not the relative 'dirtiness' ranking remains constant across time, especially over decades.

To provide some tentative answers to these questions, we compare Hettige et al. (1995) and Dean and Lovely (2008) for sectoral pollution intensity information. We adopt from Hettige et al. (1995) (also named as the Industrial Pollution Projection System, IPPS) the pollution per output estimates for 28 manufacturing sectors at ISIC 3 digit level. The sectors are ranked according to their pollution intensities in 8 different water/air pollutants (BOD, TSS, $NO_2$, PM10, $SO_2$, CO, TP and VOC)[15]. An

[14] Hettige et al. (1995: 66) also point out that even if there is considerable international variation in the absolute level of sectoral pollutant intensities, the relative ranking of intensities across sectors may be expected to remain more constant.

[15] Since all risk-weighted indices are highly correlated with total toxic intensity, IPPS has standardized on the latter. We choose the eight individual pollution intensities to create rankings of 'dirtiness'.

average ranking is then calculated by taking the mean of the eight rankings. We also rank the sectors by the aggregation of the pollutants by pound. Table 2.1 provides information on the average ranking and total ranking. Detailed pollution intensity data can be found in appendix A2.1. Sectors have very different rankings depending on the pollutant and weighting employed. Appendix 2.2 provides Spearman correlation coefficients for all the rankings. The average ranking and total ranking have a high rank correlation of 0.93. According to the average ranking, the most pollution intensive group includes: 371 (Iron and Steel), 341 (Paper and Products), 372 (Non-ferrous Metals), 351 (Other non-metallic Mineral Products) and 354 (Misc. Petroleum and Coal Products). Using information of Hettige et al. (1995), Mani and Wheeler rank top ten 3-digit ISIC industries in terms of total pollution intensities (focusing on air, water and metal pollution intensities). They select 371 (Iron and Steel), 372 (Non-ferrous Metals), 341 (Paper and Products), 369 (Other non-metallic Mineral Products) and 351 (Industrial Chemicals) as the top five 'dirty sectors' for their analysis.

In the relatively clean sectors we find 322 (Wearing Apparel), 385 (Professional and Scientific Equipments), 324 (Footwear except Rubber or Plastic), 342 (Printing and Publishing) and 356 (Plastic Products). The top five cleanest industries identified by Mani and Wheeler, 321 (Textiles), 382 (Machinery, except Electrical), 383 (Machinery, Electric), 384 (Transport Equipment) and 385 (Professional and Scientific Equipments) are also relatively clean in our ranking table.

Table 2.1 Ranking of Industrial Pollution Intensity

| ISIC code | Description | Average | Total |
|---|---|---|---|
| 371 | Iron and Steel | 1 | 1 |
| 341 | Paper and Product | 2 | 3 |
| 372 | Non-ferrous Metals | 3 | 2 |
| 351 | Industrial Chemicals | 4 | 6 |
| 354 | Misc. Petroleum and Coal Products | 5 | 5 |
| 353 | Petroleum Refineries | 6 | 7 |
| 369 | Other Non-Metallic Mineral Products | 7 | 4 |
| 352 | Other Chemicals | 8 | 8 |
| 331 | Wood Products, except Furniture | 9 | 9 |
| 313 | Beverages | 10 | 12 |
| 311 | Food Products | 11 | 15 |
| 362 | Glass and Products | 12 | 10 |
| 321 | Textiles | 13 | 16 |
| 355 | Rubber Products | 14 | 13 |
| 323 | Leather Products | 15 | 17 |
| 381 | Fabricated Metal Products | 16 | 18 |
| 332 | Furniture, except Metal | 17 | 14 |
| 361 | Pottery, china, earthenware | 18 | 20 |
| 383 | Machinery Electric | 19 | 21 |
| 382 | Machinery, Except electrical | 20 | 23 |
| 384 | Transport Equipment | 21 | 22 |
| 314 | Tobacco | 22 | 19 |
| 390 | Other Manufactured Products | 23 | 11 |
| 356 | Plastic Products | 24 | 24 |
| 342 | Printing and Publishing | 25 | 25 |
| 324 | Footwear, except Rubber or Plastic | 26 | 26 |
| 385 | Professional and Scientific Equipment | 27 | 27 |
| 322 | Wearing Apparel, except Footwear | 28 | 28 |

Source: Hettige et al. (1995) pollution intensity based on output level. Average denotes the arithmetic mean of the individual rankings of the eight pollutants. Overall denotes the sum of individual pollution emissions: BOD biochemical oxygen demand), TSS (total suspended solids), $NO_2$ (nitrogen dioxide), PM10 (particles of 10 micrometers or less), $SO_2$ (sulphur dioxide), CO (carbon monoxide), TP (total particulates), and VOC (volatile organic compound).

Dean and Lovely (2008) estimate the pollution intensities of Chinese industrial output between 1995 and 2004 in terms of four pollutants: COD, $SO_2$, Smoke and Dust. Since Chinese pollution information is given at the industrial level (GB/T4754-2002) which is similar to ISIC 3-digit classification, an attempt is made to concord the two classifications. A2.3 in the appendix presents the pollution intensities for Chinese manufacturing sectors. Although information for relevant ISIC industries are missing (for example, 354, 361 and 362), we still rank the other industries according to their actual pollution intensities (from highest to lowest using ranking in overall intensity in 1995). Although the pollution intensities for each sector have reduced dramatically between 1995 and 2004, the relative rankings do not change significantly. There is also much similarity between the rankings of pollution intensity based on the two sources. For example, 341, 369, 371 and 372 are among the dirtiest industries, while 322/324, 384, 383 and 385 have lowest pollution intensities in both rankings. Since industrial pollution intensity is heavily affected by its sectoral composition and the technologies which are employed as well as the regulations imposed, it is almost unavoidable to have a few exceptions. For example, 313 (Beverage Production) and 311 (Food Production), which have been grouped into medium low and low pollution intensive industries according to Hettige et al. (1995), are ranked among the heavy polluters in China.

Another source of industrial pollution intensity ranking is Lu and Huang (2008) which uses pollution abatement costs and expenditures (PACE) and pollution abatement operating costs (PAOC) in the US in 1999. It also provides similar rankings to table 2.1 although the industrial classification in PACE and PAOC is North America Industrial Classification System (NAICS).

Since there is no universal ranking of pollution intensities, we use the ranking in table 2.1 to provide tentative answers and use them for the following analysis.

## 2.5 CHINA'S TRADE STRUCTURE

The trade data used in this chapter comes from the World Bank database *Trade, Production and Protection 1976-2004* developed by Nicita and Olarreaga (2006). The industry classification system for the database is the 3-digit level ISIC revision 2 which covers 28 manufacturing sectors across 100 countries. We only focus on manufactured goods for three reasons. The first is that primary goods are subject to subsidies, quotas and other arrangements which mask enduring sources of comparative advantage. Additionally, relative ranking of pollution intensity for primary goods are not readily available and comparable. Lastly, for China as well as the industrialized countries, the manufactured goods constitute a large proportion of all traded goods.

Except the reported trade flow values (official data reported by each country), the database also contains the mirrored trade flow values which represent the imports/exports value of the reporting countries observed as exports/imports values from partner countries. The reported and mirrored data may differ significantly from each other due to transportation costs not to mention the different goods classification systems used by individual countries. Despite their high correlation coefficients[16], we would use mirrored data which provides a more complete dataset and may be more precise than the reported one because trade flows are usually better recorded in entrance (Nicita and Olarreaga, 2006).

### 2.5.1 Aggregate trends

Trends in trade data often provide a straightforward impression of a country's stance on trade openness. We take a first look at the time series data. Before the economic reform and opening up, Chinese exports and imports were roughly balanced with low levels of trade values. Foreign trade, as well as other economic activities, were strictly controlled by the central government. This situation did not change much throughout

[16] It turns out that reported data and mirrored data have a high positive correlation (the correlation coefficient for imports is 0.9903, while that of the exports is 0.9730).

the early and mid 1980s, although foreign trade reform actually started in July 1979[17]. From the late 1980s on, both imports and exports volumes increased dramatically. In the meantime, the gap between exports and imports (trade surplus) has widened[18]. In 2004, the trade surplus in manufactured goods has risen to over 300 billion US dollars[19]. (See figure 2.2)

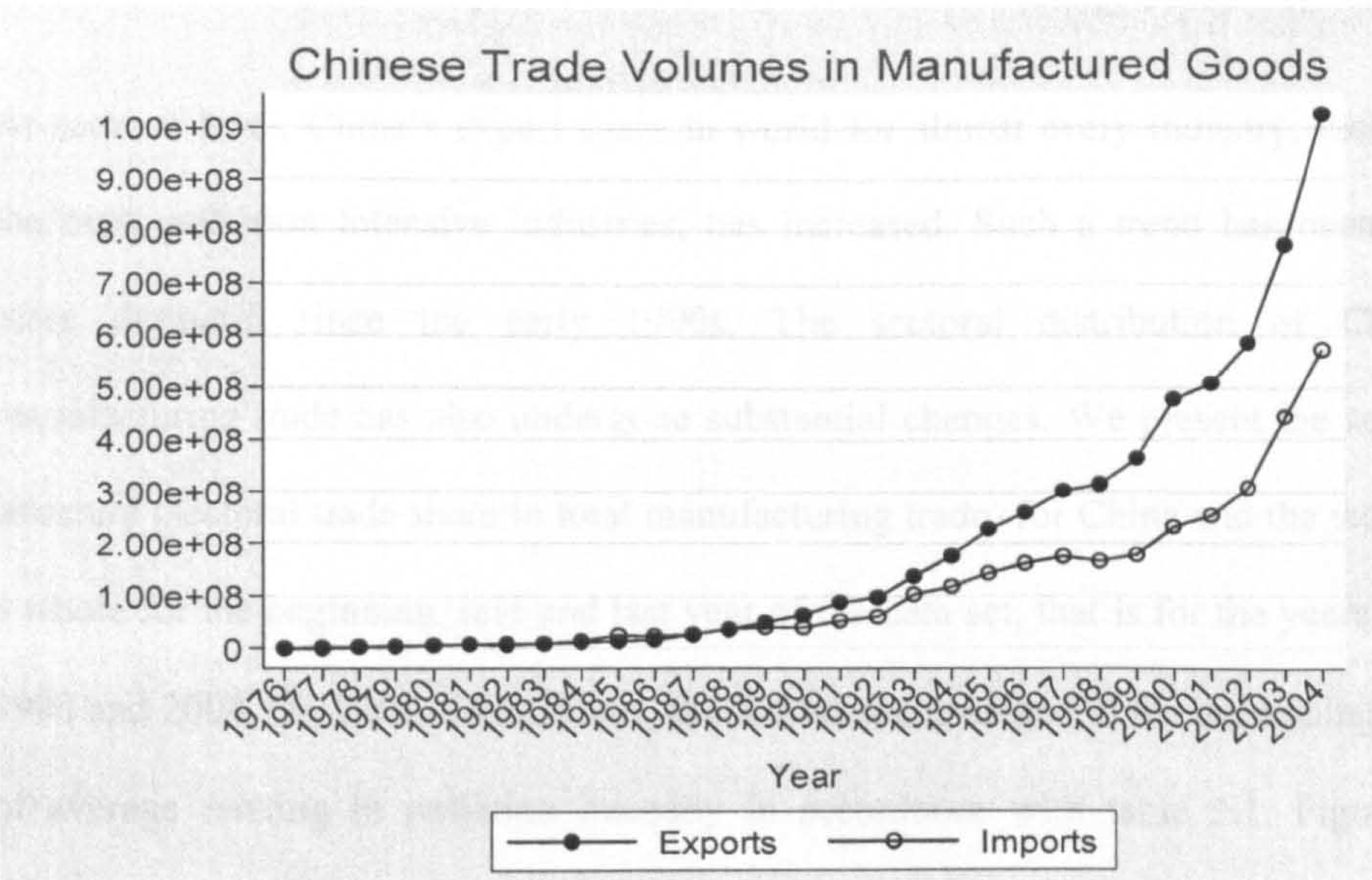
Although the worldwide trade flows of manufactured goods simultaneously increased, the share of Chinese exports and imports in world trade has grown phenomenally; the share of exports rising from below 2% to over 10% and the share of imports rising from below 1% to about 6% (figure 2.3).

[17] This is because during the first five years of opening-up, the right to conduct foreign trade was still centrally determined through state-owned corporations. Only a few provinces (Guangdong and Fujian among the first few) enjoyed flexible policies while others enjoyed little autonomy in conducting foreign trade. A report on full scale opening-up as well as other decentralization measures was submitted by the then newly established Ministry of Foreign Economic Relations and Trade (MOFERT). It was approved by the State Council in September 1984 (Luo, 2000). Hence we consider this as an effective start of trade openness for individual provinces/firms when the right of conducting foreign trade was decentralized to local governments.

[18] Many quantitative restrictions such as export controls, import licensing and quotas were gradually abolished. Instead of strictly planning, guidance plans were used in conducting foreign trade. The local governments now had more incentive to promote foreign trade thanks to the foreign exchange retention scheme. Trade and payments were regulated at local level through the export-and-import-agency system which was an improvement from the conventional 'airlock' system. During this period, agricultural goods constituted a significant share of Chinese exports while capital goods were the main imports. It is also argued (Word Bank, 1994; Zhang et al., 1998; Dean, 2002) that the Chinese trade regime remained quite protectionist until 1991.

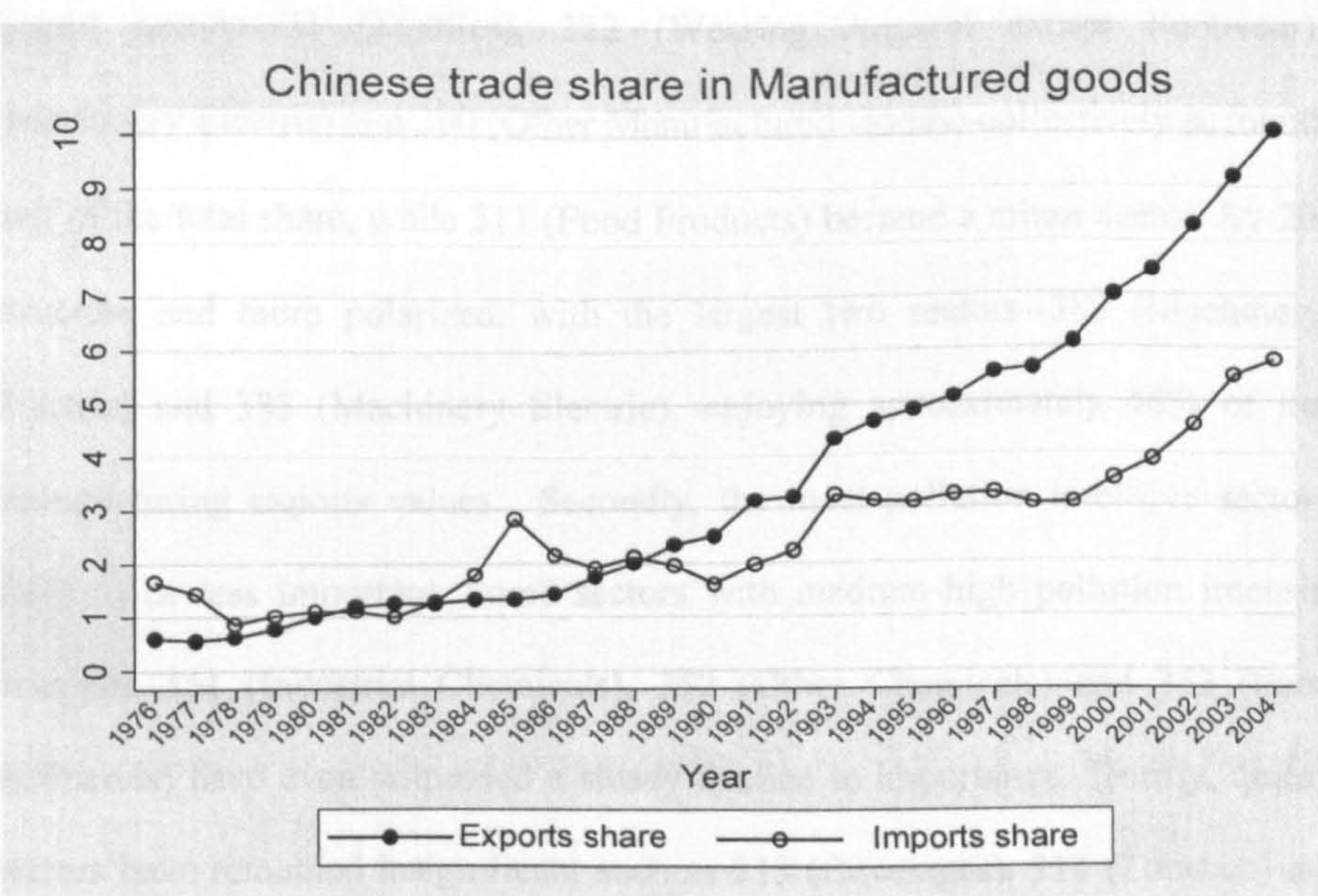
[19] This figure based on mirrored trade data is much larger than the figure calculated using reported trade data.

**Figure 2.2 Chinese Trade Volumes in Manufactured Goods**




Note: Inflation figures for US dollars are obtained from the inflation calculator at US Bureau of Labor Statistics; data from Nicita and Olarreaga (2006).

**Figure 2.3 Chinese Trade Share in Manufactured Goods**

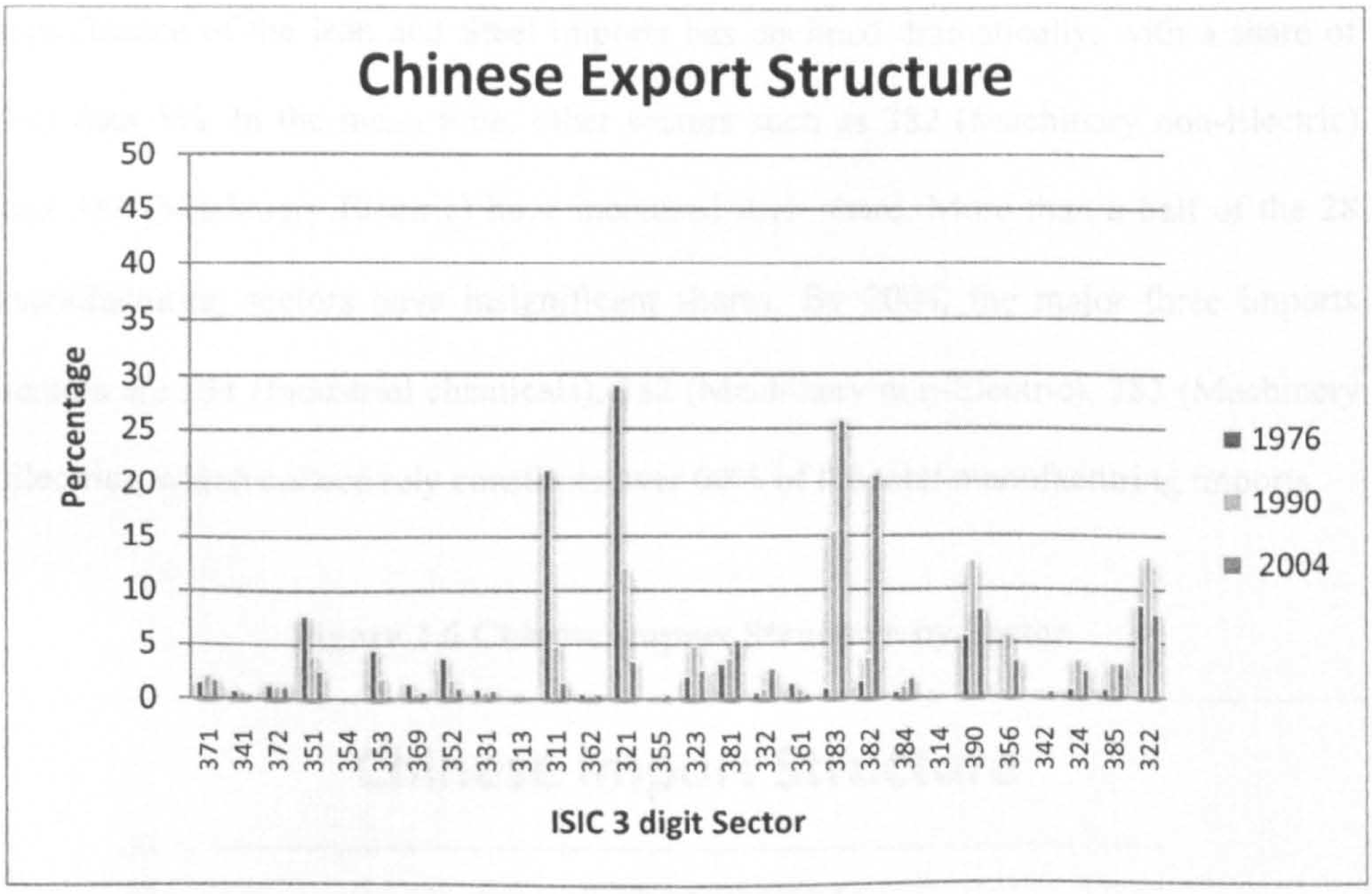



Data source: Nicita and Olarreaga (2006).

### 2.5.2 Sectoral distribution

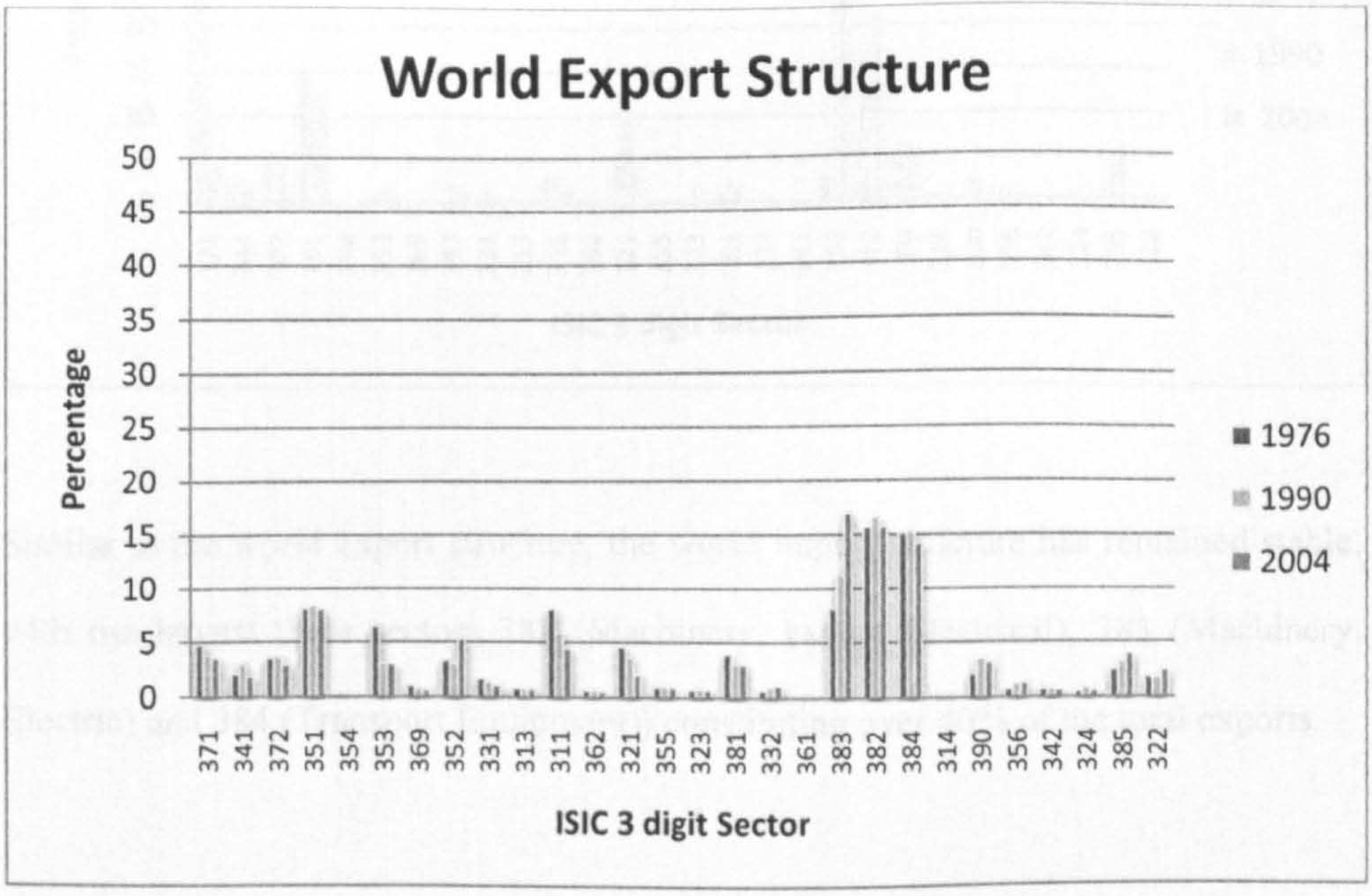
At sectoral level, China's export share in world for almost every industry, including the most pollution intensive industries, has increased. Such a trend has been even more dramatic since the early 1990s. The sectoral distribution of Chinese manufacturing trade has also undergone substantial changes. We present the sectoral structure (sectoral trade share in total manufacturing trade) for China and the world as a whole for the beginning, mid and last year of the data set, that is for the years 1976, 1990 and 2004. On the horizontal axis, the sectors are arranged in the decreasing order of average ranking in pollution intensity in accordance with table 2.1. Figure 2.4 focuses on comparing the export structure in China across time. There are notable changes within China. Firstly, the major sectors are not fixed. In the planned economy period (before 1979), 311 (Food Products) and 321 (Textiles) constituted over half of the manufacturing exports in China. All the other sectors had less than 10% share each. By 1990, the sectoral distribution had changed significantly, with the four largest sectors-321 (Textiles), 322 (Wearing Apparel except Footwear), 383 (Machinery Electric) and 390 (Other Manufactured Goods)-collectively accounting for half of the total share, while 311 (Food Products) became a minor sector. By 2004 the structure had more polarized, with the largest two sectors--382 (Machinery non-Electric) and 383 (Machinery Electric) -enjoying approximately 46% of the total manufacturing exports values. Secondly, the most pollution intensive sectors now seem to be less important. Some sectors with medium-high pollution intensity (for example, 351 (Industrial Chemicals), 352 (Other Chemicals) and 353 (Petroleum Refineries) have even witnessed a steady decline in importance. Thirdly, quite a few sectors have remained insignificant such as 313 (Beverages), 314 (Tobacco) and 354 (Miscellaneous Petroleum and Coal Products). The small size of these sectors may be in part due to an aggregation effect, with other sectors comprising more sub-divisions. This is suggested also by the small sizes of these sectors in the world exports distribution (figure 2.5). The world exports structure has remained relatively stable over the years. The largest three sectors, 382 (Machinery, except Electrical), 383 (Machinery, Electric) and 384 (Transport Equipment) comprise of over 40% of the total world manufactures exports.

**Figure 2.4 Chinese Export Structure by Sector**



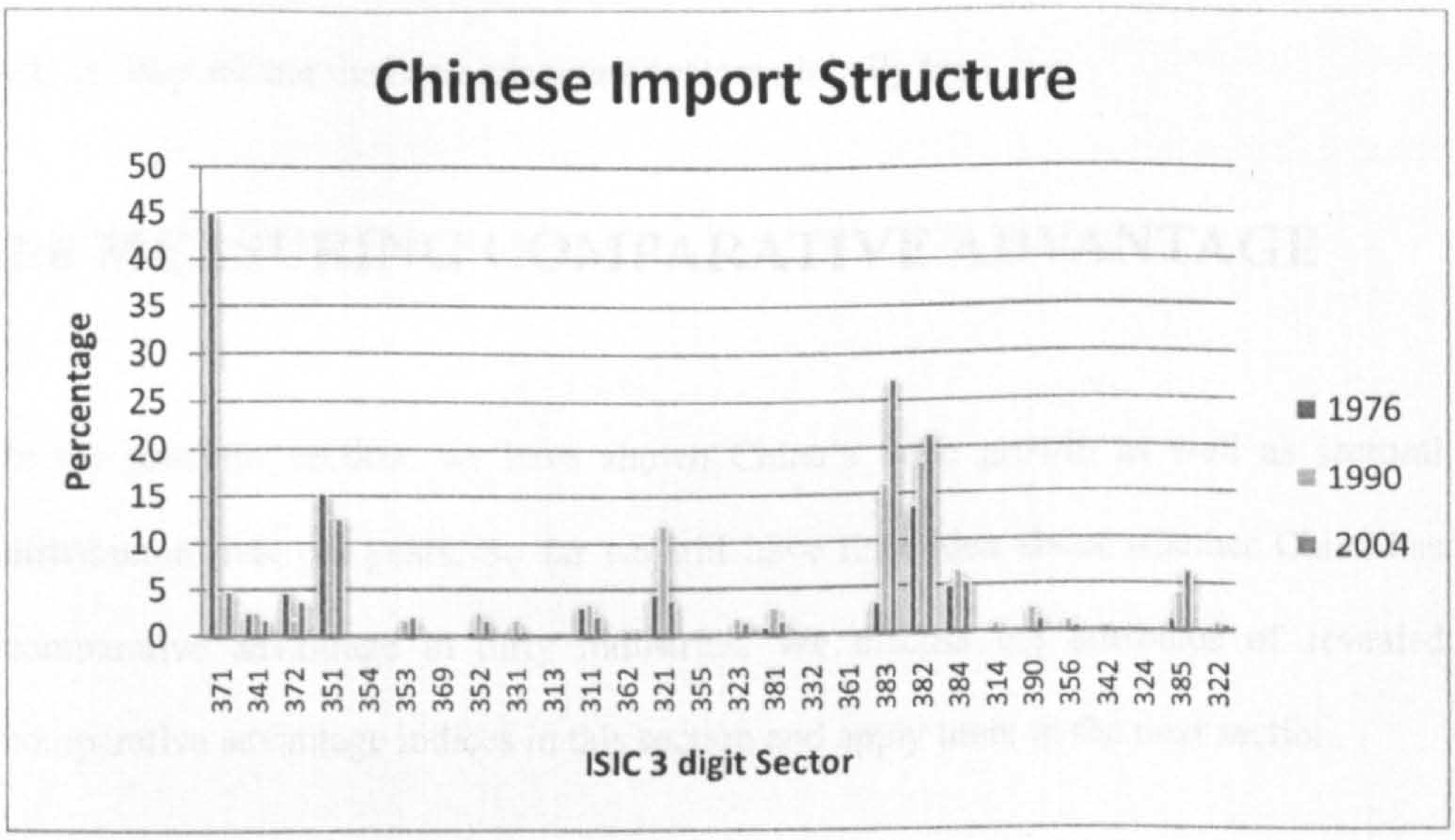

Data source: Nicita and Olarreaga (2006); same for all the following figures except otherwise explained.

**Figure 2.5 World Export Structure by Sector**



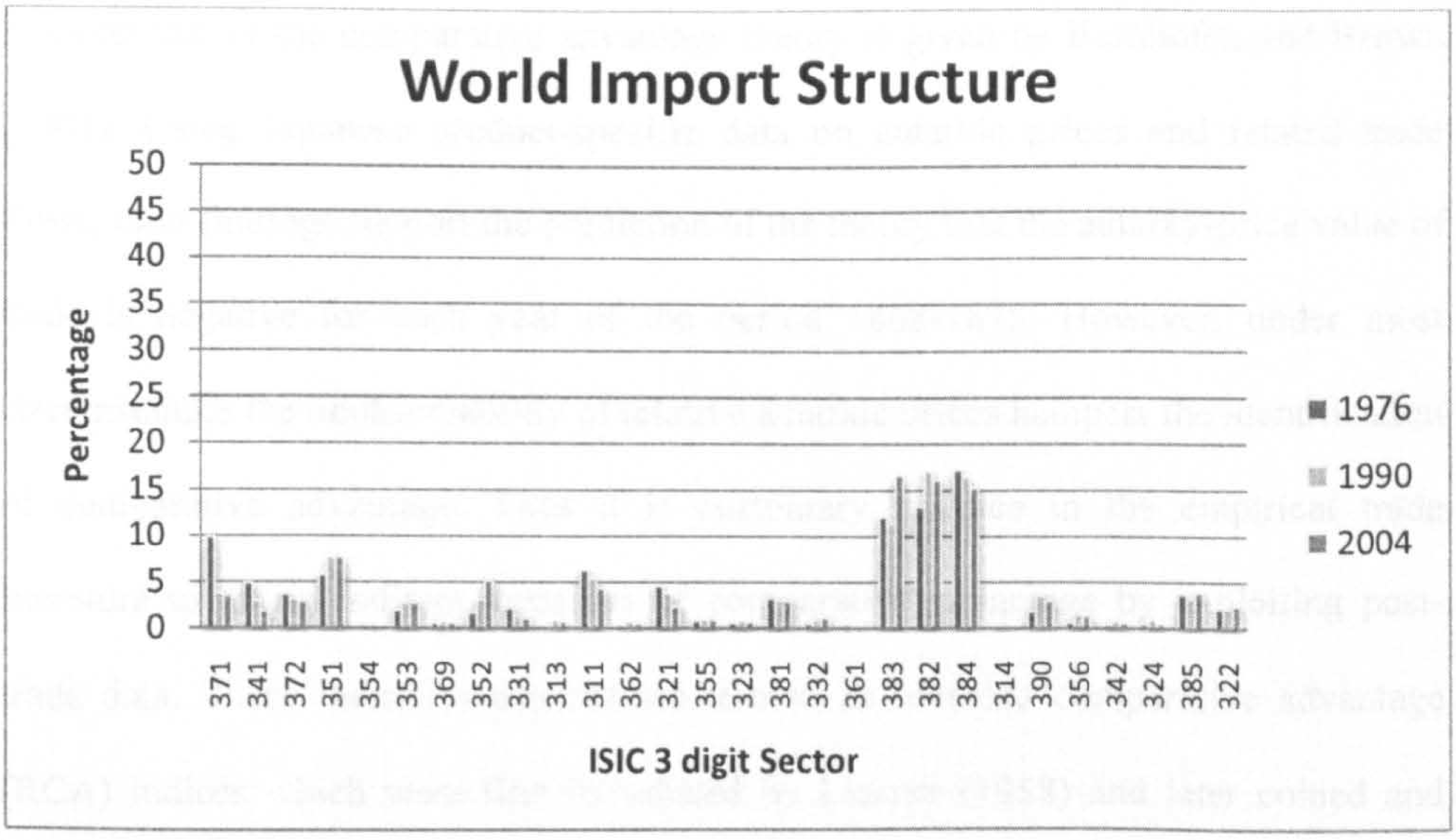
To give a more detailed picture of the sectoral specialization, we also present the imports structure for China (figure 2.6) and the world (figure 2.7). Before the economic reform, China's main imports sector is 371 (Iron and Steel) which alone constituted about 45% of total manufacturing imports. 351 (Industrial Chemicals) and 382 (Machinery, non-Electric) each had approximately 15% each. By 1990, the significance of the Iron and Steel imports has declined dramatically, with a share of less than 5%. In the mean time, other sectors such as 382 (Machinery non-Electric) and 383 (Machinery Electric) have increased their share. More than a half of the 28 manufacturing sectors have insignificant shares. By 2004, the major three imports sectors are 351 (Industrial chemicals), 382 (Machinery non-Electric), 383 (Machinery Electric), which collectively constitute over 60% of the total manufacturing imports.

**Figure 2.6 Chinese Import Structure by Sector**




Similar to the world export structure, the world import structure has remained stable, with the largest three sectors 382 (Machinery, except Electrical), 383 (Machinery, Electric) and 384 (Transport Equipment)) constituting over 40% of the total exports.

**Figure 2.7 World Import Structure by Sector**

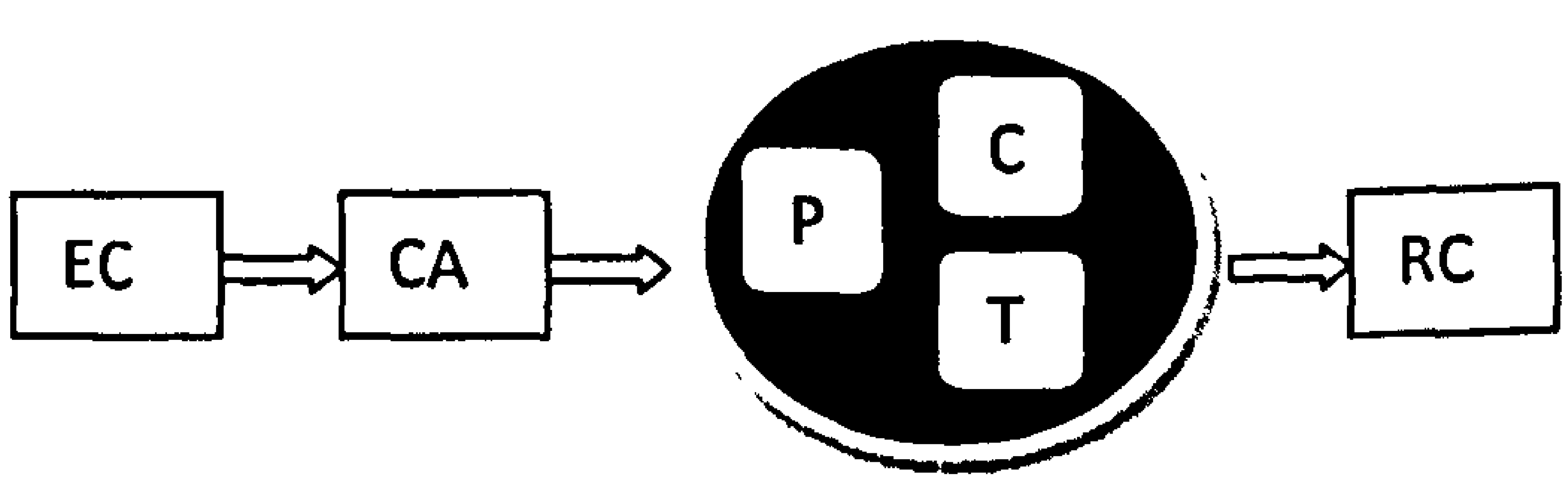



The above analysis identifies the major exports/imports sectors in China as well as globally. Although the pollution intensive industries are minor exports sectors in China, they are not the most important sectors globally too.

## 2.6 MEASURING COMPARATIVE ADVANTAGE

In the previous section, we have shown China's trade growth as well as sectoral distribution over the years. So far we still have little idea about whether China has comparative advantage in dirty industries. We discuss the attributes of revealed comparative advantage indices in this section and apply them in the next section.

The intuition of the comparative advantage theory is straightforward. But difficulties arise when one comes to empirical application of the theory due to the real world complexities. One major problem lies in the fact that the autarky-price formulation of the comparative advantage[20] is confronted with unobservable pre-trade relative prices. A direct test of the comparative advantage theory is given by Bernhofen and Brown (2004). Using Japanese product-specific data on autarkic prices and related trade flows, their findings support the prediction of the theory that the autarky-price value of trade is negative for each year of the period 1868-1875. However, under most circumstances the unobservability of relative autarkic prices hampers the identification of comparative advantage. Thus it is customary practice in the empirical trade literature to obtain indirect measures of comparative advantage by exploiting post-trade data. These indirect measures are termed as revealed comparative advantage (RCA) indices which were first introduced by Liesner (1958) and later coined and popularized by Balassa (1965, 1977). The causal links between theory and real-world are illustrated in the flow chart below (Balance et al., 1987). Economic conditions (such as endowments and technologies) determine comparative advantage for the trading countries which in turn governs post-trade variables such as trade flows, consumption and production. Indices constructed using these post-trade variables are termed as revealed comparative advantage indices (RCAs).




EC-economic conditions, CA-comparative advantage, P-production, C-consumption, T-trade, RCA-revealed comparative advantage indices

This extrapolation approach implies that there can be as many RCA indices as there are combinations and transformations of the post-trade variables. Each revealed

[20] The correlation version of the law of comparative advantage (Deardorff, 1980) asserts that an economy's net export vector evaluated at autarky prices is negative. Recent literature, for example, Galor (1992) on overlapping-generations and Cordella (1998) on oligopoly theory, questions the validity of using autarkic relative prices to predict true comparative advantage arguing that the autarkic equilibrium is not necessarily a good predictor of the long-run equilibrium.

comparative advantage index may reflect distinct information of international trade patterns. Balance et al. (1987) found considerable inconsistency among alternative RCA measures. In the following, we discuss the merits and limits of the commonly used RCA measures.

The common approach of a RCA measure is to compare national sectoral shares with their international analogies[21] and to infer the existence of comparative advantage through the examination of actual trade flows and/or output. Balance et al. (1987) divide these indices are into two groups: 1) trade-only indices which include the Balassa's index and alternative RCAs which seek to improve the statistical properties; 2) trade-cum-production indices which employ production and consumption data as well as trade data. As production and consumption data are recorded in different classifications and less comparable across countries, we only focus on trade data in this chapter and hence a discussion on trade only measures is provided in the following.

## 2.6.1 Trade only RCA measures

While there is no consensus on the most appropriate index of RCA, the index based on relative export shares proposed by Balassa (1965) has been used extensively, the recent examples including Dalum et al. (1998), Hiley (1999), Thongdee et al. (2003) and Hinloopen and van Marrewijk (2004). We denote it as Balassa's Revealed Comparative Advantage (BRCA) which is the ratio of a product (or product group) i's share in total exports in a country (denoted by the superscript c) to its share in total

[21] By this criterion, other trade intensity indices such as trade specialization index (TSI), the Michaely index as well as the ratio of net trade to total domestic production which uses trade data (or other related economic data such as output and value added) on only one country fall out of this framework. We do not discuss such indices in this chapter.

exports in a group of reference countries (denoted by the superscript ref, which also includes the case of all countries in the world). It takes the form of:

$$BRCA_i^c = \frac{X_i^c / \sum_i X_i^c}{X_i^{ref} / \sum_i X_i^{ref}} = \frac{X_i^c / X_i^{ref}}{\sum_i X_i^c / \sum_i X_i^{ref}} \qquad (2.1)$$

It is equivalent to scaling the share of country c's exports in world trade (represented by a group of reference countries) of good i by its share of total world trade. This ratio ranges from 0 to a positive number which varies across the selection of reference countries and across time[22]. Any value of BRCA that is greater (less) than unity is said to indicate the country has comparative advantage (disadvantage) in product (product group) i.

BRCA is tractable and easily interpretable, but it suffers from a risk of non-normality, namely, it gives too much weight to the values above one. Taking the logarithm of BRCA index (similar operation seen in Vollrath (1991)) could make it more symmetrical but a commodity with zero export would be undefined under this modified index.

$$LSCA_i^c = \log(BRCA_i^c) \qquad (2.2)$$

Laursen (1998) suggests a symmetrically transformed BRCA index. It is given as follows:

$$SRCA_i^c = \frac{BRCA_i^c - 1}{BRCA_i^c + 1} = 1 - \frac{2}{BRCA_i^c + 1} \qquad (2.3)$$

For both LBCA and SRCA, a positive value indicates comparative advantage while a negative one indicates comparative disadvantage.

[22] In general, the BRCA ranges from 0 to $+\infty$; but it has variable upper bound according to the selection of reference countries and time.

Proudman and Redding (1998) propose a weighed version of BRCA for an individual product with the arithmetic mean of the country's BRCA scores. We term it as WRCA:

$$WRCA_i^c = \frac{BRCA_i^c}{\frac{1}{N}\sum_i BRCA_i^c} \tag{2.4}$$

where N is the total number of products (or product groups). The comparative advantage neutral point for WRCA is not fixed. For a product i, if its BRCA value is greater (less) than the average BRCA value across products in country c (at period t), we say that country c (at period t) has comparative advantage (disadvantage) in product i.

Since their early appearance in empirical analysis, the above traditional RCA indices have received many criticisms (Hillman, 1980; Bowen, 1983, 1985, 1986; Balance et al., 1985, 1986; Yeats, 1985; Deardorff, 1994; De Benedictis and Tamberi, 2001; Hoen and Oosterhaven, 2006). Apart from the asymmetry property, the BRCA index also has small country bias and small industry bias, which implies that a small country or a small industry is more likely to obtain extremely high values of BRCA. Although the transformed versions of BRCA have been proposed to improve the statistical properties, they are, notwithstanding, defective. In particular, De Benedictis and Tamberi (2001) point out three defects of the WRCA index which makes the economic interpretation difficult: 1) dismissing country effect; 2) giving too much emphasis to the first moment and 3) inconsistent with BRCA. If econometric analysis is not required, these transformations are not necessary since their defects may obscure the dynamics of the original index.

According to Hoen and Oosterhaven (2006), the root cause of all these problems with the BRCA index (and hence its transformations) lies in the multiplicative character of the index. They outline several peculiar statistical properties of the original BRCA (which they name as multiplicative RCA). Firstly, the distribution of BRCA is not centred on 1 since the mean of the sectoral MRCAs is above 1[23] (which means that the average sector has a net comparative advantage). Secondly, it is shown the distribution of the BRCAs around this mean is asymmetric and skewed. Thirdly, the number of countries (the reference group) also influences the distribution of BRCAs. Fourthly, the number of sectors influences the size and distribution of the BRCAs. Finally, at higher levels of sectoral details, the BRCAs can have more extreme values. To solve the problems, they propose an additive index which takes the form of the following:

$$ARCA_i = \frac{X_i^c}{\sum_i X_i^c} - \frac{X_i^{ref}}{\sum_i X_i^{ref}} \qquad (2.5)$$

ARCA is greater than zero if the country of interest has a revealed comparative advantage in sector i and it is smaller than zero if instead the country has a revealed comparative disadvantage. Compared to BRCA and its transformations, ARCA has a stable mean independent of the number and classification of the sectors or countries and a more symmetrical distribution as evidenced by their empirical findings. However, the ARCA index is biased when the country of interest is included in the group of reference countries (Hoen, 2002; Hoen and Oosterhaven, 2005). To obtain non-biasedness, the country of interest has to be excluded from the group of reference countries.

The above RCA indices can be incorporated into the framework of comparing actual and expected trade flows (Kunimoto, 1977) or a 'hypothetical comparative advantage neutral' world as in Bowen (1983). This framework is suggested by Vollrath (1991) as a guide to appraise trade intensity indices. Following the concept of an imaginary world without geographical specialization of international trade in Kumimoto (1977),

[23] It finds support from the empirical results from Hinloopen and van Marrewijk (2001).

the BRCA can be expressed in terms of the ratio of actual-to-expected exports (see Bowen (1983). For example,

$$BRCA_i^c = \frac{X_i^c}{E(X_i^c)} = \frac{X_i^c}{X_i^{ref}\dfrac{\sum_i X_i^c}{\sum_i X_i^{ref}}} \qquad (2.6)$$

where the expected export of i in country c equals to the product i's total exports ($X_i^{ref}$), multiplied by country c's relative size. This index actually measures the degree of deviation in sector i's (in country c) actual exports from its expected exports level (or comparative-advantage-neutral point[24]). Deviations of the index from unity indicate the presence of factors which influence the distribution of a country's trade among countries without affecting the level of its trade. Similarly, ARCA can also be expressed in the terms of actual-minus-expected exports scaled by total exports of country c.

$$ARCA_i^c = \frac{1}{\sum_i X_i^c}(X_i^c - E(X_i^c)) = \frac{X_i^c}{\sum_i X_i^c} - \frac{X_i^{ref}}{\sum_i X_i^c}\frac{\sum_i X_i^c}{\sum_i X_i^{ref}} \qquad (2.7)$$

Instead of scaling the difference between actual and expected trade flows by country c's total exports, we can simply use the difference of the actual and expected exports. However, to make it comparable across time, a scale has to be adopted[25]. A scale that does not change the statistical properties should be a scale that is both country and commodity invariant. Scaling the difference by the sum of exports in all the countries

[24] Vollrath also points out that neutral comparative advantage does not necessarily exclude trade when we focus on a composite commodity (industry or sector) and on a country with diverse decision makers.

[25] Suppose if all exports of each i in each c increase by a factor of g in the next period, the value of $X_i^c - X_i^{ref}\dfrac{\sum_i X_i^c}{\sum_i X_i^{ref}}$ will also increase by a factor of g. In the mean time, the position of comparative advantage for product i in country c in fact remain the same as the period before.

in the reference group and all products ($\sum_c \sum_i X_i^c$) satisfies this requirement. Such an index is found in Yu et al. (2009). Their normalized revealed comparative advantage index (NRCA) can be expressed as:

$$NRCA_i^c = \frac{X_i^c}{\sum_i X_i^{ref}} - \frac{X_i^{ref} \sum_i X_i^c}{\sum_i X_i^{ref} \sum_i X_i^{ref}} = \frac{1}{\sum_c \sum_i X_i^c}(X_i^c - E(X_i^c))$$

(2.8)

The NRCA index measures the degree of deviation of a country's actual export from its comparative-advantage-neutral level in terms of its relative scale with respect to the world export market. A positive NRCA indicates that a country's actual export of sector i is higher than its comparative-advantage-neutral level. It has nice properties such as:

$$\sum_i NRCA_i^c = 0$$

$$\sum_c NRCA_i^c = 0$$

Where $\sum_c X_i^c = X_i^{ref}$ and country c should be included in the group of reference countries.

## 2.6.2 What constitutes a good RCA index?

From the above discussion, we have shown that all measures related to revealed comparative advantages/specialization have their pros and cons. The next question is which RCA index to choose. To evaluate a RCA index, fitting in the theoretical framework of comparing actual and expected trade flows seems to be a good general criterion. Focusing on the statistical properties, Hoen and Oosterhaven (2006) propose four guidelines for an ideal RCA index:

1) It should have a stable mean or median.

2) It should have symmetry around the mean or median.

3) Its distribution should be independent of the number and classification of the commodities or sectors used.

4) Its distribution should be should be stable, such that the individual sectoral values may be compared across time and space.

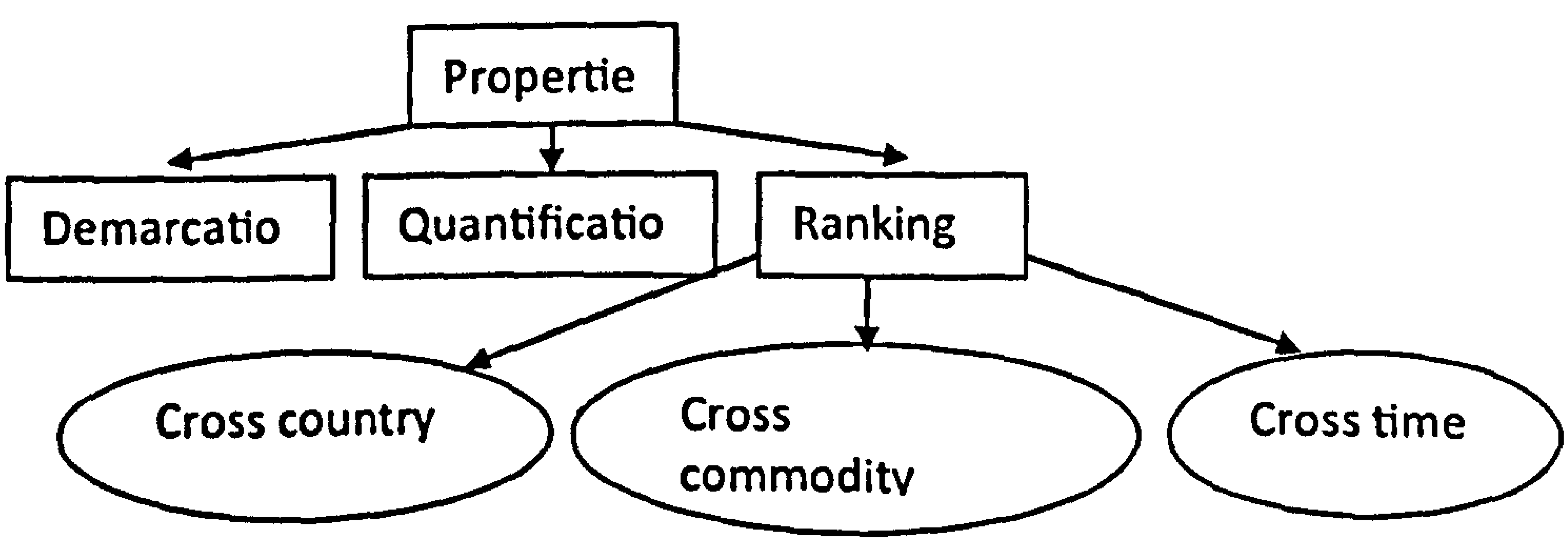
Empirically, a good RCA index should also embody threefold interpretation (Balance et al., 1987; Benedictis and Tamberi, 2001):

1) Dichotomous: it provides a demarcation between countries that reveal a comparative advantage in a particular sector and those do not.

2) Cardinal: it should quantify the commodity-specific degree of comparative advantage enjoyed by one country vis-à-vis any other country.

3) Ordinal: it should provide commodity specific ranking of countries of degree of comparative advantage.

These criteria can be summarized in the figure below. Most RCA indices have a fixed demarcation point (or comparative neutral point). The quantification property belongs to the BRCA and its transformed versions although in the latter cases the economic interpretation is less clear. For the ranking feature, it is further divided into three comparability requirements: cross-country, cross commodity and cross time.



While the BRCA index has often been used to compare comparative advantage across commodities, countries and over time, such comparisons are not soundly founded. Hillman (1980) examines the correspondence between the Balassa index and autarkic relative prices in cross commodity and cross country comparisons. For cross commodity comparison, his diagrammatical illustration shows that the BRCA values are independent of whether one good is relatively less expensive than the other in the autarkic equilibrium. Hillman also derives a theoretically necessary and sufficient condition for cross-country comparison for a specific good under homothetic preferences in the reference countries. Specifically, the condition is that:

$$1-\frac{X_i^c}{X_i^{ref}} > \frac{X_i^c}{\sum_i X_i^c}\left(1-\frac{\sum_i X_i^c}{\sum_i X_i^{ref}}\right) \tag{2.9}$$

In general approximation the Hillman condition is not satisfied for a small country (i.e. $\frac{\sum_i X_i^c}{\sum_i X_i^{ref}}$ is small) when it specializes in the good i (i.e. $\frac{X_i^c}{\sum_i X_i^c}$ is equal to unity) and/or when it has monopoly power in good i in the international market (i.e. $\frac{X_i^c}{X_i^{ref}}$ is equal to unity). This condition is less stringent for large countries with disaggregated trade data[26].

Hillman's theoretical analysis was focused on the BRCA only while we want to evaluate the comparability of alternative indices. Since comparative advantage is a relative term, we can view the notion in two aspects: 1) any trading country has both goods with comparative advantage and goods with comparative disadvantage, but overall it is comparative advantage neutral, i.e. $\sum_i RCA_i^c = 0$ ; 2) any good is a comparative advantage good in one country while comparative disadvantage in the

[26] Supportive empirical evidence can be found in Hinloopen and van Marrewijk (2005).

others as a whole, but overall it is comparative advantage neutral, i.e. $\sum_c RCA_i^c = 0$.

Of all the RCA indices we reviewed, only NRCA seems to meet the two requirements. In the following table 2.2, we summarize the trade-only RCAs.

**Table 2.2 Summary of Trade-only RCAs**

| Index | Source | Range | Comparative Advantage neutral point[a] | Cross-country | Cross-commodity | Cross-time |
|---|---|---|---|---|---|---|
| BRCA | Balassa (1965) | $[0,+\infty)$[27] | 1 | × | × | × |
| LRCA | Vollrath(1991) | $(-\infty,+\infty)$ | 0 | × | × | × |
| SRCA | Laursen (1998) | [-1,+1] | 0 | × | × | × |
| WRCA | Proudman and Redding ( | [0, ? ) | 1 | × | √ | × |
| ARCA | Hoen and Oosterhaven | [-1,+1] | 0 | × | √ | × |
| NRCA | Yu et al (2009) | [-1/4, +1/4][28] | 0 | √ | √ | √ |

Note: a. Comparative Advantage neutral point refers to a state that is neither in comparative advantage nor in comparative disadvantage.

## 2.7 REVEALED COMPARATIVE ADVANTAGE EVIDENCE

For our research purpose, the BRCA and NRCA are both chosen to 'reveal' comparative advantage:

[27] The upper bound is not fixed.

[28] See Yu et al. (2009) for the derivation of the boundaries [-1/4, 1/4]

$$BRCA_i^c = \frac{X_i^c}{E(X_i^c)} = \frac{X_i^c}{X_i^{ref}\frac{\sum_i X_i^c}{\sum_i X_i^{ref}}}$$

$$NRCA_i^c = \frac{1}{\sum_c \sum_i X_i^c}(X_i^c - E(X_i^c)) = \frac{X_i^c}{\sum_i X_i^{ref}} - \frac{X_i^{ref}\sum_i X_i^c}{\sum_i X_i^{ref}\sum_i X_i^{ref}}$$

While the indices are expressed using data on the exports side, similar indices can be constructed using imports data[29]. Then the comparative export advantage and comparative import advantage are compared to reveal the overall comparative advantage[30]. In this chapter, however, we only focus on the export side.

We use trade flows from the database of Nicitita and Olarreaga (2006) which covers 100 developing and developed countries over the period 1976-2004 for 28 (3-digit ISIC Rev.2) manufacturing sectors. The list of 100 countries is displayed in A2.5. For the reasons explained earlier, we use mirrored trade data. Both BRCA and NRCA are calculated for each industry in every country over time. Emphasis will be laid on evidence revealed by NRCA since we believe NRCA is better than BRCA in terms of comparability over time. To examine whether 'dirty' industries have gained comparative advantage in China, we examine evolution of the BRCA and NRCA values for each industry according to their ranking in 'dirtiness'. To compare the changing trade patterns in the North, we also present revealed comparative advantage evidence for five developed countries (the US, Japan, Germany, the UK and France) which are also China's major export markets.

[29] At the time when BRCA was proposed in the 1960s, Balassa justified taking only exports data on the grounds that policy-induced distortions are more severe on the imports side. See also Vollrath (1991). Lafay (1992) points out the necessity of using imports data since import protection has been reduced by multilateral negotiations while policy intervention has been increased on the export side.

[30] This has been done by several researches such as Vollrath (1991), Murrell (1990), Lafay (1992) and Lim (1997).

### 2.7.1 Overall patterns of BRCA and NRCA

The table below (table 2.3) presents the statistical attributes of BRCA and NRCA based on exports for China and the five selected developed countries between 1976 and 2004. While the mean of NRCA is consistently zero across country and time, we find that the mean of BRCA indices is indeed not fixed. Among the six countries, China has the highest mean BRCA value and Japan has the lowest mean BRCA value. Standard deviation of the indices provides information on the variation of comparative advantage. However, as we have explained earlier these BRCA statistics (mean and variation) do not have much economic meaning.

**Table 2.3 Statistical Properties of BRCA and NRCA for Selected Economies**

| Variable | | | BRCA | | | |
|---|---|---|---|---|---|---|
| **Country** | **China** | **Germany** | **France** | **UK** | **Japan** | **USA** |
| **Obs** | 812 | 812 | 812 | 812 | 812 | 812 |
| **Mean** | 1.41 | 0.92 | 1.05 | 1.08 | 0.63 | 0.86 |
| **Std. Dev.** | 1.66 | 0.41 | 0.79 | 0.61 | 0.57 | 0.55 |
| **Min** | 0 | 0.11 | 0.22 | 0.09 | 0 | 0.04 |
| **Max** | 8.57 | 3.55 | 5.28 | 3.45 | 2.34 | 3.07 |
| | | | NRCA | | | |
| **Country** | **China** | **Germany** | **France** | **UK** | **Japan** | **USA** |
| **Obs** | 812 | 812 | 812 | 812 | 812 | 812 |
| **Mean** | 0 | 0 | 0 | 0 | 0 | 0 |
| **Std. Dev.** | 1.90E-03 | 2.40E-03 | 1.30E-03 | 8.80E-04 | 3.90E-03 | 2.50E-03 |
| **Min** | -0.01 | -0.01 | 0 | 0 | -0.01 | -0.01 |
| **Max** | 0.01 | 0.01 | 0.01 | 0 | 0.02 | 0.02 |

Source: Nicitita and Olarreaga (2006).

Tables 2.4 and 2.5 present five economies with the largest BRCA/NRCA values based on exports for both dirtiest industries and cleanest industries in 1976, 1990 and 2004 (to conserve space, we only present the top five economies in the three years). We find evidence of small country bias in terms of BRCA values as pointed out by the criticisms of BRCA index, i.e. small countries tend to have larger values[31]. China is not listed among the top 5 in terms of dirty industries. Except for industries 341 and 354, most developed countries do not seem to have highest BRCA values compared to other small developing countries. In terms of clean industries, China has increased BRCA values in industry 356 and listed among top 5 in 1990 and 2004.

Based on the NRCA values, we pick out the five economies with highest NRCA values for each industry. The rankings of the economies that have the largest revealed comparative advantage in dirty industries have changed dramatically and China is again not on the list. The most developed countries such as USA, Japan, Germany, UK and France are found to have the largest comparative advantage in a few dirty industries. However, the top 5 list is changing. Except for industry 354, these most developed countries have gradually lost their position to other developed countries and developing countries. Notably, Russia, Brazil and South Africa seem to have specialized in dirty industries in recent years. The clean industries were dominated by developed countries in the 1970s. China began to gain comparative advantage in these industries during 1980s. By 2004, China is listed as the top economies in 3 out of 5 clean industries; they are 356 (Plastic Products), 324 (Footwear, except Rubber or Plastic) and 322 (Wearing Apparel, except Footwear). The developed economies seem to maintain their revealed comparative advantage in certain clean industries. For example, the US, UK and Germany still hold a strong position in 342 (Printing and Publishing); while UK, Germany and Japan hold a strong position in 385 (Professional and Scientific Equipment). Italy seems to maintain its strong position in 324 (Footwear, except Rubber or Plastic).

[31] The highest BRCA value based on exports is for industry 354 in Gabon in 1981.

**Table 2.4 Top Five Economies with Highest BRCA Values (based on exports)**

| | Dirty industries | | | | | Clean industries | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Year | 371 | 341 | 372 | 351 | 354 | 356 | 342 | 324 | 385 | 322 |
| 1976 | Hungary | Canada | Peru | Bulgaria | Ireland | Cyprus | Egypt | Cyprus | Switzerland | Macau |
| | Bulgaria | Finland | Cameroon | Israel | Poland | Denmark | Ecuador | Morocco | Mauritius | Malta |
| | South Africa | Chile | Chile | Netherlands | UK | Hongkong | Mauritius | Senegal | Hongkong | Hongkong |
| | India | Tunisia | Bolivia | Switzerland | Germany | Senegal | Colombia | Portugal | Ecuador | Turkey |
| | Greece | Sweden | Mexico | Belgium-Luxemburg | USA | Malaysia | Mexico | Italy | Ireland | Korea |
| 1990 | Mozambique | Finland | Chile | Jordan | USA | China | Colombia | Portugal | Switzerland | Bangladesh |
| | Brazil | Sweden | Ghana | Gabon | Netherlands | Taiwan | UK | Korea | Oman | Mauritius |
| | Romania | Canada | Bolivia | Qatar | Belgium-Luxemburg | Costa Rica | Hongkong | Brazil | Hongkong | Macau |
| | Trinidad and Tobago | El Salvador | South Africa | Morocco | UK | El Salvador | Denmark | El Salvador | Malta | Honduras |
| | Turkey | Norway | Peru | Trinidad and Tobago | Denmark | Denmark | El Salvador | Italy | UK | Sri Lanka |
| 2004 | Ukraine | Finland | Mozambique | Qatar | USA | Kyrgyzstan | Colombia | Macau | Switzerland | Bangladesh |
| | Moldova | Sweden | Chile | Senegal | Denmark | China | Malta | Romania | Ireland | Honduras |
| | Russia | Chile | Peru | Trinidad and Tobago | South Africa | Uruguay | Hongkong | Portugal | USA | Macau |
| | Venezuela | Canada | Iceland | Jordan | UK | Nepal | Uganda | Moldova | Japan | Mongolia |
| | Iran | India | South Africa | Ireland | Canada | Denmark | UK | Myanmar | Costa Rica | El Salvador |

**Table 2.5 Top Five Economies with Highest NRCA Values (based on exports)**

| | Dirty industries | | | | | Clean industries | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Year | 371 | 341 | 372 | 351 | 354 | 356 | 342 | 324 | 385 | 322 |
| 1976 | Japan | Sweden | Canada | Bulgaria | UK | Denmark | France | Italy | USA | Korea |
| | France | Canada | Switzerland | Israel | Germany | Sweden | Germany | Austria | Switzerland | Hongkong |
| | Belgium-Luxemburg | Finland | Australia | Netherlands | USA | Italy | UK | Korea | Germany | Finland |
| | Germany | USA | Malaysia | Switzerland | Poland | Finland | Sweden | Taiwan | Japan | Taiwan |
| | Austria | Norway | South Africa | Belgium-Luxemburg | Ireland | Norway | Denmark | Portugal | Hongkong | Portugal |
| 1990 | Belgium-Luxemburg | Canada | Switzerland | Jordan | USA | China | Spain | Italy | USA | China |
| | Brazil | Finland | Canada | Gabon | Netherlands | Taiwan | UK | Korea | Switzerland | Korea |
| | France | Sweden | South Africa | Qatar | Belgium-Luxemburg | Italy | USA | China | Japan | Italy |
| | Korea | Austria | Australia | Morocco | UK | Germany | Denmark | Brazil | Hongkong | Hongkong |
| | Sweden | Norway | Chile | Trinidad and Tobago | Italy | Denmark | France | Taiwan | Germany | Turkey |
| 2004 | Russia | Canada | Russia | Qatar | USA | China | UK | China | USA | China |
| | Ukraine | Sweden | Switzerland | Senegal | Germany | Italy | USA | Italy | Japan | Turkey |
| | Belgium-Luxemburg | Finland | South Africa | Trinidad and Tobago | UK | Germany | Germany | Portugal | Switzerland | Bangladesh |
| | Brazil | Brazil | Chile | Jordan | Canada | Denmark | Hongkong | Brazil | Taiwan | Hongkong |
| | South Africa | Indonesia | Australia | Ireland | Italy | Austria | Spain | Romania | Ireland | India |

### 2.7.2 Dynamics of China's revealed comparative advantage

Between 1976 and 2004, China enjoyed a revealed comparative advantage in the world export market in 10-13 out of 28 manufacturing sectors, which account for 65%-84% of Chinese manufacturing exports in monetary value. The BRCA index gives more weight to small sectors while the NRCA index emphasizes the importance of large sectors. The two measures have been reasonably consistent in values. This is illustrated by the positive and significant Spearman rank correlation coefficients (see table A2.6 in the appendix). In terms of relative ranking, however, the two differ considerably. Only about 26% of the 812 observations have the same rank order in terms of BRCA and NRCA[32]. For example, 383 (Machinery, Electric) is identified by NRCA as the highest revealed comparative advantage sector in 2004, while BRCA only places it tenth in ranking (see table A2.4 in the appendix).

Figures 2.8 and 2.9 present the sectoral distribution of the indices for the years 1976, 1990 and 2004. Sectoral pollution intensity is in descending order on the horizontal axis. China barely has any revealed comparative advantage (i.e. BRCA>1 or NRCA>0) in the top ten pollution intensive industries. One exception is 369 (Non-Metallic Mineral Products) which a comparative advantage is revealed in some of the years. For chemical and petroleum refinery industries (351, 352, 353), revealed comparative disadvantage has deepened. These two figures also show that the industries that China has comparative advantage are concentrated on the relatively clean end (to the right). Figure 2.9 (with NRCA values) shows that the line of 1976 has fewer fluctuations than those of 1990 and 2004. It gives the impression that before the opening-up, China has a similar distribution of industries to the world (which is

[32] Yu et al. (2009) also found 25% of the two have the same ranking, although they focus on agricultural products in the US Mainland market.

denoted by the reference line NRCA=0). As the process of economic reform and opening-up has deepened, some clean industries have gained comparative advantage while several of the dirtiest industries have increased comparative disadvantage.

**Figure 2.8 BRCA Values for Selected Years in China**
**(Based on exports)**

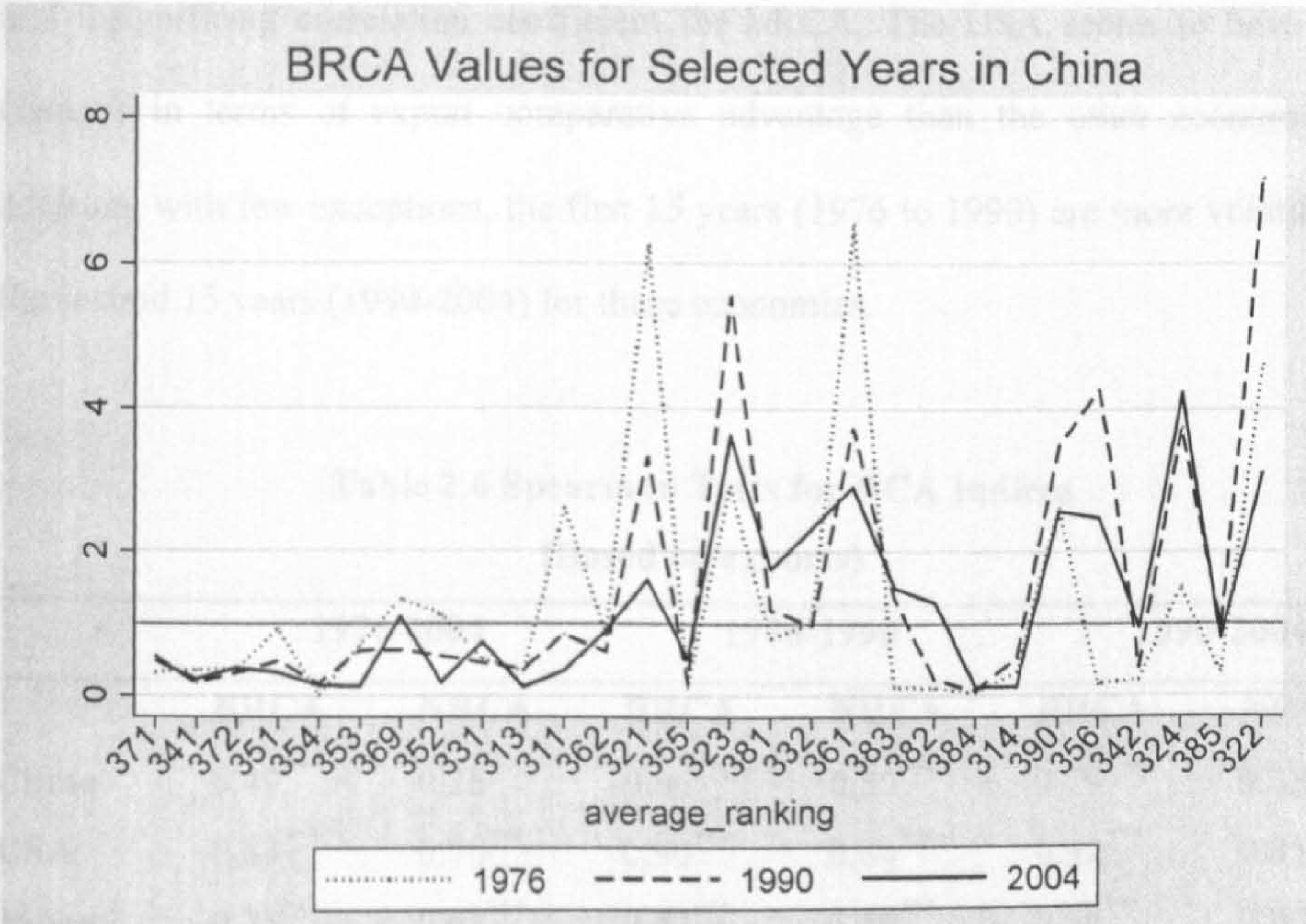
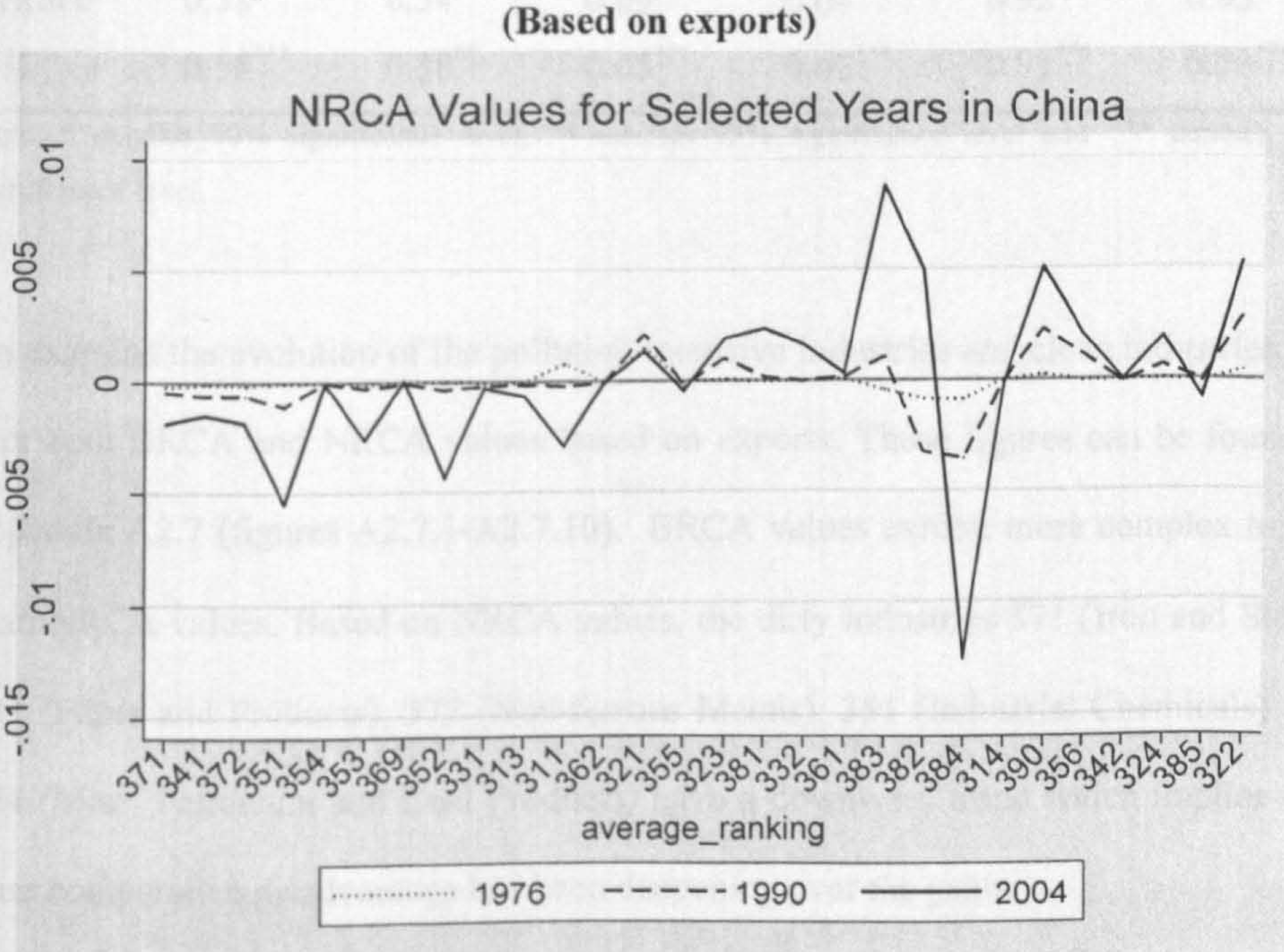



**Figure 2.9 NRCA Values for Selected Years in China**
**(Based on exports)**



To detect evidence of structural changes in comparative advantage, we present Spearman test results for China as well as the five developed countries as follows (table 2.6). Among the six economies, China has undergone the most dramatic changes in revealed comparative advantage between 1976 and 2004, which is evidenced by the lowest significant correlation coefficient for BRCA and the lowest and insignificant correlation coefficient for NRCA. The USA seems to have fewer changes in terms of export comparative advantage than the other economies. In addition, with few exceptions, the first 15 years (1976 to 1990) are more volatile than the second 15 years (1990-2004) for these economies.

**Table 2.6 Spearman Tests for RCA Indices**
**(Based on exports)**

| | 1976-2004 | | 1976-1990 | | 1990-2004 | |
|---|---|---|---|---|---|---|
| | BRCA | NRCA | BRCA | NRCA | BRCA | NRCA |
| China | 0.49*** | 0.26 | 0.66*** | 0.57*** | 0.79*** | 0.78*** |
| USA | 0.84*** | 0.70*** | 0.90*** | 0.84*** | 0.92*** | 0.85*** |
| Japan | 0.75*** | 0.67*** | 0.82*** | 0.59*** | 0.96*** | 0.90*** |
| Germany | 0.54*** | 0.61*** | 0.78*** | 0.75*** | 0.80*** | 0.88*** |
| France | 0.58*** | 0.54*** | 0.69*** | 0.64*** | 0.92*** | 0.93*** |
| UK | 0.58*** | 0.38** | 0.65*** | 0.63*** | 0.93*** | 0.59*** |

Note: * denotes 90% significance level, ** denotes 95% significance level and *** denotes 99% significance level.

To examine the evolution of the pollution intensive industries and clean industries, we plot both BRCA and NRCA values based on exports. These figures can be found in appendix A2.7 (figures A2.7.1-A2.7.10). BRCA values exhibit more complex trends than NRCA values. Based on NRCA values, the dirty industries 371 (Iron and Steel), 341 (Paper and Products), 372 (Non-ferrous Metals), 351 (Industrial Chemicals) and 354 (Misc. Petroleum and Coal Products) have a downward trend which implies that their comparative disadvantage has been deepening over the years.

As for the five cleanest industries, China only have revealed comparative advantage in 322 (Wearing Apparel except Footwear), 324 (Footwear except Rubber or Plastic) and 356 (Plastic Products), which exhibit a similar trend: at first revealed comparative advantage in terms of NRCA increases (in the case of 324, this increasing trend shows only since late 1980s); starting from approximately 1994, the trend flattens and it also seems to go downwards since 2000. For 385 (Professional and Scientific Equipment), China does not have revealed comparative advantage for most of the years with exceptions between 1997 and 1999. The trend shows that the revealed comparative disadvantage has even increased in industry 385 in recent years. For 342 (Printing and Publishing), China has first revealed comparative disadvantage increased and then it recovered to the initial level in 2004, although still at a revealed comparative disadvantage position.

Since NRCA values are additive, we also plot an aggregate of top five dirty industries and an aggregate of top five clean industries in figure A2.7.11 in appendix A2.7. In the first few years, the two aggregates were around zero which is the revealed comparative neutral point. Starting with a narrow gap, the two aggregates seem to part from each other from the beginning of the economic reform. The aggregate of top five dirty industries continue to have greater revealed comparative disadvantage over time. The opposite seems true for the top five clean industries which experienced steep growth in revealed comparative advantage until 1993. The trend has been stagnant since early 1990s and even seems to decrease since 2000.

These RCA figures are only based on exports and the indices themselves have various issues. To complement the analysis based on RCA indices, we also present trade specialization figures by industries in China.

$$TSI = \frac{X_{it} - M_{it}}{X_{it} + M_{it}} \qquad (2.10)$$

This index is constructed as percentage share of net trade in total trade volume. Its value ranges from -1 when there are no exports to +1 when there are no imports. The larger TSI is, the more specialized the sector will be. This index could tell the relative importance of net exports in total trade of a particular industry. Figures 2.10 and 2.11 present the evolution of TSI for top five dirty industries and top five lean industries respectively. Although the trends seem to be volatile, the negative trade specialization values imply that China has not been specialized in these dirty over the years. To the contrary, China has been very much specialized in 322 (Wearing Apparel except Footwear) and 324 (Footwear except Rubber or Plastic) with TSI value close to 1. In addition, 356 (Plastic Products) has increased specialization from 0.4 to 0.8. The other two industries 385 (Professional and Scientific Equipment) and 342 (Printing and Publishing) have also increased their TSI values indicating growing specialization.

**Figure 2.10 Trade Specialization Index of Top Five Dirty Industries in China**

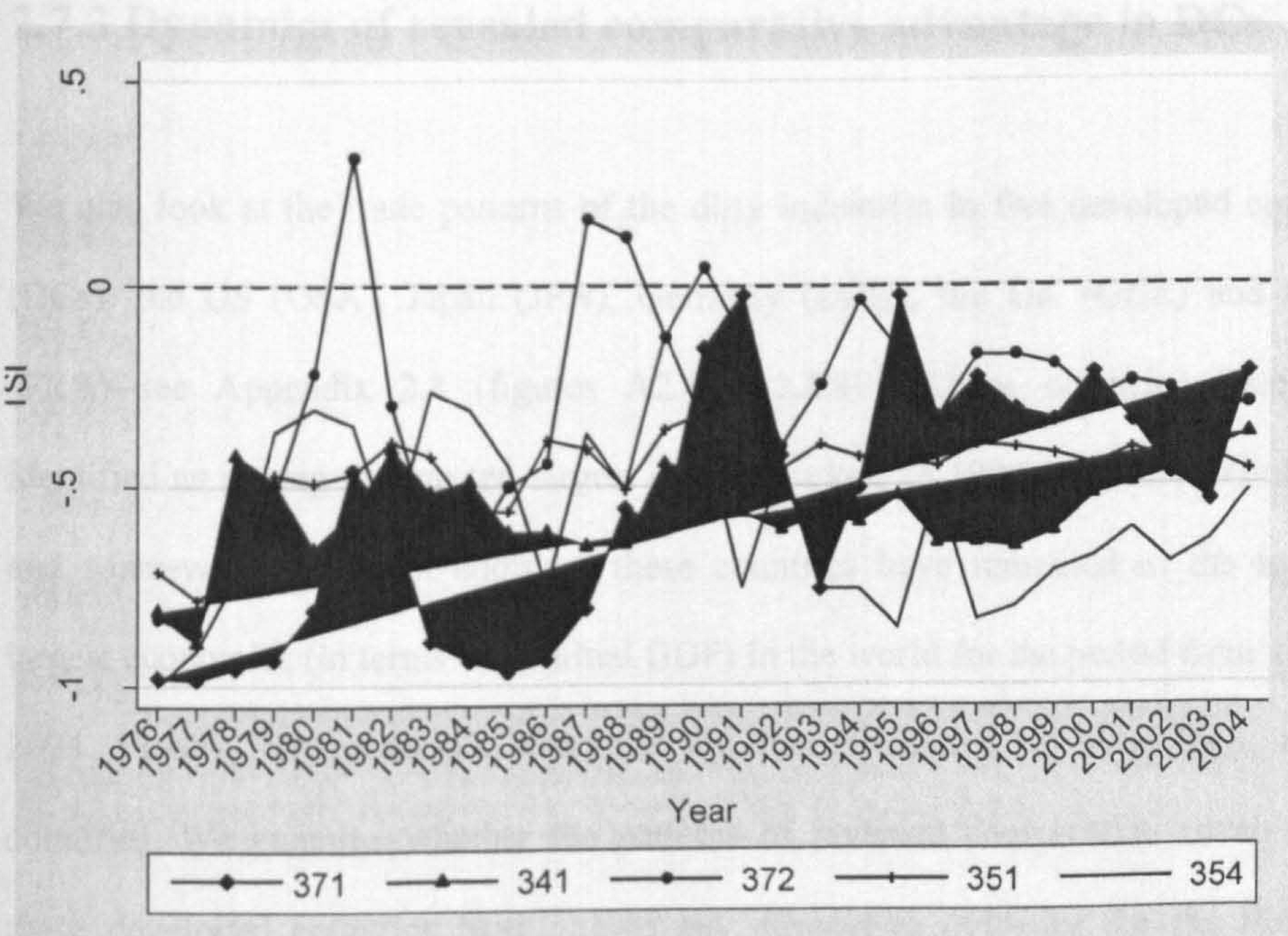
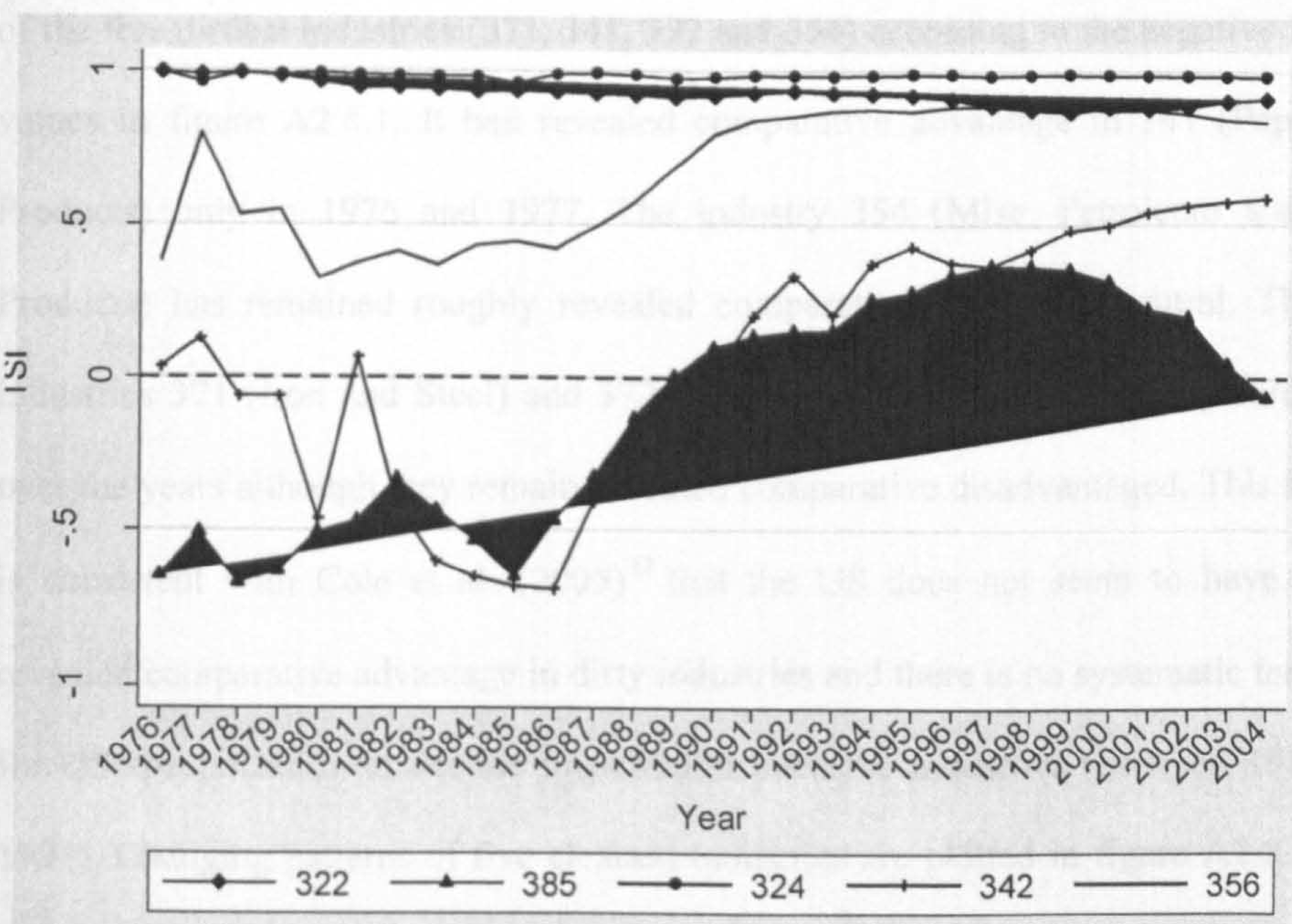


**Figure 2.11 Trade Specialization Index of Top Five Clean Industries in China**




## 2.7.3 Dynamics of revealed comparative advantage in DCs

We also look at the trade patterns of the dirty industries in five developed countries (DCs): the US (USA), Japan (JPN), Germany (DEU), the UK (GBR) and France (FRA)--see Appendix 2.8 (figures A2.8.1-A2.8.10). These countries have been identified as among the top ten largest export markets in 1997 for China (Hinloopen and Marrewijk, 2004). In addition, these countries have remained as the top five largest economies (in terms of nominal GDP) in the world for the period from 1976 to 2004. Finally, environmental standards are more stringent in these high income countries. We examine whether the patterns of revealed comparative advantage in these developed countries have shown any supportive evidence for the Pollution Haven Hypothesis.

The US does not seem to have significant revealed comparative advantage in the four of the five dirtiest industries (371, 341, 372 and 354) according to the negative NRCA values in figure A2.8.1. It had revealed comparative advantage in 341 (Paper and Products) only in 1976 and 1977. The industry 354 (Misc. Petroleum and Coal Products) has remained roughly revealed comparative advantage neutral. The two industries 371 (Iron and Steel) and 372 (Non-ferrous Metals) have an upward trend over the years although they remain revealed comparative disadvantaged. This finding is consistent with Cole et al. (2005)[33] that the US does not seem to have strong revealed comparative advantage in dirty industries and there is no systematic tendency for US specialization to decline in pollution intensive industries (between 1978 and 1994). Changing patterns of five cleanest industries are plotted in figure A2.8.6. The US has strong revealed comparative advantage in 385 (Professional and Scientific Equipment) which has further strengthened itself over the years. The industries 342 (Printing and Publishing) and 356 (Plastic Products) have a weak revealed comparative advantage. The other two clean industries 322 (Wearing Apparel except Footwear) and 324 (Footwear except Rubber or Plastic) have remained revealed comparative disadvantaged and their initial positions are restored at the end of 2004.

Figure A2.8.2 shows structural changes of five dirties industries for Japan. Japan initially had significant revealed comparative advantage of 371 (Iron and Steel) but it decreased over the years and levelled off since late 1980s around revealed comparative neutral state. Little fluctuation is detected for 354 (Misc. Petroleum and Coal Products) which stays roughly revealed comparative advantage neutral. Japan has revealed comparative disadvantage in 372 (Non-ferrous Metals), 351 (Industrial Chemicals) and 341 (Paper and Products) which have experienced a decrease in the first 10-15 years and an increase afterwards. Figure A2.8.7 shows structural change of

[33] They use BRCA for a slightly different set of dirty industries classified by SIC.

five cleanest industries, in which Japan only has revealed comparative advantage in 385 (Professional and Scientific Equipment). The strongest disadvantaged is 322 (Wearing Apparel, except Footwear). Other three cleanest industries are revealed comparative disadvantaged and are relatively stable over time.

In Germany, there is little evidence of revealed comparative advantage in top five dirty industries apart from 351 (Industrial Chemicals) which has a downward trend. The industries 371 (Iron and Steel) and 354 (Misc. Petroleum and Coal Products) had revealed comparative advantage in early years while the industry 372 (Non-ferrous Metals) remains revealed comparative disadvantaged despite of a constant increase over time. Overall, we see a convergence tendency to revealed comparative advantage neutral state for the five dirtiest industries (figure A2.8.3). Structural change of cleanest five industries in Germany is presented in figure A2.8.8. Industries 322 (Wearing Apparel, except Footwear) and 324 (Footwear except Rubber or Plastic) are significantly revealed comparative disadvantaged while the other three seem to be revealed comparative advantage neutral.

Figure A2.8.4 presents changing patterns of dirty industries in France. A convergence pattern similar to that of the USA and Japan seems to have happened in France. The dirtiest industry 371 (Iron and Steel) has been decreasing in revealed comparative advantage while other dirty industries have either remained neutral (see 354 (Misc. Petroleum and Coal Products)) or have decreased revealed comparative disadvantage (341 (Paper and Products) and 372 (Non-ferrous Metals)). Much fluctuation is seen in 351 (Industrial Chemicals) but it stays around the revealed comparative advantage neutral state at the end of the examination period. For the clean industries (figure A2.8.9), they have remained relatively stable. France only has revealed comparative advantage in 342 (Printing and Publishing) among the five cleanest industries.

Structural change in dirty industries in the UK (figure A2.8.5) also exhibits a convergence tendency towards comparative advantage neutral state. Industry 351 (Industrial Chemicals) shows significant revealed comparative advantage over the years. Industry 372 (Non-ferrous Metal) shows significant revealed comparative advantage in the early years but it decreases gradually. Other dirtiest industries have been either approximately neutral or negative in revealed comparative advantage. As for the five cleanest industries, figure A2.8.10 shows that 342 (Printing and Publishing) is the only one that maintains its comparative advantage state over the years. However, UK has experienced considerable changes with 322 (Wearing Apparel) which has changed from an industry with revealed comparative advantage to disadvantaged while 385 (Professional and Scientific Equipment) improves its situation in revealed comparative advantage.

In general, we do not find strong evidence of dirty industries having declined revealed comparative advantage between 1976 and 2004 in these developed countries. One exception is 371 (Iron and Steel) which has been decreasing revealed comparative advantage for Japan, Germany and France. In addition, 351 (Industrial Chemicals) has seen decreasing revealed comparative advantage for Germany. On the other hand, there are some dirty industries in developed countries which seem to improve their situation by reducing their revealed comparative disadvantage. While these developed countries enjoy revealed comparative advantage in one or two clean industries, fewer variations are found in the clean industries.

# 2.8 CONCLUSIONS

This chapter uses cross-section and time-series trade flows information of manufacturing industries to examine whether the fear of dirty industries migrating from developed countries to developing countries is evident in the case of China as well as five other selected developed economies between 1976 and 2004. Support for the PHH or FEH is sought. Having compared the information on industrial pollution from Hettige et al. (1995) and Dean and Lovely (2004), we first rank the 28 manufacturing industries according to their emission intensities. Different indices of trade performance are then considered for identifying revealed comparative advantage. We employ both BRCA and NRCA indices to measure revealed comparative advantage in industries. An emphasis is played on the changing trade patterns revealed by the NRCA since the BRCA index is less comparable across industries, across countries and across time than the NRCA index.

Overall, China does not seem to have revealed comparative advantage in most of the dirtiest industries, while it has revealed comparative advantage in 3 out of the top 5 cleanest industries. To compare revealed comparative advantage across industries and over time, we also examine the dynamic feature of the trade patterns using NRCA. The aggregate of five cleanest industries in China displayed an upward trend in revealed comparative advantage, while that of five dirtiest industries showed an increase in revealed comparative disadvantage between the years 1976 and 2004. Investigation of individual industries shows China has an increased revealed comparative disadvantage in top five dirty industries. Most of the cleanest industries in China have undergone phenomenal increase in revealed comparative advantage, although this trend has slowed down or even reversed since 2000. Two industries 385 (Professional and Scientific Equipment) and 342 (Printing and Publishing) have experienced marked variations in revealed trade performance during the period of analysis although they remain revealed comparative disadvantaged industries. In short, there is no support for a pollution haven story in China on the basis of revealed comparative advantage analysis.

The five high income countries also do not have significant revealed comparative advantage in the dirtiest industries. One exception is 371 (Iron and Steel) in which Japan, Germany and France have revealed comparative advantage, albeit with a downward trend. In addition, while 354 (Misc. Petroleum and Coal Products) in the high income countries seem to maintain their position with revealed comparative advantage around a neutral point, other dirty industries seem to converge towards the neutral point. As for the five cleanest industries, the patterns of revealed comparative advantage are less volatile in the high income countries. To sum up, except for 371(Iron and Steel) and 351 (Industrial Chemicals), we do not see much evidence of dirty industries having reduced revealed comparative advantage from these high income countries. Additionally, some dirty industries have decreased revealed comparative disadvantage. Hence the evidence does not seem to strongly support the Pollution Haven Hypothesis on the developed countries side.

The above results with regard to China are not surprising. In the first place, differences in labour, capital and natural resources are more likely to have contributed to the international division of labour. Given China's huge labour supply, the FEH effect might dominate the PHH effect. Secondly, dirty industries may not be footloose enough to immigrate into China. Most of the dirty industries such as iron and steel, petroleum refineries are still largely controlled and protected in China as well as in the developed world. Lastly, the pollution haven effect is self-limiting since environment protection is a normal good. With increases in GDP and income growth, environmental regulatory framework in China has strengthened over time since mid-1980s.

For the developed countries we selected, they do not have significant revealed comparative advantages in dirty industries in the first place. Instead of finding dirty industries having increased revealed comparative advantages, we find that most dirty industries have actually decreased revealed comparative disadvantages and there is a convergence tendency to comparative neutral point for these dirty industries in these high income countries.

In closing this chapter, we draw attention to a few limitations that we have to bear in mind together with findings. One limitation in this chapter is concerned with the methodology. Revealed comparative advantage indices capture the effects of changes in relative factor endowments as well as in environmental policies. However, they cannot distinguish and attribute the changes in trade patterns to factor endowments and/or policy changes. It is argued that changing patterns of production and trade could also be caused by other factors such as changes in energy price and trade policy as well as by unobserved heterogeneity.

Another limitation concerns data. Our focus was on manufacturing industries. However, natural-resource extracting, electricity production and road transport also place a large burden on the environment. The impact of international trade on natural resource depletion[34] in developing countries is hence not included in this analysis.

In addition, the definition of "dirtiness" at ISIC 3-digit level by lumping together different emission intensities may cause some aggregation bias. At finer level of classification and/or for individual pollutants, different trade and specialization adjustments might be found.

[34] Lopez (1997) shows that a deepening of trade liberalization is likely to induce further losses of biomass and deforestation in the case of Ghana.

# APPENDICES TO CHAPTER TWO

## A2.1 Pollution intensity of US industrial output, pounds per 1987 US million dollars

| CODE | DESCRIPTION | BOD | TSS | $NO_2$ | PM10 | $SO_2$ | CO | TP | VOC |
|---|---|---|---|---|---|---|---|---|---|
| 311 | Food Products | 1621.1 | 404.6 | 1192.5 | 557.03 | 1189.6 | 324.37 | 1090.4 | 309.87 |
| 313 | Beverages | 942.22 | 1699.2 | 1397.1 | 30.877 | 2194.2 | 115.23 | 142.7 | 2371.7 |
| 314 | Tobacco | 1.5334 | 1.8727 | 765.67 | 9.9349 | 1265.2 | 99.735 | 23.632 | 251.65 |
| 321 | Textiles | 49.119 | 76.737 | 1649.6 | 33.413 | 1255.8 | 231.53 | 263.37 | 755.14 |
| 322 | Wearing apparel, except Footwear | 0 | 0 | 11.879 | 0.29486 | 31.55 | 3.3277 | 1.4743 | 7.877 |
| 323 | Leather Products | 257.42 | 613.21 | 199.62 | 20.73 | 792.64 | 58.231 | 441.63 | 1303 |
| 324 | Footwear, except Rubber or Plastic | 100.62 | 98.666 | 1.848 | 0 | 15.708 | 0 | 0.924 | 134.44 |
| 331 | Wood Products, except Furniture | 88.552 | 417.05 | 2218 | 219.43 | 1147.2 | 5546.7 | 3229.3 | 2671.9 |
| 332 | Furniture, except Metal | 0.003298 | 0.025084 | 171.58 | 160.16 | 242.84 | 182.08 | 546.65 | 5509.8 |
| 341 | Paper and Products | 6351.2 | 21375 | 6509.2 | 663.79 | 11822 | 13403 | 2305.1 | 2154.3 |
| 342 | Printing and Publishing | 4.0646 | 2.2252 | 33.603 | 0.33588 | 25.848 | 129.39 | 13.893 | 862.22 |
| 351 | Industrial Chemicals | 2509.1 | 4485 | 9835.1 | 245.36 | 8907.4 | 4759.3 | 1425 | 7472.4 |
| 352 | Other Chemicals | 51.283 | 5144.8 | 945.22 | 492.94 | 2436.5 | 17228 | 780.91 | 1845.4 |
| 353 | Petroleum Refineries | 158.28 | 794.37 | 7284.9 | 127.88 | 12664 | 6578.9 | 1117.3 | 6704.9 |
| 354 | Misc. Petroleum and Coal Products | 21.962 | 26.958 | 12982 | 640.61 | 20866 | 9828.5 | 8003.6 | 3259.3 |

**Table A2.1 continued**

| CODE | DESCRIPTION | BOD | TSS | $NO_2$ | PM10 | $SO_2$ | CO | TP | VOC |
|---|---|---|---|---|---|---|---|---|---|
| 355 | Rubber Products | 0.28528 | 1281.1 | 803.42 | 33.603 | 2320 | 98.812 | 257.43 | 2497.3 |
| 356 | Plastic Products | 518.3 | 11.2 | 12.196 | 11.699 | 56.046 | 4.0033 | 17.099 | 676.4 |
| 361 | Pottery, china, Earthenware | 44.743 | 111.03 | 148.15 | 0 | 295.45 | 102.77 | 348.55 | 1151 |
| 362 | Glass and Products | 1.4666 | 10.377 | 6720.8 | 142.45 | 3377.6 | 1810.3 | 1348.4 | 862.18 |
| 369 | Other Non-metallic Mineral Products | 19.357 | 327.46 | 9986.6 | 14257 | 17669 | 1856.4 | 13101 | 516.73 |
| 371 | Iron and Steel | 13.218 | 1.95E+05 | 7761.1 | 4938.2 | 17867 | 27843 | 4139.7 | 2391.7 |
| 372 | Non-ferrous Metals | 2963 | 42831 | 1258.8 | 355.07 | 38646 | 17977 | 3245.7 | 1405.9 |
| 381 | Fabricated Metal Products | 13.764 | 385.5 | 508.78 | 6.5933 | 150.6 | 1013.7 | 82.027 | 1232.6 |
| 382 | Machinery, except Electrical | 1.5343 | 32.867 | 186.22 | 1.3547 | 414.56 | 448.31 | 61.334 | 471.35 |
| 383 | Machinery Electric | 24.833 | 35.384 | 314.14 | 3.8993 | 638.99 | 351.27 | 68.803 | 427.56 |
| 384 | Transport Equipment | 0.47754 | 3.5541 | 143.14 | 21.741 | 275.47 | 193.72 | 113.77 | 1028.7 |
| 385 | Professional and Scientific Equipment | 0.67936 | 0.74208 | 27.611 | 0 | 16.296 | 2.9583 | 5.2264 | 38.976 |
| 390 | Other Manufactured Products | 0.046539 | 10130 | 43.382 | 12.587 | 61.088 | 14.181 | 35.075 | 407.9 |

Source: WORLD BANK/PRDEI, INDUSTRIAL POLLUTION PROJECTIONS PROJECT 1995.

Note: BOD-Biological oxygen demand; TSS-Total suspended solids; NO2-Nitrogen dioxide; PM10-Fine particulates that are less than 10 microns in diameter; SO2-Sulphur dioxide; CO-Carbon monoxide; TP-Total suspended particulates; VOC-Volatile organic compounds.

## A2.2 Spearman correlation coefficients for pollution intensity rankings

| | BOD | TSS | $NO_2$ | PM10 | $SO_2$ | CO | TP | VOC | Average | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| **BOD** | 1 | | | | | | | | | |
| **TSS** | 0.5605* | 1 | | | | | | | | |
| **$NO_2$** | 0.3755* | 0.4893* | 1 | | | | | | | |
| **PM10** | 0.3366 | 0.5293* | 0.8276* | 1 | | | | | | |
| **$SO_2$** | 0.3892* | 0.5621* | 0.9168* | 0.8287* | 1 | | | | | |
| **CO** | 0.364 | 0.5036* | 0.7997* | 0.7663* | 0.7909* | 1 | | | | |
| **TP** | 0.3853* | 0.5244* | 0.8790* | 0.9020* | 0.8621* | 0.8243* | 1 | | | |
| **VOC** | 0.2961 | 0.4663* | 0.5966* | 0.5774* | 0.5692* | 0.5889* | 0.6606* | 1 | | |
| **Average** | 0.5397* | 0.7006* | 0.9135* | 0.8829* | 0.9157* | 0.8648* | 0.9299* | 0.7148* | 1 | |
| **Total** | 0.3689 | 0.7165* | 0.8654* | 0.8987* | 0.8883* | 0.7980* | 0.9042* | 0.6645* | 0.9349* | 1 |

Note: rankings are created for individual pollutants; average ranking is calculated based on the individual rankings; total ranking is calculated based on the aggregation of pollutants by pound.

## A2.3 Pollution Intensity of Chinese Industry in 1995 and 2004 ranked from largest to smallest using 1995 data.

| ISIC 3 | GB/T4754-2002 | Division | COD | | $SO_2$ | | Smoke | | Dust | | Overall | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | 1995 | 2004 | 1995 | 2004 | 1995 | 2004 | 1995 | 2004 | 1995 | 2004 |
| 341 | 22 | Papermaking and Paper Products | 70.02 | 7.22 | 7.08 | 1.9 | 4.8 | 1.11 | 0.63 | 0.07 | 82.53 | 10.3 |
| 369 | 31 | Nonmetal Mineral Products | 0.36 | 0.14 | 10.73 | 4.33 | 6.59 | 3.29 | 40.3 | 14.3 | 57.94 | 22.05 |
| 313 | 15 | Beverage Production | 9.57 | 1.26 | 3.38 | 0.72 | 2.4 | 0.61 | 0.07 | 0.02 | 15.42 | 2.61 |
| 371 | 32 | Smelting & Pressing of Ferrous Metals | 1.05 | 0.14 | 4.63 | 0.98 | 2.25 | 0.47 | 5.56 | 1.05 | 13.49 | 2.64 |
| 351 | 26 | Raw Chemical Material & Chemical Products | 3.07 | 0.65 | 5.08 | 1.34 | 2.77 | 0.66 | 0.78 | 0.22 | 11.7 | 2.87 |
| 372 | 33 | Smelting & Pressing of Non-ferrous Metals | 0.24 | 0.09 | 8.01 | 2.2 | 1.87 | 0.63 | 1.49 | 0.59 | 11.61 | 3.51 |
| 311 | 14 | Food Production | 7.65 | 1.10 | 2.47 | 0.62 | 1.09 | 0.38 | 0.08 | 0.02 | 11.29 | 2.12 |
| 351 | 28 | Chemical Fiber | 3.42 | 0.69 | 2.34 | 0.89 | 1.33 | 0.28 | 0.17 | 0.02 | 7.26 | 1.88 |
| 353 | 25 | Petroleum Processing, Coking and Nuclear Fuel | 0.79 | 0.08 | 2.85 | 0.85 | 1.67 | 0.58 | 1.15 | 0.19 | 6.46 | 1.7 |
| 352 | 27 | Medical and Pharmaceutical Products | 3.51 | 0.72 | 1.71 | 0.45 | 0.99 | 0.22 | 0.02 | 0.01 | 6.23 | 1.4 |
| 323 | 19 | Leather, Furs, Down and Related Products | 2.57 | 0.87 | 0.74 | 0.22 | 0.47 | 0.17 | 0.03 | 0.00 | 3.81 | 1.26 |
| 332 | 21 | Furniture Manufacturing | 0.94 | 0.14 | 1.07 | 0.22 | 1.25 | 0.16 | 0.54 | 0.01 | 3.8 | 0.53 |
| 321 | 17 | Textile Industry | 1.07 | 0.74 | 1.53 | 0.72 | 0.84 | 0.28 | 0.03 | 0.03 | 3.47 | 1.77 |
| 355 | 29 | Rubber Products | 0.33 | 0.08 | 1.77 | 0.41 | 0.82 | 0.18 | 0.15 | 0.00 | 3.07 | 0.67 |
| 382 | 36 | Special Equipment Manufacturing | 0.21 | 0.07 | 0.98 | 0.17 | 0.72 | 0.08 | 0.10 | 0.03 | 2.01 | 0.35 |

Table A2.3 continued

| ISIC 3 | GB/T4754-2002 | Division | COD | | $SO_2$ | | Smoke | | Dust | | Overall | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 382 | 35 | Ordinary Machinery Manufacturing | 0.11 | 0.06 | 0.97 | 0.22 | 0.78 | 0.14 | 0.13 | 0.09 | 1.99 | 0.51 |
| 381 | 34 | Metal Products | 0.11 | 0.08 | 1.02 | 0.17 | 0.65 | 0.09 | 0.07 | 0.05 | 1.85 | 0.39 |
| 356 | 30 | Plastic Products | 0.1 | 0.11 | 0.79 | 0.2 | 0.31 | 0.08 | 0.01 | 0.07 | 1.21 | 0.46 |
| 322/324 | 18 | Clothes, Shoes and Hat Manufacture | 0.31 | 0.33 | 0.56 | 0.29 | 0.31 | 0.14 | 0.01 | 0.02 | 1.19 | 0.78 |
| 342 | 23 | Printing and Record Medium Reproduction | 0.18 | 0.08 | 0.64 | 0.09 | 0.32 | 0.07 | 0.00 | 0.00 | 1.14 | 0.24 |
| 384 | 37 | Transport Equipment Manufacturing | 0.12 | 0.06 | 0.43 | 0.06 | 0.37 | 0.07 | 0.10 | 0.06 | 1.02 | 0.25 |
| 383 | 39 | Electric Machines and Apparatuses Manufacturing | 0.13 | 0.02 | 0.54 | 0.04 | 0.31 | 0.03 | 0.02 | 0.02 | 1 | 0.11 |
| 383 | 40 | Communications Equipment, Computer and Other Electronic Equipment Manufacturing | 0.08 | 0.03 | 0.35 | 0.03 | 0.23 | 0.03 | 0.01 | 0.01 | 0.67 | 0.1 |
| 314 | 16 | Tobacco Products Processing | 0.2 | 0.02 | 0.28 | 0.05 | 0.1 | 0.03 | 0.03 | 0.01 | 0.61 | 0.11 |
| 385 | 41 | Instruments, Meters, Cultural and Office Machinery | 0.11 | 0.05 | 0.24 | 0.07 | 0.08 | 0.01 | 0.00 | 0.00 | 0.43 | 0.13 |
| 390 | 24 | Cultural, Educational and Sports Articles Production | n/a | 0.09 | n/a | 0.31 | n/a | 0.18 | n/a | 0.29 | n/a | 0.87 |
| 390 | 42 | Craftwork and Other Manufactures | n/a | 0.09 | n/a | 0.13 | n/a | 0.08 | n/a | 0.09 | n/a | 0.39 |

Source: Dean and Lovely (2008). Overall data is the sum of the four pollution intensities. Unit: Kilos per 1000 Yuan, 1995 price level

## A2.4 BRCA and NRCA rankings for Chinese sectors (BRCA rankings in italic)

| ISIC | Pollution intensity | 2004 | | 2000 | 1996 | 1992 | | 1988 | 1984 | | 1980 | 1976 | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 371 | 1 | 23 | *18* | 20 | *19* | 20 | *18* | 23 | *21* | 24 | 16 | 24 | *23* | 24 |
| 341 | 3 | 21 | *22* | 21 | *25* | 23 | *26* | 24 | *26* | 25 | 26 | 22 | *18* | 23 |
| 372 | 2 | 22 | *19* | 23 | *21* | 22 | *23* | 22 | *23* | 23 | 15 | 23 | *22* | 25 |
| 351 | 6 | 27 | *21* | 27 | *20* | 26 | *20* | 26 | *20* | 26 | 17 | 25 | *13* | 21 |
| 354 | 5 | 15 | *24* | 14 | *28* | 14 | *27* | 13 | *28* | 12 | 24 | 13 | *25* | 13 |
| 353 | 7 | 24 | *25* | 24 | *23* | 21 | *25* | 20 | *19* | 16 | 13 | 3 | *6* | 3 |
| 369 | 4 | 12 | *12* | 12 | *11* | 13 | *12* | 15 | *13* | 18 | 21 | 17 | *16* | 12 |
| 352 | 8 | 26 | *23* | 25 | *22* | 25 | *21* | 21 | *18* | 21 | 14 | 11 | *12* | 7 |
| 331 | 9 | 17 | *16* | 17 | *16* | 17 | *16* | 18 | *17* | 22 | 22 | 20 | *21* | 20 |
| 313 | 12 | 19 | *27* | 19 | *24* | 18 | *24* | 17 | *22* | 15 | 19 | 16 | *14* | 17 |
| 311 | 15 | 25 | *20* | 22 | *17* | 24 | *17* | 25 | *15* | 6 | 8 | 4 | *9* | 4 |
| 362 | 10 | 14 | *14* | 15 | *14* | 15 | *14* | 14 | *14* | 14 | 18 | 15 | *15* | 15 |
| 321 | 16 | 10 | *9* | 8 | *9* | 7 | *7* | 4 | *7* | 1 | 3 | 1 | *1* | 1 |
| 355 | 13 | 18 | *17* | 18 | *18* | 19 | *22* | 19 | *25* | 20 | 27 | 19 | *20* | 19 |
| 323 | 17 | 8 | *2* | 6 | *2* | 5 | *2* | 5 | *1* | 4 | 2 | 6 | *4* | 6 |
| 381 | 18 | 5 | *8* | 7 | *8* | 8 | *8* | 8 | *8* | 9 | 9 | 9 | *11* | 11 |
| 332 | 14 | 9 | *7* | 9 | *7* | 10 | *9* | 11 | *10* | 10 | 10 | 12 | *10* | 10 |
| 361 | 20 | 11 | *4* | 10 | *3* | 9 | *5* | 9 | *4* | 8 | 4 | 8 | *3* | 8 |
| 383 | 21 | 1 | *10* | 3 | *10* | 6 | *10* | 7 | *9* | 11 | 11 | 26 | *19* | 26 |
| 382 | 23 | 4 | *11* | 26 | *15* | 27 | *19* | 27 | *24* | 27 | 25 | 27 | *26* | 27 |
| 384 | 22 | 28 | *28* | 28 | *27* | 28 | *28* | 28 | *27* | 28 | 28 | 28 | *27* | 28 |
| 314 | 19 | 16 | *26* | 16 | *26* | 12 | *13* | 12 | *11* | 13 | 20 | 14 | *28* | 14 |
| 390 | 11 | 3 | *5* | 2 | *6* | 2 | *6* | 1 | *6* | 3 | 5 | 5 | *7* | 5 |
| 356 | 24 | 6 | *6* | 4 | *5* | 3 | *3* | 3 | *3* | 5 | 6 | 7 | *5* | 16 |
| 342 | 25 | 13 | *13* | 13 | *13* | 16 | *15* | 16 | *16* | 19 | 23 | 18 | *24* | 18 |
| 324 | 26 | 7 | *1* | 5 | *1* | 4 | *1* | 6 | *2* | 7 | 7 | 10 | *8* | 9 |
| 385 | 27 | 20 | *15* | 11 | *12* | 11 | *11* | 10 | *12* | 17 | 12 | 21 | *17* | 22 |
| 322 | 28 | 2 | *3* | 1 | *4* | 1 | *4* | 2 | *5* | 2 | 1 | 2 | *2* | 2 |

## A2.5 List of countries served as the reference group

| County Name | Code |
|---|---|
| Algeria | DZA |
| Argentina | ARG |
| Armenia | ARM |
| Australia | AUS |
| Austria | AUT |
| Azerbaijan | AZE |
| Bangladesh | BGD |
| Belgium-Luxemburg | BLX |
| Benin | BEN |
| Bolivia | BOL |
| Botswana | BWA |
| Brazil | BRA |
| Bulgaria | BGR |
| Cameroon | CMR |
| Canada | CAN |
| Chile | CHL |
| China | CHN |
| Colombia | COL |
| Costa Rica | CRI |
| Cote D'Ivoire | CIV |
| Cyprus | CYP |
| Czech Republic | CZE |
| Denmark | DNK |
| Ecuador | ECU |
| Egypt | EGY |
| El Salvador | SLV |
| Ethiopia | ETH |
| Finland | FIN |
| France | FRA |
| Gabon | GAB |
| Germany (76-90 West) | DEU |
| Ghana | GHA |
| Greece | GRC |
| Guatemala | GTM |
| Honduras | HND |
| Hong Kong | HKG |
| Hungary | HUN |
| Iceland | ISL |
| India | IND |
| Indonesia | IDN |
| Iran | IRN |
| Ireland | IRL |
| Israel | ISR |
| Italy | ITA |
| Japan | JPN |
| Jordan | JOR |
| Kenya | KEN |
| Korea | KOR |
| Kuwait | KWT |
| Kyrgyzstan | KGZ |

**Table A2.5 continued**

| | |
|---|---|
| Latvia | LVA |
| Lithuania | LTU |
| Macau | MAC |
| Malawi | MWI |
| Malaysia | MYS |
| Malta | MLT |
| Mauritius | MUS |
| Mexico | MEX |
| Moldova | MDA |
| Mongolia | MNG |
| Morocco | MAR |
| Mozambique | MOZ |
| Myanmar | MMR |
| Nepal | NPL |
| County Name | Code |
| Netherlands | NLD |
| New Zealand | NZL |
| Nigeria | NGA |
| Norway | NOR |
| Oman | OMN |
| Pakistan | PAK |
| Panama | PAN |
| Peru | PER |
| Philippines | PHL |
| Poland | POL |
| Portugal | PRT |
| Qatar | QAT |
| Romania | ROM |
| Russian Federation | RUS |
| Senegal | SEN |
| Singapore | SGP |
| Slovakia | SVK |
| Slovenia | SVN |
| South Africa | ZAF |
| Spain | ESP |
| Sri Lanka | LKA |
| Sweden | SWE |
| Switzerland | CHE |
| Taiwan | TWN |
| Tanzania | TZA |
| Thailand | THA |
| Trinidad and Tobago | TTO |
| Tunisia | TUN |
| Turkey | TUR |
| Uganda | UGA |
| Ukraine | UKR |
| United Kingdom | GBR |
| United States | USA |
| Uruguay | URY |
| Venezuela | VEN |
| Yemen | YEM |

## A2.6 Spearman Test for BRCA and NRCA (China)

| obs 812 | BRCA(exports) | BRCA(imports) | NRCA(exports) | NRCA(imports) |
|---|---|---|---|---|
| BRCA(exports) | 1 | | | |
| BRCA(imports) | -0.1382** | 1 | | |
| NRCA(exports) | 0.8181** | -0.2284** | 1 | |
| NRCA(imports) | -0.0725** | 0.6877** | 0.0961** | 1 |

Note: ** denotes significance at 95% level.

## A2.7 Changing Patterns of RCAs for China

**Figure A2.7.1 BRCA and NRCA for 371 "Iron and Steel"**

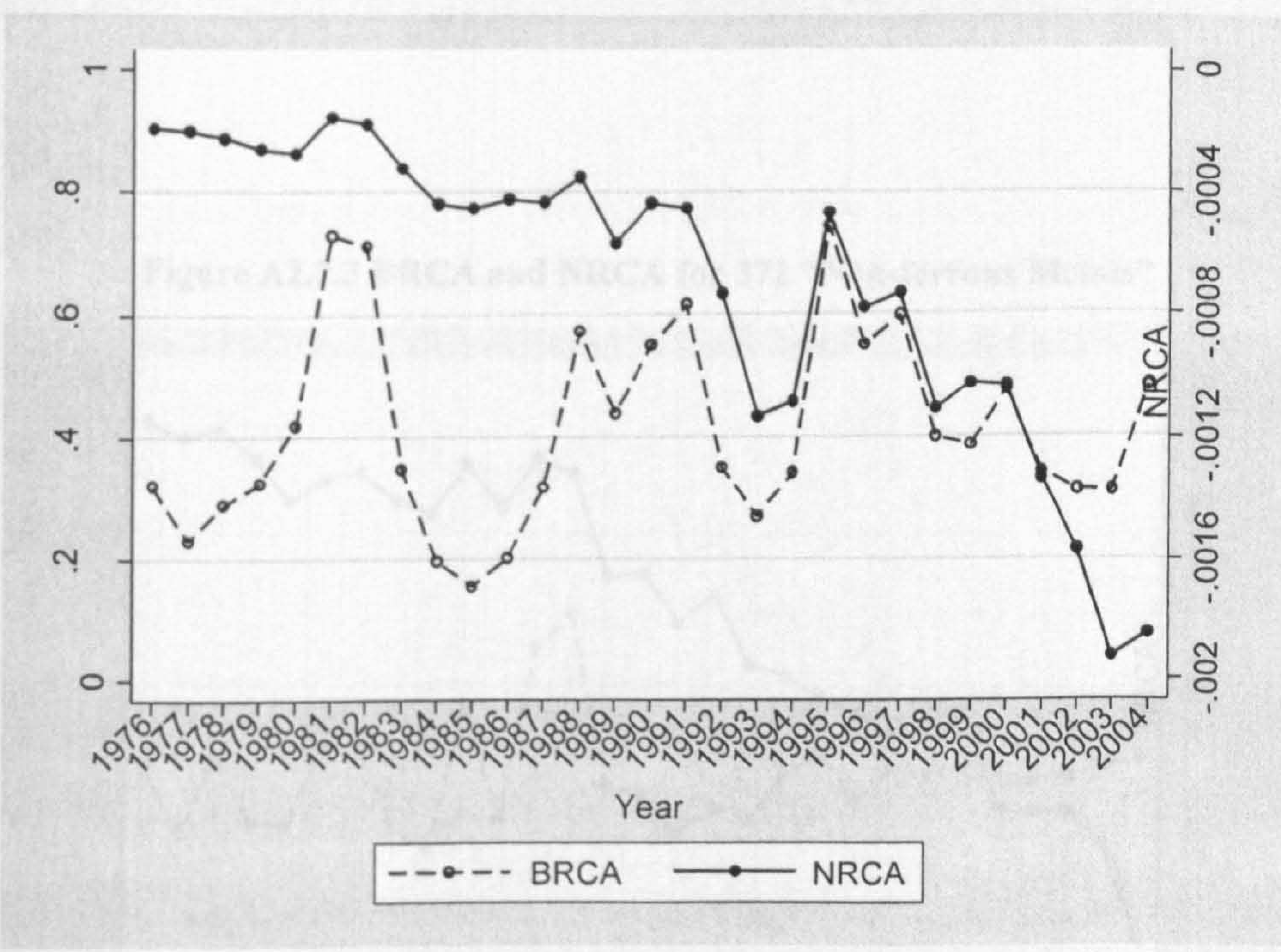


**Figure A2.7.2 BRCA and NRCA for 341 "Paper and Products"**

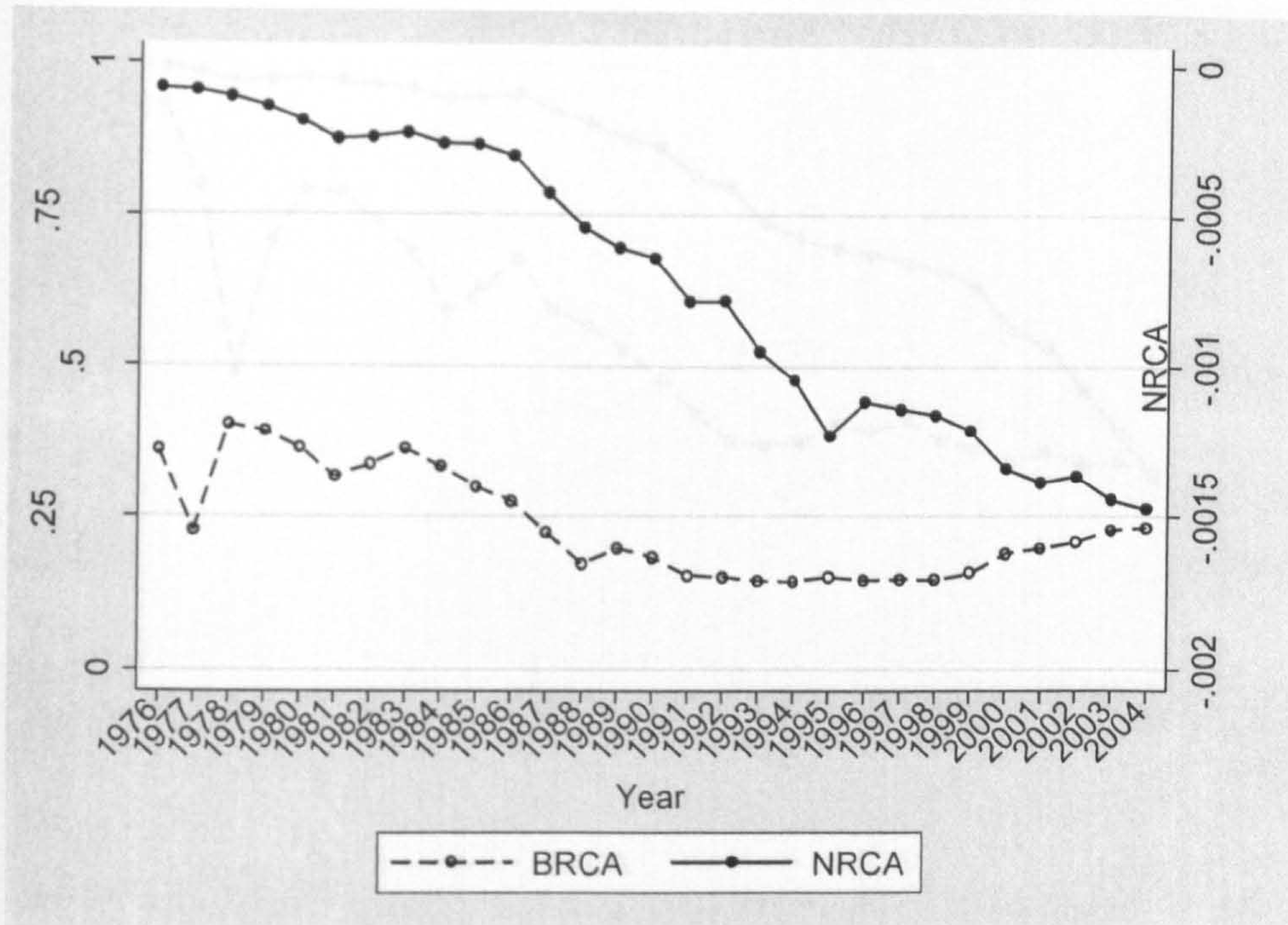



**Figure A2.7.3 BRCA and NRCA for 372 "Non-ferrous Metals"**

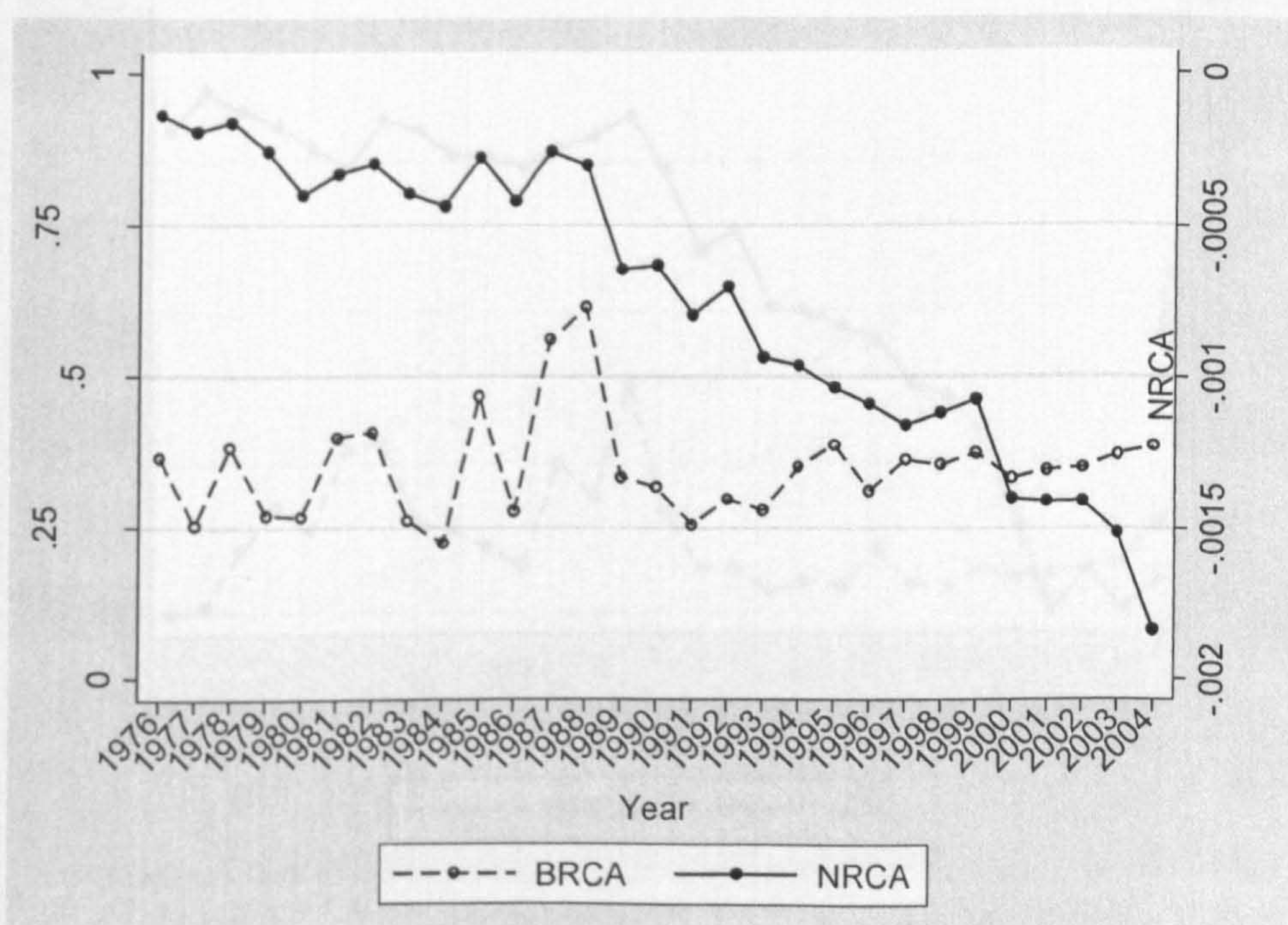


Figure A2.7.4 BRCA and NRCA for 351 "Industrial Chemicals"

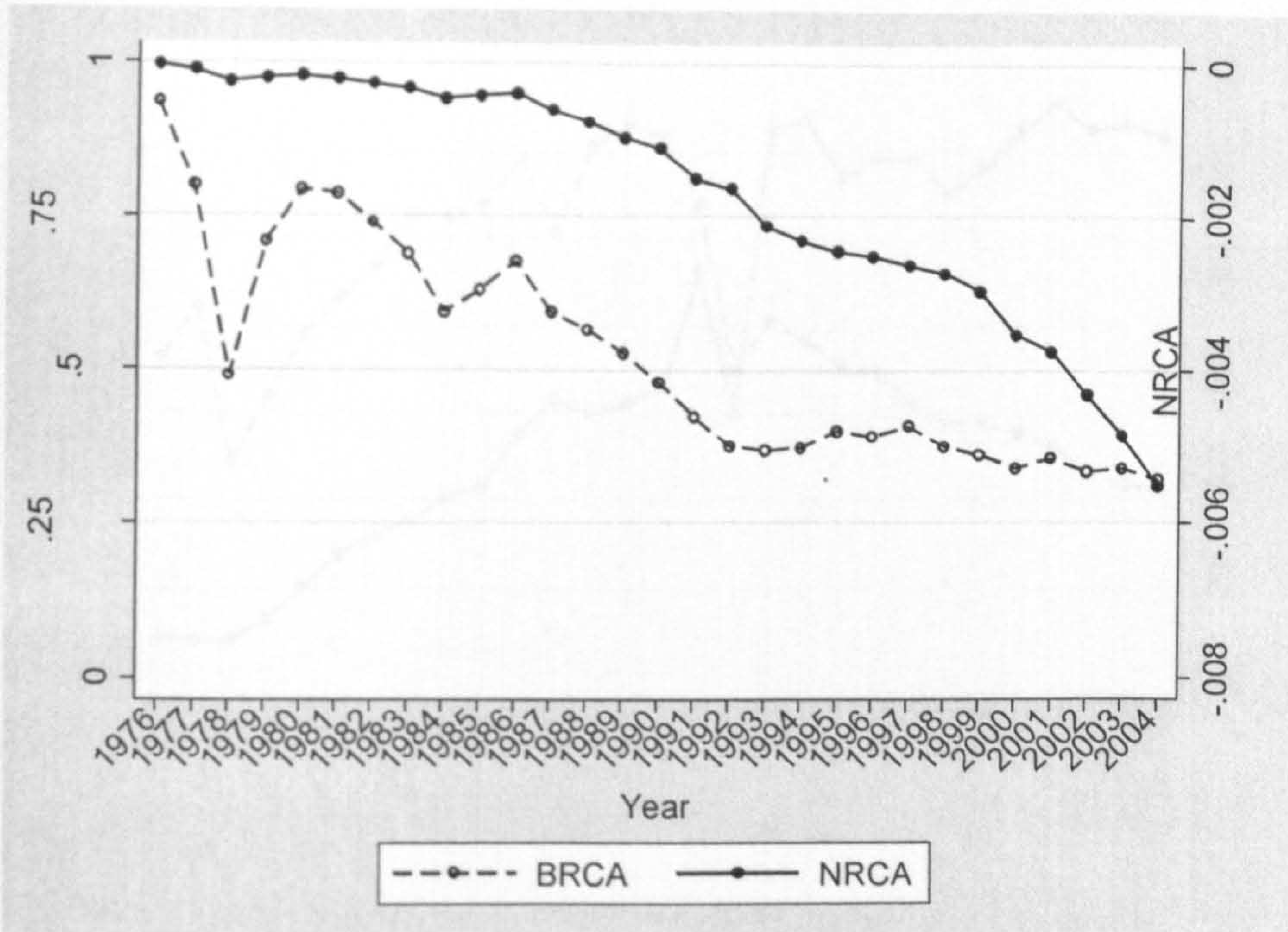



Figure A2.7.5 BRCA and NRCA for 354 "Misc. Petroleum and Coal Products"

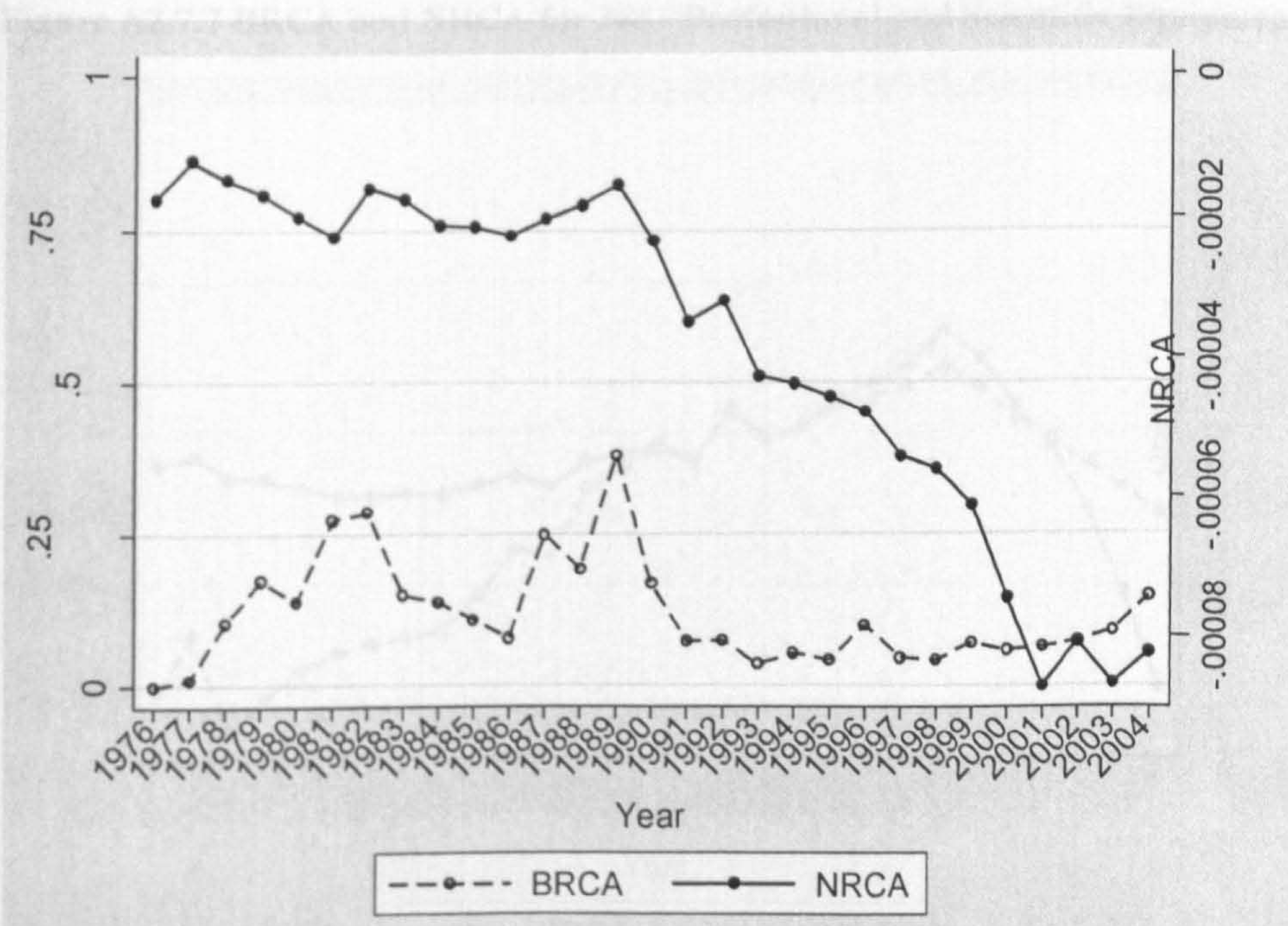


Figure A2.7.6 BRCA and NRCA for 322 "Wearing Apparel except Footwear"

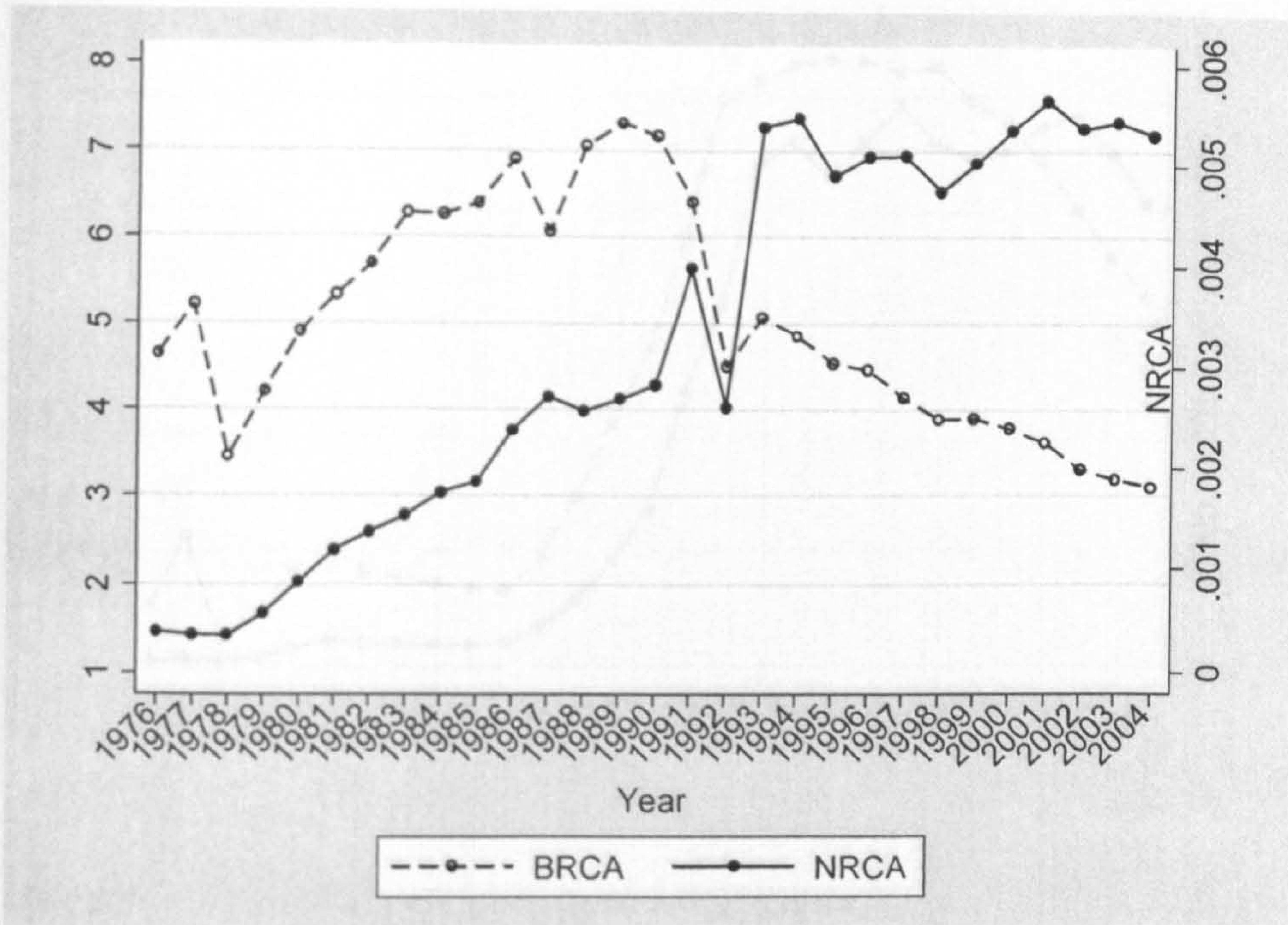



Figure A2.7.7 BRCA and NRCA for 385 "Professional and Scientific Equipment"

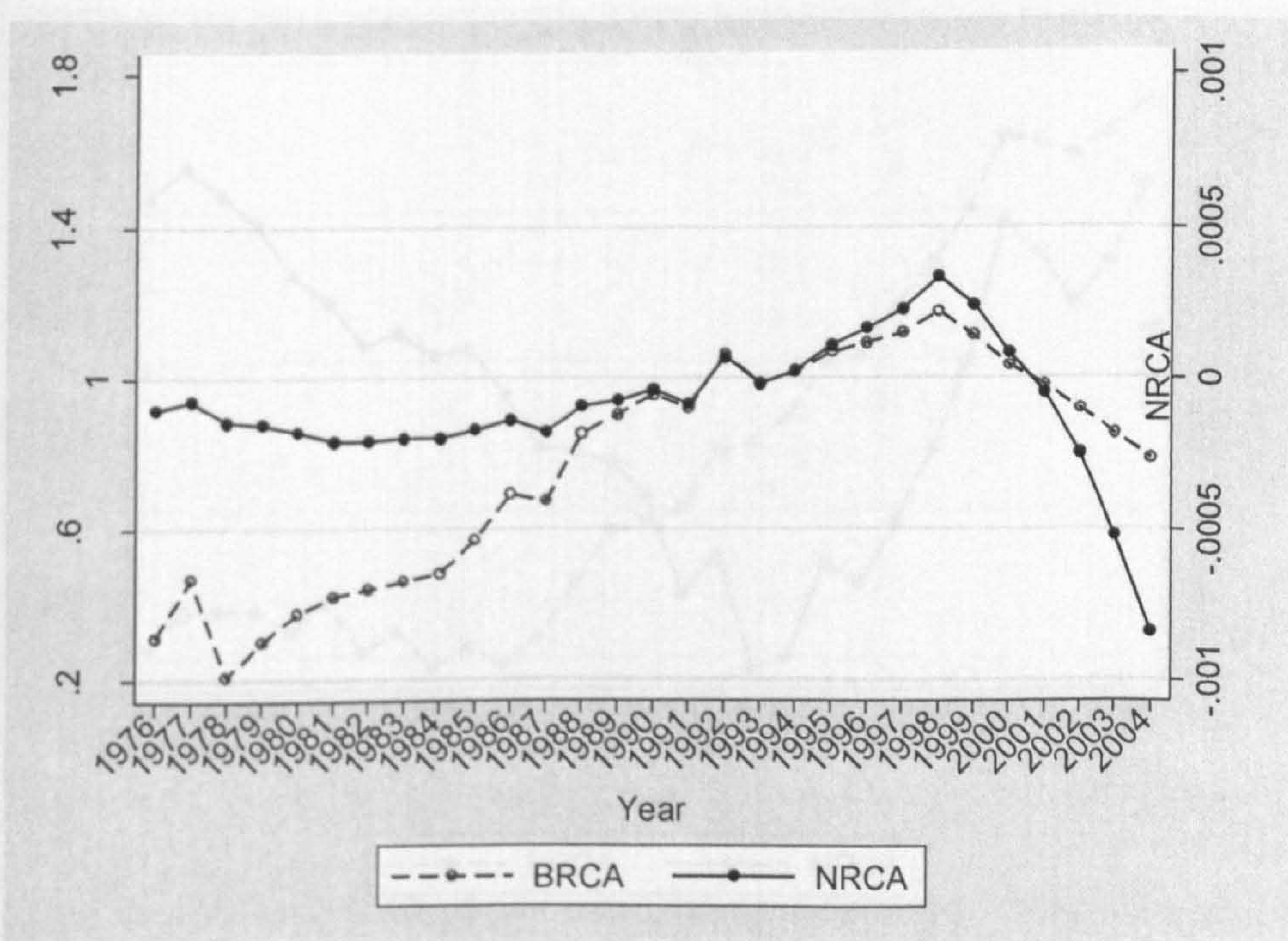


**Figure A2.7.8 BRCA and NRCA for 324 "Footwear except Rubber or Plastic"**

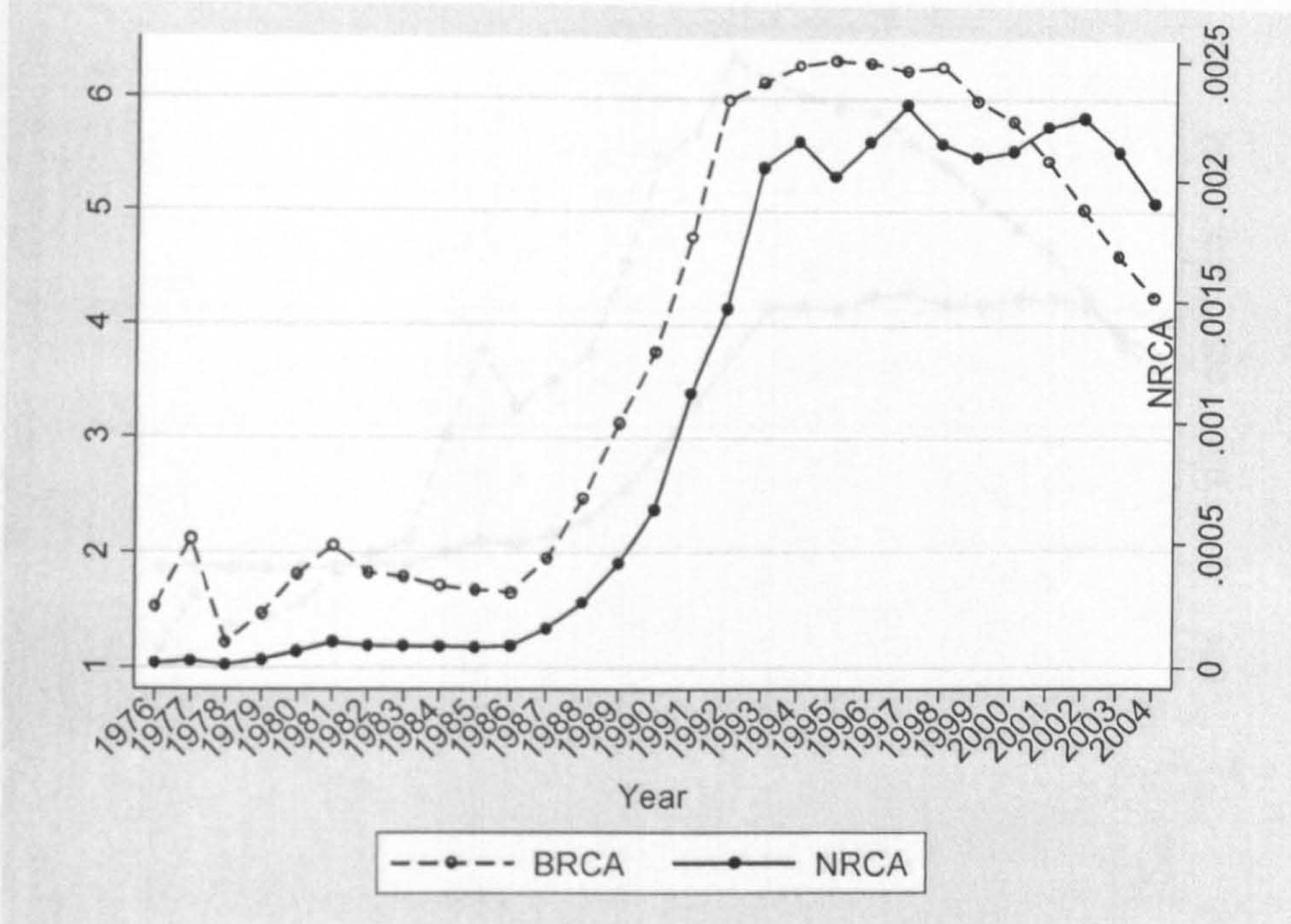



**Figure A2.7.9 BRCA and NRCA for 342 "Printing and Publishing"**

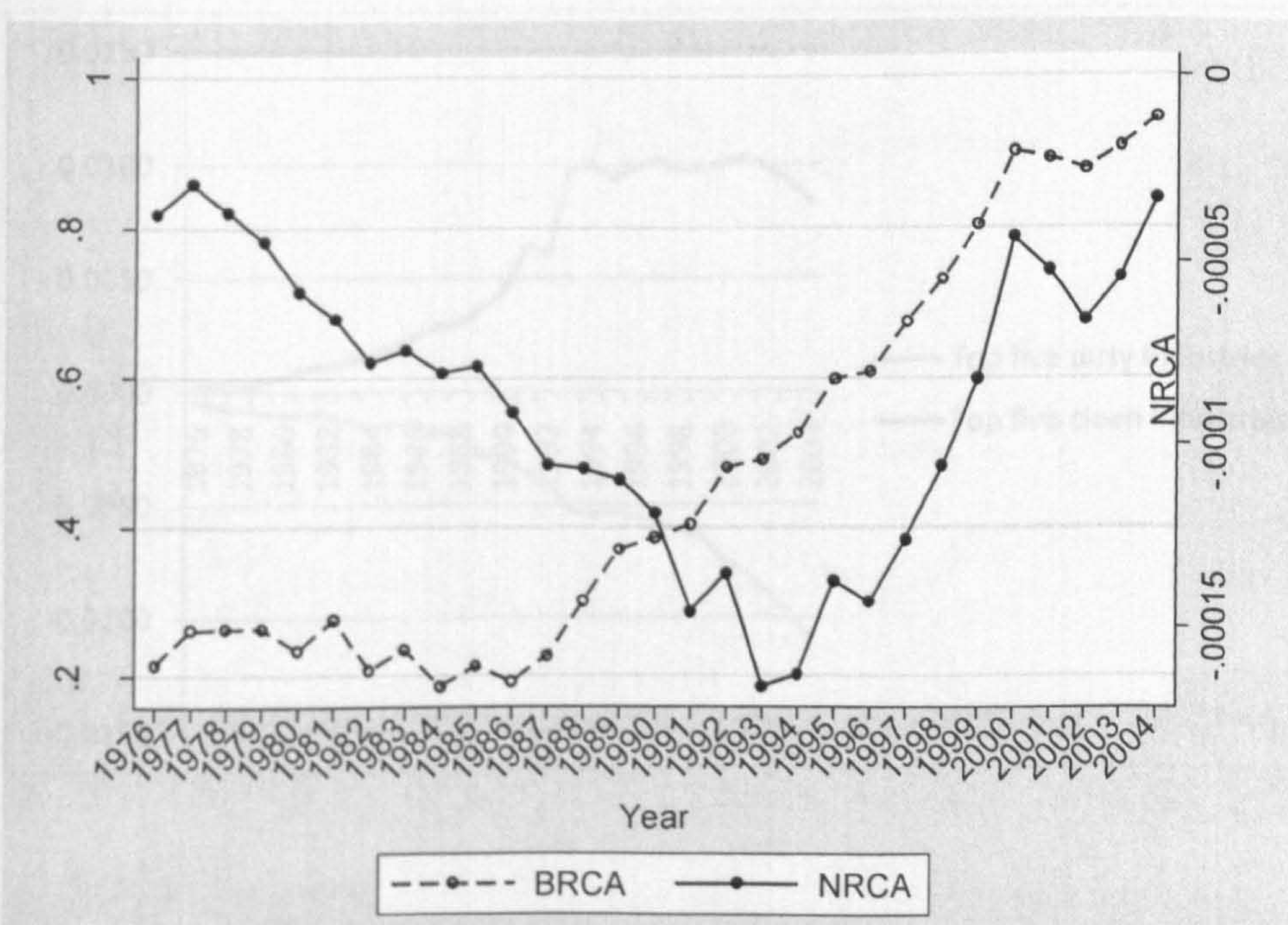


Figure A2.7.10 BRCA and NRCA for 356 "Plastic Products"

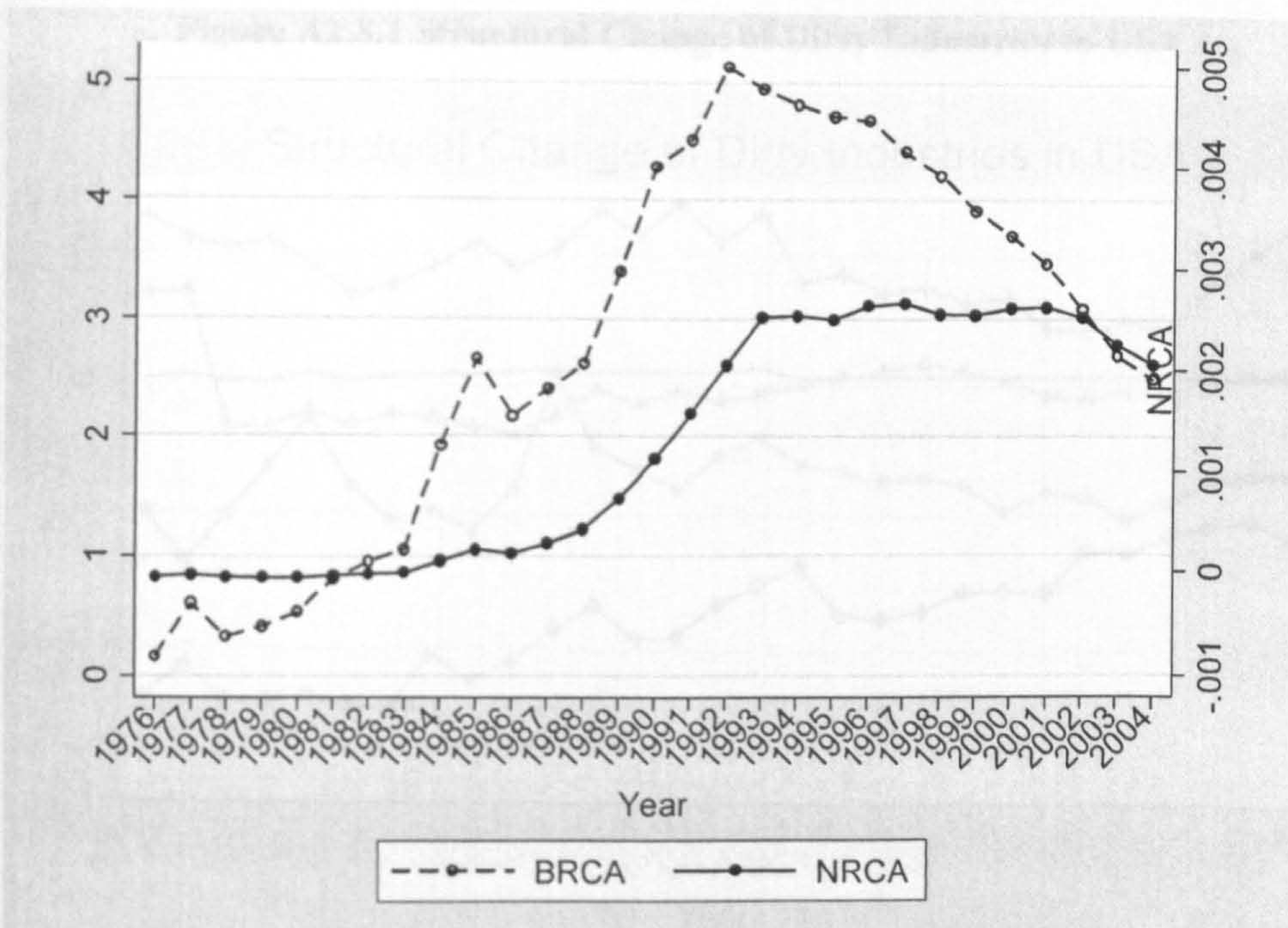
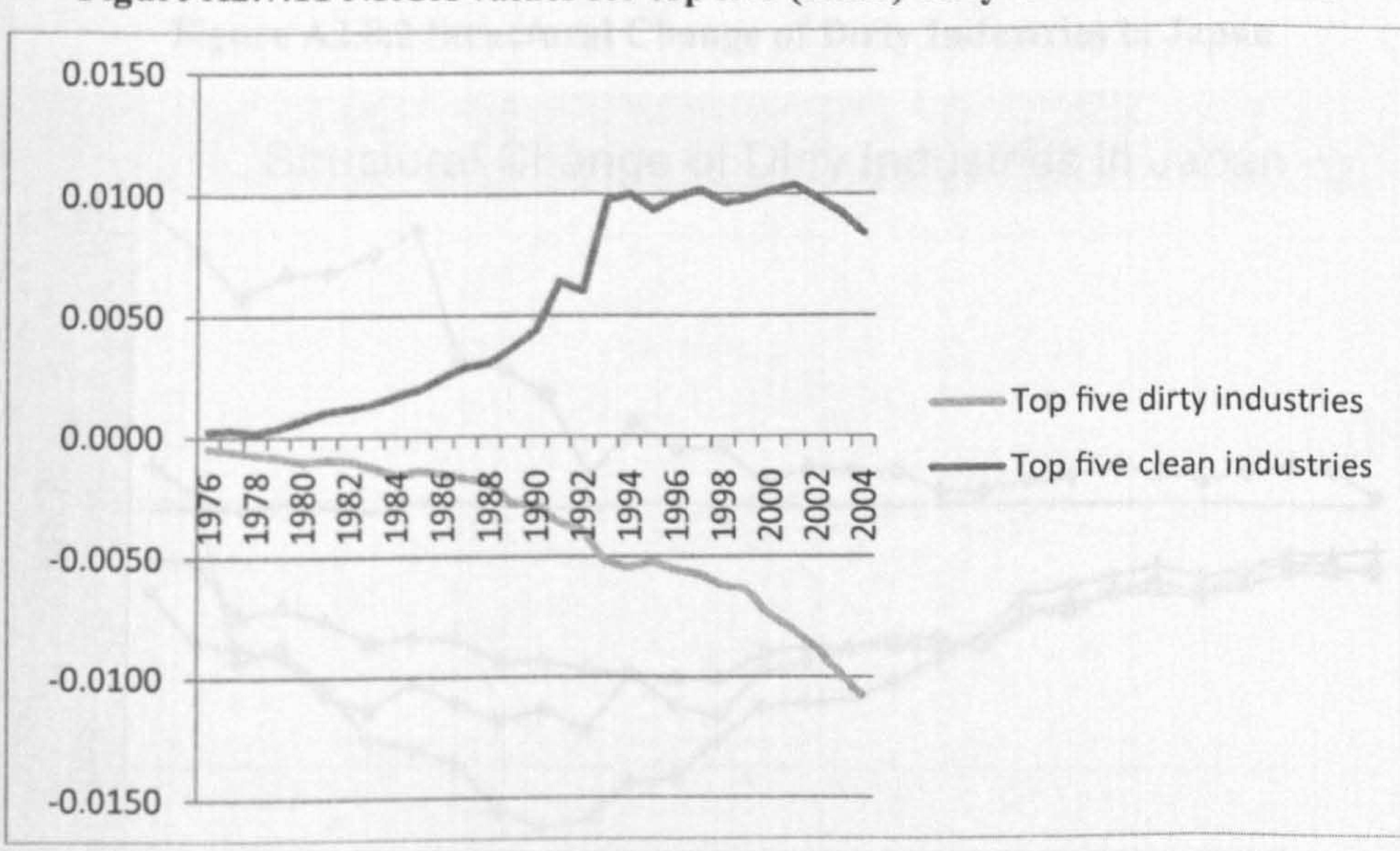



Figure A2.7.11 NRCA values for top five (clean) dirty industries in China



## A2.8 Changing Patterns of NRCA in China's Major Export Markets

**Figure A2.8.1 Structural Change of Dirty Industries in USA**

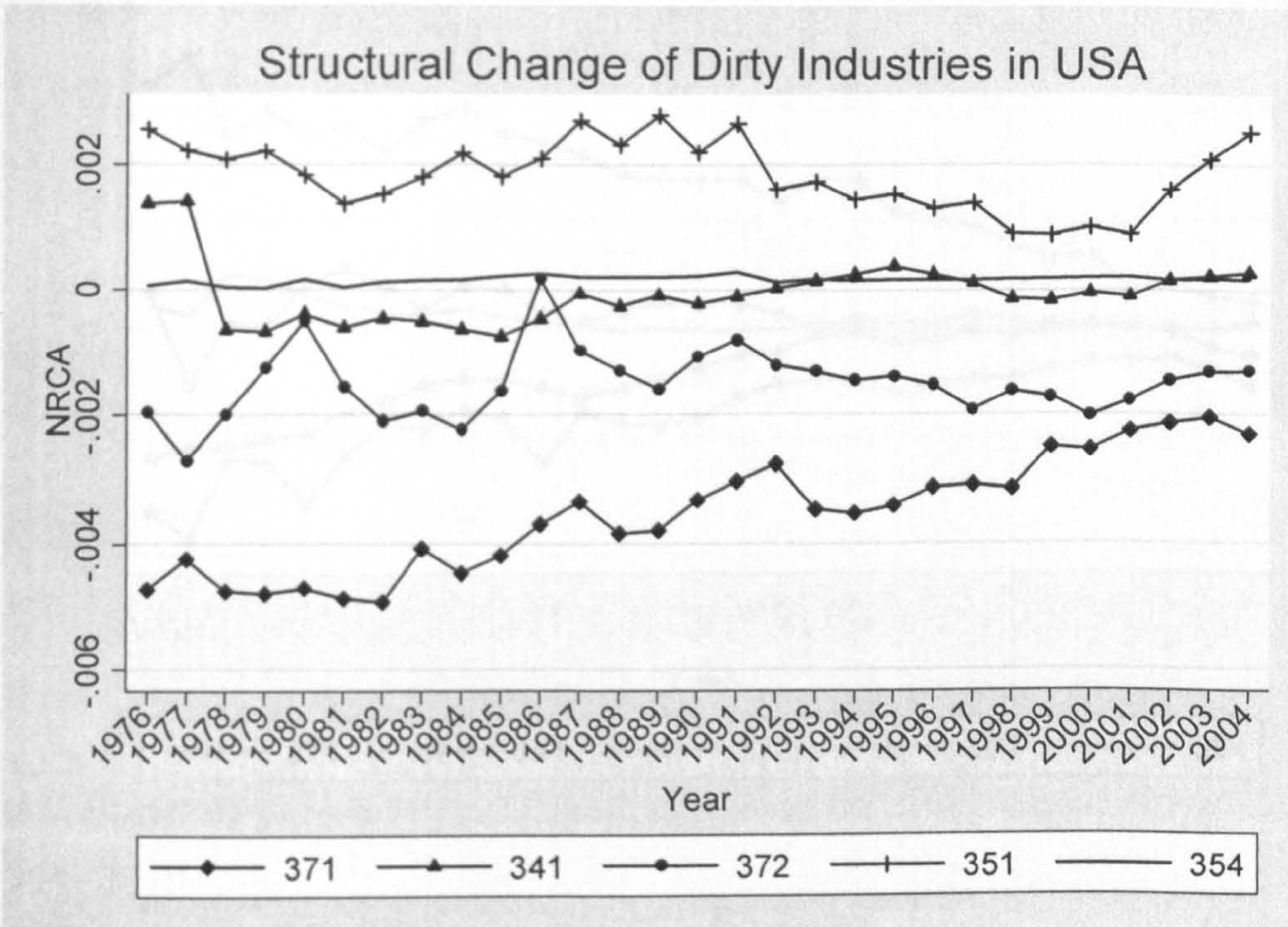



**Figure A2.8.2 Structural Change of Dirty Industries in Japan**

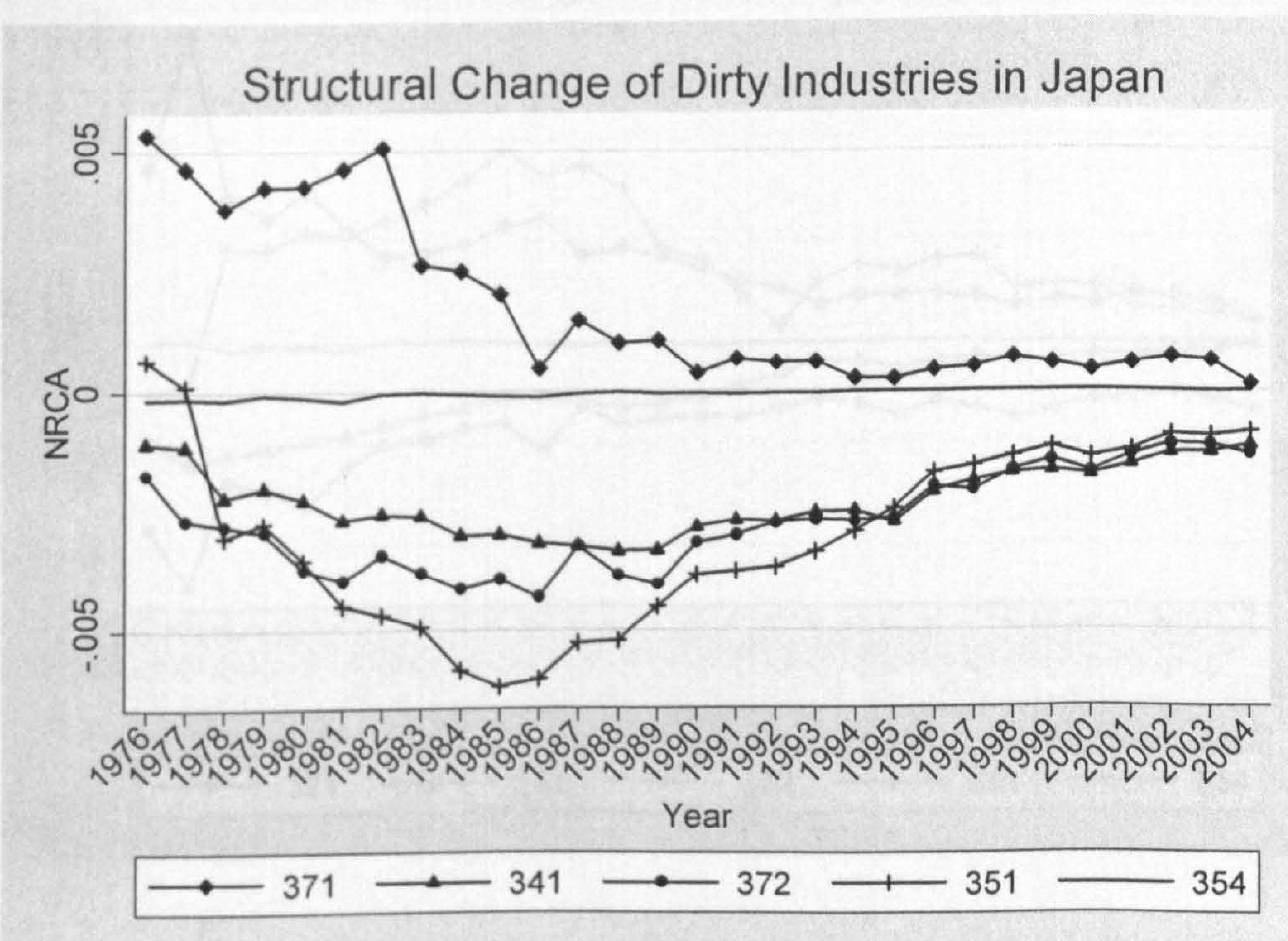


**Figure A2.8.3 Structural Change of Dirty Industries in Germany**

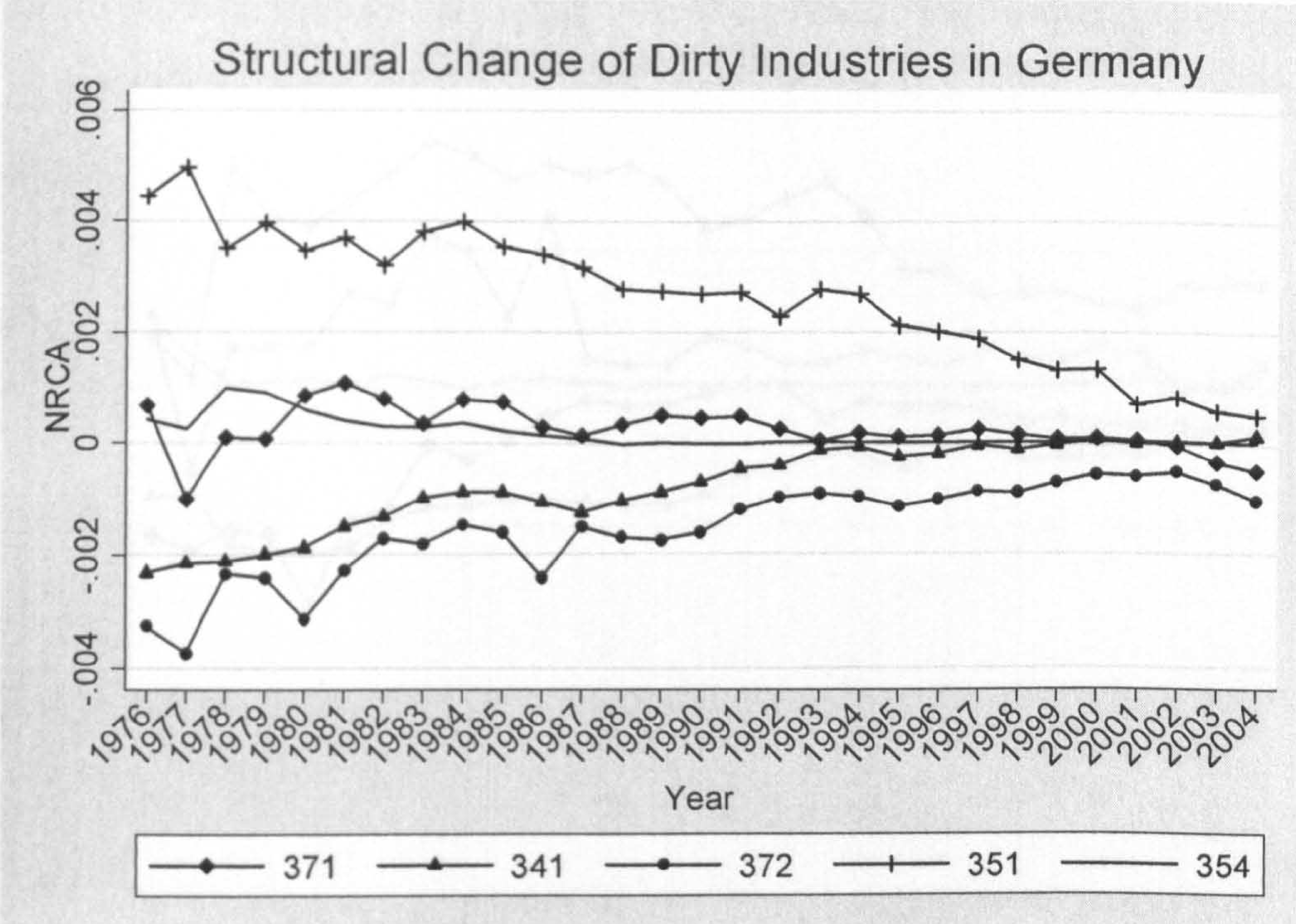



**Figure A2.8.4 Structural Change of Dirty Industries in France**

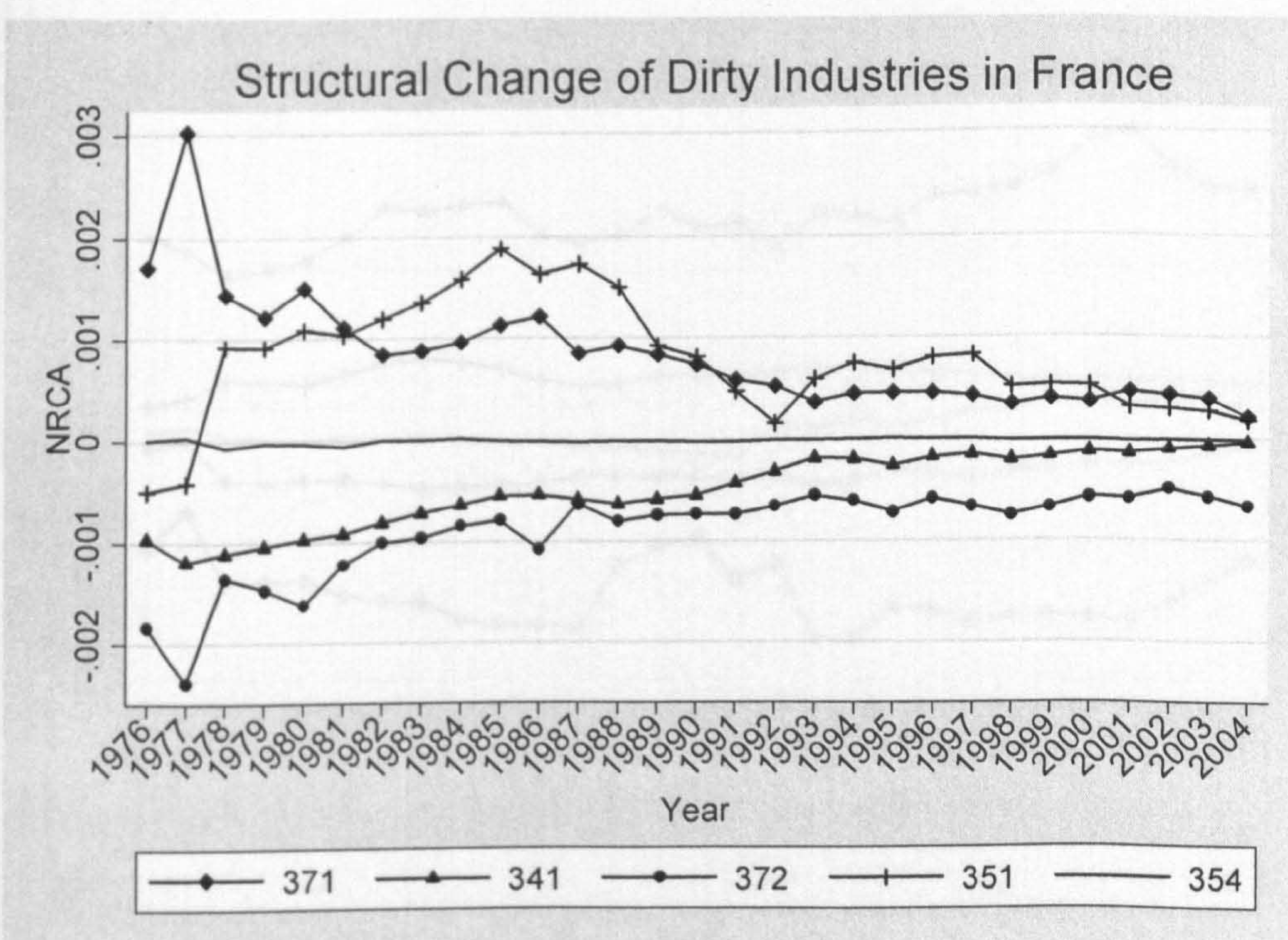


**Figure A2.8.5 Structural Change of Dirty Industries in UK**

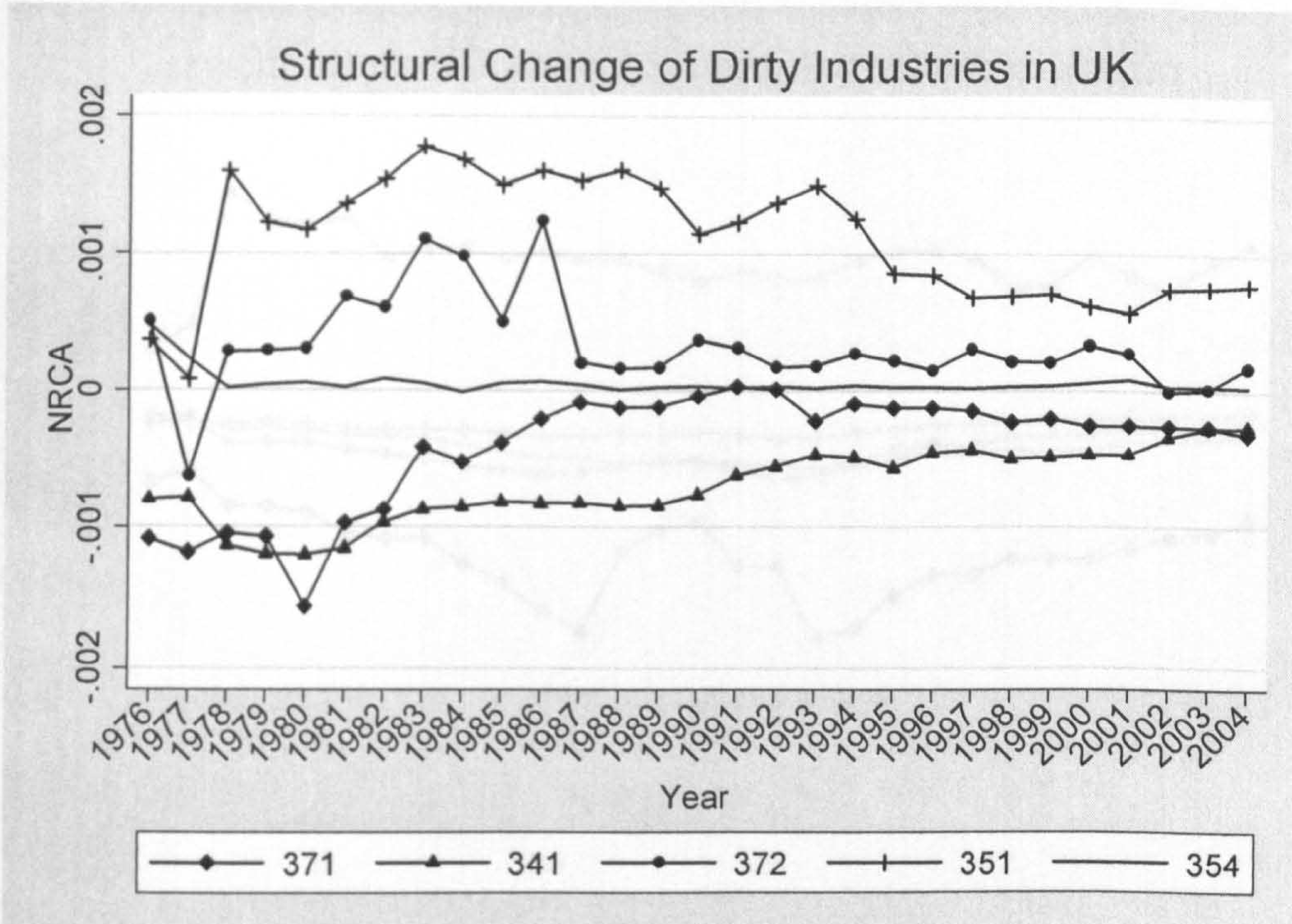



**Figure A2.8.6 Structural Change of Clean Industries in USA**

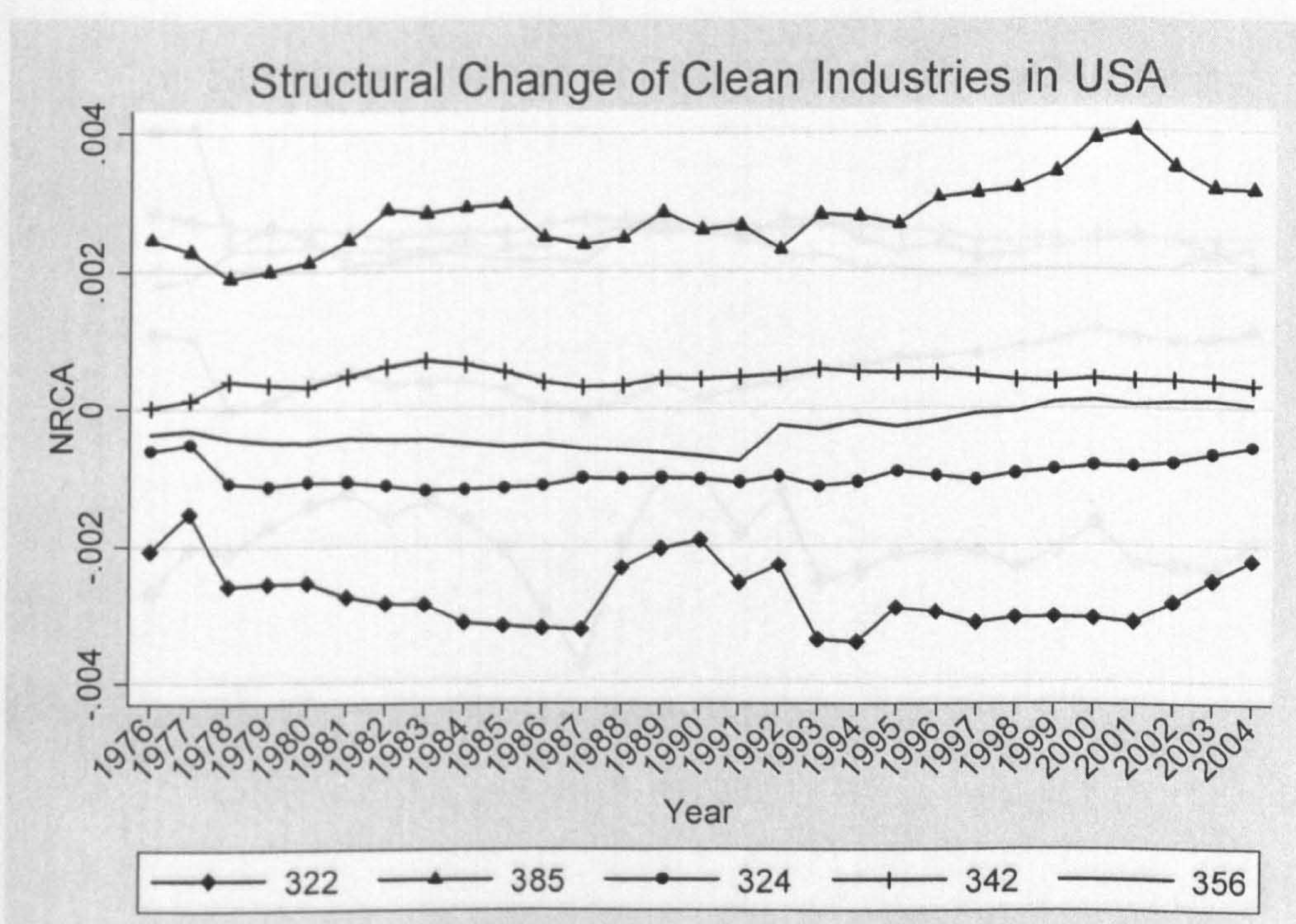


**Figure A2.8.7 Structural Change of Clean Industries in Japan**

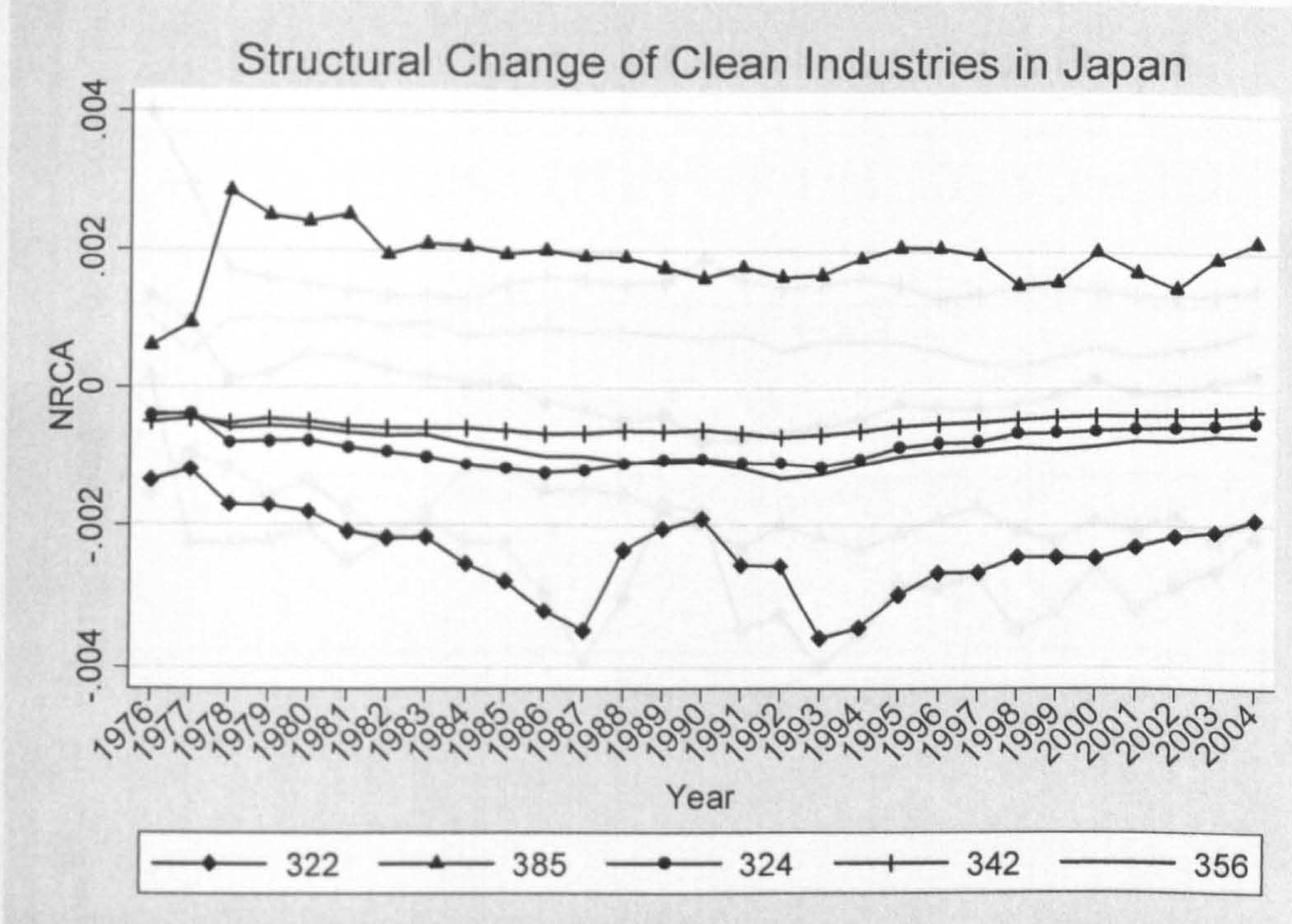



**Figure A2.8.8 Structural Change of Clean Industries in Germany**

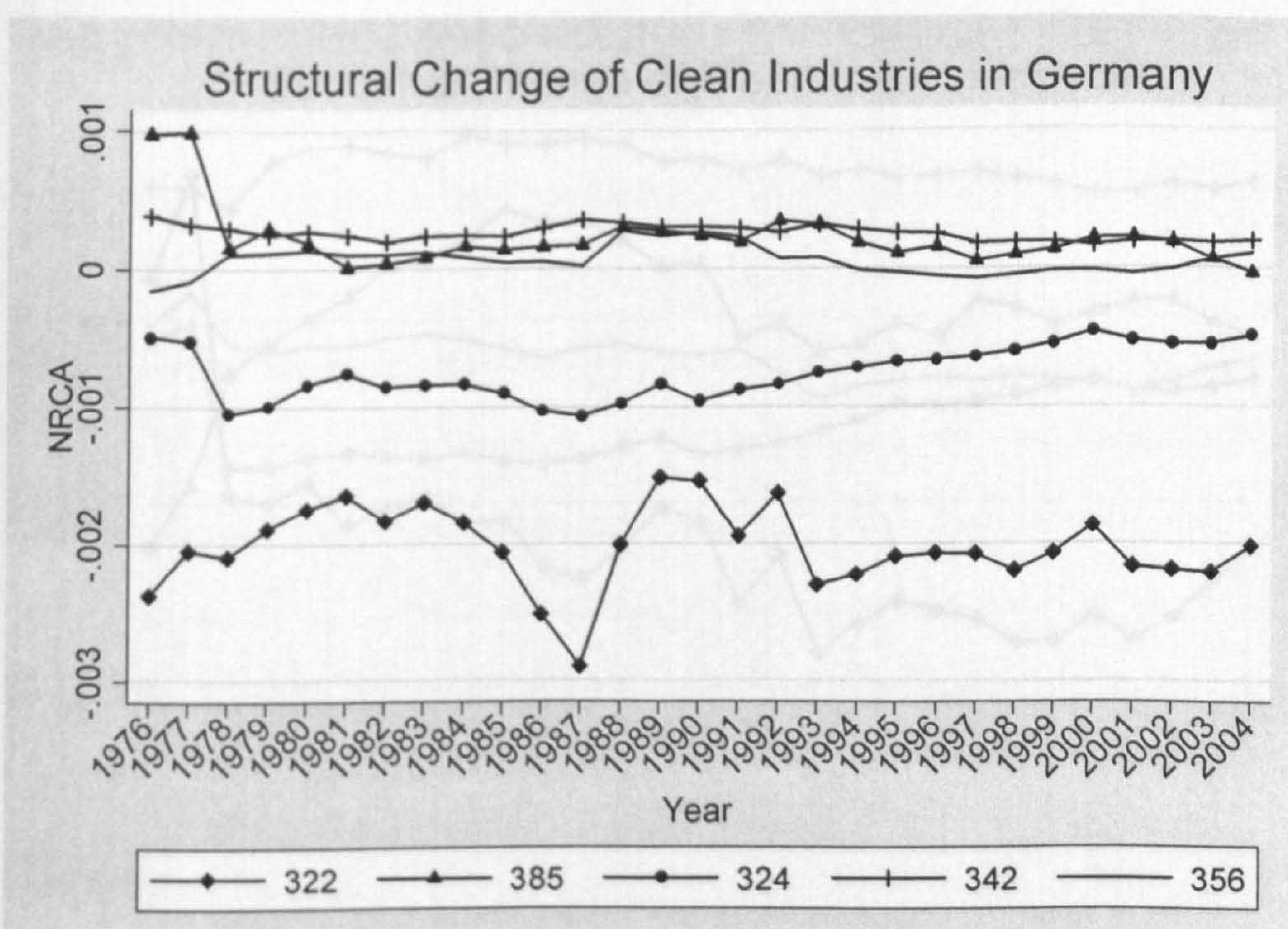


Figure A2.8.9 Structural Change of Clean Industries in France

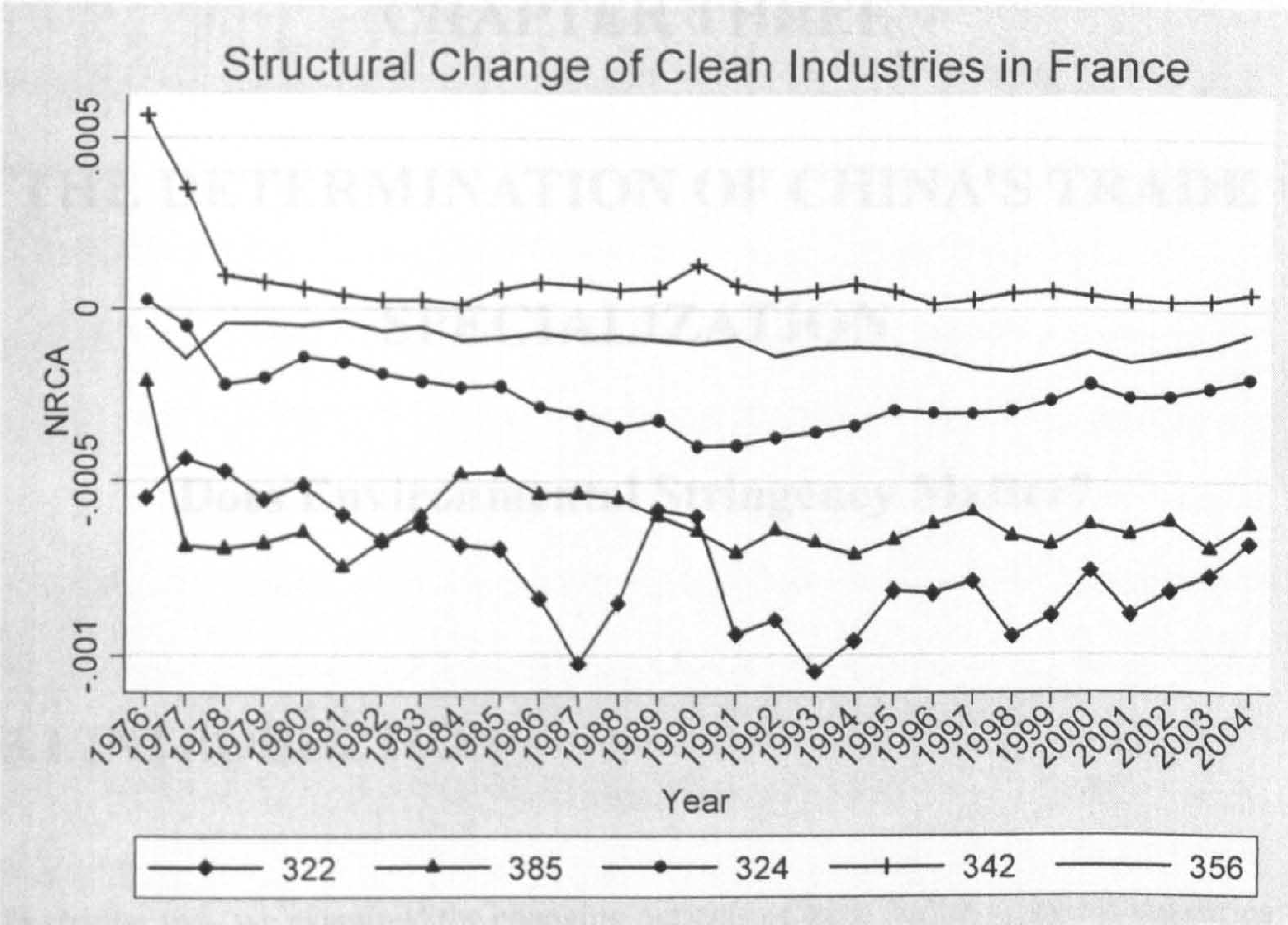
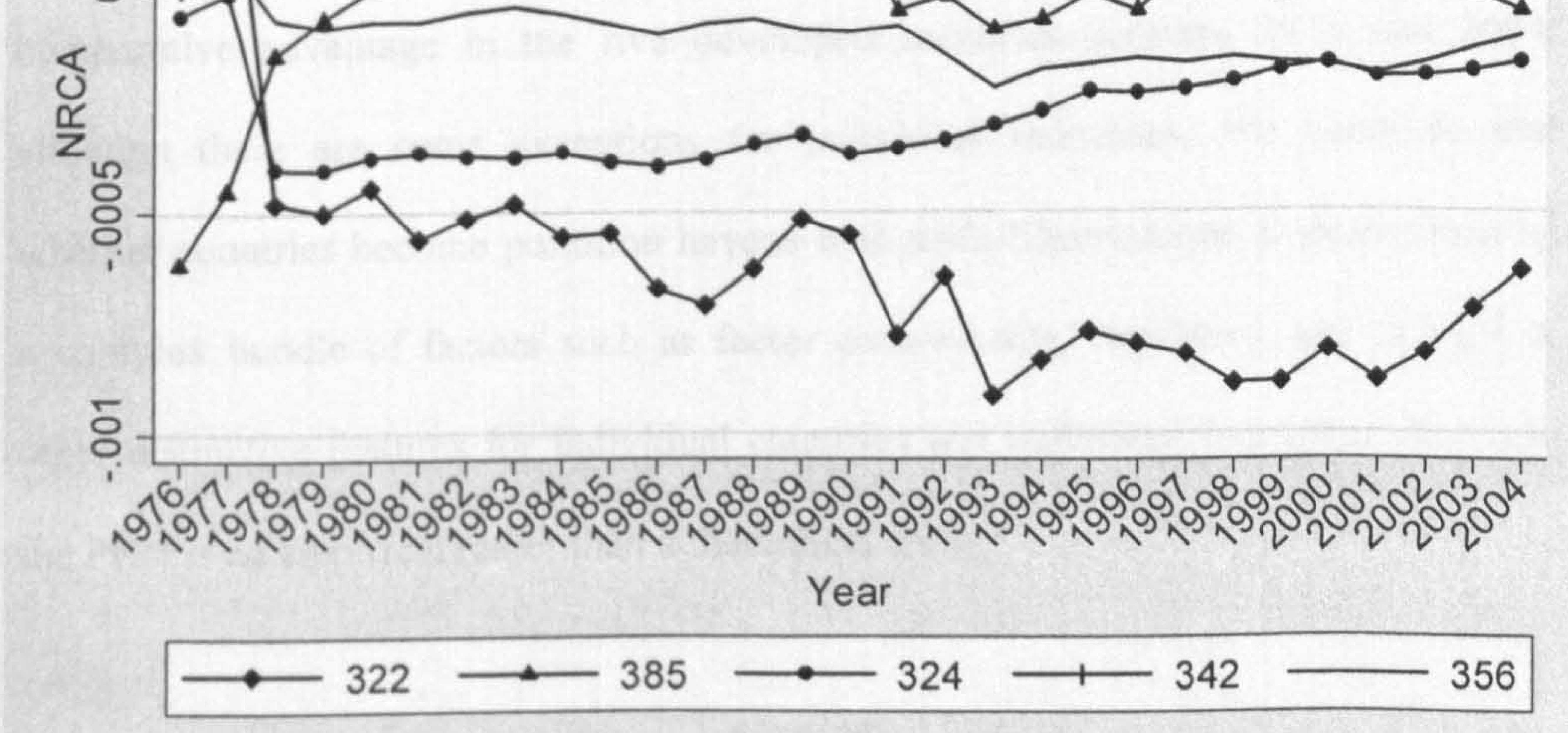



Figure A2.8.10 Structural Change of Clean Industries in UK



# CHAPTER THREE

# THE DETERMINATION OF CHINA'S TRADE SPECIALIZATION

## Does Environmental Stringency Matter?

## 3.1 INTRODUCTION

In chapter two, we examined the changing patterns of trade performance for industries with pollution intensity ranking between 1976 and 2004. We employed measures of revealed comparative advantage (RCAs) and found that China does not seem to be a 'pollution haven'. Instead, clean industries have increased their revealed comparative advantage, whilst dirty industries have increased revealed comparative disadvantage in China. The investigation of five high income countries (the US, Japan, Germany, France and the UK) shows that dirty industries have not reduced their revealed comparative advantage in the five developed countries between 1976 and 2004, although there are some exceptions for individual industries. We conclude that whether countries become pollution havens with trade liberalization is determined by a complex bundle of factors such as factor endowments, regulatory gap as well as other distinctive features for individual countries and individual industries. As such, the PHH is an empirical rather than a theoretical issue.

According to Copeland and Taylor (2003:196), there is an important distinction between the pollution haven effect and the strong form of the pollution haven hypothesis. Their model suggests that there should always be a pollution haven effect but the strong form of the pollution haven hypothesis need not hold if other factors dominate the pollution haven effect. Although support for the strong form of the pollution haven hypothesis was not found in the descriptive analysis for China, we cannot reject the existence of a pollution haven effect (which is a weak form of the pollution haven hypothesis) on this basis. To more formally identify and quantify the role of environmental stringency in trade specialization patterns, econometric analysis is required. In this chapter we examine the determinants of industrial trade patterns, especially the role of the environmental regulations in China. Due to data limitation, this chapter will focus on investigating whether environmental regulations affect cross-industry trade performance in China.

The remainder of this chapter is organized as follows. Section 2 provides some background on environmental protection in China. Section 3 presents the methodology and related empirical issues. Section 4 reports the econometric results while the conclusions and further research questions are considered in section 5.

# 3.2 ENVIRONMENTAL REGULATIONS IN CHINA

China has undergone drastic changes in environmental protection policies and enforcement in recent decades. MacBean (2007): "China now has, on paper, the most enlightened set of laws on protecting the environment of any developing nation."

## 3.2.1 Institutional settings

Contrary to the prevailing wisdom, China's first step on environmental protection started even before the Economic Reform. The 1972 UN Conference on the Human Environment in Stockholm marks China's pilot appearance in international forums of environmental protection. Soon after that, a domestic conference on air emissions control was held and its related project was formalised in the same year (Ross, 1988). In the following several years, a National Environmental Protection Office and similar settings were established at local (provincial, city etc) level. However, it took two decades for the dependent small office with little power on legislation to evolve into a full ministerial status ranking. In 1998, the National Environmental Protection Agency (NEPA) was elevated and renamed as State Environmental Protection Administration (SEPA), which is at ministerial level.

The 1978 amendment of the constitution also included protection of the environment as one of the most basic commitments made to the Chinese society (Panayotou, 1998: 434). In 1979, a trial version of the Environmental Protection Law was promulgated, which sets out requirements on environmental impact assessment, industrial location, emission and effluent standards as well as pollution discharge fees. Ten years later, the Environmental Protection Law was amended and enacted. Together with these laws, numerous environmental regulations, standards, programs and special funds for environmental protection have flourished at both national and local level.

These movements show that China was not far behind other countries in the course of enacting environmental protection laws and rules. It is reported that pollution monitoring networks in rich Western nations have only been well operated since the 1960s (Smil, 1984). However, the compliance of environmental regulation in China is questionable and we will return to this topic in section 3.2.3.

### 3.2.2 Industrial pollution regulations

The environmental protection laws contain extensive rules and guidance for the establishment, operation of industrial enterprises (see articles 24-33 in China Environmental Protection Law 1989).

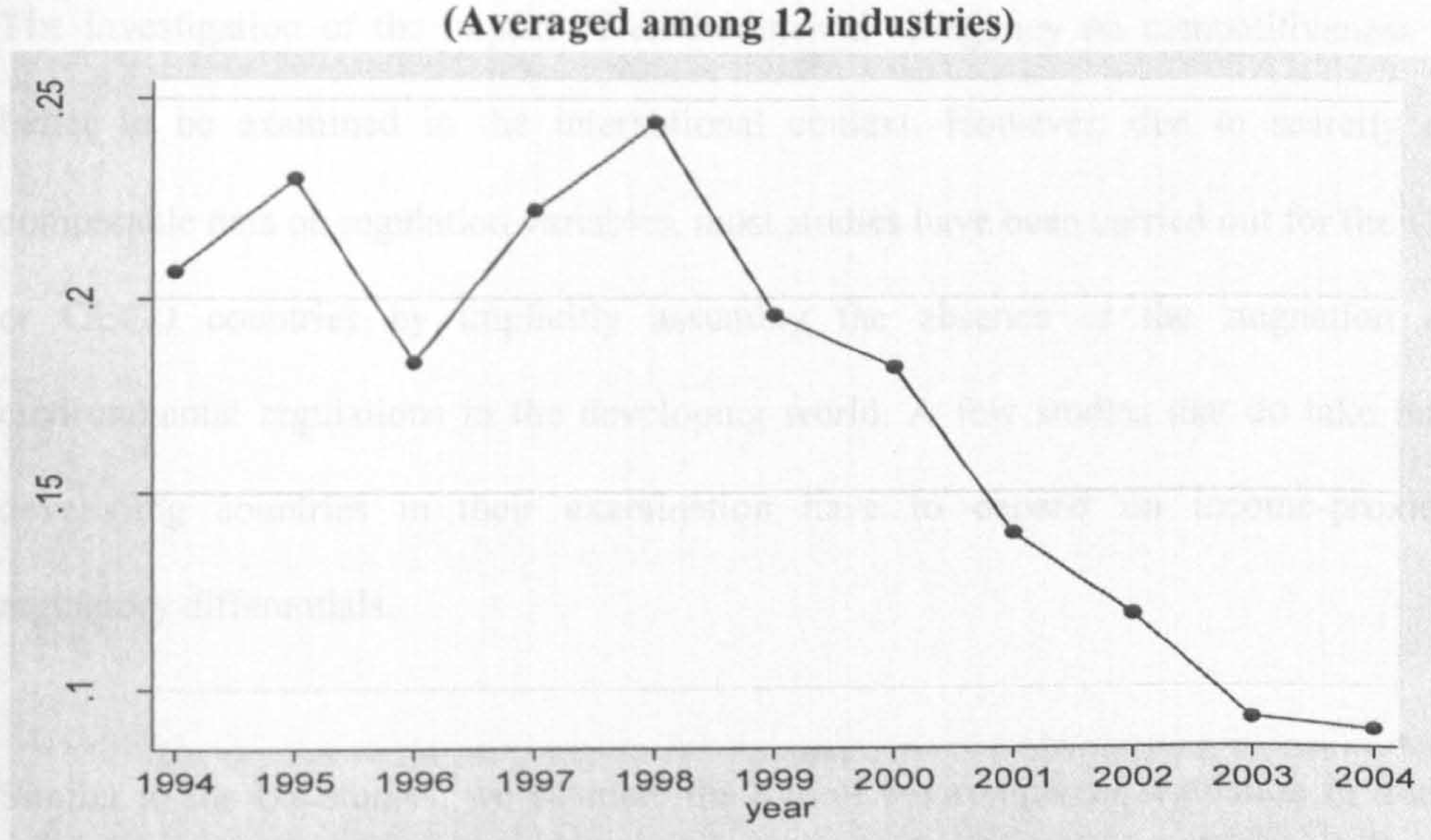
A polluter pays principle is embodied in Chinese environmental protection laws and regulations. For example, in article 28 of China's Environmental Protection Law (1989): "Enterprises and institutions discharging pollutants in excess of the prescribed national or local discharge standards shall pay a fee for excessive discharge according to state provisions and shall assume responsibility for eliminating and controlling the pollution." The provisions of Law on Prevention and Control of Water Pollution also have detailed rules for water pollution emissions and abatement. It is mandated that the income derived from the fee levied for the excessive discharge of pollutants must be used for the prevention and control of pollution and shall not be appropriated for other purposes. Charges are levied for water pollution, air pollution, solid and radioactive waste. Though criticized for some weaknesses, the levy system has been accredited by its broadest application of price-based pollution control instruments in the developing world. Wang and Wheeler (1996) comment "China's pollution levy is one of the few economic instruments with a long, documented history of application in a developing country".

### 3.2.3 Environmental compliance

It is generally admitted that China has made dramatic strides in developing a sophisticated network of environmental protection. However, more than a few researchers (Smil, 1984; Economy, 2004) blame the poor implementation of environmental laws for the ever worsening situation of China's environment. Economic development strategies, as well as interest collision between different bureaus and government agencies, often prohibit the full compliance of environmental laws, rules and norms. According to Wang and Wheeler (2000), however, plants in China were responding strongly to the levy either by abating air pollution in the production process or treating water pollution at the end-of-pipe.

It is reported that emissions of some industrial pollutants in China have been decreasing in total volumes as well as in intensity terms. Taking the example of $SO_2$, we find that the pollution intensity (in value added) is decreasing (graph 3.1), while the ratio of removed $SO_2$ to emitted $SO_2$ has an upward trend (graph 3.2) for 12 industries[35] between 1994 and 2004.

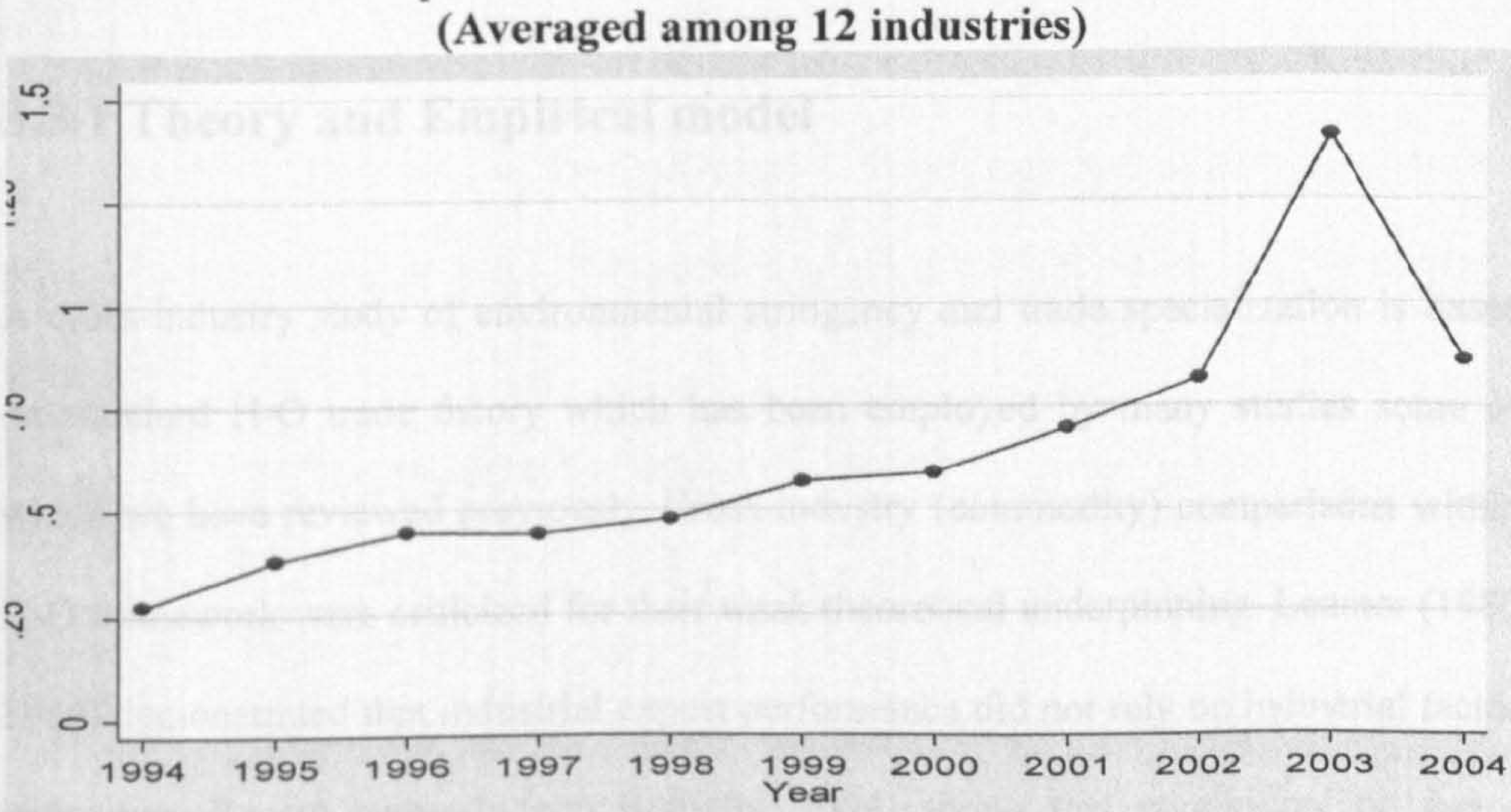
**Graph 3.1 $SO_2$ Emissions Intensity in China (Averaged among 12 industries)**




Data source: China Environment Yearbooks, various years; same for graph 3.2.

Note: in ton per 10000 RMB value added (value added deflated to 1978 price level).

**Graph 3.2 Removal Ratio of $SO_2$ in China (Averaged among 12 industries)**




[35] A list of these industries can be found in table A3.1.1 in appendix 3.1.

The data point (graph 3.2) for 2003 is much higher due to the industry 342 (Printing and Publishing) has an unusually high volume of removed $SO_2$ in that year.

## 3.3 METHODOLOGY AND DATA

The investigation of the impact of environmental stringency on competitiveness is better to be examined in the international context. However, due to scarcity of comparable data on regulation variables, most studies have been carried out for the US or OECD countries by implicitly assuming the absence or the stagnation of environmental regulations in the developing world. A few studies that do take into developing countries in their examination have to depend on income-proxied regulatory differentials.

Similar to the US studies, we estimate the role of environmental regulation in trade specialization together with factor endowments (factor intensities) and trade barriers in Chinese industries. Due the shortage of comparable data, we do cross-industry regressions based on an H-O-S framework rather than cross-country investigation.

### 3.3.1 Theory and Empirical model

A cross-industry study of environmental stringency and trade specialization is based on standard H-O trade theory which has been employed by many studies some of which we have reviewed previously. Cross-industry (commodity) comparisons within H-O framework were criticized for their weak theoretical underpinning. Leamer (1980, 1984) demonstrated that industrial export performance did not rely on industrial factor intensities. Recent research (e.g. Romalis, 2004) shows that conditional on factor prices (allowing for non-factor price equalization), industry export performance in a quasi-H-O model is determined by industry factor intensities and relative factor prices.

Due to data constraints, however, we still adopt the traditional specification of cross-industry comparisons. The general form of the empirical model takes the form of:

$$NX = f(X, ENV, \varepsilon) \qquad (3.1)$$

where NX is a vector of net exports of commodities, X is a matrix of control variables including factor intensities and tariffs, ENV is a measure of environmental compliance costs, and $\varepsilon$ is a vector of the composite error term which consists of time-specific effect and individual effect as well as an idiosyncratic error.

#### 3.3.1.1 Measuring trade specialization

Specialization is a measure of the trade pattern. Numerous measures of trade specialization have been discussed and used in testing trade theories (see the discussion in Deardorff, 1984). In the literature of environmental regulation and industrial competitiveness, net exports scaled by value added (or import penetration by similar construction) is broadly used. Cole et al. (2005) employ different measures of specialization and obtain consistent results of a negative impact on specialization of environmental stringency. In this chapter, we also explore the relationship between environmental regulations and trade specialization by exploiting different measures of specialization.

**A. Trade specialization index (TSI)**

$$TSI = \frac{X-M}{X+M} \qquad (3.2)$$

This index is constructed as the percentage share of net trade (X-M) in total trade volume (X+M). Its value ranges from -1 when there are no exports at all to +1 when there are no imports. The larger TSI value, the more export specialized is the sector.

This index tells the relative importance of net exports in total trade of a particular industry; but it overlooks differences in trade volume both between industries and across time. For example, an industry with little trade volume may have the same TSI level as an industry with massive trade volume. Similarly, when an industry grows in terms of trade volume, its TSI level may remain consistent. The absolute value of this index also represents the portion of inter-industry trade in the total trade of the concerned industry. Cole et al. (2005) also use this index as one of the dependent variables which is then estimated as a function of inter-industry differences in factor intensities.

**B. Michaely index**

$$Michaely = \frac{X}{\sum X} - \frac{M}{\sum M} \tag{3.3}$$

Originated from Michaely (1962), this index is constructed as the percentage share of industry exports in total exports minus the percentage share of industry imports in total imports. A positive value suggests that the industry is more involved in the exporting activities than importing, i.e. more export specialization; the opposite means less export specialization. Its range is [-1, 1].

**C. Net exports share in value added**

$$Netva = \frac{X-M}{VA} \tag{3.4}$$

This index evaluates the share of net exports in industry value added. Increasing value of the index implies the sector is increasing its specialization and vice versa. It takes care of the importance of net exports in an industry's value added. This index, as well as its transformation net imports (import penetration), has been widely employed in the literature, for example, Grossman and Kruger (1992), Cole et al. (2005) and Levinson and Taylor (2004).

### 3.3.1.2 Measuring environmental stringency

A reliable measure of environmental stringency is required for the econometric testing of the hypothesis that environmental stringency exerts a negative effect on trade performance, especially for the pollution-intensive industries. One measure of environmental stringency is qualitative. For example, based on the 1976 UNCTAD survey Walter and Ugelow (1979) measure the degree of environmental stringency from one (tolerant) to seven (strict) for a number of counties. This qualitative variable has been adopted in Tobey (1990), as we mentioned in the section of empirical evidence. Wilson et al. (2002) adopt two qualitative variables for environmental regulation, the scope of environmental regulation and the control mechanism for environmental enforcement, are constructed based on the performance indices of countries in terms of environmental regulation.

Other measures are developed for the US states, such as the Conservation Foundation index that measures each state's 'effort to provide a quality environment for citizens'; the FREE (Fund for Renewable Energy and the Environment) index which measures the strength of environmental program in each state; and the Green index which measures the number of statutes that each state has from a list of 50 common environmental laws. Levinson (1996) includes these measures in his study of environmental regulation and manufacturers' location choices. Although these qualitative measures of environmental stringency take into account of multi-dimensional property and are comparable across regions, they usually do not have a time dimension to match panel data estimation.

A cost-based measure, such as pollution abatement cost and expenditures, has been adopted in previous studies as a measure of environmental stringency. Although cost-based stringency measures normally are confined in terms of measuring different dimensions of environmental regulations[36], they are widely used due to their availability over time.

At the Chinese industrial level, data for pollution abatement and environmental protection staff are available since the 1990s. We construct two measures of environmental stringency, one based on pollution abatement operating cost and another on the number of environmental protection personnel.

### *A. ENV1=pollution abatement operating cost/ value added*

Annual pollution abatement operating cost refers to annual expenditures on operation pollution treatment facilities. Available data show the annual pollution abatement operating cost at industrial level in China. The effect of environmental regulation on competitiveness depends on abatement technologies. As new facilities (with new technologies embodied) are implemented, pollution abatement operating costs as share of value added may actually go down. This decrease in ENV1 has little to do with relaxing environmental stringency (or deregulating). Lacking research and development data (R&D) at 3-digit ISIC industrial level, we count on time dummies and industry dummies to control for these unobserved influences.

### *B. ENV2=environmental personnel*wage/value added*

Another measure of environmental stringency is related to the number of environment protection personnel in an industry. The increase in the number of environmental protection personnel shows increasing effort in regulatory enforcement. We assume that environmental personnel earn the same wage as the industrial average wage. The payment to environmental protection personnel is then scaled by industrial value added. Similar to ENV1, the increase in ENV2 may not reflect the extent of increased

[36] Jaffe et al. (1995) also point out that a substantial share of compliance costs for some federal regulations fall on state and local governments rather than private firms.

environmental stringency. Time dummies and industry dummies are adopted to control for the omitted variables.

### 3.3.1.3 Measuring other control variables

Human capital intensity (HCI) is defined as the payroll paid to skilled workers divided by value added. Since the distinction between skilled and unskilled workers is not well recorded at the industrial level in China Statistics Yearbooks, we follow the definition of HCI in Grossman and Kruger (1991, 1994) as well as in other similar studies (Cole et al., 2005).

$$HCI_{it} = \frac{(W_{it} - \tilde{W}_t) * L_{it}}{VA_{it}} \qquad (3.5)$$

where $W_{it}$ represents the average wage in each industry i at year t, $\tilde{W}_t$ represents the average wage in the lowest paying industry at year t. VA represents value added and L for the number of employees.

Physical capital intensity (PCI) is constructed as the non-wage share of value added, as adopted in Balassa and Noland (1989), Grossman and Krueger (1993) and Cole et al. (2005).

$$PCI_{it} = 1 - \frac{W_{it} * L_{it}}{VA_{it}} \qquad (3.6)$$

A more direct measure of physical capital intensity is to use the ratio of fixed assets to value added. We refer to it as man-made physical capital and denote it as MK.

$$MK_{it} = \frac{FixedAssets_{it}}{VA_{it}} \qquad (3.7)$$

Tariffs refer to import tariffs. We use weighted average tariffs as import barriers. Non-tariff barrier data are not available.

### 3.3.1.4 Empirical models

In this chapter, the variables used are all in levels since the dependent variable contains negative values. Following the previous studies based on H-O framework, a benchmark model is set out:

$$SPEC_{it} = \beta_1 ENV_{it} + \beta_2 HCI_{it} + \beta_3 PCI_{it} + \beta_4 tariff_{it} + \varepsilon_{it} \qquad (3.8)$$

where,

i : industry code.

t: the year.

SPEC: trade specialization index (TSI, Michaely, Netva).

$\varepsilon=\eta+\gamma+v$: the composite error term, $\eta_i$ industry specific effect, $\gamma_t$ time specific effect and $v_{it}$ the idiosyncratic error term.

ENV: environmental stringency.

HCI: human capital intensity.

PCI: physical capital intensity.

tariff: weighted import tariffs as proxy for trade barriers.

This specification examines the relationship between trade patterns and a set of independent variables including an environmental pricing factor together with traditional factor endowments. With environmental stringency and factor intensities varying across industries and over the years, it is possible to estimate the effects of the independent variables on the dependent variable.

To explore the heterogeneous effect of environmental regulation on pollution-intensive industries, we use an interaction term of environmental stringency and pollution intensity ('dirtiness' variable) which is defined as the ratio of emissions to value added in constant prices (due to data limitation, we only use two pollutants, $SO_2$ and COD).

$$SPEC_{it} = \beta_1 ENV_{it} + \beta_2 HCI_{it} + \beta_3 PCI_{it} + \beta_4 tariff_{it} + \beta_5 ENV_{it} * dirtiness_{it} + \varepsilon_{it} \tag{3.9}$$

Other things equal, an increase in environmental regulations in industry i means higher pollution taxes or greater pollution abatement efforts which will lead to an increase in production costs (or a comparative price disadvantage). As a result, domestic production and exports may contract and imports may expand. It is hence hypothesized that the environmental stringency has negative impact on trade performance, i.e. $\beta_1$ (the coefficient of environmental stringency) is expected to be negative.

The sign of each coefficient for factor inputs in the inter-industry regression indicates whether the corresponding factor is a source of comparative cost advantage in the country being examined. Since the relative abundance of factors determines comparative costs in the H-O-S model, a positive (negative) sign is taken to indicate that the corresponding factor is abundance (scarce) within the country. In some empirical studies that based on US industries (for example, Cole et al. (2005)), a positive effect is found for the human capital intensity and physical capital intensity on industrial competitiveness. Conventional wisdom believes that human capital intensity and physical capital intensity are relatively scarce in China and hence are not sources of comparative cost advantage for China, which points to the prediction of negative-signed $\beta_2$ (coefficient of human capital intensity) and $\beta_3$ (coefficient of physical capital intensity). However, our cost-based measures of capital intensities may not reflect correctly the factor intensities as measured internationally. An increase in these variables may correlate to increasing productivity and profitability, which adds to the difficulty of sign prediction. As a sensitivity check, we use MK as an alternative measure of physical capital intensity.

The impact of import barriers on trade specialization is predicted to be positive since import tariffs are set up to protect domestic industries and control imports. On the other hand, tariff scale is influenced by the trade liberalization process. The interaction term between environmental stringency and dirtiness is predicted to be negative as we expect to see a more significant effect of environmental stringency on dirtier industries' trade performance.

### 3.3.2 Data Description

The datasets from TPPS by Nicita and Olarreaga (2006), UNIDO and CSID as well as China Statistical Yearbooks and China Environment Yearbooks enable our study on the determinants of China's trade pattern. The industry classification system for the database TPPS is the 3-digit level ISIC revision 2 which covers 28 manufacturing sectors. To make the data compatible across different sources, we have merged the manufacturing industries in 23 categories (see the description of the concordance in appendix 3.1). Detailed data sources and variable definitions can be found in table A3.2.1 in appendix 3.2.

Most observations in our dataset are for the period of 1994-2004, because less information on pollution abatement operating cost and environmental protection at industrial level are available for previous years. According to the availability of environmental stringency measures, we split our datasets into two sub-samples: sample one, 2001-2004 for 22 industries (390 "Other Manufactured Goods" are excluded because of its complex composition of goods) and sample two 1994-2004 for 12 industries.

From the correlation tables 3.1 and 3.2 (for the two sub samples), we can see there are high positive correlations between the three specialization indices. However, the relative ranking of each industry is considerably different in the three trade variables (see appendix 3.3). The two measures of environmental stringency are also highly and positively correlated. The simple correlations between trade specialization indices and environmental stringency indicators show a negative link between trade specialization and environmental stringency. Physical capital intensity and human capital intensity are negatively related to all three trade specialization indices. Tariff is positively correlated with TSI and Netva, while it is negatively correlated to the Michaely index in sample two. The interaction terms of environmental stringency and pollution intensity seem to be negatively correlated with trade specialization indices. The interaction terms are positively correlated to the related measure of environmental stringency which may cause a multicollinearity problem. In the regressions we will experiment with and without the interaction terms. Descriptive statistics for the two samples can be found in the Appendix 3.1.

**Table 3.1 Correlations of variables for sample one (2001-2004, 22 industries)**

| Obs=108 | TSI | Netva | Michaely | ENV1 | ENV2 | PCI | HCI | Tariff | ENV1*dirtiness | ENV2*dirtiness |
|---|---|---|---|---|---|---|---|---|---|---|
| TSI | 1 | | | | | | | | | |
| Netva | 0.9326 | 1 | | | | | | | | |
| Michaely | 0.7513 | 0.7758 | 1 | | | | | | | |
| ENV1 | -0.5904 | -0.644 | -0.3808 | 1 | | | | | | |
| ENV2 | -0.3518 | -0.4466 | -0.2158 | 0.7482 | 1 | | | | | |
| PCI | -0.2562 | -0.1271 | -0.1575 | 0.1679 | -0.0262 | 1 | | | | |
| HCI | -0.2729 | -0.2518 | -0.2904 | -0.0076 | -0.1762 | -0.3047 | 1 | | | |
| Tariff | 0.2696 | 0.0633 | -0.0128 | 0.1025 | 0.3097 | -0.2582 | -0.1281 | 1 | | |
| ENV1*dirtiness | -0.481 | -0.5039 | -0.2031 | 0.5846 | 0.5746 | 0.0329 | -0.1943 | -0.0603 | 1 | |
| ENV2*dirtiness | -0.4247 | -0.4544 | -0.1752 | 0.4773 | 0.5825 | -0.0202 | -0.2029 | -0.0068 | 0.9439 | 1 |

**Table 3.2 Correlations of variables for sample two (1994-2004, 12 industries)**

| Obs=88 | TSI | Netva | Michaely | ENV1 | ENV2 | PCI | HCI | Tariff | ENV1*dirtiness | ENV2*dirtiness |
|---|---|---|---|---|---|---|---|---|---|---|
| TSI | 1 | | | | | | | | | |
| Netva | 0.7737 | 1 | | | | | | | | |
| Michaely | 0.7476 | 0.7575 | 1 | | | | | | | |
| ENV1 | -0.4886 | -0.3367 | -0.2376 | 1 | | | | | | |
| ENV2 | -0.3692 | -0.2975 | -0.1698 | 0.8654 | 1 | | | | | |
| PCI | -0.3869 | -0.214 | -0.2363 | -0.1349 | -0.196 | 1 | | | | |
| HCI | -0.164 | -0.3714 | -0.3733 | 0.0739 | -0.0028 | -0.3147 | 1 | | | |
| Tariff | 0.4605 | 0.2498 | 0.3138 | 0.0769 | 0.0948 | -0.3076 | 0.1687 | 1 | | |
| ENV1*dirtiness | -0.4104 | -0.2351 | -0.1358 | 0.7089 | 0.7469 | -0.193 | 0.0388 | -0.0474 | 1 | |
| ENV2*dirtiness | -0.3844 | -0.2244 | -0.1259 | 0.6785 | 0.7555 | -0.2167 | 0.0337 | -0.0318 | 0.994 | 1 |

**Table 3.3 Average values of Energy intensity, PCI, HCI, tariff and environmental stringency between 2001 and 2004 for 23 industries**

| id | Energy[a] | PCI | HCI | Tariff (%) | ENV1 | ENV2 |
|---|---|---|---|---|---|---|
| 371 Iron and Steel | 3.13 | 0.83 | 0.10 | 6.51 | 0.0239 | 0.0005 |
| 369 Non-metallic Mineral Products | 2.69 | 0.79 | 0.03 | 38.38 | 0.0378 | 0.0020 |
| 353 Petroleum | 2.64 | 0.91 | 0.05 | 15.53 | 0.0200 | 0.0008 |
| 372 Non-ferrous Metals | 2.05 | 0.82 | 0.08 | 4.35 | 0.0246 | 0.0008 |
| 351 Chemicals | 1.87 | 0.84 | 0.06 | 21.08 | 0.0177 | 0.0009 |
| 341 Paper and Products | 1.29 | 0.84 | 0.03 | 5.65 | 0.0422 | 0.0020 |
| 390[b] Other Manufactured Products | 1.25 | 0.70 | 0.08 | 9.85 | 0.0013 | 0.0009 |
| 355 Rubber Products | 0.75 | 0.81 | 0.05 | 11.52 | 0.0028 | 0.0003 |
| 321 Textiles | 0.65 | 0.79 | 0.01 | 15.55 | 0.0215 | 0.0007 |
| 381 Fabricated Metal Products | 0.58 | 0.81 | 0.06 | 9.41 | 0.0071 | 0.0010 |
| 331 Wood Products, except Furniture | 0.55 | 0.83 | 0.00 | 4.46 | 0.0024 | 0.0003 |
| 311 Food Products | 0.49 | 0.87 | 0.02 | 23.84 | 0.0091 | 0.0005 |
| 356 Plastic Products | 0.39 | 0.81 | 0.05 | 12.54 | 0.0013 | 0.0002 |
| 382 Machinery, except Electrical | 0.35 | 0.77 | 0.08 | 7.70 | 0.0019 | 0.0003 |
| 313 Beverages | 0.32 | 0.89 | 0.02 | 35.27 | 0.0116 | 0.0006 |
| 342 Printing and Publishing | 0.30 | 0.78 | 0.08 | 6.59 | 0.0009 | 0.0002 |
| 384 Transport Equipment | 0.23 | 0.82 | 0.09 | 17.69 | 0.0019 | 0.0002 |
| 332 Furniture, except Metal | 0.21 | 0.80 | 0.03 | 13.54 | 0.0015 | 0.0001 |
| 385 Professional and Scientific Equipment | 0.17 | 0.78 | 0.09 | 9.17 | 0.0045 | 0.0003 |
| 322 Wearing apparel, except Rubber or Plastic | 0.16 | 0.71 | 0.06 | 37.81 | 0.0011 | 0.0001 |
| 323 Leather Products | 0.15 | 0.74 | 0.04 | 9.69 | 0.0040 | 0.0004 |
| 383 Machinery, except Electrical | 0.12 | 0.86 | 0.06 | 6.10 | 0.0014 | 0.0001 |
| 314 Tobacco | 0.06 | 0.96 | 0.03 | 40.03 | 0.0007 | 0.0001 |

Note: the industries are ranked from largest to smallest in energy intensity.

a. Energy intensity, constructed as the ratio of energy consumption to value added, is in ton SCE per thousand 1978 constant RMB value added.

b. Industry 390 is not included in regressions as this industry is consisted of "other manufacturing goods" which have marked differences in 'dirtiness' and environmental stringency.

Table 3.3 shows the average values of energy intensity, physical capital intensity, human capital intensity, weighted tariff as well as the two environmental stringency variables, ranked from highest to lowest in energy intensity. The industries with highest energy intensity include the four dirtiest industries we identified in chapter two: 371 (Iron and Steel), 372 (Non-ferrous Metals), 351 (Chemicals) and 341 (Paper and Products). It seems that pollution intensive industries are also highly energy intensive. Pollution intensive industries seem also to be physical capital and human capital intensive. Weighted tariffs are variable across industries with 314 (Tobacco), 369 (Non-metallic Mineral Products), 322 (Wearing Apparels) and 313 (Beverages) having the highest average tariff levels. The measures of environmental stringency are positively correlated with energy intensity. To sum up, the more energy intensive an industry is, the dirtier and the higher pollution abatement operating cost ratio it is. It is less clear about the link between the $SO_2$ removal ratio and other statistics.

We also present environmental stringency measures for each of the 12 industries in sample one between 1994 and 2004 in table 3.4. Pollution abatement operating cost to value added (ENV1) seems to support the view of 'small environmental costs'. On average, it is less than 2 percent of value added. Since industrial value added in China is only about 25% of gross output, operating abatement operating costs account for less than 0.5% of gross output on average.

In addition, the value of ENV2 is smaller than that of ENV1.

**Table 3.4 Environmental stringency by industry between 1994 and 2004 ($*10^{-2}$)**

| Industry | Stringency | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 321 Textiles | ENV1 | | | 1.07 | 0.87 | 1.04 | 0.81 | 0.93 | 1.71 | 4.88 | 0.95 | 1.05 |
| | ENV2 | 0.05 | 0.08 | 0.27 | 0.06 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.06 | 0.06 |
| 323 Leather Products | ENV1 | | | 0.16 | 0.32 | 0.40 | 0.41 | 0.38 | 0.42 | 0.42 | 0.35 | 0.43 |
| | ENV2 | 0.03 | 0.04 | 0.02 | 0.06 | 0.05 | 0.05 | 0.05 | 0.04 | 0.04 | 0.03 | 0.05 |
| 341 Paper and Products | ENV1 | | | 1.61 | 2.48 | 2.90 | 3.27 | 6.17 | 4.62 | 3.91 | 3.75 | 4.61 |
| | ENV2 | 0.10 | 0.11 | 0.06 | 0.19 | 0.19 | 0.19 | 0.21 | 0.21 | 0.20 | 0.18 | 0.19 |
| 342 Printing and Publishing | ENV1 | | | 0.02 | 0.10 | 0.58 | 0.06 | 0.10 | 0.12 | 0.09 | 0.09 | 0.06 |
| | ENV2 | 0.03 | 0.04 | 0.01 | 0.02 | 0.03 | 0.02 | 0.03 | 0.03 | 0.02 | 0.02 | 0.02 |
| 351 Chemicals | ENV1 | | | 3.29 | 1.82 | 1.78 | 1.66 | 1.58 | 2.12 | 1.89 | 1.48 | 1.60 |
| | ENV2 | 0.13 | 0.13 | 0.08 | 0.09 | 0.12 | 0.11 | 0.10 | 0.10 | 0.10 | 0.08 | 0.08 |
| 353 Petroleum | ENV1 | | | 1.83 | 2.18 | 3.22 | 2.71 | 2.36 | 2.37 | 2.23 | 1.91 | 1.49 |
| | ENV2 | 0.08 | 0.07 | 0.08 | 0.07 | 0.11 | 0.13 | 0.10 | 0.09 | 0.08 | 0.07 | 0.06 |
| 355 Rubber Products | ENV1 | | | 0.14 | 1.87 | 0.17 | 0.30 | 0.34 | 0.20 | 0.25 | 0.24 | 0.43 |
| | ENV2 | 0.05 | 0.05 | 0.02 | 0.07 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.03 | 0.02 |
| 356 Plastic Products | ENV1 | | | 0.05 | 0.07 | 0.07 | 0.07 | 0.08 | 0.19 | 0.10 | 0.11 | 0.11 |
| | ENV2 | 0.02 | 0.03 | 0.01 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 | 0.01 | 0.01 |

**Table 3.4 continued**

| Industry | Stringency | 1994 | 1995 | 1996 | 1997 | 1998 | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 369 Non-metallic Mineral Products | ENV1 | | | 0.79 | 2.67 | 1.80 | 2.02 | 2.48 | 4.14 | 4.67 | 2.69 | 3.61 |
| | ENV2 | 0.10 | 0.11 | 0.07 | 0.13 | 0.21 | 0.18 | 0.19 | 0.21 | 0.22 | 0.19 | 0.17 |
| 371 Iron and Steel | ENV1 | | | 1.68 | 1.84 | 2.19 | 1.94 | 2.39 | 2.27 | 2.60 | 2.82 | 1.89 |
| | ENV2 | 0.05 | 0.07 | 0.05 | 0.06 | 0.06 | 0.06 | 0.19 | 0.06 | 0.06 | 0.04 | 0.03 |
| 372 Non-ferrous Metals | ENV1 | | | 2.49 | 2.90 | 2.90 | 2.24 | 2.37 | 2.96 | 2.62 | 2.35 | 1.92 |
| | ENV2 | 0.09 | 0.11 | 0.10 | 0.12 | 0.11 | 0.10 | 0.11 | 0.11 | 0.10 | 0.07 | 0.06 |
| 381 Fabricated Metal Products | ENV1 | | | 0.12 | 0.49 | 0.68 | 0.47 | 0.67 | 0.96 | 0.71 | 0.61 | 0.57 |
| | ENV2 | 0.04 | 0.05 | 0.02 | 0.06 | 0.09 | 0.09 | 0.10 | 0.10 | 0.11 | 0.09 | 0.08 |
| Average | ENV1 | | | 1.02 | 1.36 | 1.36 | 1.23 | 1.53 | 1.70 | 1.88 | 1.33 | 1.37 |
| | ENV2 | 0.06 | 0.07 | 0.06 | 0.07 | 0.08 | 0.08 | 0.09 | 0.08 | 0.08 | 0.07 | 0.06 |

### 3.3.3 Selection of estimators

Pooled Ordinary Least Squares (POLS) estimation is identical to the cross-sectional data analysis predominantly adopted in the early literature of environmental stringency and industrial competitiveness. Using pooled cross-sectional data analysis may cause biased[37]results due to the existence of unobservable, unmeasured characteristics that are correlated with the included explanatory variables. Compared to cross-section data, panel datasets allow us to explore the unobserved but fixed characteristics of industries that may be correlated with dependent variables and key independent variables. The most common technique for accounting for heterogeneity is panel data. The fixed effects (FE) model and random effects (RE) model estimators have their own caveats and strengths. FE allows individual specific effects to be correlated with explanatory variables while RE does not. However, the FE is inferior to the RE in terms of degrees of freedom; and the estimated coefficients from FE tend to be less significant due to high correlation between the fixed effects and the explanatory variables. OLS, FE and RE estimation in STATA are designed to take into account of heteroscedasticity and provide robust estimates. However, they are not designed to correct for autocorrelation.

In table 3.5 we present test results for heteroscedasticity. Though not always rejected, we find evidence that there is heteroscedasticity in some specifications. First-order autocorrelation is tested and the results are presented in table 3.6. At A 95% significance level, we reject the null hypothesis that there is no first order autocorrelation for all the specifications.

[37] Hsiao (1986:6-7) demonstrates the occurrence of heterogeneity bias in slope coefficients, when omitting group-specific intercepts to account for heterogeneous cross-sectional units in panel data sets.

**Table 3.5 Breusch-Pagan/Cook-Weisberg test ($H_O$: constant variance)**

| | | ENV1 | | | ENV2 | | |
|---|---|---|---|---|---|---|---|
| | | TSI | Michaely | Netva | TSI | Michaely | Netva |
| Sample 1 | Chi-square | 8.80 | 2.64 | 1.56 | 9.38 | 2.68 | 12.21 |
| | p value | 0.0030 | 0.1043 | 0.2116 | 0.0022 | 0.1013 | 0.0005 |
| Sample 2 | Chi-square | 1.91 | 0.02 | 6.48 | 5.24 | 14.96 | 12.00 |
| | p value | 0.1668 | 0.8900 | 0.0109 | 0.0221 | 0.0001 | 0.0005 |

**Table 3.6 Wooldridge test ($H_O$: no first order autocorrelation)**

| | | ENV1 | | | ENV2 | | |
|---|---|---|---|---|---|---|---|
| | | TSI | Michaely | Netva | TSI | Michaely | Netva |
| Sample 1 | F-test | 22.260 | 42.120 | 16.879 | 19.639 | 44.026 | 107.721 |
| | p value | 0.0001 | 0.0000 | 0.0005 | 0.0002 | 0.0000 | 0.0000 |
| Sample 2 | F-test | 24.456 | 5.287 | 7.069 | 20.770 | 6.314 | 10.346 |
| | p value | 0.0004 | 0.0421 | 0.0222 | 0.0008 | 0.0288 | 0.0082 |

In consideration of both heterogeneity and autocorrelation (non i.i.d, i.e. non independent and identically distributed disturbances), generalised least squares (GLS) estimators are not feasible with the variance-covariance matrix unknown. We adopt feasible generalized least squares (FGLS thereafter) estimator which transforms the data controlling for both heterogeneity and autocorrelation (only AR(1) is controlled in our case).

# 3.4 RESULTS

## 3.4.1 Main results

Table 3.7 presents estimation results based on ENV1 (pollution abatement operating cost as share of value added) for 22 industries between 2001 and 2004. We find that the sign and magnitude of estimated coefficients vary across the three alternative measures of trade specialization. Environmental stringency has a significantly negative impact on TSI and Netva; however, the coefficient on the Michaely index is counter-intuitively positive though insignificant. Human capital intensity and physical capital intensity seem to be significantly and positively influencing both TSI and Michaely which are contrary to our prediction. Only for Netva, human capital intensity and physical capital intensity seem to have expected negative signs. The unexpected factor intensity results may partly come from some measurement problem. For example, the wage information used to construct HCI may have little to do with human capital intensity itself. Other factors such as state intervention than human capital intensity lead Tobacco industry has higher wage level. It should also be noted that some Chinese exports may be relatively capital intensive by Chinese, but not international, standards.

The coefficient of the interaction term between environmental stringency and pollution intensity is negative across the last three columns though insignificant for TSI. They provide evidence that dirtier industries seem to suffer more from stringent regulations. The tariff effect has mixed signs and significance levels. Only in the case of TSI, tariff seems to have a significant and positive sign, but the exogeneity of this variable is questionable as tariff design is often influenced by trade performance.

**Table 3.7 FGLS results with ENV1 based on sample one**

**2001-2004 22 industries**

| | TSI | Michaely | Netva | TSI | Michaely | Netva |
|---|---|---|---|---|---|---|
| ENV1 | -2.469** | 0.013 | -4.892* | -2.226** | 0.013 | -3.384 |
| | (-2.471) | (0.188) | (-1.747) | (-2.205) | (0.186) | (-1.337) |
| HCI | 0.870** | 0.377*** | -0.499 | 0.795** | 0.277*** | -1.114 |
| | (2.511) | (7.762) | (-0.406) | (2.271) | (4.263) | (-0.934) |
| PCI | 0.835*** | 0.246*** | -1.398* | 0.768*** | 0.189*** | -1.702** |
| | (3.450) | (7.386) | (-1.816) | (3.104) | (4.599) | (-2.222) |
| Tariff | 0.002** | -0.000 | 0.002 | 0.002*** | -0.000 | 0.002 |
| | (2.429) | (-0.013) | (1.483) | (2.651) | (-0.165) | (1.292) |
| ENV1*dirtiness | | | | -0.683 | -0.089** | -4.066*** |
| | | | | (-1.222) | (-1.985) | (-3.160) |
| _cons | -0.563** | -0.216*** | 1.390** | -0.508** | -0.16*** | 1.663** |
| | (-2.540) | (-7.236) | (1.970) | (-2.258) | (-4.436) | (2.376) |
| chi2 | 1.77e+05 | 10141.158 | 16872.236 | 1.89e+05 | 9680.394 | 21531.279 |
| N | 88 | 88 | 88 | 88 | 88 | 88 |

Note: with time and industry dummies included. t-statistics in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

Based on sample one, we use the alternative measure of environmental stringency, ENV2. The regression results are provided in table 3.8. The results share similarity with table 3.7: the estimated coefficient of environmental stringency turns out to be significantly negative for the three different trade specialization variables; human capital intensity and physical capital intensity are unexpectedly positive and significant for TSI and Michaely while their impact seems to be insignificant and sometimes negative on Netva; the tariff coefficient is only significantly positive for TSI. However, for the interaction terms between environmental stringency and pollution intensity, there is no significantly negative effect. Hence the hypothesis that dirtier industries tend to suffer more from increasing environmental stringency is not supported here.

**Table 3.8 FGLS results with ENV2 based on sample one 2001-2004 22 manufacturing industries**

| | TSI | Michaely | Netva | TSI | Michaely | Netva |
|---|---|---|---|---|---|---|
| ENV2 | -90.82** | -9.239* | -492.525*** | -80.807* | -5.563 | -543.63** |
| | (-2.42) | (-1.739) | (-2.850) | (-1.880) | (-0.786) | (-2.556) |
| HCI | 1.213*** | 0.326*** | 0.143 | 1.056** | 0.314*** | 0.454 |
| | (3.42) | (5.484) | (0.086) | (2.539) | (4.295) | (0.251) |
| PCI | 0.810*** | 0.193*** | -1.773 | 0.747*** | 0.196*** | -1.793 |
| | (3.13) | (4.526) | (-1.383) | (2.778) | (4.365) | (-1.423) |
| Tariff | 0.002** | -0.000 | 0.001 | 0.002** | -0.000 | 0.001 |
| | (2.26) | (-0.795) | (0.398) | (2.295) | (-0.413) | (0.542) |
| ENV2*dirtiness | | | | -3.139 | -1.190 | 16.243 |
| | | | | (-0.426) | (-0.820) | (0.386) |
| _cons | -0.532** | -0.164*** | 1.942 | -0.480* | -0.169*** | 1.974* |
| | (-2.16) | (-4.160) | (1.614) | (-1.889) | (-4.080) | (1.671) |
| chi2 | 3.08e+05 | 10954.182 | 15560.994 | 2.51e+05 | 12312.848 | 18652.49 |
| N | 88 | 88 | 88 | 88 | 88 | 88 |

Note: with time and industry dummies included. t-statistics in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

We also present results using a panel of 12 industries with longer time span of 1996 and 2004 (sample two). Most of these industries included in the sample are more pollution intensive than those that are not included. Table 3.9 gives the results based on ENV1. In the first three columns of estimates, we find that pollution abatement cost only has a significantly negative impact on Netva while it is insignificant in terms of TSI and Michaely. Same as the results from sample one, we find that human capital intensity seems to have positive impact on trade specialization indices, though the effect is not significant in the case of Netva. Physical capital intensity has insignificant impact on trade specialization indices. The tariff now has a significant (though very small marginal effect) negative impact on Michaely, while it is insignificant for the other two trade specialization indices. The interaction term of environmental stringency and dirtiness has negative coefficient for all the three dependent variables, although it is not significant for TSI. This suggests that dirtier industries do seem to have more negative impact from increasing environmental stringency.

Table 3.9 FGLS results with ENV1 based on sample two

1994-2004 12 industries

| | TSI | Michaely | Netva | TSI | Michaely | Netva |
|---|---|---|---|---|---|---|
| ENV1 | -0.595 | 0.018 | -1.672* | -0.638 | 0.060* | -1.173 |
| | (-1.119) | (-0.574) | (-1.902) | (-1.057) | (-1.759) | (-1.293) |
| HCI | 1.669*** | 0.102*** | 0.788 | 1.701*** | 0.104*** | 0.432 |
| | (-2.643) | (-3.231) | (-0.93) | (-2.609) | (-3.206) | (-0.502) |
| PCI | 0.13 | 0.016 | -0.517 | 0.15 | 0.014 | -0.713 |
| | (-0.407) | (-0.932) | (-1.126) | (-0.459) | (-0.81) | (-1.547) |
| Tariff | 0.000 | -0.000** | -0.002 | 0.000 | -0.000** | -0.002 |
| | (-0.203) | (-2.550) | (-1.305) | (-0.238) | (-2.409) | (-1.521) |
| ENV1*Dirtiness | | | | -0.116 | -0.075*** | -1.752** |
| | | | | (-0.426) | (-4.046) | (-2.421) |
| _cons | -0.536* | -0.041*** | -0.086 | -0.553* | -0.039** | 0.111 |
| | (-1.722) | (-2.580) | (-0.196) | (-1.742) | (-2.492) | (-0.251) |
| chi2 | 7726.097 | 2779.563 | 1097.148 | 6657.574 | 3384.174 | 1465.274 |
| N | 108 | 108 | 108 | 108 | 108 | 108 |

Note: with time and industry dummies included. t-statistics in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

If we use environmental protection staff information (ENV2) to proxy environmental stringency (see table 3.10), a significant, negative effect from environmental stringency can be found for TSI and Netva. The positive and significant coefficient for human capital intensity is consistent with earlier findings. For physical capital intensity, the coefficient remains insignificant across dependent variables. Tariff now turns out to be a negative effect and is significant in the cases of TSI and Netva. The interaction term between environmental stringency and dirtiness has mixed signs and remains insignificant across alternative trade specialization indices.

Table 3.10 FGLS results with ENV2 based on sample two

1994-2004 12 industries

| | TSI | Michaely | Netva | TSI | Michaely | Netva |
|---|---|---|---|---|---|---|
| ENV2 | -26.934** | -0.906 | -49.193*** | -25.447** | -0.482 | -41.403** |
| | (-2.283) | (-0.648) | (-3.053) | (-1.977) | (-0.333) | (-2.309) |
| HCI | 1.871*** | 0.080** | 1.958** | 1.963*** | 0.088*** | 1.746** |
| | (-3.08) | (-2.563) | (-2.567) | (-3.2) | (-2.904) | (-2.201) |
| PCI | 0.093 | 0.018 | -0.267 | 0.134 | 0.019 | -0.426 |
| | (-0.336) | (-1.363) | (-0.795) | (-0.459) | (-1.458) | (-1.209) |
| Tariff | -0.002*** | 0.000 | -0.004*** | -0.002*** | 0.000 | -0.004*** |
| | (-4.650) | (-0.038) | (-5.146) | (-4.581) | (-0.050) | (-5.115) |
| ENV2*Dirtiness | | | | 2.264 | -0.504 | -14.282 |
| | | | | (-0.555) | (-1.368) | (-1.220) |
| _cons | -0.511* | -0.038*** | -0.371 | -0.557* | -0.040*** | -0.223 |
| | (-1.861) | (-2.916) | (-1.112) | (-1.935) | (-3.149) | (-0.637) |
| chi2 | 5083.696 | 1329.007 | 1450.34 | 3880.473 | 1465.273 | 1576.689 |
| N | 132 | 132 | 132 | 132 | 132 | 132 |

Note: with time and industry dummies included. t-statistics in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

Given the unexpected signs on some variables, appendix 3.4 provides estimates when the explanatory variables are added incrementally into regression models. In table A3.4.1 (sample one with ENV1), the sign of HCI seems to be influenced by the inclusion of PCI. However, other results (ENV2 with sample one as well as the estimates based on sample two) show that the inclusion of PCI as well as other control variables does not change the sign of HCI.

*Elasticities*

To evaluate the impact of each explanatory variable on the dependent variable we estimate the elasticities. Due to the differences in measurement of environmental stringency, trade specialization and even dataset, there are a wide range of elasticities. Based on sample one, we find that a 1% increase in ENV1 would lead to a reduction of about 0.16% in TSI and Netva. The increase in ENV2 would result in 0.3 % reduction in TSI and a considerably larger reduction of 0.9 % in net exports. Human capital intensity effect is also small in magnitude: a 1% increase in HCI would lead to 0.26-0.36% increase in TSI, while the effect is insignificant for Netva. Physical capital intensity is much larger in magnitude: a 1% increase in PCI would lead to about 4% increase in TSI, but about a 4% decrease in net exports. The impact from tariff seems to be small and positive: the elasticity is about 0.2% and insignificant in the case of net exports.

**Table 3.11 Estimated Elasticities**

**(For sample one: 2001-2004 22 industries)**

| | TSI | TSI | Netva | Netva |
|---|---|---|---|---|
| ENV1 | -0.157** | | -0.163* | |
| | (-2.46) | | (-1.72) | |
| ENV2 | | -0.298** | | -0.858*** |
| | | (-2.42) | | (-2.77) |
| HCI | 0.255** | 0.356*** | -0.077 | 0.022 |
| | (2.50) | (3.39) | (-0.41) | (0.09) |
| PCI | 3.994*** | 3.876*** | -3.514* | -4.508 |
| | (3.45) | (3.45) | (-1.79) | (-1.37) |
| Tariff | 0.172** | 0.204** | 0.11 | 0.031 |
| | (2.42) | (2.25) | (1.47) | (0.40) |

Note: elasticities are obtained using the command mfx with option eyex (calculate elasticities in the form of d(lny)/d(lnx)) in STATA: for negative predicted values, the elasticities are not estimated; z-statistics are in paretheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

**Table 3.12 Estimated Elasticities**

**(For sample two: 1996-2004 12 industries)**

| | TSI | TSI | Netva |
|---|---|---|---|
| ENV1 | -0.172 | | -4.892* |
| | (-1.10) | | (-1.75) |
| ENV2 | | -0.629* | |
| | | (-1.78) | |
| HCI | 2.001** | 3.61** | -0.499 |
| | (2.24) | (2.08) | (-0.41) |
| PCI | 1.932 | 2.114 | -1.398* |
| | (0.687) | (0.33) | (-1.82) |
| Tariff | 0.069 | -1.429** | 0.002 |
| | (0.40) | (0.40) | (1.48) |

Note: elasticities are obtained using the command mfx with option eyex (calculate elasticities in the form of d(lny)/d(lnx)) in STATA: for negative predicted values, the elasticities are not estimated; z-statistics are in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

Table 3.12 presents estimated elasticities for sample two. The magnitudes of each effect change dramatically. Human capital intensity seems to be the largest in explaining TSI. For net exports, the impact from ENV1 is much larger than the estimates obtained from sample one.

## 3.4.2 Robustness check

We have seen in different model specifications that the coefficients of physical capital intensity and human capital intensity have an unexpected sign, i.e. they are positively and significantly correlated with trade variables (TSI and Michaely). Since China is believed to have comparative advantage in labour intensive industries and comparative disadvantage in capital intensive ones, this finding is indeed puzzling. One possible explanation is that both physical capital and human capital intensities are endogenously influenced by trade performance. An industry with strong international competitiveness would have faster capital accumulation rate than other industries. In addition, the payroll-related measures of human capital intensity and physical capital intensity may be correlated with profitability of an industry.

To provide robustness check, we employ a more direct measure of physical capital intensity which is man-made capital (fixed capital divided by value added). The results based on sample one and two are reported in tables3.13 and 3.14. Table 3.13 shows that MK is significantly negative for TSI and Michaely index. But for Netva, MK shows a positive effect. ENV1 is still negative though less significant across trade variables. By contrast, ENV2 is significantly negative for all the three trade indices. We find HCI a positive influence, while tariff has mixed signs and significance levels. In table 3.13 the man-made physical capital intensity is significant and negative for TSI while it is significantly positive for Netva. With sample two (see table 3.14), however, MK has an insignificant effect on all trade indices.

**Table 3.13 Robustness check: FGLS with sample one**

| Variable | TSI | TSI | Michaely | Michaely | Netva | Netva |
|---|---|---|---|---|---|---|
| ENV1 | -1.940 | | -0.038 | | -4.367* | |
| | (-1.843) | | (-0.533) | | (-1.995) | |
| ENV2 | | -96.305* | | -19.75*** | | -486.26** |
| | | (-2.572) | | (-5.296) | | (-2.812) |
| HCI | 0.185 | 0.542** | 0.111** | 0.147*** | 0.798 | 1.363 |
| | (1.236) | (2.857) | (2.67) | (4.061) | (1.052) | (1.417) |
| MK | -0.086*** | -0.087** | -0.010*** | -0.006 | 0.007 | 0.143* |
| | (-4.325) | (-3.186) | (-4.273) | (-1.567) | (0.157) | (2.032) |
| Tariff | 0.002*** | 0.002** | 0.000 | -0.000 | 0.001 | 0.001 |
| | (4.598) | (2.712) | (0.422) | (-0.488) | (0.413) | (0.377) |
| _cons | 0.261*** | 0.278*** | 0.015*** | 0.018*** | 0.165* | 0.206** |
| | (4.441) | (5.132) | (4.808) | (5.602) | (2.006) | (2.692) |
| N | 88 | 88 | 88 | 88 | 88 | 88 |
| chi2 | 914417.02 | 483173.52 | 11868.432 | 13793.824 | 15177.461 | 7387.874 |

Note: with time and industry dummies included. t-statistics in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

**Table 3.14 Robustness check: FGLS with sample two**

| Variable | TSI | TSI | Michaely | Michaely | Netva | Netva |
|---|---|---|---|---|---|---|
| ENV1 | -0.741 | | 0.015 | | -1.583 | |
| | (-1.332) | | (0.427) | | (-1.828) | |
| ENV2 | | -30.484* | | -1.271 | | -55.4*** |
| | | (-2.366) | | (-0.878) | | (-3.472) |
| HCI | 1.497*** | 1.626*** | 0.083** | 0.062* | 1.225* | 1.689** |
| | (3.464) | (4.727) | (3.078) | (2.070) | (2.010) | (2.918) |
| MK | 0.025 | 0.027 | -0.000 | 0.001 | 0.030 | 0.063 |
| | (0.989) | (1.284) | (-0.032) | (0.453) | (0.797) | (1.915) |
| Tariff | 0.001 | -0.002*** | -0.000 | -0.000 | -0.001 | -0.003*** |
| | (0.513) | (-4.562) | (-0.867) | (-0.451) | (-1.085) | (-4.036) |
| _cons | 0.432*** | 0.254*** | 0.013 | 0.007** | 0.270** | 0.529*** |
| | (6.696) | (6.932) | (1.786) | (3.003) | (2.620) | (14.461) |
| N | 108 | 132 | 108 | 132 | 108 | 132 |
| chi2 | 8002.397 | 6053.258 | 2432.215 | 1263.377 | 1170.89 | 1380.742 |

Note: with time and industry dummies included. t-statistics in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

### 3.4.3 Endogeneity concerns

As already summarized in the literature section, several studies (Ederington and Minier, 2000, 2001; Levinson and Taylor, 2004; Cole et al., 2005) suggest that environmental regulations are subject to endogeneity concerns. In addition, the counterintuitive signs of physical capital intensity and human capital intensity from our regressions also suggest a possibility of endogeneity in these variables. Approaches to eliminate the problem of endogeneity include taking lags and instrumentation. Taking lags would further reduce the number of our observations. Moreover, the number of lags, if not carefully considered, will lead to biased estimates. An IV estimator and a (difference or system) GMM estimator both can be applied to deal with the endogeneity issue. IV estimator requires valid instruments which must be correlated with environmental stringency measures but uncorrelated with any elements left in the error term. Another concern about using IV approach is that it causes loss of efficiency (Nakamura and Nakamura, 1998). The GMM approach is a general estimation method that includes OLS, IV and MLE as special cases. Due to panel size constraint, we look for outside instruments of environmental stringency.

Levinson and Taylor (2004) propose two instruments which employ information on geographical dispersion of industries and state (their study is on the US) characteristics. The first one is based on pollution demand which is a weighted average of pollution emissions (excluding own industry's emissions) in the states and the second is based on pollution supply which is weighted average of income per capita in the states. The weights are industry i's value added in each state in the beginning of data period. Data on pollution emissions for each industry in each province at year t are less available. We use the instrument constructed with income per capita as follows:

$$INS_{it}=\frac{\sum_{p=1}^{30} GDP_{pt} * VA_{ip,1994}}{VA_{i,1994}} \tag{3.10}$$

where i refers to an industry, t refers to year, p refers to province, $GDP_{pt}$ is provincial gross product at year t, VA is value added. The instrument may fail (Levinson and Taylor, 2004) since: 1. 'small industry' assumption may not hold and industry size may affect environmental stringency and 2. Geographic dispersion of industries may be influenced by trade liberalization. Since we use 1994 weights, the movement of industry to take advantage of preferential policies (opening up ports, tax rebate etc) may have been going on for a while and those industry with greater mobility may have been attracted to the coastal provinces. Another concern is that the instrument is not highly correlated to stringency measures. To increase the explanatory power of the instrument, we include the instrument and other explanatory variables in the first-stage regression. In the second-stage regression, the standard errors are corrected using a correction factor introduced in Gujarati (2004).

Davidson-MacKinnon test statistics show that the endogeneity of stringency measures as instrumented by INS is not very meaningful. Despite this, we still carry out IV estimation and report the results for the two subsamples in table 3.15 and table 3.16. Most of the results are consistent with previous estimates and the environmental stringency variables are negatively influencing trade performance. When we use sample two and instrument ENV1 by INS, however, environmental stringency seems to be positively and sometimes significantly correlated to trade performance.

Table 3.15 IV-FGLS with sample one

2001-2004 22 industries

| | TSI | Michaely | Netva | TSI | Michaely | Netva |
|---|---|---|---|---|---|---|
| ENV1 | -0.92 | -2.090*** | -81.292*** | | | |
| | (-0.174) | (-5.838) | (-9.127) | | | |
| ENV2 | | | | -20.733 | -47.102*** | -1832.388*** |
| | | | | (-0.174) | (-5.838) | (-9.127) |
| HCI | 1.048** | 0.378*** | -0.507 | 1.048** | 0.378*** | -0.507 |
| | (-2.293) | (-8.721) | (-0.651) | (-2.293) | (-8.721) | (-0.651) |
| PCI | 0.946*** | 0.224*** | -2.305*** | 0.946*** | 0.224*** | -2.305*** |
| | (-4) | (-7.295) | (-4.772) | (-4) | (-7.295) | (-4.772) |
| Tariff | 0.002* | 0.000* | 0.004** | 0.002* | 0.000* | 0.004** |
| | (-1.746) | (-1.656) | (-2.032) | (-1.746) | (-1.656) | (-2.032) |
| _cons | -0.675*** | -0.182*** | 2.747*** | -0.673*** | -0.177*** | 2.954*** |
| | (-3.102) | (-6.673) | (-5.67) | (-3.034) | (-6.477) | (-5.998) |
| chi2 | 73296.65 | 17183.77 | 35106.19 | 73296.62 | 17183.76 | 35105.98 |
| N | 88 | 88 | 88 | 88 | 88 | 88 |
| D-M (p-value) | 0.36 | 0.31 | 0.12 | 0.06 | 0.99 | 0.36 |

Note: with time and industry dummies included. t-statistics in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

Table 3.16 IV-FGLS with sample two

1994-2004 12 industries

| | TSI | Michaely | Netva | TSI | Michaely | Netva |
|---|---|---|---|---|---|---|
| ENV1 | 13.704*** | 0.114 | 18.848*** | | | |
| | (-3.973) | (-0.396) | (-3.821) | | | |
| ENV2 | | | | -457.101*** | -7.12 | -649.196*** |
| | | | | (-5.206) | (-0.889) | (-4.748) |
| HCI | 0.891 | 0.080* | 0.309 | 5.178*** | 0.143** | 6.535*** |
| | (-1.358) | (-1.807) | (-0.363) | (-6.406) | (-2.193) | (-5.358) |
| PCI | -0.217 | 0.019 | -0.676* | 0.193 | 0.024 | -0.036 |
| | (-0.760) | (-1.026) | (-1.954) | (-0.735) | (-1.447) | (-0.113) |
| Tariff | 0.006*** | 0.000 | 0.007** | -0.007*** | 0.000 | -0.010*** |
| | (-2.603) | (-0.35) | (-2.369) | (-7.681) | (-0.687) | (-6.848) |
| _cons | -0.498* | -0.042*** | -0.343 | -0.494* | -0.043*** | -0.408 |
| | (-1.826) | (-2.700) | (-1.054) | (-1.899) | (-2.666) | (-1.297) |
| chi2 | 3379.42 | 1392.296 | 1362.451 | 3715.088 | 1435.657 | 1353.656 |
| N | 132 | 132 | 132 | 132 | 132 | 132 |
| D-M (p-value) | 0.41 | 0.16 | 0.09 | 0.22 | 0.31 | 0.35 |

Note: with time and industry dummies included. t-statistics in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

## 3.5 CONCLUSIONS

In this chapter, we use cross-industry regressions to examine the role of environmental stringency in shaping trade patterns in China. Following the existing literature, we adopt the factor share version of Heckscher-Olin theory of trade. Specifically, trade variables (the dependent) are measured by three proxies: TSI, the Michaely and Net exports scaled by value added (Netva). Environmental stringency is measured by two proxies: the ratio of pollution abatement operating costs to value added and the payment to environment protection staff scaled by value added. Human capital intensity and physical capital intensity are constructed based on payroll. Tariff is also included as a control variable.

Based on the availability of data, we divide the dataset into two sub-samples: sample one with more cross-section units (22 industries) but shorter time periods (2001-2004) whilst sample two with small cross-section units (12 industries) but longer periods (1994-2004). To control for unobserved heterogeneity in industries and only time-varying elements, we include both time and industry specific effects in our specifications. Also to control for both heterogeneity and autocorrelation, FGLS estimator is employed. In general, using the payment to environment protection staff as a proxy for environmental stringency (ENV2) gives us negative and significant coefficients across subsamples and trade variables. When environmental stringency is proxied by pollution abatement operating cost (ENV1), we find its impact becomes positive though insignificant for the Michaely index, whilst the negative coefficient is still found for TSI and Netva. These two measures also differ in the coefficients of their interaction with pollution intensity. For the traditional pollution abatement operating costs, we find that dirtier industries tend to be more affected by increasing environmental stringency [38], in terms of export performance, with increasing environmental stringency; this finding, however, receives no support from the other measure of environmental stringency.

For human capital intensity and physical capital intensity, we find that they both seem to have a positive impact on TSI and Michaely (especially so for human capital intensity). Their impact on Netva is insignificant most of the time. The tariff effect is inconclusive with varying signs and significance levels across different specifications and subsamples.

To further investigate the counterintuitive result for PCI, we employ a more direct measure of physical capital intensity which is the fixed capital scaled by value added, MK. It is found in sample one that MK is negatively (and significantly sometimes) for TSI and Michaely; however, the impact of MK on net exports now turns to be positive and significant. For sample one, MK has mixed signs and is insignificant. Both elasticities and endogeneity concerns are discussed.

We also run cross-section regressions without industry fixed effects (results are not reported to conserve space). Coefficients on environmental stringency are still significantly negative, while those for the physical capital intensity and human capital intensity are significantly negative as expected.

There are some deficiencies of the present study. Firstly, a methodological issue, the unobserved foreign industry characteristics (rest of the world, ROW) are assumed as constant (relative to China) over time which is not very plausible. A better treatment

[38] When pollution-intensive is proxied by average environmental cost, Ederington et al. (2003, 2005) find no evidence for the hypothesis that trade flows are more sensitive to changing environmental regulations in the more pollution-intensive industries. Measurement of pollution-intensive may have influence on the coefficient.

will be studying trade flows and relative industrial characteristics in a cross-country setting or even in a bilateral setting. Secondly, the cost-based stringency measures are rather partial in the sense that pollution abatement operating cost (or payment to environment protection staff) as a fraction of value added may not necessarily increase when environmental policy tightens in the presence of advanced and more efficient pollution abatement technologies and management. Indeed, we find that both measures are not increasing over time despite the increase in the removal ratio for $SO_2$. Lastly, the exogeneity of other right hand side variables besides environmental stringency may be questioned.

# APPENDICES TO CHAPTER THREE

## Appendix 3.1 Concordance between industry classifications

There are 28 3-digit manufacturing industries defined by ISIC (International Standard Industry Classification). Because pollution abatement costs for Chinese industries were reported on CSIC (Chinese Standard Industry Classification) 2 digit level, we have to convert the two classifications to make them compatible. To make data compatible, some industries are aggregated into a bigger industry. In particular, 322 (Wearing Apparel except Footwear) and 324 (Footwear except Rubber or Plastics) are merged into a new industry 322F (Wearing Apparel except Rubber or Plastics); 351 (Industrial Chemicals) and 352 (Other Chemicals) are aggregated into 351A (Chemicals); 353 (Petroleum Refineries) and 354 (Misc. Petroleum and Coal Products) are aggregated into 353A (Petroleum); 361 (Pottery, china, earthenware), 362 (Glass and Products) and 369 (Other Non-metallic Mineral Products) are aggregated into 369K (Non-metallic Mineral Products). All these changes are listed in table A3.1.1.

The conversion between CSIC industries and ISIC industries is detailed in table A3.1.2. Recycling as a sub-sector of manufacturing is excluded since there is not enough trade data.

**TableA3.1.1 23 3-digit ISIC manufacturing data**

| Industries | sample | ISIC 3-digit | Description |
|---|---|---|---|
| 311 | 1 | 311 | Food Products |
| 313 | 1 | 313 | Beverages |
| 314 | 1 | 314 | Tobacco |
| 321 | 1,2 | 321 | Textiles |
| 323 | 1,2 | 323 | Leather products |
| 322F | 1 | 322+324 | Wearing Apparels except Rubber or Plastics |
| 331 | 1 | 331 | Wood Products, except Furniture |
| 332 | 1 | 332 | Furniture, except Metal |
| 341 | 1,2 | 341 | Paper and Products |
| 342 | 1,2 | 342 | Printing and Publishing |
| 351A | 1,2 | 351+352 | Chemicals |
| 353A | 1,2 | 353+354 | Petroleum |
| 355 | 1,2 | 355 | Rubber Products |
| 356 | 1,2 | 356 | Plastic Products |
| 369K | 1,2 | 361+362+369 | Non-metallic Mineral Products |
| 371 | 1,2 | 371 | Iron and Steel |
| 372 | 1,2 | 372 | Non-ferrous Metals |
| 381 | 1,2 | 381 | Fabricated Metal Products |
| 382 | 1 | 382 | Machinery, except Electrical |
| 383 | 1 | 383 | Machinery, Electric |
| 384 | 1 | 384 | Transport Equipment |
| 385 | 1 | 385 | Professional and Scientific Equipment |
| 390 | / | 390 | Other Manufactured Products |

Table A3.1.2 CSIC Industries Coded into ISIC Rev.2

| CSIC Industries | ISIC (Rev.2) 3-digit |
|---|---|
| Food Processing | 311 |
| Food Manufacture | 311 |
| Beverages | 313 |
| Tobacco | 314 |
| Textiles | 321 |
| Wearing Apparel | 322 |
| Leather products | 323 |
| Wood Products, except Furniture | 331 |
| Furniture | 332 |
| Paper and Products | 341 |
| Printing and Publishing | 342 |
| Education and Sports Products | 390 |
| Petroleum Refineries | 353 |
| Manufacture of Industrial Chemicals | 351 |
| Manufacture of Pharmaceuticals, Medicinal Products | 351 |
| Manufacture of Chemical Fibre | 351 |
| Rubber Products | 355 |
| Plastic Product | 356 |
| Non-metallic Mineral Products including: manufacture of cement | 369 |
| Processing of Ferrous Metals | 371 |
| Processing of Non Ferrous Metals | 372 |
| Fabricated Metal Products | 381 |
| Manufacture of General Purpose Machinery | 382 |
| Manufacture of Special Purpose Machinery | 382 |
| Transport Equipment | 384 |
| Manufacture of Arms | 382 |
| Manufacture of Electrical Machinery and Apparatus | 383 |
| Manufacture of Electronic and Communication Equipment | 383 |
| Manufacture of Office, Accounting and Computing Machinery | 385 |
| Other Manufacturing Industries | 390 |

## Appendix 3.2 Data sources and Variable description

**Table A3.2.1 Data information**

| Variable | Description and data sources |
|---|---|
| TSI | As defined in equation (3.2).<br>Exports and imports data from reported trade data in Nicita and Olarreaga (2006). |
| Michaely | As defined in equation (3.3).<br>Exports and imports data from reported trade data in Nicita and Olarreaga (2006) |
| Netva | As defined in equation (3.4)<br>Exports and imports data from reported trade data in Nicita and Olarreaga (2006) |
| ENV1 | ENV1=pollution abatement operating costs/ industrial value added<br>Source: China Sustainable Industrial Development database (CSID) |
| ENV2 | ENV2=average wage in a industry*number of Environment protection personnel/industrial value added<br>Source: China Sustainable Industrial Development database (CSID) |
| HCI | Ad defined in equation (3.5)<br>The share of skilled payroll in industrial value added. Skilled payroll equals the difference of payroll and unskilled payroll. Unskilled payroll equals the product of unskilled sectoral wage and the number of employees. Unskilled wage is proxied by average manufacturing wage, lowest sectoral wage in a year or the wage in the textiles industry.<br>Sources: Nicita and Olarreaga (2006), China Statistics Yearbooks (various years), China Labour Statistics Yearbooks (various years) |
| PCI | Ad defined in equation (3.6)<br>Equal to non-wage share of value added and constructed as 1-payroll/value added where payroll equals the product of average sectoral wage and number of employees<br>Sources: Chinese Statistics Yearbooks and Nicita and Olarreaga (2006). |
| MK | Ad defined in equation (3.7)<br>Fixed assets divided by value added<br>Sources: Chinese Statistics Yearbooks and Nicita and Olarreaga (2006). |
| Tariff | Imports weighted tariffs from TRAINS; Nicita and Olarreaga (2006). |

**TableA3.2.2 Descriptive statistics for sample one**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| TSI | 92 | 0.1944496 | 0.460998 | -0.6877717 | 0.955217 |
| Netva | 92 | 0.4647142 | 1.414144 | -3.238198 | 4.208955 |
| Michaely | 92 | -7.03E-10 | 0.0398915 | -0.1064446 | 0.127553 |
| ENV1 | 92 | 0.0104938 | 0.0129121 | 0.000409 | 0.048785 |
| ENV2 | 92 | 0.0005776 | 0.0005726 | 0.000055 | 0.002872 |
| PCI | 92 | 0.8163789 | 0.0619048 | 0.6705454 | 0.968925 |
| HCI | 92 | 0.0517742 | 0.0288925 | 0 | 0.121942 |
| Tariff | 92 | 15.7506 | 12.40285 | 2.21 | 57.83 |

**Table A3.2.3 Descriptive statistics for sample two**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| TSI | 132 | 0.033868 | 0.442885 | -0.77935 | 0.796757 |
| Netva | 132 | 0.07772 | 0.628251 | -1.14582 | 1.588088 |
| Michaely | 132 | -0.00726 | 0.034864 | -0.11385 | 0.03909 |
| ENV1 | 108 | 0.015368 | 0.013375 | 0.000244 | 0.061699 |
| ENV2 | 132 | 0.000803 | 0.000564 | 8.75E-05 | 0.002656 |
| PCI | 132 | 0.785892 | 0.054597 | 0.654917 | 0.927782 |
| HCI | 132 | 0.066384 | 0.034627 | 0 | 0.168622 |
| Tariff | 132 | 20.25424 | 18.17498 | 2.79 | 123.64 |

## Appendix 3.3 Trade Specialization in 2004

| ID | Description | TSI | Michaely | Netva |
|---|---|---|---|---|
| 322 | Wearing Apparels except Rubber or Plastics | 0.955 | 0.096 | 4.209 |
| 332 | Furniture, except Metal | 0.890 | 0.019 | 3.809 |
| 356 | Plastic Products | 0.724 | 0.023 | 1.160 |
| 390 | Other Manufactured Products | 0.642 | 0.036 | 2.512 |
| 314 | Tobacco | 0.614 | 0.000 | 0.009 |
| 381 | Fabricated Metal Products | 0.588 | 0.034 | 1.294 |
| 369 | Non-metallic Mineral Products | 0.506 | 0.011 | 0.242 |
| 313 | Beverages | 0.456 | 0.001 | 0.042 |
| 321 | Textiles | 0.397 | 0.028 | 0.614 |
| 323 | Leather Products | 0.392 | 0.008 | 0.637 |
| 331 | Wood Products, except Furniture | 0.387 | 0.004 | 0.635 |
| 355 | Rubber Products | 0.315 | 0.003 | 0.323 |
| 342 | Printing and Publishing | 0.192 | 0.001 | 0.124 |
| 382 | Machinery, except Electrical | 0.130 | 0.024 | 0.687 |
| 311 | Food Products | 0.094 | 0.001 | 0.082 |
| 384 | Transport Equipment | 0.012 | -0.005 | 0.012 |
| 383 | Machinery, Electric | -0.037 | -0.058 | -0.113 |
| 371 | Iron and Steel | -0.219 | -0.022 | -0.153 |
| 372 | Non-ferrous Metals | -0.314 | -0.021 | -0.521 |
| 385 | Professional and Scientific Equipment | -0.397 | -0.052 | -3.238 |
| 353 | Petroleum | -0.426 | -0.016 | -0.324 |
| 351 | Chemicals | -0.444 | -0.097 | -0.738 |
| 341 | Paper and Products | -0.629 | -0.016 | -0.733 |

## Appendix 3.4 Variables Added Incrementally

**Table A3.4.1 FGLS results with ENV1 based on sample one**

| | TSI | TSI | TSI | TSI | TSI | Michaely | Michaely | Michaely | Michaely | Michaely | Netva | Netva | Netva | Netva | Netva |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ENV1 | -2.891$^{***}$ | -3.117$^{***}$ | -1.615$^{*}$ | -2.469$^{**}$ | -2.226$^{**}$ | -0.167$^{***}$ | -0.102 | 0.039 | 0 013 | 0.013 | -6.442$^{***}$ | -5.031$^{**}$ | -3.794 | -4.892$^{*}$ | -3.384 |
| | (-3.056) | (-2.790) | (-1.782) | (-2.471) | (-2.205) | (-3.359) | (-1.487) | (-0.847) | (-0 188) | (-0 186) | (-3.961) | (-2.532) | (-1 445) | (-1.747) | (-1.337) |
| HCI | | -0.662$^{***}$ | 1 069$^{***}$ | 0 870$^{**}$ | 0.795$^{**}$ | | 0.016 | 0 395$^{***}$ | 0 377$^{***}$ | 0.277$^{***}$ | | 1.247$^{**}$ | -0 255 | -0.499 | -1.114 |
| | | (-3.170) | (-3.287) | (-2.511) | (-2.271) | | (-1.265) | (-8 878) | (-7.762) | (-4.263) | | (-2.145) | (-0.209) | (-0 406) | (-0.934) |
| PCI | | | 1.162$^{***}$ | 0.835$^{***}$ | 0.768$^{***}$ | | | 0.258$^{***}$ | 0 246$^{***}$ | 0.189$^{***}$ | | | -1.119 | -1.398$^{*}$ | -1.702$^{**}$ |
| | | | (-5.119) | (-3.45) | (-3.104) | | | (-9 227) | (-7.386) | (-4.599) | | | (-1 505) | (-1.816) | (-2 222) |
| Tariff | | | | 0.002$^{**}$ | 0.002$^{***}$ | | | | 0 | 0 | | | | 0.002 | 0 002 |
| | | | | (-2.429) | (-2.651) | | | | (-0 013) | (-0.165) | | | | (-1.483) | (-1.292) |
| ENV1*Dirtiness | | | | | -0.683 | | | | | -0.089$^{**}$ | | | | | -4.066$^{***}$ |
| | | | | | (-1.222) | | | | | (-1 985) | | | | | (-3.160) |
| _cons | 0 228$^{***}$ | 0 239$^{***}$ | -0.820$^{***}$ | -0.563$^{**}$ | -0.508$^{**}$ | 0.008$^{**}$ | 0.007$^{**}$ | -0.227$^{***}$ | -0 216$^{***}$ | -0.164$^{***}$ | 0.220$^{***}$ | 0.181$^{***}$ | 1 179$^{*}$ | 1.390$^{**}$ | 1.663$^{**}$ |
| | (-3.943) | (-4.416) | (-3 816) | (-2.540) | (-2.258) | (-2.461) | (-2.03) | (-9.012) | (-7.236) | (-4.436) | (-4.328) | (-2.889) | (-1.707) | (-1.97) | (-2.376) |
| chi2 | 1.03E+05 | 1 09E+05 | 1.62E+05 | 1.77E+05 | 1.89E+05 | 24366 73 | 20995.69 | 12008.33 | 10141.16 | 9680.394 | 36353.12 | 18106.01 | 16560 25 | 16872.24 | 21531 28 |
| N | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 |

Note: with time and industry dummies included. t-statistics in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

Table A3.4.2 FGLS results with ENV2 based on sample one

| | TSI | TSI | TSI | TSI | TSI | Michaely | Michaely | Michaely | Michaely | Michaely | Netva | Netva | Netva | Netva | Netva |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ENV2 | -189.75*** | -198.97*** | -100.17*** | -90.82** | -80.81* | -16.13*** | -21.66*** | -7.09 | -9.24* | -5.56 | -428.97*** | -619.73*** | -535.72*** | -492.53*** | -543.63** |
| | (-8 32) | (-7 37) | (-2.64) | (-2 42) | (-1.88) | (-4.17) | (-8.01) | (-1.41) | (-1.74) | (-0 79) | (-5.43) | (-6 99) | (-3.19) | (-2.85) | (-2 56) |
| HCI | | 0.088 | 1.179*** | 1.213*** | 1.056** | | 0.096*** | 0.330*** | 0.326*** | 0.314*** | | 2.998*** | 0 069 | 0 143 | 0 454 |
| | | (-0.408) | (-3.309) | (-3.418) | (-2.539) | | (-5.531) | (-5.367) | (-5.484) | (-4.295) | | (-4.328) | (-0.047) | (-0 086) | (-0 251) |
| PCI | | | 0.894*** | 0.810*** | 0.747*** | | | 0.196*** | 0 193*** | 0.196*** | | | -1.736 | -1 773 | -1.79 |
| | | | (-3.366) | (-3.13) | (-2.778) | | | (-4.49) | (-4.526) | (-4.365) | | | (-1.461) | (-1.383) | (-1 42) |
| Tariff | | | | 0.002** | 0.002** | | | | 0 | 0 | | | | 0 001 | 0.001 |
| | | | | (-2.26) | (-2.295) | | | | (-0.795) | (-0.413) | | | | (-0 398) | (-0.542) |
| ENV2*Dirtiness | | | | | -3.139 | | | | | -1 19 | | | | | 16.24 |
| | | | | | (-0.426) | | | | | (-0.820) | | | | | (0.56) |
| _cons | 0.290*** | 0 289*** | -0.556** | -0.532** | -0.480* | 0.014*** | 0.015*** | -0.168*** | -0.164*** | -0.169*** | 0.356*** | 0.401*** | 1.937* | 1.942 | 1.974* |
| | (-6 434) | (-6 43) | (-2.178) | (-2.156) | (-1.889) | (-5.265) | (-6.044) | (-4 151) | (-4 160) | (-4.080) | (-8.165) | (-9.638) | (-1.73) | (-1.614) | (-1 671) |
| chi2 | 2 16E+05 | 2.08E+05 | 2.11E+05 | 3.08E+05 | 2.51E+05 | 8161.2 | 32023.2 | 10052.9 | 10954.2 | 12312.8 | 26914.6 | 19770.5 | 14054.1 | 1556099 | 18652.5 |
| N | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 | 88 |

Note: with time and industry dummies included. t-statistics in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

**Table A3.4.3 FGLS results with ENV1 based on sample two**

| | TSI | TSI | TSI | TSI | TSI | Michaely | Michaely | Michaely | Michaely | Michaely | Netva | Netva | Netva | Netva | Netva |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ENV1 | -0.264 | -0.688 | -0.634 | -0 595 | -0.638 | 0.009 | 0 023 | 0 029 | 0.018 | 0.060* | -1.255* | -1.16 | -1.239 | -1 672* | -1.173 |
| | (-0 596) | (-1.373) | (-1.258) | (-1.119) | (-1.057) | (-0.281) | (-0 653) | (-0 811) | (-0 574) | (-1.759) | (-1.885) | (-1.403) | (-1 490) | (-1 902) | (-1 293) |
| HCI | | 1.627*** | 1.700*** | 1.669*** | 1.701*** | | 0.074*** | 0 078** | 0 102*** | 0.104*** | | 1.161** | 0 646 | 0.788 | 0 432 |
| | | (-4.307) | (-2.811) | (-2.643) | (-2.609) | | (-2.91) | (-2.376) | (-3 231) | (-3.206) | | (-2.014) | (-0 784) | (-0 93) | (-0.502) |
| PCI | | | 0.115 | 0 13 | 0.15 | | | 0 008 | 0 016 | 0 014 | | | -0.421 | -0.517 | -0.713 |
| | | | (-0.359) | (-0.407) | (-0.459) | | | (-0.504) | (-0 932) | (-0.81) | | | (-0.929) | (-1 126) | (-1.547) |
| Tariff | | | | 0 | 0 | | | | -0.000** | -0.000** | | | | -0.002 | -0.002 |
| | | | | (-0.203) | (-0.238) | | | | (-2 550) | (-2.409) | | | | (-1.305) | (-1.521) |
| ENV1*Dirtiness | | | | | 0 116 | | | | | -0 075*** | | | | | -1.752** |
| | | | | | (-0.426) | | | | | (-4.046) | | | | | (-2.421) |
| _cons | 0 537*** | 0 474*** | 0.373 | 0.361 | 0.346 | 0 031*** | 0.028*** | 0.021 | 0.016 | 0.017 | 1.027*** | 0.988*** | 1.368*** | 1.451*** | 1.624*** |
| | (-15.6) | (-17.571) | (-1 279) | (-1.236) | (-1.163) | (-13.73) | (-12.655) | (-1.459) | (-1 074) | (-1.161) | (-7.958) | (-8.199) | (-3 236) | (-3.386) | (-3 734) |
| chi2 | 3574.99 | 7950.621 | 7988.003 | 7726.097 | 6657.574 | 2214.536 | 2305.061 | 2583 341 | 2779.563 | 3384.174 | 1016.732 | 1092.802 | 1104.645 | 1097.148 | 1465.274 |
| N | 108 | 108 | 108 | 108 | 108 | 108 | 108 | 108 | 108 | 108 | 108 | 108 | 108 | 108 | 108 |

Note: with time and industry dummies included. t-statistics in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

Table A3.4.4 FGLS results with ENV2 based on sample two

| | TSI | TSI | TSI | TSI | TSI | Michaely | Michaely | Michaely | Michaely | Michaely | Netva | Netva | Netva | Netva | Netva |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ENV2 | -11 966 | -11.435 | -12.603 | -26.934** | -25.447** | -1.547 | -0.931 | -0.899 | -0.906 | -0.482 | -18.165 | -34 360** | -31 008* | -49 193*** | -41 403** |
| | (-1 208) | (-1.284) | (-1.471) | (-2.283) | (-1.977) | (-1 433) | (-0.716) | (-0 684) | (-0.648) | (-0.333) | (-1.011) | (-2.230) | (-1 897) | (-3 053) | (-2 309) |
| HCI | | 1 049*** | 1.788*** | 1.871*** | 1.963*** | | 0.053** | 0.080** | 0 080** | 0.088*** | | 1.107** | 0.689 | 1.958** | 1 746** |
| | | (-3.89) | (-3.2) | (-3 08) | (-3.2) | | (-2.457) | (-2.527) | (-2.563) | (-2.904) | | (-2.373) | (-0.87) | (-2.567) | (-2 201) |
| PCI | | | 0.412 | 0.093 | 0 134 | | | 0.018 | 0.018 | 0 019 | | | -0 229 | -0.267 | -0 426 |
| | | | (-1.577) | (-0 336) | (-0.459) | | | (-1.259) | (-1.363) | (-1.458) | | | (-0.593) | (-0.795) | (-1 209) |
| Tariff | | | | -0.002*** | -0.002*** | | | | 0 | 0 | | | | -0.004*** | -0.004*** |
| | | | | (-4 650) | (-4 581) | | | | (-0.038) | (-0.050) | | | | (-5.146) | (-5.115) |
| ENV2*Dirtiness | | | | | 2.264 | | | | | -0.504 | | | | | -14 282 |
| | | | | | -0.555 | | | | | (-1.368) | | | | | (-1.220) |
| _cons | 0.488*** | 0.430*** | 0.057 | 0.372 | 0.332 | 0.031*** | 0.028*** | 0 012 | 0.012 | 0 011 | 0.905*** | 0.865*** | 1.073*** | 1.130*** | 1.265*** |
| | (-11.219) | (-10 759) | (-0.237) | (-1.466) | (-1.245) | (-11.124) | (-10.535) | (-0.961) | (-0.964) | (-0.935) | (-6.19) | (-5.945) | (-2.863) | (-3.415) | (-3.668) |
| chi2 | 4279.125 | 5294.882 | 5144 82 | 5083.696 | 3880.473 | 967.092 | 1320.001 | 1320.337 | 1329.007 | 1465.273 | 1208.004 | 1266.397 | 1300 982 | 1450 34 | 1576.689 |
| N | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 | 132 |

Note: with time and industry dummies included. t-statistics in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%.

# CHAPTER FOUR

# THE POLLUTION CONTENT IN CHINA'S TRADE

## 4.1 INTRODUCTION

Environmental quality is strongly related to the overall level of economic activity, including international trade activity. However, in most conventional comparative advantage frameworks, especially those of neoclassical ones, the role of the environment had been largely ignored. With rising global awareness of climate change, industrial pollution, species extinction and human welfare, the importance of the environment in accommodating production as well as in assimilating pollution is increasingly recognized and examined. As Leontief (1970) states, "frequently unnoticed and too often disregarded, undesirable by-products as well as certain valuable but unpaid-for natural inputs are linked directly to the network of physical relationships that govern the day-to-day operations of an economic system." The increasing magnitude of international trade combined with the upsurge of foreign direct investment also triggers the concern over economic welfare across borders. Some studies (D'Arge and Kneese, 1972; Pethig, 1976; Copeland and Taylor, 2003) have modelled the environment or environmental policy as a factor affecting production and serving as a determinant of comparative advantage.

As we already mentioned in chapter two, two related hypotheses have been proposed about the trade-environment relationship. The Pollution Haven Hypothesis suggests that developing countries with relative laxer environmental regulations could gain advantage in producing dirty goods, and they could become pollution havens for dirty industries migrating from developed countries. By contrast, the Factor Endowment Hypothesis predicts that developed countries will have a comparative advantage in producing dirty goods, since polluting industries also intensively use physical capital and human capital with which developed countries are relatively well endowed. Numerous studies (Grossman and Krueger, 1992; Mani and Wheeler, 1997; Copeland and Taylor, 2003; Cole et al., 2005) have been carried out to investigate these two hypotheses. The empirical results are quite mixed. However, as Copeland and Taylor (2003) emphasize, these two hypotheses do not necessarily work against each other; as a matter of fact, both motives have their merits in determining the trade pattern. The question remains about what weight each effect has and which dominates. A cross-industry study for the US by Cole et al. (2005) found that, while environmental stringency (proxied by the ratio of pollution abatement costs to value added) is a statistically significant negative determinant of revealed comparative advantage, factor intensities seem to play a more important role in determining specialization in the US dirty industries. To sum up, a strong form pollution haven hypothesis is not supported by most of the literature but a weak form pollution haven effect has been identified in a few studies.

A generalization from the PHH implies that with relatively laxer environmental regulations China would have a tendency to develop and accommodate dirty industries. As China involves itself to a greater extent in international trade, it is suspected that the environment has been sacrificed for GDP growth. However, China is relatively scarce in capital compared to its major trading partners (mainly OECD countries). According to the FEH, there is the possibility that trade liberalization has induced greater specialization in clean (labour intensive) goods. In chapter two, we have shown that clean industries have increased their revealed comparative advantage, while dirty ones have increased their revealed comparative disadvantage in China between 1976 and 2004. In this chapter, we do not directly test the two hypotheses in econometric regressions either; rather we look at the pollution content of international trade in China, in a similar fashion to that used by trade economists to measure the factor content of countries' trade which goes back to the pioneering work of Leontief (1953). We explore whether the pollution embodied in China's exports exceeds that of the imports and whether China's exports are more pollution intensive than its imports as the PHH implies. We rely initially on the assumption of a common technology across countries, which has traditionally been employed in empirical factor content studies of trade because the standard H-O model of international trade explains trade in terms of endowment differences across countries with assumed common technologies. It is, however, now widely recognised as a very strong assumption, and one that does not hold, especially across countries with marked development differences. It is, therefore, now common to allow for technological differences in the factor content testing of H-O trade models (Trefler and Zhu, 2000; Davis and Weinstein, 2001; Cabral et al., 2006, 2009). To account for technological differences, we adopt the Japanese I-O table as reference for the production of Chinese imports.

Under the common technology assumption, we find that not only does China avoid more pollution by importing than exporting but also China's exports appear to be cleaner than imports in terms of air pollution intensities ($CO_2$, $SO_2$ and $NO_x$). The results are confirmed by sensitivity checks. Using the technology matrix of the year 2002, the projection of pollution embodiment in trade for recent years seems to confirm that trade mix (composition effect) is good for China's environment. However, the results based on heterogeneous technologies show that the actual pollution embodiment in China's exports is greater than China's imports and that Chinese exports are much dirtier than its imports.

The remainder of the chapter is organized as follows: section 2 provides a summary of literature review on measuring pollution content in international trade; the framework of the Leontief-type model and alternative assumptions are described in section 3; section 4 presents the data and sets out the main findings as well as extends to include pollution embodiment in Sino-Japanese trade and project pollution embodiment for the recent years; conclusions can be found in section 5.

# 4.2 LITERATURE REVIEW

Trade can be either conceived as the overt exchange of goods suggested by traditional theories or as the exchange of the services of production factors. Vanek (1968) introduced the factor services version (factor content) of the H-O model of trade, which we traditionally view in terms of factors of production such as capital and labour. Accordingly, the input of environmental factors or in other words the output of pollutants in producing a good is usually termed as the "pollution content" or "pollution embodiment" in many recent studies.

In the process of globalization, international trade is increasingly playing a role in forging an economy's structure; the more open the economy is, the more influence international trade has on the economy. Pollution embodied in international trade has provoked intensive awareness in this regard. Since it is almost impossible to cover the huge existing literature[39] on the relationship of trade and the environment, we only review a selection of studies which are closely related to the pollution content of trade.

There are a number of ways to estimate the pollution embodiment in production/trade which vary in accuracy and level of aggregation. A number of studies have measured the pollution content of trade, either using simple, direct measures of the emissions associated with production of exports compared with import-substitutes (e.g. Grether et al., 2006) or more ambitious measures of the direct and indirect emissions using input-output (I-O) techniques (Leontief, 1970; Walter, 1973; Machado et al., 2001). We group them into two broad schools according to the criteria whether the study catches only the direct pollution emissions or the overall effect (sometimes termed as the life-cycle effect).

### 4.2.1 Measurement of direct effects

Some studies measure only the direct pollution content of trade by multiplying the industrial emission intensities with the levels of industrial production corresponding with these trade volumes. Due to data limitations, quite a few studies of industrial pollution problems rely heavily on US industrial pollution emissions databases such as the Industrial Pollution Projection System (IPPS) database (Hettige et al., 1995). Lucas et al. (2002) admit that the assumption of constant, US-based, output intensities limits the usefulness of some of their analysis (and similar studies). The assumption of constant and common output pollution intensities embodies three questionable components: that similar technologies and enforcement standards exist across countries; that there is a similar mix of products within each industry across countries; and that emissions are related to output not value added.

[39] For comprehensive reviews on this topic, see Chua, 1999; Copeland and Taylor, 2004; UNEP, IISD, 2005.

Muradian et al. (2001) provided an insightful picture of the pollution embodiment in trade for 18 industrialized countries for various years over the period from 1976 to 1994. Using the emissions intensities of five air pollutants from the Industrial Pollution Projection System (IPPS) database, the authors find that in the 1990s the industrialised world's embodied emissions in imports tend to be larger than that in exports for these industrial countries. By investigating further into individual industrial countries and individual pollutants, the authors find different patterns of the evolution of environmental terms of trade.

Also using IPPS coefficients, Grether et al. (2005) measure the amount of pollution emitted per dollar of imports. The authors explore, in a gravity framework, the determinants of pollution content in trade as well as the influential factors of trade specialization for 16 different pollutants in more than 50 countries over the 1986-1996 periods. Using $CO_2$ emissions per dollar of GDP as preferred proxy for environmental stringency, their results suggest an influence of both standard factor endowment and laxer environmental standards on patterns of international specialization. However, data limitation greatly restrains the results since the IPPS coefficients they use are only available for 1987 for US industries.

Cole (2004) examines US environmental load displacement over the period 1974-2001 using IPPS coefficients. The results show that the US has experienced environmental load displacement (the pollution embodied in total US imports is greater than that embodied in exports) over the period due to the fact that US imports were growing more rapidly than exports. Furthermore, the results provide no evidence that the US is increasingly displacing its pollution to Mexico despite the concern that the creation of NAFTA would be detrimental to the environment in Mexico. The econometric analysis shows that the US's relatively stringent environmental regulations have contributed to environmental load displacement.

Using trade flow data with the country specific $CO_2$ emissions per unit of GDP from China's trading partners, Wang and Watson (2007) estimate that about a quarter of Chinese $CO_2$ emissions in 2004 can be attributed to the net exports of goods and services. However, they recognize this figure might be an over-estimate since they don't distinguish $CO_2$ emissions intensities for different traded products while a large proportion of Chinese exports have low or medium level of carbon intensity.

With growing data availability in China, more studies on China's environment now turn to the Chinese-specific industrial datasets such as those reported by China's State Environmental Protection Agency (SEPA). One example is Chai (2002) which finds that freer trade enables China to specialize in labor intensive, cleaner industries and that the aggregate pollution intensity in imports was much more intensive than that of its exports during the periods 1980-1982 and 1996-1998.

To account for pollution emission intensity differences across industries, Dean and Lovely (2008) apply annual Chinese pollution intensities across industries and annual trade data for the years 1995 to 2004. Their results suggest that Chinese exports are much cleaner than Chinese imports. Of the four pollutants (COD, $SO_2$, smoke and dust) being examined, they find the first three are more intensive in Chinese exports than in imports under the inherent assumption that imports were produced using Chinese technologies. While both exports and imports are becoming cleaner over time, they find that the difference in pollution intensity in exports and imports is also diminishing.

### 4.2.2 Measurement of overall effects: I-O techniques

Most studies on this topic have applied input-output (I-O) techniques which have increasingly become popular in estimating pollution embodiment. Since Leontief's seminal work, Input-Output analysis has been employed among studies on various economic issues. It had already been used to analyze the interrelationships between the structures of economy and the factor endowments and comparative advantages before it was introduced into the area of the ecological economics.

Walter (1973) examines the product-profile of US exports and imports and compares it with a pollution profile. Pollution content is defined as environmental control costs consisting of R&D, operating costs, capital cost and appreciation of equipments. For each product group, the direct environmental management cost is estimated and the 1966 US input-output coefficients are applied to account for the indirect costs in intermediate inputs attributable to environmental management. Using 1968-1970 imports and exports data, the author finds that the average annual overall environmental cost loadings in exports as a ratio of exports was insignificant though slightly larger than that of imports using common technology assumption.

Contrary to Walter (1973), most studies investigating pollution content measure the physical flows of emissions such as greenhouse gases.

Wyckoff and Roop (1994) argue that many greenhouse gas policies are flawed in the sense that by targeting at domestic emissions they ignore carbon embodied in international trade flows. In order to assess the magnitude of the importation of carbon rich products, they estimate the amount of carbon contained in imports of manufactured goods for six of the largest OECD countries in the mid-1980s: Canada, France, Germany, Japan, the UK and the USA. They use country specific input-output tables, origin specific imports[40], country and industry specific energy use data, and carbon conversion ratio for each fuel type. The authors conclude that the embodiment

[40] It is assumed that imports from any country other than the six OECD countries have been produced using the same technology as the importing country.

of carbon in manufactured goods is significant in the mid-1980s with about 13% of the total carbon emissions of the six countries estimated to be embodied in manufactured imports (excluding imports of refined petroleum products).

Antweiler (1996) uses a notion of pollution terms of trade index to eliminate the balance of trade effect in pollution embodiment calculations and assigns weights to different pollutants to get a unique physical dimension. Using the US 1987 I-O table, identical technologies assumption (US industrial pollution data) and trade flows, the author calculated the index values for 164 countries in 1987. The results suggest that exports of highly industrialized countries appear to be less environmentally clean than their imports while the opposite holds for the developing countries (including China).

Hayami et al. (1997) investigate the applications of I-O techniques in environmental management. The emission of global warming gases in Japan is simulated conditional on the production technology (e.g. choice of cement production approaches) and consumer preferences. The authors also compare the $SO_2$ emission in Japan and China in 1987. Replacing certain characteristics of the Chinese economy by the Japanese counterparts, they find that China could have increased $SO_2$ emission by adopting Japanese consumption patterns. By contrast a substantial reduction in emissions would have occurred had Japanese energy usage (patterns, energy efficiency and removal ratio of sulphur and $SO_x$) been adopted in the Chinese economy.

As international treaties such as the Kyoto protocol push the issue of global warming into higher platform, a number of researches have been carried out to investigate the question whether producer's responsibility or consumer's responsibility should be accounted for in burden sharing of GHG emissions reduction. For example, Proops et al. (1993) distinguish "$CO_2$ emission" from "$CO_2$ responsibility" in a comparative input-output study of Germany and the UK. Assuming identical technologies in imports, Munksgaard and Pedersen (2001) use "consumer responsibility" and "producer responsibility" to examine the time series change in Danish $CO_2$ production and consumption. Using country specific IO tables mostly produced/converted by the OECD Secretariat, Ahmad and Wyckoff (2003) compare "domestic consumption" and "domestic production" in 24 countries (responsible for 80% of global $CO_2$ emissions) in the mid-1990s. Increased data availability has enabled related studies focus on the developing countries such as Brazil, Thailand, India and China. Machado et al. (2001) use the so-called hybrid input-output model (energy commodities in physical units and non-energy commodities in monetary units) and convert energy data to carbon figures using IPCC 1996 guidelines. They find that, in terms of energy and carbon embodiment in trade, Brazil is not only a net exporter in non-energy goods but also the embodiment in exports is more substantially intensive than that in imports in 1995.

Using Indian input-output tables for 1991/1992 and 1996/1997 and IPCC guidelines, the two related papers Mukhopadhyay and Chakraborty (2005) and Dietzenbacher and Mukhopadhyay (2007) examine the embodiment of the three pollutants, Carbon Dioxide, Sulphur Dioxide and Nitrogen Oxides ($CO_2$, $SO_2$, $NO_x$) in India's trade. They find that pollution emissions intensity in India's exports is smaller than those in its imports in 1991/1992 and 1996/1997 given Indian technology mix. They suggest that the results challenge the Pollution Haven Hypothesis.

Using the same assumptions and I-O modelling as in the above two papers, Mukhopadhyay (2006)[41] explores the PHH and FEH for Thailand's trade with OECD countries in the years 1980, 1990 and 2000. It is concluded that Thailand moved from a net importer of pollution embodiment in earlier years to a net exporter of pollution

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[41] Contrary to Copeland and Taylor (2004), the author views the two hypotheses in direct conflict with each other.

embodiment in 2000. It is also implied that the pollution embodied in FDI promoted exports accounts for more than 80% of the total pollution from the export sectors.

Following the same I-O modelling and assumptions, Temurshoev (2006) examines the PHH and FEH for the US and China by estimating the air pollutants emitted from fossil fuel combustion. The author concludes from the results that China gains and the US lose in terms of $CO_2$, $SO_2$ and $NO_x$ in 1992 and 1997 in terms of pollution emissions in the same amount of extra imports and extra exports. Due to data limitation, the factor endowment embodied in trade was only calculated for the US and it turns out that, similar to the Leontief Paradox, the US is not exporting capital intensive goods.

A "content" version of the "pollution haven hypothesis" could be phrased as: developed countries may relocate dirty industries to the countries with laxer environmental regulations by producing and exporting goods that embody less pollution than the imported goods (from developing countries). As a result, their consumption contains more pollution embodiment than their production does. The empirical results are inconclusive and the impression from the selected literature is that a developing country may well be a net importer of pollution content or importer of pollution intensive goods. The existing studies also show that the pollution content in trade changes as the trade volume (scale effect), trade mix (composition effect) and technology of production (technique effect) change. We aim to investigate these issues in the context of China's trade.

# 4.3 METHODOLOGY

## 4.3.1 Pollutants chosen

In this study, we focus on three air pollutants: Carbon Dioxide ($CO_2$), Sulphur Dioxide ($SO_2$) and Nitrous Oxides ($NO_x$) which are directly linked to acid rain and volumes of total suspending particulates. It is estimated that the use of solid fuels (coal), liquid fuels (oil) and gaseous fuels (natural gas) contributes to over 90% of $CO_2$ emissions from fossil fuel combustion[42]. Since these primary energy commodities are built in I-O tables, we assume[43] that all the coal, oil and natural gas are combusted whenever they are used as an intermediate input generating greenhouse gases. Combustion process and abatement technologies also affect the final release of air pollutant emissions. We estimate the emissions generated from combustion process but not the removal of them in the abatement process. The combustion process is assumed to derive the maximum amount of energy per unit of fuel consumed, hence delivering the maximum amount of air emissions.

## 4.3.2 Methodology: the Environmental I-O Analysis

The environmental input-output analysis (Leontief, 1970) demonstrates how "externalities" (e.g. pollution) can be incorporated into the conventional input-output picture of an economy. As available input-output tables do not treat pollutants explicitly as "bads" in the input-output matrix, the magnitude of pollution has to be

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[42] Emissions can be generated from other sources such as biological metabolism, chemical reactions, and volcanic eruptions, burning wood etc. The magnitude of the emissions generated from these sources may not be negligible. However, they are not explicately analyzed in this study.

[43] See also in Mukhopadhyay and Chakraborty (2005), Temurshoev (2006) and Dietzenbacher and Mukhopadhyay (2007)

estimated through detailed analysis of the underlying technical relationships and energy dependence.

Compared to measuring the direct pollution emissions in production, the I-O formula is advantageous in that it captures the life cycle effect. For example, the life cycle effect of pollution emission in the transport sector not only includes pollution in operation of vehicles but also contains pollution from manufacture and maintenance of vehicles as well as other induced demand. We adopt the environmental I-O analysis developed in Miller and Blair (1985). This methodology has been used in a number of subsequent studies, for example, Ahmad and Wyckoff (2003), Dietzenbacher and Mukhopadhyay (2007), Mukhopadhyay and Chakraborty (2005), and Temurshoev (2006). It combines the basic concepts of the I-O framework and the emission factors suggested by IPCC guidelines[44]. The linear relationships of the interlinked sectors in a Leontief model enable us to investigate the impact of demand (final consumption deliveries) on production and hence on pollution. The model basics are described as follows:

In a particular year **t**, for an individual country **c**, there are **N** commodities each serving as final deliveries as well as intermediate inputs for themselves and other commodities. All the energies are derived from **M** primary energy commodities: Raw Coal, Crude Oil and Natural Gas. Let $a_{ij}$ represent the input coefficient, i.e. the number of units of commodity **i** needed to produce one unit of commodity **j** (i, j=1, 2..., N).

[44] IPCC 1996, the manufacture fraction of secondary fuels should be ignored in the main calculation, as the carbon in these fuels has already been accounted for in the supply of primary fuels from which they are derived. Refined fuel products are for information only. In the case of fuel combustion, the emissions of non-$CO_2$ gases contain very small amounts of carbon compared to the $CO_2$ estimate and, at Tier 1; it is more accurate to base the $CO_2$ estimate on the total carbon in the fuel. This is because the total carbon in the fuel depends on the fuel alone while the emissions of the non-$CO_2$ gases depend on many factors such as technologies, maintenance etc which, in general, are not well known. At higher tiers, the amount of carbon in these non-$CO_2$ gases can be accounted for.

An N * N matrix of input coefficients is represented by A= $\{a_{ij}\}$. X is an N * 1 vector denoting domestic output of commodities and Y is an N * 1 vector denoting the final demand. The equilibrium condition of supply equalling demand is captured by the following equation:

$$X=AX+Y \tag{4.1}$$

where Y can be further decomposed into final consumption of domestic goods ($Y^D$), final consumption of imported goods ($Y^M$) and goods that are exported ($Y^X$).

By matrix operational rules, we can solve X as

$$X=(I-A)^{-1}Y \tag{4.2}$$

The N * N matrix $(I-A)^{-1}$ is often referred to as "the Leontief inverse" which represents the totality of the direct and indirect input requirements on domestic goods. This relationship implies that any change in the components of final demand would affect domestic production and in turn any change in domestic production would result in the change of pollution emissions and on the environment if we view pollution emissions as "consumption" of domestic environment.

The commodities Coal, Crude oil and Natural gas are the basic fossil fuels. We denote the energy requirement matrix (extracted from matrix A) as **B** of order M * N. Hence $b_{ij}$[45] refers to the requirement in monetary units on energy commodity i per unit of the output of commodity j.

Chemical emission factors are the product of the net calorific values for each fuel and the chemicals (Carbon, C; Sulphur, S; Nitrogen, N) content in net calorific values as suggested in IPCC guidelines. Denote **E** as a 3*M emission matrix for the three air emissions per SCE (Standard Coal Equivalent) of combustion for each fuel type.

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[45] As Chinese I-O tables don't report imported intermediate inputs separately, this coefficient denotes fuel inputs both domestically produced and imported.

Since the coefficients in B are in monetary units while the coefficients in the emission matrix E are in physical units, we have to reconcile the two before multiplication. Comparing the physical units and the monetary units in total fuel output, we could get an approximation for the ratio of SCE/RMB[46] for each energy type in producer's price. Denote the ratios in M*M diagonal matrix as R. Hence the pollution embodied in a final delivery Y (could be output, imports, exports etc.) can be calculated using the formula:

$$P = ERB(I-A)^{-1}Y \tag{4.3}$$

We also break down the pollution intensity into three elements: direct pollution intensity (DPI) which is related to the direct combustion of fuel in producing a unit of goods or services; overall pollution intensity (OPI) is the total emissions induced by producing one unit of goods or services. Indirect pollution intensity (IPI) is the difference of OPI and DPI; Mathematically,

$$\mathrm{DPI}=E*R*B \tag{4.4}$$

$$\mathrm{IPI}=E*R*B*[(I-A)^{-1}-I] \tag{4.5}$$

$$\mathrm{OPI}=E*R*B*(I-A)^{-1} \tag{4.6}$$

We use two measures to describe the pollution embodiment in trade: the balance of emissions terms of trade and the pollution terms of trade. The balance of emissions terms of trade (BETT thereafter) can be denoted as the difference of pollution embodied in exports and pollution embodied in imports:

$$\mathrm{BETT}=E_cR_cB_c(I-A_c)^{-1}Y^X-\sum_f E_fR_fB_f(I-A_f)^{-1}Y_f^M \tag{4.7}$$

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[46] SCE is an acronym of Standard Coal Equivalent which is applied in China and RMB is in current prices.

where c refers to China and f refers to a trading partner that has produced the relevant imports. BETT indicates the net pollution embodiment in China's trade. A positive BETT value suggests that China's exports contain more pollution content than its imports and vice versa. When using identical technologies for Chinese exports and imports, BETT represents the difference between pollution generated from exporting and pollution avoided from importing which can be simplified as:

$$\text{BETT}=ERB(I-A)^{-1}(Y^X-Y^M) \tag{4.8}$$

Similar to Antweiler (1996) but without assigning weights to pollutants, the pollution term of trade (PTOT) for a pollutant is constructed as the ratio of total pollution intensity in exports and total pollution intensity in imports:

$$\text{PTOT}=\frac{F^X}{F^M}=\frac{ERB(I-A)^{-1}Y^X / j_l'Y^X}{ERB(I-A)^{-1}Y^M / j_l'Y^M} \tag{4.9}$$

Where $j'_l$= (1,.., 1) is a 1 by N vector. If the ratio for a GHG emission is greater than one, the country can be viewed as relatively more pollution intensive in exports than in imports and vice versa.

Compared to BETT, PTOT is a per unit effect which allows for trade imbalance. BETT answers the question whether China's exports embody more pollution content than its imports while PTOT answers the question whether China's exports are dirtier than its imports.

### 4.3.3 Assumptions of imported intermediate goods

Since Chinese I-O tables do not distinguish domestic intermediate inputs from imported intermediate inputs, we have to impose alternative assumptions to gauge the estimation and check the robustness. The two alternative assumptions are explained in details in the following two sections.

*Assumption 1: intermediate inputs are locally produced only*

By assuming no imported intermediate inputs, we adopt matrix A to construct Leontief inverse L. The product matrix of ERB (3*N) denotes emissions in physical units (in tonnes) generated by one monetary unit of output j. The product of the Leontief matrix $(I-A)^{-1}$ and any exogenously defined final demand Y (be it $Y^D, Y^X and/or Y^M$) denotes the overall requirement on domestic production.

*Assumption 2: import proportionality*

Since this study focuses on the impact of trade on pollution emissions by taking into full account of the interdependences of industries, the distinction between domestic produced intermediates and imported intermediates is crucial. Without adjustment, the results based on the technology matrix A will be overestimated (Dietzenbacher et al., 2005; Lahr, 2001).

However, the available technology matrices in the Chinese I-O tables don't distinguish the domestic intermediate inputs and the imported intermediate inputs. If the supply-use matrix is applied directly as in assumption 1, it is equal to assuming that imports are all final goods. This obviously ignores the role of China in international vertical specialization. When one looks at the fact that China imports of intermediate goods in bulk to process and eventually to export[47], this omission may imply some serious measurement error. For example, it is estimated by Ping (2006) that China's vertical specialization ratio rose from 14.2% in 1992 to around 22% in 2003 implying a high volume of China's exports consists of processing trade. Since Chinese I-O tables do not give the details of the flows of imported goods (Dietzenbacher et al., 2005), we

[47] "Processing trade" accounts for almost half of China's total international trade since 1995.

have to make the assumption that imported goods are used as substitutes for domestic goods from which two propositions are generated as follows[48]:

1. *Imported goods are proportional in domestic use, be it final deliveries (which includes the possibility of re-exports) or intermediate use;*
2. *Imported goods are proportional as intermediate use for other sectors.*

It is constructed in Chinese I-O tables that the sum of gross output and imports equal the sum of intermediate inputs and final demand.

Hence, $a_{ij}$ denotes the input requirement of combined (domestic produced and imported) good i to produce one unit of good j. One unit of good i imported is treated as final good as well as substitutive domestic input. Suppose $p_i$ unit of it is used as intermediate goods while $1-p_i$ unit of it is used as final goods. $p_i$ is calculated as $p_i = \frac{IM_i}{\text{Gross Output}_i + IM_i}$ where $IM_i$ is imports of good i and Gross Output is domestic production of good i. The above two proposition also imply that the ratio of imported input is identical across sectors.

We denote the diagonal matrices of the ratios as follows[49]:

$$\hat{D} = \begin{pmatrix} 1-p_1 & & 0 \\ & \ddots & \\ 0 & & 1-p_n \end{pmatrix} \tag{4.10}$$

The change in the coefficient matrix changes the components of pollution intensity ( IPI and OPI).

$$DPI=E*R*B \qquad (4.4)'$$

[48] It is also referred to as Import proportionality assumption which is used by OECD countries to help construct imported goods flow tables. See also Hummels et al. (2001) and Feenstra and Hanson (1999).

[49] According to convention, a "hat" denotes that the off-diagonal elements are all 0s. By doing so, we calculate commodity specific pollution content in trade.

IPI=E*R*B*[(I-$\hat{D}$A)$^{-1}$-I] (4.5)'

OPI=E*R*B*(I-$\hat{D}$A)$^{-1}$ (4.6)'

The domestic Leontief inverse matrix becomes $(I-\hat{D}A)^{-1}$ . This changes the BETT formula in (4.8) to:

BETT=$ERB(I-\hat{D}A)^{-1}(Y^X-Y^M)$ (4.8)'

And PTOT in (4.9) becomes:

$$\text{PTOT}=\frac{F^X}{F^M}=\frac{ERB(I-\hat{D}A)^{-1}Y^X / j_l'Y^X}{ERB(I-\hat{D}A)^{-1}Y^M / j_l'Y^M} \qquad (4.9)'$$

# 4.4 DATA AND RESULTS

## 4.4.1 Data

In China, basic I-O tables are published both at national and provincial level every five years. Up to now, four basic national I-O tables have been published for the years 1987, 1992, 1997 and 2002. Based on the basic I-O tables, China also produces extended I-O tables every two or three years after a basic one is produced. Available extended I-O tables are for the years 1987, 1990, 1992, 1995, 1997, 2000 and 2002. The basic I-O tables are more detailed in commodity classifications (over 100 commodities) than extended I-O tables which are aggregated into only dozens of commodities. All the four basic I-O tables in China were composed using different commodity classifications highlighting the improved classifications of service sectors. The extended I-O tables are less complicated on classifications. The definitions of sectors in extended I-O tables are reported in Appendix 4.1.

We use the basic I-O tables to calculate the pollution content and pollution intensity embodied in China's trade. The results obtained by employing extended I-O tables can serve as a sensitivity check for aggregation effects. Because of lack of comprehensive data on technology matrix A, we assume initially identical technologies across countries, or in other words "if imports were made at home", which is common practice (see Trefler, 1995; Antweiler, 1996; Mukhopadyay and Chakraborty, 2005) in the study on pollution content of trade. Later we will relax this assumption by using the technologies of a reference country (Japan).

Accurate gas emissions from fuel combustion depend on knowledge of several interrelated factors such as fuel types, combustion technology as well as abatement efficiency. Yet, $CO_2$ emissions are primarily dependent on the carbon content of the fuel which enables calculation at a highly aggregated level (IPCC, 1996). However, for $SO_2$ and $NO_x$, IPCC guidelines suggest that they are calculated on a detailed activity/technology level. Detailed discussion and calculation of the emission factors can be found in appendix 4.2. We adopt the following emission factors to construct matrix E.

**Table 4.1 Matrix E : Average Emission Factors (TON/SCE)**

| | Raw coal | Crude oil | Natural gas |
|---|---|---|---|
| $CO_2$ | 2.712 | 2.15 | 1.633 |
| $SO_2$ | 0.0225 | 0.0070 | 0 |
| $NO_x$ | 0.0088 | 0.0059 | 0.0044 |

Note: since crude oil and natural gas are reported together in the 2002 basic IO table and all the extended IO tables, we recalculate the emission factors according to the mix of crude oil and natural gas using annual Chinese energy consumption data.

Data on energy outputs in monetary units is obtained from Chinese I-O tables and energy outputs in physical units are obtained from the Chinese Statistical Yearbooks. We construct the diagonal matrix R as follows:

**Table 4.2 Matrix R ($10^{-3}$ SCE/RMB)**

| Year | Raw Coal | Crude Oil | Natural Gas |
|---|---|---|---|
| 1987 | 24.27 | 7.72 | 10.77 |
| 1992 | 10.98 | 3.40 | 15.81 |
| 1997 | 4.40 | 1.50 | 2.56 |
| 2002 | 2.59 | 0.86* | 0.86* |

* In 2002 Chinese I-O table, we only have two primary energy sectors since crude oil and natural gas are reported in a combined manner. We treat producer's prices of crude oil and natural gas as the same.

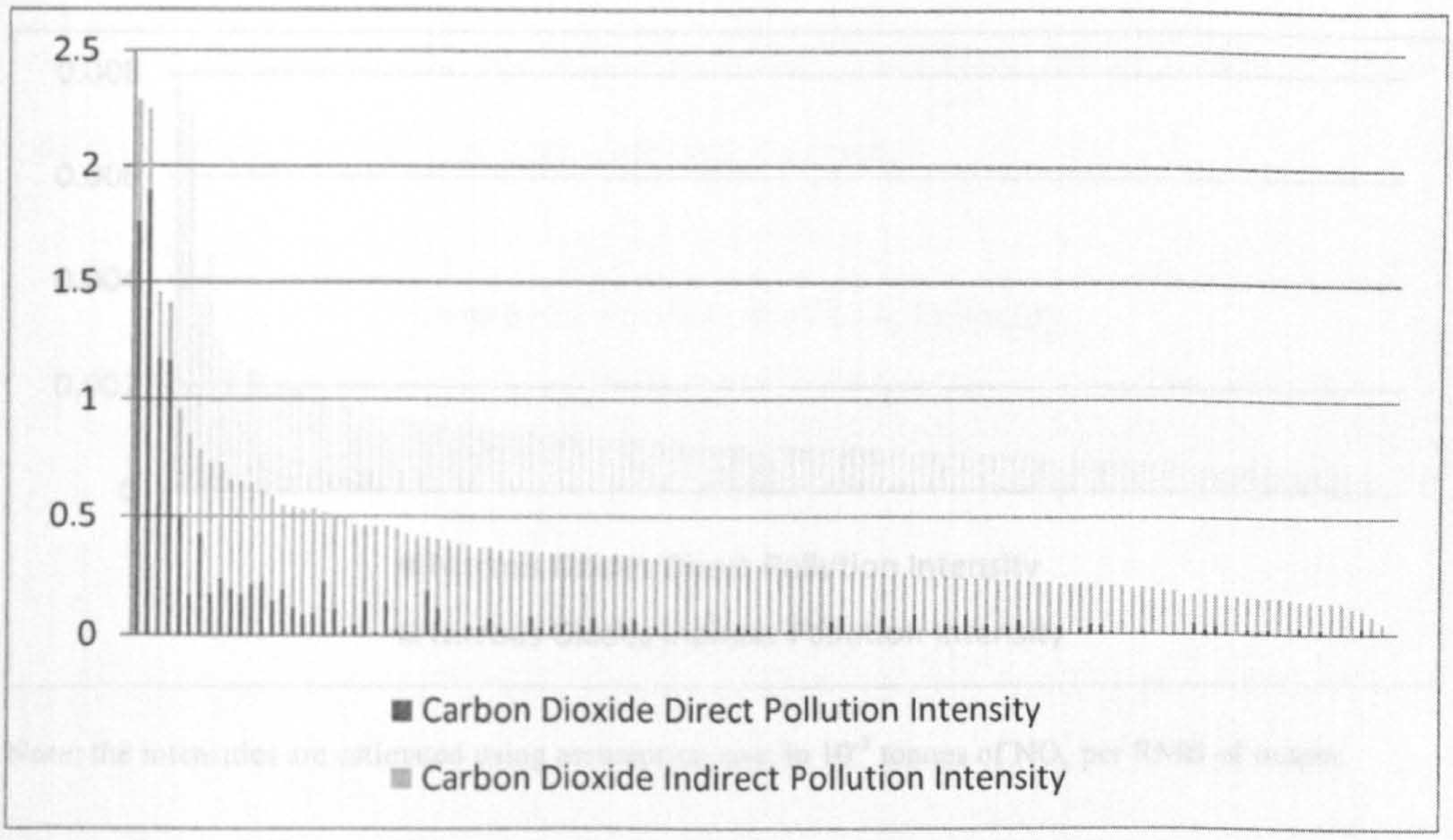
The entries of matrix R can be viewed as the producer's price of energy, i.e., the unit of energy content can be bought per unit of RMB. The producer's price of energy differs significantly across fuel type. Crude oil is the most expensive fuel in terms of energy content while raw coal only costs about a third of crude oil. The relative prices of fuels are to great extent consistent with the affluence of resources endowments in China. Also we notice that the prices of fuels have been increasing (even under constant RMB) over the years due to sectoral price level changes.

## 4.4.2 Results

### 4.4.2.1 Sectoral pollution intensity breakdown

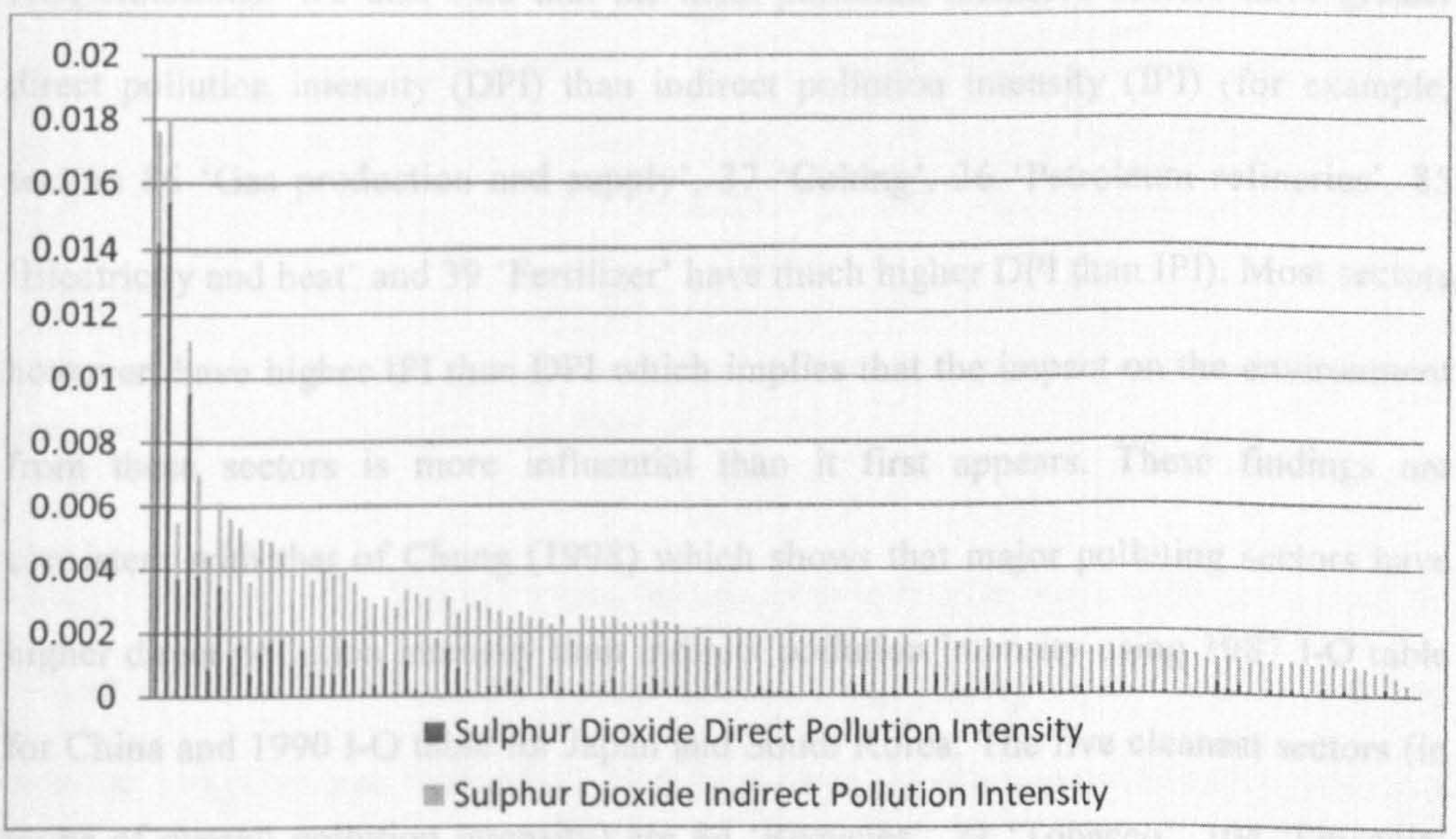
We first show the overall pollution intensity (OPI) at sectoral level with the breakdown into indirect (IPI) and direct pollution intensity (DPI). Taking the example of the 122-sector 2002 I-O table, the sectoral pollution intensities are plotted in columns (Carbon Dioxide are plotted in graph 4.1, Sulphur Dioxide in graph 4.2 and Nitrous Oxides plotted in graph 4.3). The sectors are ranked in descending order of overall $CO_2$ on the horizontal axis for all the three tables. Due to space limitation, the codes for sectors are not shown in the graphs.

**Graph 4.1 Sectoral Pollution Intensities $CO_2$ (2002 122-sector I-O)**



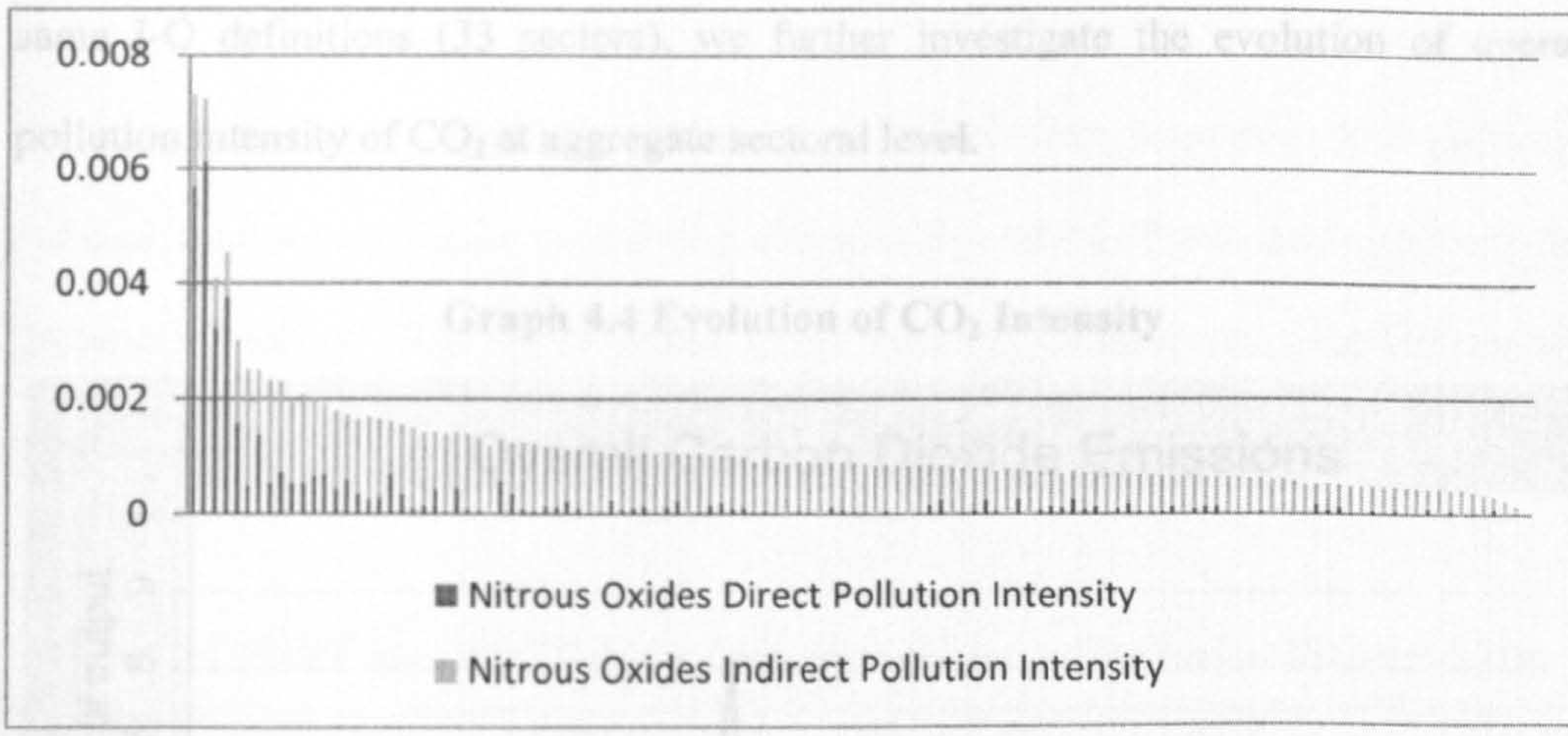

Note: the intensities are estimated using assumption one; in $10^{-3}$ tonnes of $CO_2$ per RMB of output.

**Graph 4.2 Sectoral Pollution Intensities $SO_2$ (2002 122-sector I-O)**




Note: the intensities are estimated using assumption one; in $10^{-3}$ tonnes of $SO_2$ per RMB of output.

**Graph 4.3 Sectoral Pollution Intensities $NO_x$ (2002 122-sector I-O)**

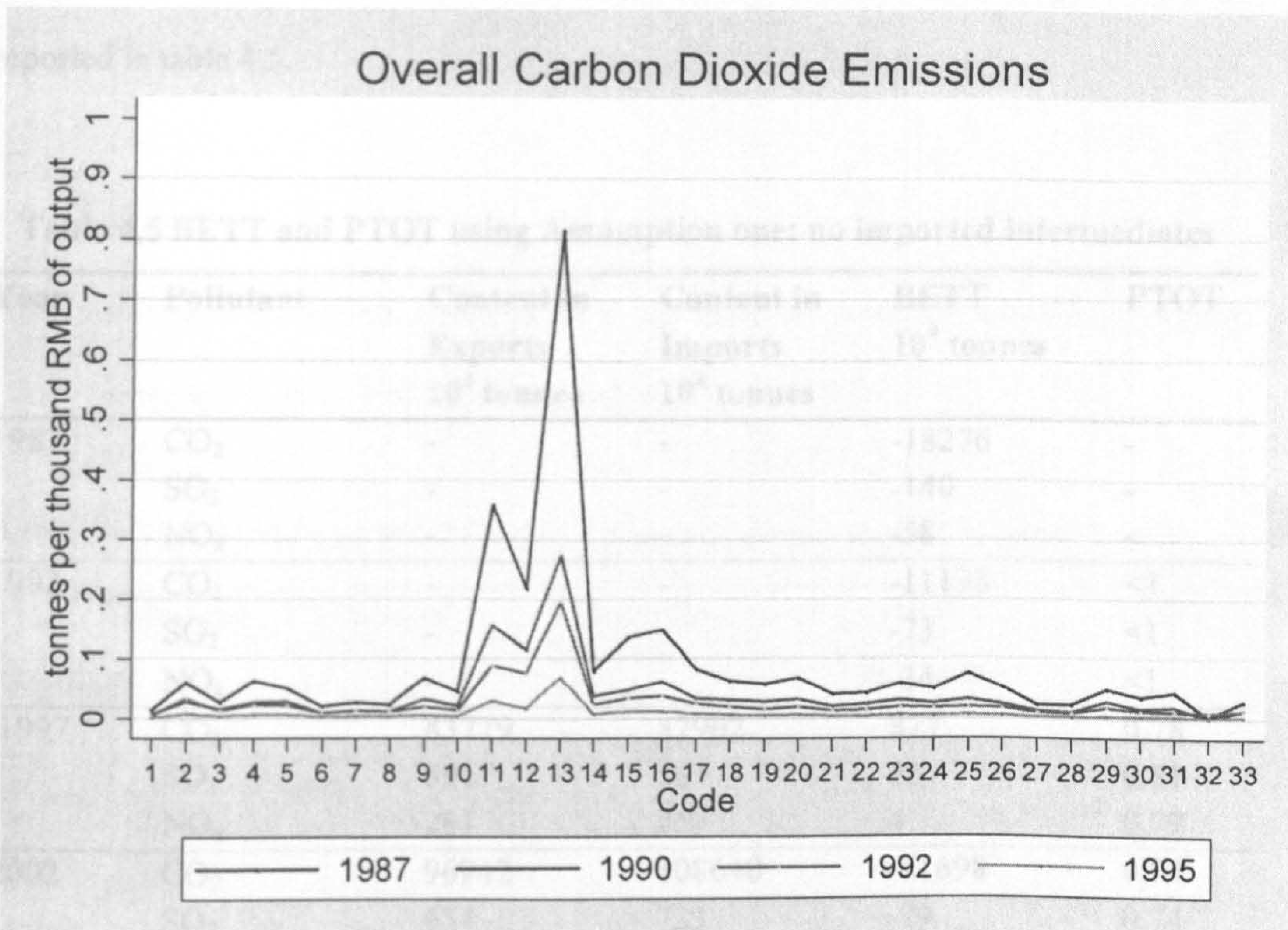



Note: the intensities are estimated using assumption one; in $10^{-3}$ tonnes of $NO_x$ per RMB of output.

Comparing the three tables, we find that they share great similarity in intensity rankings. Sectors which are intensive in $CO_2$ emissions tend to be intensive in $SO_2$ and $NO_x$ emissions. We also find that the most pollution intensive sectors have greater direct pollution intensity (DPI) than indirect pollution intensity (IPI) (for example, sectors 86 'Gas production and supply', 37 'Coking', 36 'Petroleum refineries', 85 'Electricity and heat' and 39 'Fertilizer' have much higher DPI than IPI). Most sectors, however, have higher IPI than DPI which implies that the impact on the environment from these sectors is more influential than it first appears. These findings are consistent with that of Chung (1998) which shows that major polluting sectors have higher direct pollution intensity than indirect pollution intensity using 1987 I-O table for China and 1990 I-O table for Japan and South Korea. The five cleanest sectors (in terms of overall pollution intensity) are 84 'Recycles', 22 'Tobacco', 104 'Financial services', 106 'Real estate' and 109 'Tourism'. Same conclusions can be drawn when we use other Chinese I-O tables under different assumptions: the most pollution intensive sectors normally have higher direct pollution intensity than indirect pollution intensity while other sectors mostly have the opposite trend.

Since the extended I-O tables for 1987, 1990, 1992 and 1995 are constructed using the same I-O definitions (33 sectors), we further investigate the evolution of overall pollution intensity of $CO_2$ at aggregate sectoral level.

**Graph 4.4 Evolution of $CO_2$ Intensity**




Note: To enable compatibility, all prices are inflated to 2002 level; price indices are from China statistical yearbooks; $10^{-3}$ tonnes of $CO_2$ per RMB of output.

Graph 4.4 shows that over the years the emission intensities have been decreasing for almost all the sectors, with the most dramatic changes being for the heavily polluting sectors: 11 (Petroleum refineries), 12 (Chemicals), 13 (Non-metal mineral products), 15 (Metal products), and 16 (Machinery). The most noticeable decrease in overall pollution intensity lies in 13 (Non-metal mineral products, including cement, stone and clay products which are in many studies listed as notorious heavy polluters); the overall pollution intensity of this sector decreased from over 0.8 tonnes $CO_2$ per RMB of output to 0.27 tonnes $CO_2$ per RMB of output.

#### 4.4.2.2 Potential pollution content (common technologies)

We report the basic results for pollution generated from exporting and pollution avoided from importing using existing Chinese I-O tables. Trade data are from the Chinese I-O tables[50]. The results based on the basic I-O tables and assumption one are reported in table 4.5.

**Table 4.5 BETT and PTOT using Assumption one: no imported intermediates**

| Year | Pollutant | Content in Exports $10^4$ tonnes | Content in Imports $10^4$ tonnes | BETT $10^4$ tonnes | PTOT |
|---|---|---|---|---|---|
| 1987 | $CO_2$ | - | - | -18276 | - |
| | $SO_2$ | - | - | -140 | - |
| | $NO_x$ | - | - | -58 | - |
| 1992 | $CO_2$ | - | - | -11138 | <1 |
| | $SO_2$ | - | - | -73 | <1 |
| | $NO_x$ | - | - | -34 | <1 |
| 1997 | $CO_2$ | 83779 | 82902 | 877 | 0.78 |
| | $SO_2$ | 591 | 563 | 28 | 0.81 |
| | $NO_x$ | 261 | 257 | 4 | 0.79 |
| 2002 | $CO_2$ | 96942 | 108640 | -11698 | 0.74 |
| | $SO_2$ | 654 | 733 | -79 | 0.74 |
| | $NO_x$ | 300 | 336 | -36 | 0.77 |

Note: In 1987 and 1992 IO tables, only net exports are reported. In 1987, China has trade deficit equalling to 4343416 ($10^4$ RMB) and in 1992 net exports is 2507565 ($10^4$ RMB).

Assuming same Chinese technologies to produce exports and imports (common technology assumption), it seems that China does not fit in the term "pollution haven" well. The table above shows that the China's pollution content in net exports turns out to be negative for the three air pollutants in the years except 1997[51]. This absolute measure suggests that in most of the years investigated China has "pollution deficit"

[50] There are some data quality issues concerning the trade data in Chinese I-O tables; firstly, imports are recorded as CIF while exports are recorded as FOB. In other words, transportation and insurance costs lift the nominal value of imports. Secondly, imports also include custom duties. Ahmad and Wyckoff (2003) assume 10% of the import value reflects both transportation and insurance costs.

[51] Ahmad and Wyckoff (2003) also report positive net pollution exports for China in 1997.

relative to the rest of the world from international trade. The implication is surprising given that China has an enormous trade surplus since 1990s. The PTOT index shows that in terms of any of the three pollutants China's imports are more pollution intensive than its exports in 1992[52], 1997 and 2002. Also the results suggest that China's exports are becoming slightly less pollution intensive from 1997 to 2002, which may be caused by advancement in production technologies and changes in trade mix.

Now we turn to the results obtained from the adjusted domestic technology matrix (using assumption two). The results are reported in table 4.6.

**Table 4.6 BETT and PTOT using Assumption two: import proportionality**

| Year | Pollutant | Content in Exports $10^4$ tonnes | Content in Imports $10^4$ tonnes | BETT $10^4$ tonnes | PTOT |
|---|---|---|---|---|---|
| 1997 | $CO_2$ | 67623 | 68873 | -1250 | 0.76 |
| | $SO_2$ | 482 | 468 | -14 | 0.79 |
| | $NO_2$ | 211 | 213 | -2 | 0.77 |
| 2002 | $CO_2$ | 71152 | 84055 | -12903 | 0.74 |
| | $SO_2$ | 483 | 569 | -86 | 0.74 |
| | $NO_2$ | 221 | 260 | -39 | 0.74 |

Given that the I-O tables of 1987 and 1992 do not report imports and exports of commodities separately, our import proportionality approach could only apply to the 1997 and 2002 I-O tables. The values of pollution content in both exports and imports are now smaller than those obtained without "proportionality". The BETT values in the table above shows that despite a substantial trade surplus in goods China runs a "pollution deficit", with imports embodying more pollutants than its exports, in both 1997 and 2002. The average per unit content of exports must be significantly lower

[52] It is inferred from the data that the PTOT index for China in 1992 is less than 1.

than that of imports. After excluding the pollution embodied in imported intermediate inputs, the BETT values for 1997 change from positive in the previous estimation to negative in the table above, which may indicate the importance of processing trade in some polluting industries in China as well as measurement error due to the simple approach of "import proportionality".

With smaller magnitudes than before, the PTOT ratios still suggest China's imports are more pollution intensive than its exports. And China's exports are becoming slightly less pollution intensive from 1997 to 2002. These results are consistent with other findings (discussed in the introduction) and with China having a comparative advantage in "cleaner" industries based on labour endowment advantages and with China "gaining" environmentally (in terms of local pollutants only; $CO_2$ is a global pollutant) from trade overall and from matched expansions of exports and imports.

We also use the more aggregated extended I-O tables to carry out a sensitivity check. There are 33 sectors for the 1987,1990,1992,1995 extended I-O tables, 40 sectors for 1997, and 42 sectors for 2002. Same methodologies and assumptions are applied to obtain BETT and PTOT values.

**Table 4.7 BEET in $10^4$ tonnes (Robustness Check)**

| Year | Assumption | Sectors | $CO_2$ | $SO_2$ | $NO_x$ |
|---|---|---|---|---|---|
| 1987 | 1 | 33 | -15511.1 | -125.2 | -50 |
| 1990 | 1 | 33 | -879.3 | -15.7 | -3.6 |
| 1992 | 1 | 33 | -5903.7 | -40.7 | -18.4 |
| 1995 | 1 | 33 | -2768.7 | -9.9 | -7.7 |
| 1997 | 1 | 40 | 3801.1 | 41.0 | 13.2 |
| 1997 | 2 | 40 | 2181.7 | 30.0 | 8.2 |
| 2002 | 1 | 42 | -2365.6 | -9.8 | -6.7 |
| 2002 | 2 | 42 | -2652.3 | -11.3 | -7.6 |

The conclusion from our previous analysis hold in the sensitivity check for most of the years, i.e. China runs a "pollution deficit" in most of the years except 1997. It is also shown that even under the "import proportionality" approach; we find that China has more pollution embodiment in exports than that in imports in 1997. This does not coincide with the earlier results from using the basic 1997 I-O table. It seems that aggregation level would affect the results. Should we use a more disaggregated I-O table, the results for BEET may change too.

The following table presents the PTOT values. Though larger than the previous results, the PTOT values consistently suggest China's imports are more pollution intensive than its exports. However, contrary to the previous estimation based on the basic I-O tables, the values are getting bigger from 1997 to 2002. It seems that to some extent aggregation level also matters to PTOT values. Extra care should be taken towards our earlier conclusion on whether China is moving further away from "pollution haven".

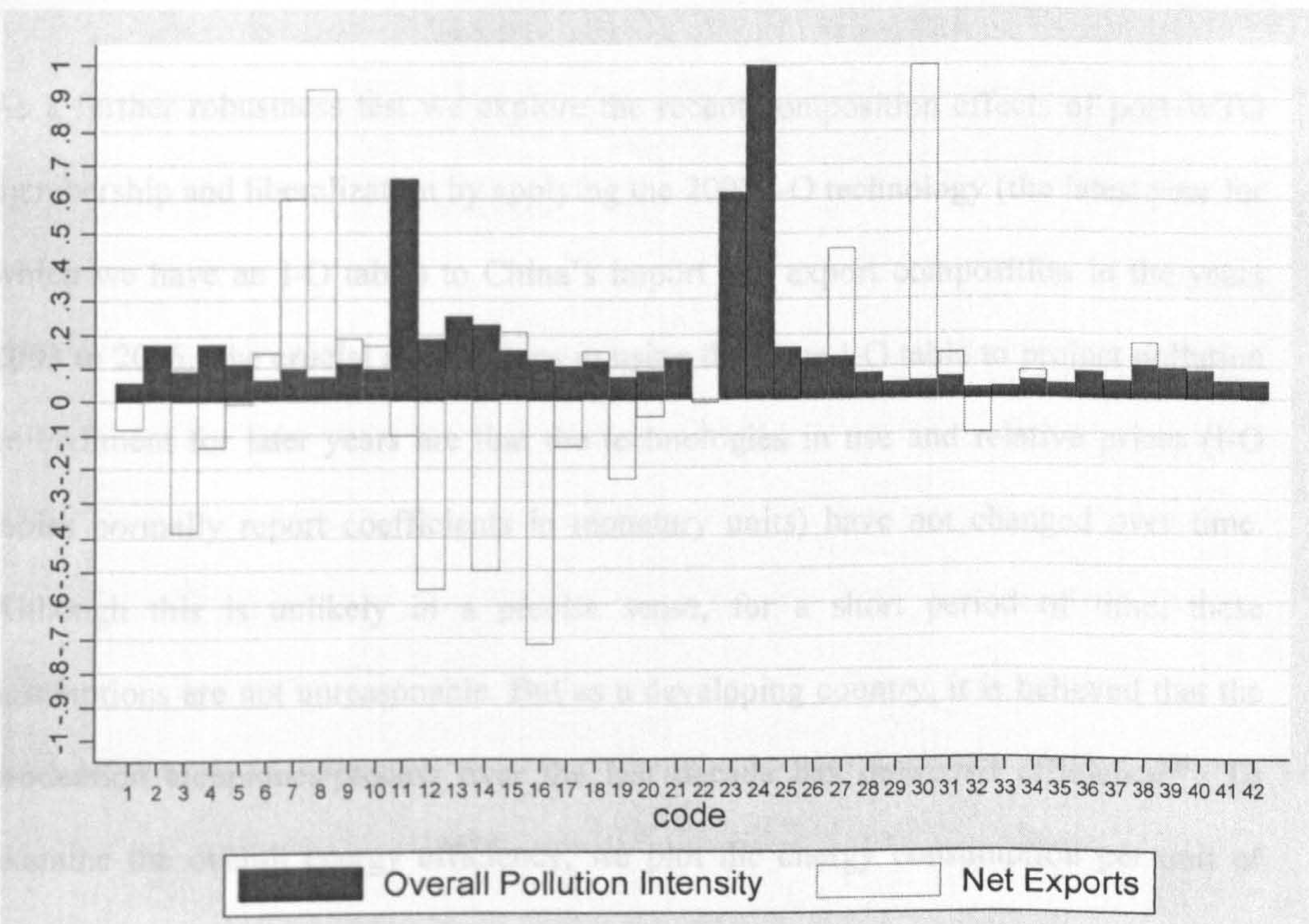
**Table 4.8 PTOT from Extended I-O tables (Robustness Check)**

| Year | Assumption | Sectors | $CO_2$ | $SO_2$ | $NO_x$ |
|---|---|---|---|---|---|
| 1997 | 1 | 40 | 0.81 | 0.83 | 0.81 |
| 1997 | 2 | 40 | 0.80 | 0.82 | 0.80 |
| 2002 | 1 | 42 | 0.85 | 0.86 | 0.85 |
| 2002 | 2 | 42 | 0.84 | 0.85 | 0.84 |

Based on the main results and those from the robustness checks, we conclude that China's imports more pollution embodiment than its exports in most of the years except in 1997 when there is ambiguity under different aggregation levels. Besides, China's exports are less pollution intensive than its imports. In other words, China's environment would be worsened for it to stop exporting and produce the imports domestically.

The fact that China's exports are greener than its imports has its root in the sectoral trade patterns. To understand this overall result we explore the (normalised) relationship between net exports and overall pollution intensity at the sectoral level using 2002 42-sector I-O table. Normalisation is carried out for the two variables. The sector with the largest net exports value (30 wholesale and retail) is taken as 1, with the net exports of the other sectors are expressed as its ratio. Similarly, the overall pollution intensity of the most polluting sector (24 Coking) is taken as 1.

**Graph 4.5 Overall Pollution Intensity and Net Exports, 2002**




Graph 4.5 shows that China has relatively large trade surpluses in the relatively clean sectors such as (7 Textiles, 8 Wearing apparel, 27 Transportation and warehouse, 30 Wholesale and retail). In the dirty sectors, China either has a very small trade surplus (e.g. the sectors 13 Non-metal mineral products, 23 Electricity and heat and 24 Gas) or runs a trade deficit (sectors 11 Petroleum refineries, 12 Chemicals and 14 Metal smelting). These findings provide evidence to our earlier conclusions of BETT and

PTOT. It seems to suggest that China has competitive advantage in cleaner industries. If we analyse other I-O tables, similar conclusions can be drawn. To conserve space, the graphs based on other I-O tables are not reported.

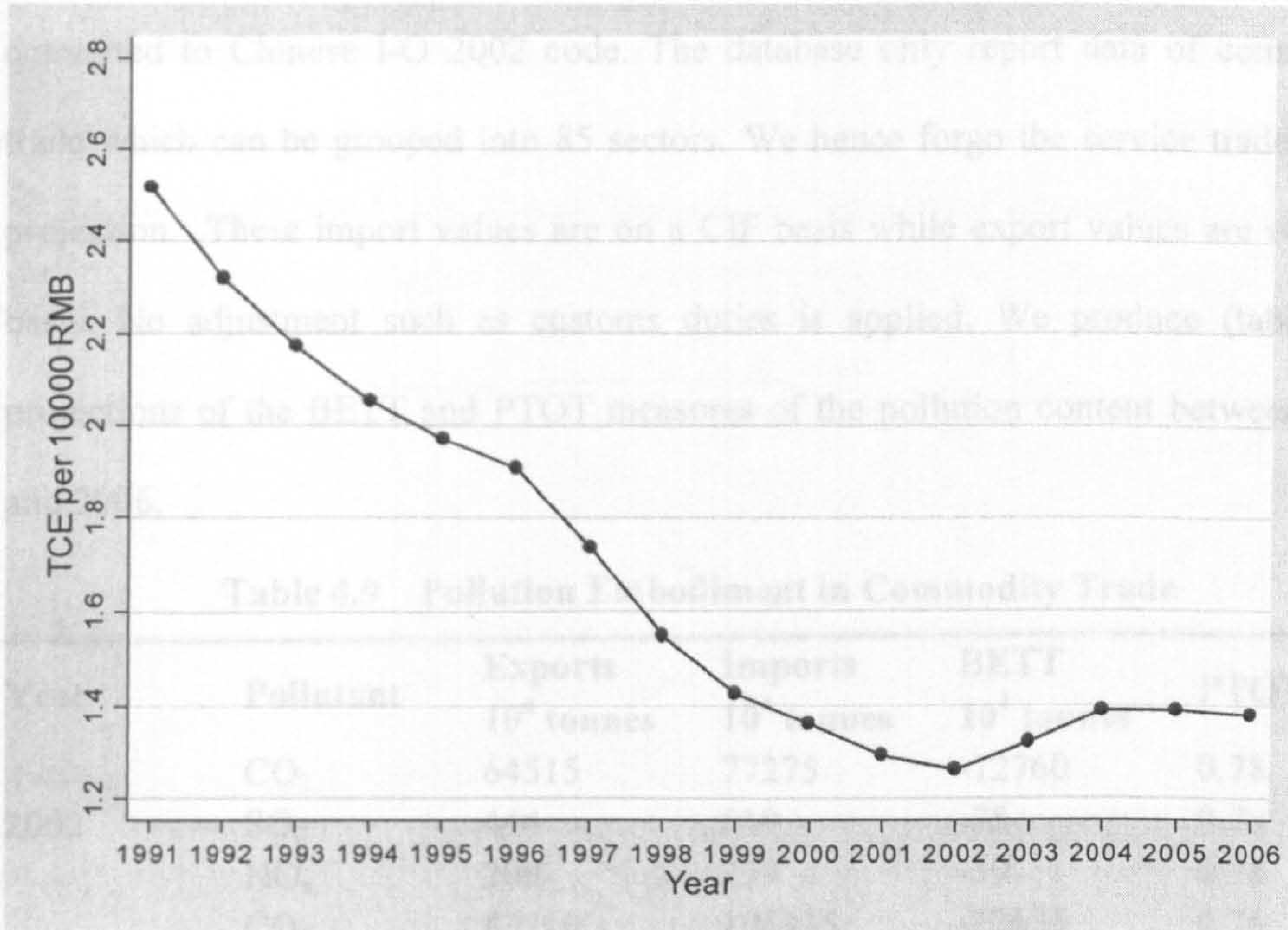
In the following analysis for pollution content projection and heterogeneous technology, we continue to adopt import proportionality approach to gauge the effect of imported intermediate goods.

#### 4.4.2.3 Projection for recent years

As a further robustness test we explore the recent composition effects of post-WTO membership and liberalization by applying the 2002 I-O technology (the latest year for which we have an I-O table) to China's import and export composition in the years 2003 to 2006. The crucial assumptions in using the same I-O table to project pollution embodiment for later years are that the technologies in use and relative prices (I-O tables normally report coefficients in monetary units) have not changed over time. Although this is unlikely in a precise sense, for a short period of time, these assumptions are not unreasonable. But as a developing country, it is believed that the production techniques/process over the last decade has improved efficiency[53]. To examine the overall energy efficiency, we plot the energy consumption per unit of output in the following graph.

[53]Gabaccio et al. (1999) suggest that much of the fall in energy-output ratio for the 1987-1992 periods was due to technical changes. Smil (1994) suggest that structural changes have been the dominant factor. Sinton and Fridley (2000) attribute the fall to a number of factors, including both structural and efficiency changes.

**Graph 4.6 Evolutions of Energy Intensities**




Source: China Energy Yearbooks various years; in 2002 constant price.

The energy requirement for per unit GDP output in China has experienced dramatic decreases in the last decade which may be attributed to a number of factors including both efficiency increase and structural adjustment. (See Garbaccio et al, 1999; Sinton and Fridley, 2000) However, this trend comes to a halt in 2002; the energy intensity in recent years has been higher than the lowest point in 2002 and remains rather stable since 2004.

However, we do not have information on sectoral energy information as well as relative prices. To compromise, we restrict the analysis to the composition effect (trade mix) only. Other things equal, will China's deepened trade with the rest of the world reverse the trend and turn China into a pollution haven (in our definition, PTOT>1)? We examine whether the composition effect could have played an important role in later years given the 2002 production technologies.

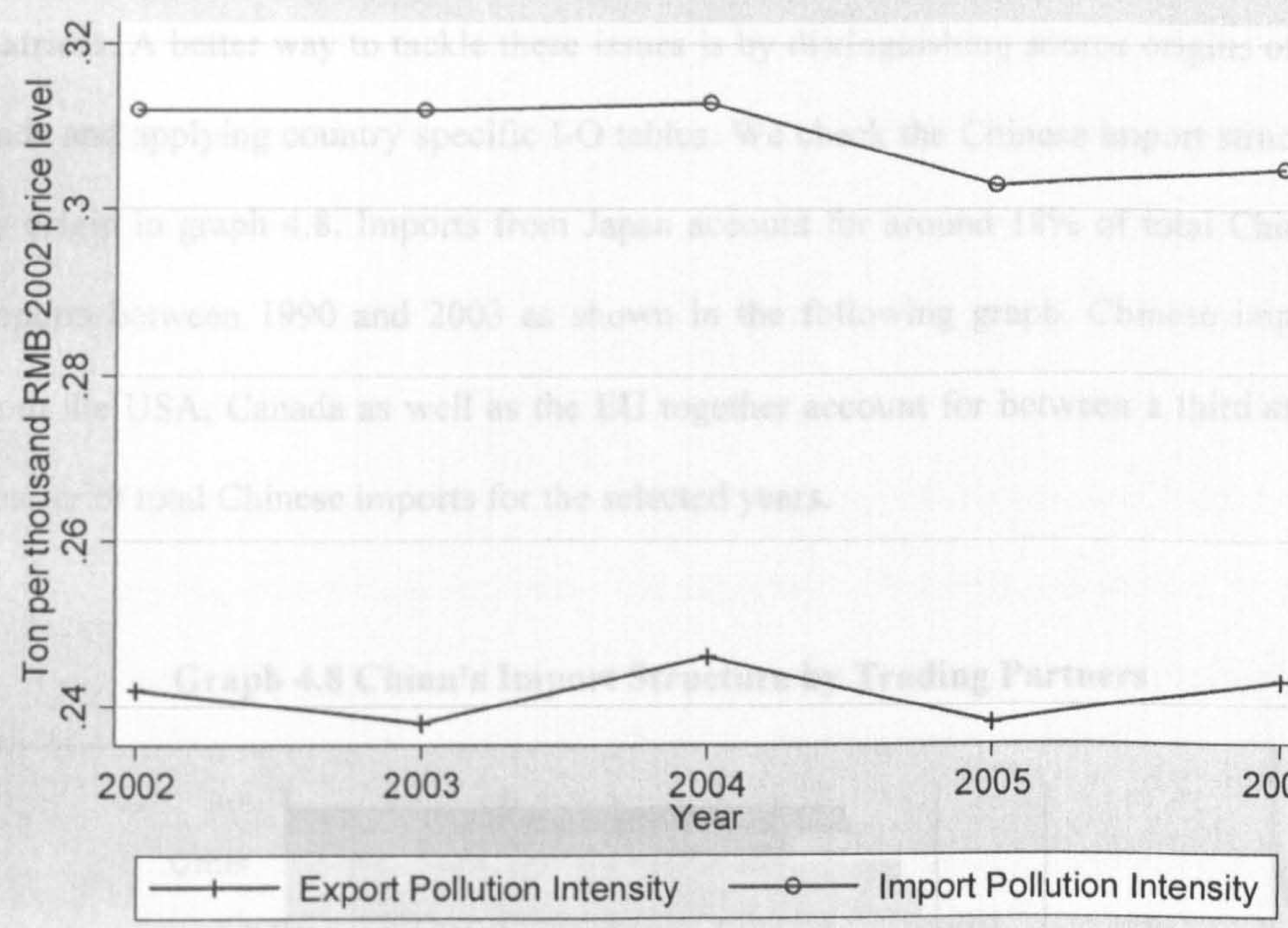
Trade data is in HS 2002 code and obtained from UNCOMTRADE database. It is then converted to Chinese I-O 2002 code. The database only report data of commodity trade which can be grouped into 85 sectors. We hence forgo the service trade in the projection. These import values are on a CIF basis while export values are on FOB basis. No adjustment such as customs duties is applied. We produce (table 4.9) projections of the BETT and PTOT measures of the pollution content between 2002 and 2006.

**Table 4.9 Pollution Embodiment in Commodity Trade**

| Year | Pollutant | Exports $10^4$ tonnes | Imports $10^4$ tonnes | BETT $10^4$ tonnes | PTOT |
|---|---|---|---|---|---|
| | $CO_2$ | 64515 | 77275 | -12760 | 0.78 |
| 2002 | $SO_2$ | 444 | 519 | -75 | 0.79 |
| | $NO_x$ | 200 | 239 | -39 | 0.78 |
| | $CO_2$ | 83710 | 106335 | -22625 | 0.76 |
| 2003 | $SO_2$ | 574 | 717 | -143 | 0.78 |
| | $NO_x$ | 260 | 329 | -69 | 0.77 |
| | $CO_2$ | 110033 | 137547 | -27514 | 0.78 |
| 2004 | $SO_2$ | 765 | 925 | -160 | 0.81 |
| | $NO_x$ | 343 | 426 | -83 | 0.79 |
| | $CO_2$ | 132676 | 150766 | -18090 | 0.79 |
| 2005 | $SO_2$ | 913 | 1012 | -99 | 0.81 |
| | $NO_x$ | 413 | 466 | -53 | 0.79 |
| | $CO_2$ | 159543 | 169163 | -9620 | 0.80 |
| 2006 | $SO_2$ | 1103 | 1121 | -18 | 0.83 |
| | $NO_x$ | 497 | 522 | -25 | 0.80 |

Both measures are consistent with earlier results. BETT values are all negative regardless of the years and pollutants. It also shows that the net avoided pollution in commodities at first increased and then decreased for all the three pollutants. It is noticed that the PTOT values also experienced some variation across the years but still remain less than 1 regardless of the years and pollutants we examined. It seems that the composition effect alone does not change the trend that Chinese exports are greener than its imports. Graph 4.7 plots overall $CO_2$ emission intensity in exports and imports between 2002 and 2006. With ups and downs in between, the export pollution intensity is roughly the same in 2002 and 2006. In the meanwhile, the imports pollution intensity has slightly decreased in 2005 and 2006.

**Graph 4.7 Pollution Intensities of Exports and Imports (Commodity Trade only)**

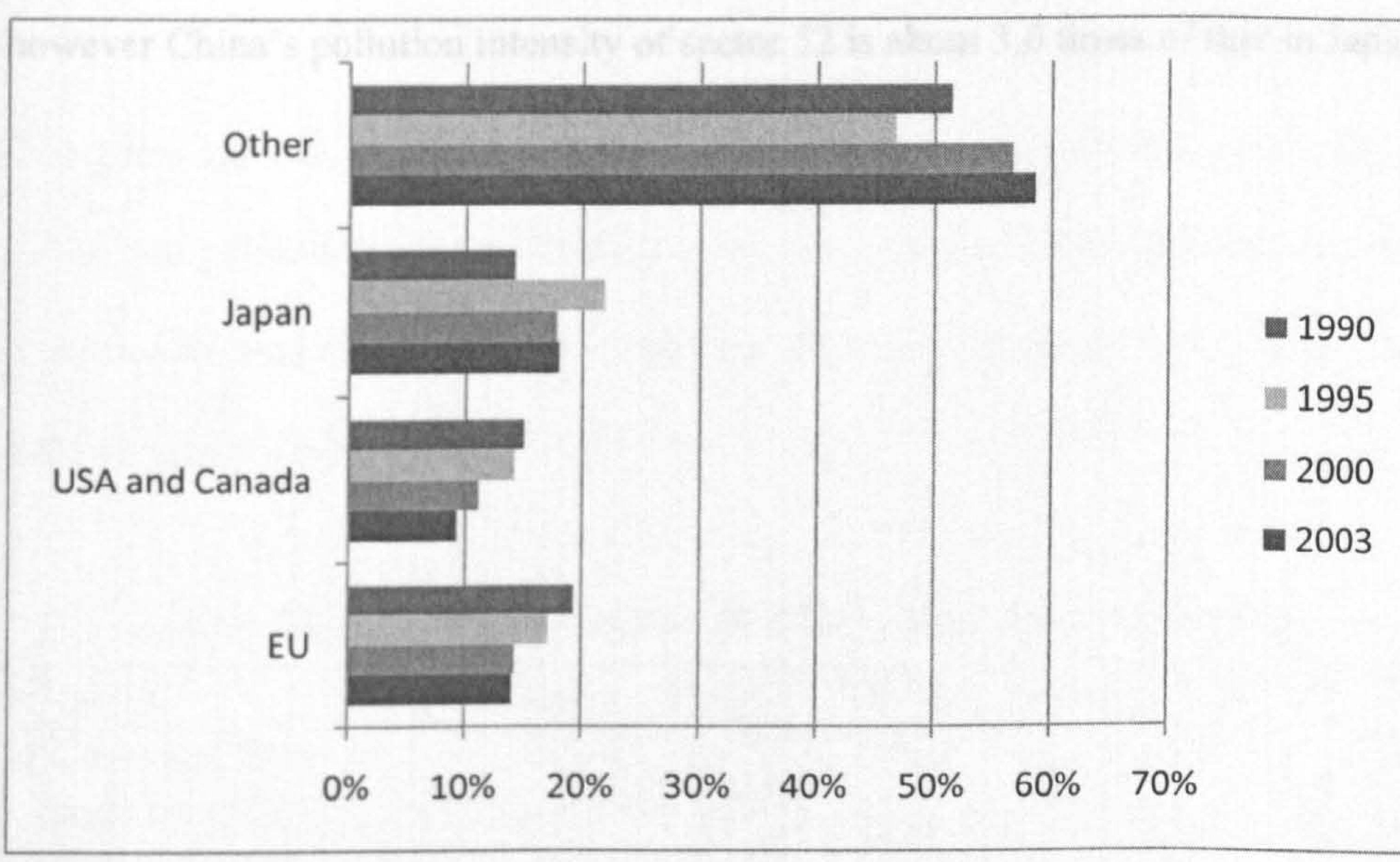



To sum up, our analysis based on common technology assumption shows that for the years we studied the volume of air pollution avoided by importing is larger than that of emitted by exporting. Also, it seems that China gains environmentally in the sense that Chinese exports are relatively less pollution intensive than imports.

### 4.4.2.4 Heterogeneous technologies

So far our calculations have been based on the implicit assumption that countries share the same production technologies. For a developing country like China that trades a lot with developed countries this assumption is likely to produce an overestimate of the actual pollution embodied in imports. Firstly, countries differ in their energy structure and energy efficiency. China has a coal predominated energy structure which depends heavily on fossil fuels, while its trading partners especially OECD countries depend more on cleaner fuels (partly due to pollution limits constrained by international agreements and national regulations). Secondly, there are also likely to be different inter- and intra-sectoral linkages across countries expressed in the differences in I-O matrices. A better way to tackle these issues is by distinguishing source origins of the trade and applying country specific I-O tables. We check the Chinese import structure by origin in graph 4.8. Imports from Japan account for around 18% of total Chinese imports between 1990 and 2003 as shown in the following graph. Chinese imports from the USA, Canada as well as the EU together account for between a third and a quarter of total Chinese imports for the selected years.

**Graph 4.8 China's Import Structure by Trading Partners**




Data source: UNCTAD Handbook of Statistics 2004.

Japan is one of the most important trading partners to China and also adopts a similar structure of commodity by commodity I-O tables as China. Due to data limitation on I-O tables, we use Japan[54] as a representative exporting country to China.

[54] Japan has since 1955 been producing extensive bench-mark I-O tables every five years and producing extended I-O tables annually. The Japanese Statistics Bureau website provides the 1995 basic I-O tables

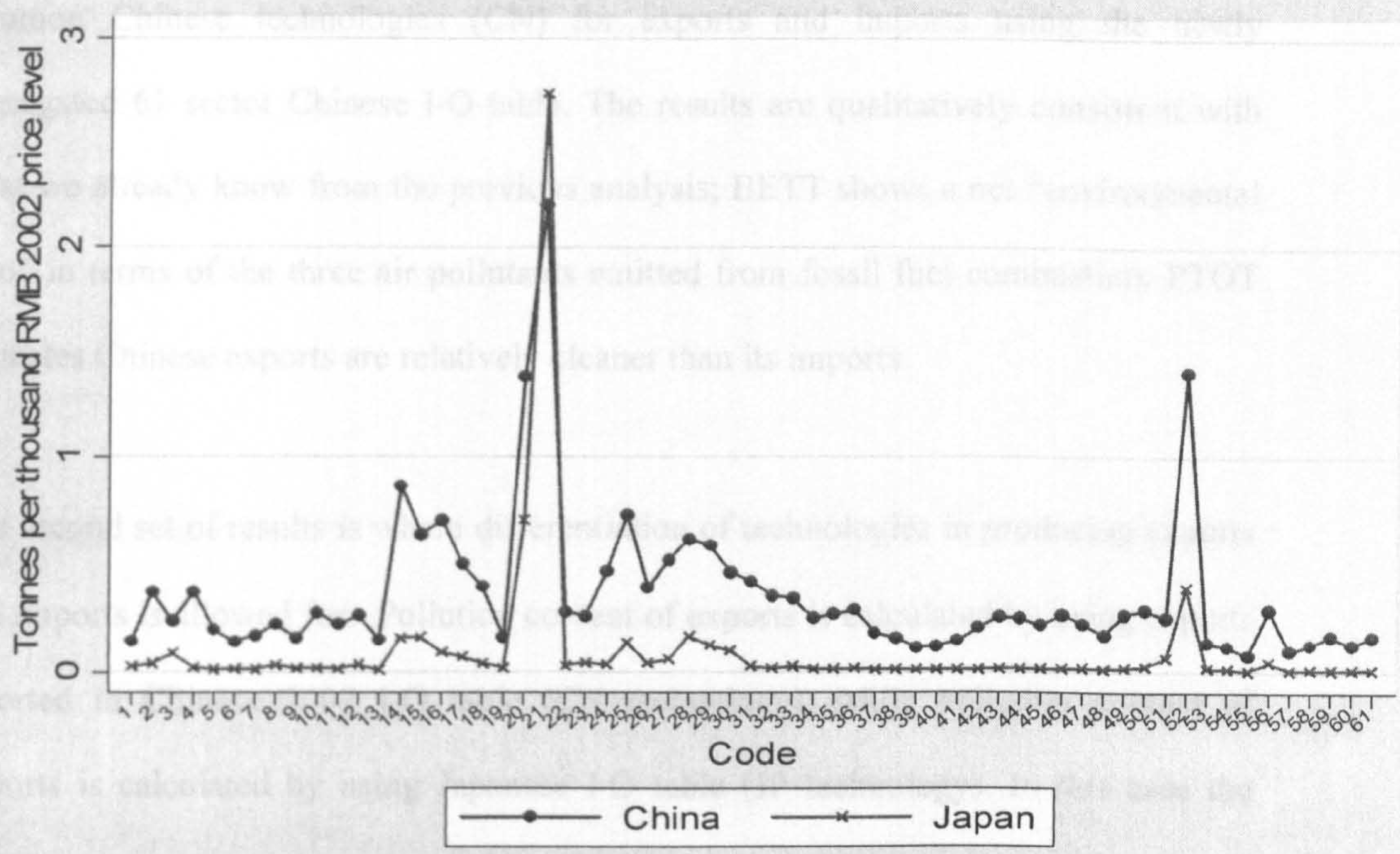
To make the I-O tables comparable, we need to aggregate the sectors. We use the 71-commodity Japanese extended I-O table (JP) and the 122-commodity bench mark Chinese I-O table (CN) for the year 2002[55]. Then we aggregate the commodities into 61 sectors. Trade data is derived from Chinese 2002 I-O table.

We initially compare the overall pollution intensities for China and Japan in 2002 in terms of carbon dioxide emissions. Graph 4.6 shows that Japan is generally more energy efficient than China. The only one exception is sector 21 (Coking), which is the most polluting industry in both economies. Japan has less sectoral variation in pollution intensity compared to China. There are several sectors in China which significantly lag behind their Japanese counterparts. For example, the second heaviest polluting sector in both economies is 52 (Electricity, steam and hot water production); however China's pollution intensity of sector 52 is about 3.6 times of that in Japan.

(93 sectors) and the 2000 basic I-O tables (104) sectors. From the website of Japanese Ministry of Economy Trade and Industry, there are also I-O tables for various years based on the basic I-O tables. There are I-O tables (71 or 50 sectors) for the years 1997 to 2002 based on the bench mark 1995 I-O tables and I-O tables (186, 73 or 50 sectors) for the years 2003 to 2006 based on the bench mark 2000.

[55] We only focus on the year 2002 since the 1997 Japanese extended I-O table only has 41 sectors and does not distinguish coal from oil and natural gas.

**Graph 4.6 Overall Pollution Intensities in China and Japan**




Using the methodologies and data outlined in the previous sections, we re-calculate actual and potential pollution content using the two alternative measures for China's international trade in 2002. The results are divided in three groups as shown in the following table (table 4.10).

**Table 4.10 Pollution Content Based on Alternative Technologies**

| IO tables | Pollutants | Exports | Imports | BETT ($10^4$ tones) | PTOT |
|---|---|---|---|---|---|
| **1) Common Tech** | $CO_2$ | 70972 | 83505 | -12533 | 0. 74 |
| Exports using CN[a] | $SO_2$ | 485 | 565 | -80 | 0. 75 |
| Imports using CN | $NO_x$ | 220 | 259 | -38 | 0. 74 |
| **2) Heterogenous Tech** | $CO_2$ | 70972 | 46974 | 23998 | 1. 32 |
| Exports using CN | $SO_2$ | 485 | 302 | 183 | 1. 40 |
| Imports using JP[b] | $NO_x$ | 220 | 144 | 76 | 1. 33 |
| **3) Common Tech** | $CO_2$ | 35673 | 46974 | -11300 | 0. 66 |
| Exports using JP | $SO_2$ | 225 | 302 | -76 | 0. 65 |
| Imports using JP | $NO_x$ | 108 | 144 | -35 | 0. 66 |

a. Represents the 61 sector Chinese IO table. b. Represents the 61 sector Japanese IO table.

The first set of results replicates the calculations of pollution content based on common Chinese technologies (CN) for exports and imports using the newly aggregated 61 sector Chinese I-O table. The results are qualitatively consistent with what we already know from the previous analysis; BETT shows a net "environmental gain" in terms of the three air pollutants emitted from fossil fuel combustion; PTOT indicates Chinese exports are relatively cleaner than its imports.

The second set of results is where differentiation of technologies in producing exports and imports is allowed for. Pollution content of exports is calculated by using exports reported in Chinese 2002 I-O table (CN technology), while pollution content of imports is calculated by using Japanese I-O table (JP technology). In this case the BETT measure is now positive and the PTOT measure is greater than unity (indeed well in excess of unity). The sign on actual pollution content of China's trade which allows for technology differences between China and its trading partners is reversed relative to the hypothetical pollution content based on the common technology assumption. The actual measure shows that China actually exported more pollution content than it imported, in total and per unit terms. The BETT measure captures in part the influence of the trade surplus, but the results indicate that on average a unit of Chinese exports actually embodies (i.e. induce emissions of) about 32% to 40% more air pollutants than embodied in a unit of imports (produced outside of China).[56] It implies that the globe as a whole could have to accommodate more air pollution because of this trade liberalization. Of course, the validity of using Japan as a reference country and the results are open to robustness checks. It is important, therefore, to recognise when it is appropriate to measure actual and potential pollution

[56] Although not explicitly reporting BETT values, Ahmad and Wyckoff (2003) and Shui and Harriss (2006) report results for China with differentiation of technology between trading partners which are consistent with our finding on the actual pollution content of China's trade. In our case the fact that PTOT is also great than unity allows us to conclude that China's exports are actually more pollution-intensive than its imports having controlled for China's trade surplus.

content of trade. Potential measures are useful for commenting on the 'gains' for a country from trade, given its endowments and technology. When searching or testing for the factors driving trade, for example when investigating the relative importance of national differences in factor endowments and environmental regulations, one needs to allow for technological differences in measuring the actual factor (pollution) content of trade.

The final set gives out the simulation results are based on the common technology assumption that China's exports and imports were produced using Japanese energy structure and technologies (i.e. 'as if China had the energy efficiency level of an advanced industrialized economy '). Not surprisingly, the pollution content of exports and imports is much lower than before. Compared to the first set of results, we see little change in net exports of pollution content and China would be a net importer of pollution content. With smaller PTOT values than those in the first set of results, China's exports would still be cleaner than its imports. The difference of PTOT values in the first and third sets of results can be viewed as the technique effect that would be generated from technological advances.

In appendix 4.3, we report the projected results for the pollution embodied in bilateral trade between China and Japan using the 2002 Chinese and Japanese I-O coefficients. Bilateral trade data for each sector are from the Japanese I-O tables between 2003 and 2006 (such bilateral trade data only available from 2003 onwards). Using bilateral trade data and Chinese technologies (table A4.3.1), China's trade with Japan seems to be friendly to domestic environment if we view imports from Japan as a replacement of domestic production. BETT values are negative except for the year 2004 when China has positive net export of pollution content. PTOT values also show that Chinese export structure is relatively cleaner than its import structure.

We also examine the actual pollution content in trade using country specific I-O coefficients. The results in table A4.3.2 show that China would be exporting more pollution content to Japan than the imports from Japan if we assume the technology matrices for both countries follow the 2002 I-O patterns. The high values of PTOT suggest that China's exports to Japan are much more pollution intensive than the imports from Japan.

### 4.4.2.5 Further adjustment on fuel products

All the above analysis is based on the assumption that the fossil fuels (Coal, oil and natural gas) are combusted in producing the final goods. However, as Dietzenbacher and Mukhopadhyay (2007) point out, the consumption of the fossil fuels count for pollution not their production. Hence the exports of these goods do not cause pollution emissions in China. Similarly, imports of these goods do not cause pollution emissions in the exporting country. Their remedy of the error is by setting both pollution embodiment in exports and imports of these fossil fuel sectors to zero. We do robustness checks by adopting the same method. The results are in appendix 4.4. Whether BETT and PTOT using basic I-O tables (table A4.4.1), or projected for recent years (table A4.4.2), or under heterogeneous technology assumptions (table A4.4.3), the new results are consistent with earlier findings.

## 4.5 CONCLUSIONS

This paper extends on the previous studies on pollution content of trade in China in a number of ways. Firstly, we use recent Chinese I-O tables which are most comprehensive in details compared to those used in other studies. This extensiveness also enables sensitivity checking on the effects of aggregation bias in measuring pollution content. Secondly, we break down pollution intensity into three elements

(DPI, IPI and OPI) based on the directness of pollution generation. Our results are in consistence with Chung (1998)'s findings. Thirdly, based on the 2002 Chinese I-O table, we explore the compositional effect of international trade on the environment since China's accession into WTO in 2001. Finally, and importantly, we calculate the 'potential' and 'actual' pollution content in trade using alternative technology assumptions (using Japan as a reference country of China's trading partners). Other research typically assumes a common technology to produce both exports and imports of an economy.

Our study shows that China "avoids" more air pollution by imports than it "puts in" by exports with few exceptions in the I-O years being examined. Given China's growing trade surplus, this finding implies that the composition effect alone overwhelms the trade imbalance effect. Our finding is also consistent with the existing evidence in that China's exports are cleaner than imports under common technology assumption. Time-series breakdown also shows that Chinese sectoral pollution intensities have been decreasing in recent years. Based on the technology matrix in 2002, we find that the composition effect continues to contribute in a positive way to China's environment and it alone overcomes trade surplus effect and benefits China's environment in terms of balances of emission terms of trade (BETT). In other words, freer trade enables China to specialize in cleaner goods production and reduce the environmentally damaging importable production.

However, the good news for China may not be good news globally as we have shown that air pollution would have been less were the Chinese exports produced using advanced technologies as in a developed country (such as Japan). There are several sectors (for example, Electricity production, Petroleum refineries and Chemical fertilizers) in China which have much higher overall pollution intensities than their Japanese counterparts and are likely to be higher than other OECD countries. The simulation results imply that China's progress in technologies matters significantly for the control of global environmental issues.

We carry out a few robustness checks to ensure our findings are not biased due to methodological manipulation. Such checks include using different assumptions for imported intermediate usage, heterogeneous production technologies, different I-O tables, as well as pollution emissions of fuel coming from consumption rather than production.

Our findings are generally consistent with many other studies as shown in the table A4.5.1 in Appendix 4.5. However, we are also aware that our study has several issues which need to be addressed in further research work. The first shortcoming stems from our adjustment method of imported intermediate inputs. The "import proportionality" assumption may be oversimplified and the results without any robustness check need to be dealt with caution. In addition, most of the pollution contents are calculated based on Chinese I-O tables. Whilst such calculations show China's trade off in terms of pollution content, they by no means exactly reflect the impact of trade liberalisation on the environment of the globe as whole. Although we have employed Japanese I-O tables to elaborate, the results are open to be scrutinized. Finally, our calculations only focus on pollution generation side (maximized pollution emissions from fuel combustion in the process of production) and ignore pollution abatement.

# APPENDICES TO CHAPTER FOUR

## Appendix 4.1 Definition of I-O codes

**Table A4.1.1 Definitions of Codes in Different Extended I-O Tables**

| Code | 1987/1990/1992/1995 | 1997 | 2002 |
|---|---|---|---|
| 1 | Agriculture | Agriculture | Agriculture |
| 2 | Coal mining and washing | Coal mining and washing | Coal mining and washing |
| 3 | Crude petroleum and natural gas | Crude petroleum and natural gas | Crude petroleum and natural gas |
| 4 | Metal mining | Metal mining | Metal mining |
| 5 | Other mining | Other mining | Other mining |
| 6 | Food and tobacco | Food and tobacco | Food and tobacco |
| 7 | Textiles | Textiles | Textiles |
| 8 | Wearing apparel | Wearing apparel | Wearing apparel |
| 9 | Wood and furniture | Wood and furniture | Wood and furniture |
| 0 | Paper and educational products | Paper and educational products | Paper and educational products |
| 11 | Electricity, steam and hot water | Petroleum | Petroleum |
| 12 | Petroleum | Chemicals | Chemicals |
| 13 | Gas and coke products | Non-metallic products | Non-metallic products |
| 14 | Chemicals | Iron and steel | Iron and steel |
| 15 | Non-metallic products | Metal products | Metal products |
| 16 | Iron and steel | Machinery, non-electric | Machinery, non-electric |
| 17 | Metal products | Transport equipment | Transport equipment |
| 18 | Machinery, non-electric | Machinery, electric | Machinery, electric |
| 19 | Transport equipment | Electronic and communication apparatus | Electronic and communication apparatus |
| 20 | Machinery, electric | Professional and scientific equipment | Professional and scientific equipment |
| 21 | Electronic and communication apparatus | Machinery repair | Other manufacturing |
| 22 | Professional and scientific equipment | Other manufacturing | Waste recycle |
| 23 | Machinery repair | Waste recycle | Electricity and steam |
| 24 | Other manufacturing | Electricity and steam | Gas production and supply |
| 25 | Construction | Gas production and supply | Water production and supply |
| 26 | Transportation and postal services | Water production and supply | Construction |
| 27 | Business | Construction | Transportation and warehouse |
| 28 | Restaurant | Transportation and warehouse | Postal services |
| 29 | Passenger transportation | Postal services | Information and software |

**Table A4.1.1 continued**

| Code | 1987/1990/1992/1995 | 1997 | 2002 |
|---|---|---|---|
| 30 | Public and residential services | Business | Whole sale and retail |
| 31 | Cultural, Educational, sports and scientific research | Restaurant | Hotel and restaurant |
| 32 | Finance and insurance | Passenger transportation | Finance and insurance |
| 33 | Administration | Finance and insurance | Real estate |
| 34 | | Real estate | Renting and business services |
| 35 | | Social services | Travel |
| 36 | | Health, sports and social welfare | Scientific research |
| 37 | | Education, arts, cultural and recreational services | General technical services |
| 38 | | Scientific research | Other social services |
| 39 | | General technical services | Education |
| 40 | | Public administration | Health and social welfare |
| 41 | | | Cultural, sports and recreational |
| 42 | | | Public administration and public organizations |

**Table A4.1.2 61 aggregate sectors for China and Japan in 2002**

| Code | Description |
|---|---|
| 1 | Agriculture |
| 2 | Metal mining |
| 3 | Other mining |
| 4 | Coal |
| 5 | Crude oil and natural gas |
| 6 | Food and tobacco |
| 7 | Beverage |
| 8 | Textiles |
| 9 | Clothing and other fiber products |
| 10 | Wood products |
| 11 | Furniture |
| 12 | Paper and paper products |
| 13 | Printing and publishing |
| 14 | Chemical fertilizers |
| 15 | Basic chemicals |
| 16 | Plastic products |
| 17 | Chemical fibers |
| 18 | Chemical products |
| 19 | Medical and pharmaceutical products |
| 20 | Petroleum |
| 21 | Coking |
| 22 | Plastic products |

**Table A4.1.2 continued**

| Code | Description |
|---|---|
| 23 | Rubber products |
| 24 | Glass and glass products |
| 25 | Cement |
| 26 | Ceramic ware |
| 27 | Other non-metal mineral products |
| 28 | Pig Iron and crude steel |
| 29 | Steel pressing |
| 30 | Steel products |
| 31 | Nonferrous metal smelting |
| 32 | Nonferrous metal processing |
| 33 | Metal products |
| 34 | General industrial machinery |
| 35 | Special industrial machinery |
| 36 | Other general industrial equipment and parts |
| 37 | Office equipment |
| 38 | Household electronic and electrical apparatuses |
| 39 | Computers and accessories |
| 40 | Communication machines |
| 41 | Other electronic instruments |
| 42 | Electronic element and device |
| 43 | Generators |
| 44 | Other electrical machinery |
| 45 | Car |
| 46 | Parts and accessories for cars |
| 47 | Other transport equipment |
| 48 | Instruments |
| 49 | Other manufacturing products |
| 50 | Construction |
| 51 | Public projects |
| 52 | Electricity, steam and hot water production and supply |
| 53 | Water production and supply |
| 54 | Commerce |
| 55 | Finance, Insurance and real estate |
| 56 | Transport |
| 57 | Communication and broadcasting |
| 58 | Official business |
| 59 | Other public services |
| 60 | Other business services |
| 61 | Other personal services |

# Appendix 4.2 Construction of Emission Factors

### 1. Emission factors used in other studies

In this study of air pollutants from fossil fuel combustion, we are concerned with the content of carbon, sulfur and nitrogen in fuels. However, there are many types of coal, oil and natural gas which vary dramatically in their chemical contents in physical units. Less variation is found in terms of emission in calorific terms. That is why most energy resources give out emissions factors in calorific terms rather than emission factors in physical terms. Because of this complexion, some emission factors are misused in some studies. The following is a comparison of average emission factors in four related studies:

**Table A4.2.1 Comparison of Emission factors**

| | | Carbon in | | | Sulfur in | | | Nitrogen in | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Author(s) | Unit | Coal | Oil | Gas | Coal | Oil | Gas | Coal | Oil | Gas |
| Mukhodpadhyay (2002) | mt/mt[a] | 0.55 | 0.77 | 0.67 | n/a[c] | n/a | n/a | n/a | n/a | n/a |
| Mukhopadhyay and Chakroborty (2005) | mt/mt | 0.55 | 0.79 | n/a | 0.003 | 0.015 | n/a | 0.018 | 0.001 | n/a |
| Dietzenbacher and Mukhopadhyay (2007) | mt/mtoe[b] | 0.55 | n/a | n/a | n/a | n/a | n/a | n/a | n/a | n/a |
| Temurshoev (2006) | mt/mtoe | 0.55 | 0.77 | n/a | 0.003 | 0.015 | n/a | 0.018 | 0.001 | n/a |

Note: a. mt/mt is acronym for million tons per million tonnes;

b. mt/mtoe is acronym for million tonnes per million tonnes oil equivalent;

c. not explicitly mentioned in the text. However the emission factors of oil and natural gas usually adopt the same values.

While we find the numbers used in these studies are almost the same, the units they are using are surprisingly different: mtoe is a measure of energy and mt is a measure of physical mass. In the case of coal, 2 mt of coal would release about 1 mtoe of energy. Hence, the emission factors in some, if not all, of the studies, are misused.

**2. Emission factors used in this study**

$CO_2$ emissions are primarily dependent on the carbon content of the fuel and hence we can calculate them from fuel combustion accurately at a highly aggregated level. But for $SO_2$ and $NO_x$, emissions estimation requires more detailed information. Accurate estimation of their emissions depends on knowledge of several interrelated factors, including combustion conditions, technology, and emission control policies, as well as fuel characteristics. IPCC guidelines suggest that they are calculated based on applied on a detailed activity/technology level.

Emission factors vary in fuel types as well as across industries and from different data sources. Peters et al. (2006) compare emission factors from Chinese Energy Statistics Yearbooks, CCCS and IPCC guidelines as well as other studies. We use these sources to construct emission factors for the three air pollutants.

**Table A4.2.2 Carbon Emission Factor and Fraction of Carbon Oxidized**

| Fuel Type | **Coal** | Soft coke | **Natural gas** | LPG | Naphtha | Motor gasoline | **Fuel oil** |
|---|---|---|---|---|---|---|---|
| Emission factors (T C/TJ) | **25.8** | 25.8 | **15.3** | 17.2 | 20.0 | 18.9 | **20.2** |
| Oxidization factors[a] | **0.98** | 0.98 | **0.995** | 0.995 | 0.99 | 0.99 | **0.99** |

Source: IPCC guidelines. a. Oxidization factor vary across industries ranging from 0.8 to 0.98. We use the default values which are overestimates for some industries.

We use the values in bold to construct our carbon dioxide emission factors. To make the values comparable to other studies and to suit the Chinese case, we also present the carbon emission factors in different units.

**Table A4.2.3 Carbon emission factors in different units**

| Fuel type | T C/TJ | T C/SCE[a] | T C/TOE[b] | T C/ T[c] |
|---|---|---|---|---|
| Raw Coal | 25.8 | 0.75613608 | 1.0801944 | 0.5394264 |
| Crude Oil | 20.2 | 0.59201352 | 0.8457336 | 0.8446832 |
| Natural gas | 15.3 | 0.44840628 | 0.6405804 | n/a |

Note: a. SCE is an acronym of Standard Coal Equivalent which refers to the amount of energy released by burning one metric ton of coal. It is widely used in Chinese energy statistics.1 SCE=$29.3076*10^{-3}$TJ

b. TOE is an acronym of Ton Oil Equivalent which refers to the amount of energy released by burning one metric ton of oil. It is accepted by many nations to record their energy statistics. 1 TOE=$41.868*10^{-3}$ TJ. 1 SCE is about 0.7 TOE.

c. T denotes one metric ton. We use net calorific values for raw coal 0.020908 TJ per ton and for crude oil 0.041816 TJ. per ton. Natural gas is often measured in volume and thereby we don't report the carbon content in physical mass.

3.66 is applied as the molecular weight ratio of carbon dioxide to carbon. The following is carbon dioxide emission factors based on the methodology and data mentioned above.

**Table A4.2.4 Carbon Dioxide Emission factors**

| Fuel type | Raw Coal | Crude Oil | Natural Gas |
|---|---|---|---|
| $CO_2$ ton per SCE | 2.712 | 2.145 | 1.633 |
| $CO_2$ ton per TOE | 3.874 | 3.064 | 2.333 |

**2.2 Sulfur Dioxide Emission Factors**

Sulfur dioxide emission factors are constructed by multiplying the sulfur content of the corresponding fuel by the fraction of sulfur oxidized and the molecular weight ratio of sulfur dioxide to sulfur.

**Table A4.2.5 Sulfur Content in Different Fuels (%)**

| Fuel type | Raw Coal | Crude Oil | Natural Gas |
|---|---|---|---|
| IPCC low | 0.5 | 1 | n/a |
| **IPCC medium** | **1.5** | **3** | **0** |
| IPCC high | 3 | 4 | n/a |
| Jingru | 1.1 | 0.5 | n/a |

Not all the sulfur content in fuels will be oxidized; there will be certain proportion of remains in ash. Sulfur content and retention in ash varies dramatically in fuel types. IPCC provides various values of sulfur content and retention in ash according to fuel types. The table below shows a variation in estimation in different data sources.

**Table A4.2.6 Sulfur Retention in Ash (%)**

| Fuel type | Raw Coal | Crude Oil | Natural Gas |
|---|---|---|---|
| IPCC, hard coal | 5 | n/a | n/a |
| IPCC, brown coal | 30 | n/a | n/a |
| Jingru | 20 | n/a | n/a |
| **CCCS, P53** | **27** | **n/a** | **n/a** |

Source: Peters et al. (2006)

We use IPCC medium sulfur content values (in bold) and sulfur retention ratio in ash 27% according to CCCS. Due to data limitation, we imply a strong assumption that sulfur removal technology is absent/ inefficient. We use 2 as the molecular weight ratio of sulfur dioxide to sulfur.

**Table A4.2.7 Sulfur Dioxide Emission Factors using jingru sulfur content**

| Fuel | t /SCE | t /TOE | t/ T | KT/PJ |
|---|---|---|---|---|
| Raw coal | **0.0225** | 0.0322 | 0.0161 | 0.768127 |
| Crude oil | **0.0070** | 0.0100 | 0.0100 | 0.2391429 |
| Natural gas | **0** | 0 | n/a | 0 |

Source: Peters et al. (2006)

### 2.3 Nitrous Oxides Emission Factors

Similar to $SO_2$, nitrous oxides from fuel combustion are highly technology dependent. Nevertheless, we use IPCC default nitrous oxides emission factors numbers for industry/energy and construction as follows.

**Table A4.2.8 Nitrous Oxides Emission Factors**

| Fuel | t /SCE | t/TOE | t/T | kg/TJ |
|---|---|---|---|---|
| Raw Coal | 0.00879228 | 0.0125604 | 0.0062724 | 300 |
| Crude Oil | 0.00586152 | 0.0083736 | 0.0083632 | 200 |
| Natural gas | 0.00439614 | 0.0062802 | n/a | 150 |

Note: Nitrogen emission factors are IPCC default numbers for the sectors Industry, Energy and Construction.

### 3. Summary

To sum up, we use emission factors as the following table listed

**Table A4.2.9 Emission factors ton/SCE**

| | $CO_2$ | $SO_2$ | $NO_X$ |
|---|---|---|---|
| Raw coal | 2.712 | 0.0225 | 0.0088 |
| Crude oil | 2.145 | 0.0070 | 0.0059 |
| Natural gas | 1.633 | 0 | 0.0044 |

For 2002, where crude oil and natural gas are referred to in the IO tables as one commodity, we recalculate the emission factors based on the mix of crude oil and natural gas in Chinese energy production/consumption.

## Appendix 4.3 Pollution content in bilateral trade

**Table A4.3.1 Pollution content in bilateral trade between China and Japan (Common technology assumption, Chinese I-O coefficients)**

| Year | Pollutant | Exports $10^4$ tonnes | Imports $10^4$ tonnes | BETT $10^4$ tonnes | PTOT |
|---|---|---|---|---|---|
| | $CO_2$ | 7069 | 9265 | -2196 | 0.82 |
| 2003 | $SO_2$ | 33 | 45 | -12 | 0.78 |
| | $NO_x$ | 165 | 208 | -43 | 0.85 |
| | $CO_2$ | 8801 | 8032 | 770 | 0.82 |
| 2004 | $SO_2$ | 40 | 39 | 2 | 0.78 |
| | $NO_x$ | 206 | 181 | 25 | 0.85 |
| | $CO_2$ | 9816 | 11774 | -1958 | 0.83 |
| 2005 | $SO_2$ | 45 | 59 | -13 | 0.77 |
| | $NO_x$ | 228 | 259 | -30 | 0.88 |
| | $CO_2$ | 9816 | 12223 | -2407 | 0.82 |
| 2006 | $SO_2$ | 46 | 61 | -15 | 0.76 |
| | $NO_x$ | 228 | 268 | -40 | 0.87 |

**Table 4.3.2 Pollution content in bilateral trade between China and Japan (Heterogeneous tech technology assumption)**

| Year | Pollutant | Exports $10^4$ tonnes | Imports $10^4$ tonnes | BETT $10^4$ tonnes | PTOT |
|---|---|---|---|---|---|
| | $CO_2$ | 7069 | 1097 | 5971 | 6.91 |
| 2003 | $SO_2$ | 33 | 8 | 24 | 4.13 |
| | $NO_x$ | 165 | 13 | 152 | 13.59 |
| | $CO_2$ | 8801 | 1059 | 7742 | 6.18 |
| 2004 | $SO_2$ | 40 | 8 | 32 | 3.66 |
| | $NO_x$ | 206 | 12 | 193 | 12.28 |
| | $CO_2$ | 9816 | 1563 | 8253 | 6.25 |
| 2005 | $SO_2$ | 45 | 13 | 33 | 3.61 |
| | $NO_x$ | 228 | 17 | 211 | 13.45 |
| | $CO_2$ | 9816 | 1621 | 8195 | 6.18 |
| 2006 | $SO_2$ | 46 | 13 | 33 | 3.57 |
| | $NO_x$ | 228 | 17 | 211 | 13.29 |

## Appendix 4.4 Further Adjustment on Fuel Products

**Table A4.4.1 Under common technology assumption BETT and PTOT (Basic I-O tables)**

| | Pollutant | Export $10^4$ tonnes | Import $10^4$ tonnes | BETT $10^4$ tonnes | PTOT |
|---|---|---|---|---|---|
| 1997 | $CO_2$ | 66423 | 67523 | -1100 | 0.76 |
| | $SO_2$ | 474 | 459 | 15 | 0.80 |
| | $NO_x$ | 208 | 209 | -1 | 0.77 |
| 2002 | $CO_2$ | 70324 | 81773 | -11449 | 0.75 |
| | $SO_2$ | 477 | 553 | -76 | 0.75 |
| | $NO_x$ | 218 | 253 | -35 | 0.75 |

**Table A4.4.2 Projected BETT and PTOT for 2003- 2006**

| Year | Pollutant | Exports $10^4$ tonnes | Import $10^4$ tonnes | BETT $10^4$ tonnes | PTOT |
|---|---|---|---|---|---|
| 2002 | $CO_2$ | 64306 | 74975 | -10669 | 0.80 |
| | $SO_2$ | 442 | 503 | -62 | 0.82 |
| | $NO_x$ | 200 | 232 | -32 | 0.80 |
| 2003 | $CO_2$ | 83448 | 102916 | -19467 | 0.79 |
| | $SO_2$ | 573 | 694 | -121 | 0.80 |
| | $NO_x$ | 259 | 319 | -59 | 0.79 |
| 2004 | $CO_2$ | 109835 | 132197 | -22362 | 0.81 |
| | $SO_2$ | 763 | 888 | -125 | 0.84 |
| | $NO_2$ | 342 | 409 | -67 | 0.82 |
| 2005 | $CO_x$ | 132299 | 143719 | -11420 | 0.82 |
| | $SO_2$ | 911 | 964 | -53 | 0.84 |
| | $NO_x$ | 411 | 445 | -33 | 0.83 |
| 2006 | $CO_2$ | 159172 | 160031 | -859 | 0.84 |
| | $SO_2$ | 1100 | 1060 | 41 | 0.88 |
| | $NO_x$ | 496 | 494 | 2 | 0.85 |

**Table A4.4.3 Heterogeneous technology assumption, BETT and PTOT**

| IO tables | Pollutants | Exports | Imports | BETT ($10^4$ tones) | PTOT |
|---|---|---|---|---|---|
| **1) Common Tech** | $CO_2$ | 70138 | 81202 | -11064 | 0.75 |
| Exports using CN[a] | $SO_2$ | 478 | 549 | -71 | 0.76 |
| Imports using CN | $NO_x$ | 218 | 252 | -34 | 0.75 |
| **2) Heterogenous Tech** | $CO_2$ | 70138 | 45912 | 24226 | 1.33 |
| Exports using CN | $SO_2$ | 478 | 295 | 183 | 1.41 |
| Imports using JP[b] | $NO_x$ | 218 | 141 | 77 | 1.35 |
| **3) Common Tech** | $CO_2$ | 35199 | 45912 | -10713 | 0.67 |
| Exports using JP | $SO_2$ | 222 | 295 | -73 | 0.65 |
| Imports using JP | $NO_x$ | 108 | 141 | -33 | 0.67 |

## Appendix 4.5 Summary of previous studies

**Table A4.5.1 Other Studies on Pollution Content in Trade for China**

| Author | Methodologies | Pollutants | Period | Findings | Consistency |
|---|---|---|---|---|---|
| Antweiler (1996) | EIOA; **Common tech** | CO; $SO_2$;$NO_2$, Lead; Particulate matter; volatile organic compounds, | 1987 | Composite PTOT: 0.544 | YES |
| Chai (2002) | Simple method: Chinese industrial pollution intensities and annual trade data | Sum of 11 water pollutants; Sum of 3 air pollutants; Sum of 7 solid waste pollutants | 1980-1982; 1996-1998 | PTOT 1980-182: 0.54 1996-1998:0.62 | YES |
| Ahmad and Wyckoff (2003) | EIOA; **Hetero tech** | $CO_2$ | 1997 | BETT>0 | YES |
| Shui and Harriss (2006) | (EIO-LCA) software; Common tech BUT Emission factors gauged for China | $CO_2$ | 1997-2003 | BETT>0 | YES |
| Umed (2006) | EIOA; US and CN I-O | $CO_2$, $SO_2$, $NO_x$ | 1992, 1997 | PTOT<1 | YES |
| Wang and Watson (2007) | Simple method; Common tech; IEA $CO_2$ emission per unit of GDP (country specific) | $CO_2$ | 2004 | BETT>0 | NO |
| Dean and Lovely (2008) | Simple method: Chinese industrial pollution intensities and annual trade data | COD; $SO_2$; Smoke; Dust | 1995-2004 | COD, $SO_2$, Smoke: PTOT>1 Dust: PTOT<1 | Yes in terms of $SO_2$ |

# CHAPTER FIVE

# THE ENVIRONMENTAL IMPACT OF TRADE LIBERALIZATION:

# THE CASE OF CHINESE PROVINCES

## 5.1 INTRODUCTION

Trade liberalization has been in the centre of political and academic debate for a long time. Despite the benefits of trade liberalization from various channels such as technology spillovers, market access, resources allocation efficiency and pro-competition effects, further international economic integration maybe constrained by concerns over loss in other aspects. On the one hand, competitiveness loss of domestic industries and increased volatility to the domestic economy are often associated with trade liberalization; on the other hand, the worldwide concern about the environmental impacts of trade liberalization is also on the rise.

China has benefited significantly from its openness policies for the past three decades. Trade liberalization and FDI inflows are key contributors to China's two digit nominal GDP growth rate. However, concerns have been expressed about the environmental situation in China such as increased pollution, deforestation, soil erosion and loss of species and habitats. The annual economic cost of air and water pollution has been estimated as being between 24 and 54 billion US dollars, approximately 3.5 and 7.7 percent, respectively, of China's GDP in 1997 (World Bank, 1997:23). When combined with degradation and resources shortage, the total cost is estimated to be between 8 percent and 12 percent of annual GDP of China (Economy, 2004:88). Other issues related to public health deterioration and social unrest also pose an enormous threat to China's sustainable economic development.

Environmental degradation in the process of industrialization is not rare in other societies and periods. But due to the extremity of degradation and the unique institutional settings, China has become a focus in almost every aspect of environmental degradation, be it global commons or local environmental devastation. Many researchers have tried to address the failure of environmental protection in China from historical, cultural and institutional perspectives (see Smil, 1984; Economy, 2004). Others have empirically examined the relationship between economic growth and environmental degradation by testing the Environmental Kuznets Curve Hypothesis (EKC) which suggests a hope for cleaning up the environment when the income level passes a certain threshold (e.g. World Bank, 1992; Shafik, 1994; Roberts and Grimes, 1997; Peng and Bao, 2006, and so on). Since early 1990s, the increasing trends in globalization have increased the attention on the environmental implications of trade liberalization. Researchers have started to investigate whether trade liberalization would bring greater harm to domestic economy or if it would instead ameliorate the environment (Lucas et al., 1992; Antweiler et al., 1998; Frankel and Rose, 2005). A rich body of research work is also growing in the context of China's environmental problems in the quest of China's growth sustainability (Zeng and Eastin, 2007; Roumasset et al., 2007; Dean and Lovely, 2008).

Since trade liberalization is an indispensible part of China's growth miracle, it is our interest to examine the relationship between trade liberalization and environmental degradation. Linkages between trade and the environment are subtle and complex, as suggested by both theory and empirical studies. Although hypotheses predict that countries may deplete natural resources and/or specialize in producing pollution intensive goods, gains in efficiency and market access from trade liberalization also increase income levels which in turn increase the demand for a cleaner environment. In addition, the spillover following trade liberalization (especially FDI flows) is likely to lead to an updating of the old-fashioned (possibly heavy-polluting) machinery used in developing countries. In line with the established related literature, we attempt to decompose the effect of trade liberalization on the environment into different channels: the scale, trade-induced composition and income effects.

This study aims to improve on the following aspects, some of which will be further discussed in next section as weaknesses of the existing literature.

1) Functional form

We adopt the theoretical ACT (developed by Antweiler, Copeland and Taylor, 1998) model but use different empirical specifications (log-log).

2) Indicators for environmental quality

To improve the understanding of more dimensions of environmental quality, we apply comprehensive measures of environmental degradation including gaseous pollution, water waste and solid waste.

3) Measuring capital abundance

Capital abundance is traditionally measured as the capital to labour ratio and is expected to be positively correlated to emissions. For example, Mani and Wheeler (1997) found that the five most pollution intensive sectors (Iron and Steel, Non-Ferrous Metals, Industrial Chemicals, Pulp and Paper, and Non-Metallic Mineral Products) are about threefold as energy intensive, twofold as physical capital intensive, and two-and-half-fold less labour intensive than the five cleanest sectors (Textiles, Non-Electrical Machinery, Electrical Machinery, Transport Equipment, and Instruments). However, there is also evidence that capital intensive industries are often technologically sophisticated and hence more environmentally benign. We incorporate a squared term of capital intensity to account for the possible nonlinear relationship between pollution intensity and capital intensity.

The remainder of the chapter is organized as follows. The next section summarizes the impact of trade liberalization on the environment by discussing the possible channels. Section 3 reviews a rich body of the theoretical and empirical literature on the environmental consequence of trade liberalization. The theoretical framework for the study is set out in section 4. The empirical methodology and data are described in section 5. Econometric results and discussions are included in section 6, with conclusions set out in the final section.

# 5.2 TRADE'S IMPACT ON THE ENVIRONMENT

We have seen in the last section both the importance of trade liberalization to China's rapid growth and the severity of environmental degradation caused by economic growth. A natural question to be asked is: does trade liberalization worsen the environment, in the context of China? The debate between environmentalists and economists on this question has been contentious. However, there is no clear cut answer to the question due to the complex and conflicting channels through which trade liberalization can affect the environment. It can work through the economic growth caused by increasing trade and FDI flows or through income increase, technology spillover and production specialization. The possible channels or linkages are grouped in what follows into two schools according to their effects on the environment.

## 5.2.1 Trade liberalization as a source of harm to the environment

Opponents of free trade claim that trade liberalization causes harm to the local environment and/or the global environment. Their arguments are grouped into three negative effects.

### 1) The detrimental scale effect via economic growth

Economic activities use environment services as production factors and may also use the environment as a dump for wastes. The scaling up of economic activities will therefore harm the environment: by inducing more use of environment resources or by emitting more pollution. Grossman and Krueger (1995:353) argue that "[I]f the composition of output and the methods of production were immutable, then damage to the environment would be linked unavoidably to the scale of global economic activity". Following the literature, this impact of simply scaling up is termed the "scale effect". Under the presumption that trade liberalization increases market access and the size of economy in China, the scale effect of trade liberalization is viewed as having a negative impact on the environment.

### 2) Specialization in dirty industries

According to neoclassical trade theories, trade liberalization induces greater specialization according to comparative advantages. For economies with comparative advantage in producing dirty goods, trade liberalization will induce more dirty production and the environment of these countries will suffer. The Pollution Haven Hypothesis (PHH) predicts pessimistically for developing countries, that weak environmental regulations will boost dirty production in these countries, making them pollution havens for pollution intensive industries. However, the Factor Endowment

Hypothesis (FEH) infers that developed countries with more capital endowments than developing countries will have a comparative advantage in producing dirty goods which are also capital intensive. Theoretical predictions are quite mixed and the nature of the compositional (structural) effect from trade liberalization depends on country characteristics. Much of the empirical literature, however, suggests the compositional effect of trade is not necessarily detrimental to the environment of developing countries because a) the effect of environmental regulatory differences on trade specialization is relatively small and b) developing countries tend to have comparative advantage in labour-intensive industries which tend to be relatively cleaner than capital intensive industries. It is generally agreed that China exports more labour-intensive goods, many of which are not heavily polluting.

### 3) Regulatory chill and 'Race to bottom'

We have discussed thus far about passive reaction from the economy following trade liberalization. However, the issue of the endogeneity of environmental regulations merits more attention. In a pessimistic view, trade endangers standards of environmental regulations which results in damage to the environment. The so called 'Regulatory chill' or worse 'Race to bottom' hypothesis depicts the possibility of downgrading environmental regulations in individual economies to protect the competitiveness of domestic industries. The presumption here is that stringent environmental regulations are costly for firms to comply with; in fear of loss of international competitiveness, economies in general will adopt laxer standards of environmental regulations. There may, however, be offsetting pressures to raise environmental standards where consumers are concerned about such effects and firms are interested to market "green" standards. In the case of China, it is frequently reported that local governments have lowered compliance for employment consideration in return for financial inducements (e.g. bribery to individual corrupted bureaucrats).

## 5.2.2 Trade liberalization as a source of benefit for the environment

While the pessimistic arguments towards the nexus of trade and the environment are credible, there are equally convincing counter-arguments from the optimists' side. In fact, in the viewpoint of optimists, 'trade is the best way to protect the environment.' (Eiras et al., 2001)

### 1) Efficient allocation of resources

Economies with comparative advantage in producing clean goods will enjoy a cleaner environment whilst consuming imported pollution-intensive goods. Further, trade liberalization allows more efficient allocation of resources by reducing policy distortions and brings the benefits of specialization following international differences in comparative advantage. According to Neumayer (2001)'s argument, "if goods and services are produced according to comparative advantage, then scarce resources are not wasted and no environmental pollution is *unnecessarily* created."

### 2) Technology and management improvement

It is claimed that trade liberalization could also encourage the exports of environmental regulatory and product standards from advanced economies to less-regulated economies. With trade protection, domestic firms tend to be content with old technologies or may be limited in their ability to innovate. When subject to international competition, it is believed that domestic firms will have more incentive to employ the newest technologies available. An optimistic view (for example, see Frankel, 2003) claims that trade speeds up the absorption of frontier technologies and best-practice management and demand for higher environmental quality which will translate into effective regulation and the desired reduction in pollution. However, it is also claimed that developed countries transfer out-of-dated technology to developing countries and worsen the environment in developing countries. China has seen technological spillovers and management improvement through international cooperation over the past three decades.

### 3) Income effect

It is claimed by some research (Beghin, 2000) that poverty is a key contributor to environmental degradation in many developing countries. Poorer countries with rich natural resource endowments tend to trade off environment and economic growth. The income effect stems from the gains-from-trade hypothesis. Given that environmental quality is often posited as a normal good, agents will increase their demand for a clean environment if trade liberalization raises real income. Also with rising real income, a country will be better equipped with financial and regulatory capacity to design and enforce environmental policies.

### 4) International cooperation of environmental activism

Increased openness and intertwined exchange enhances international cooperation of environmental activities. According to ACEF (All-China Environment Federation), by 2008 there are over 3000 groups of environmental protection in China, many of which are linked with international environmental protection groups. Case studies show that international links helps to strengthen environmental protection. Also China has subscribed to many environment related trade treaties.

Focusing on Chinese provinces between 1985 and 2007, this study investigates only some of the mechanisms discussed above, namely, the scale, composition (trade-induced composition) and technique effects, which are broadly used in the literature (Grossman and Krueger, 1992, 1995; Antweiler et al., 2001).

# 5.3 LITERATURE REVIEW

General public awareness of the environmental implications of trade liberalization has been raised by the multinational trade negotiations such as the Uruguay Round of General Agreement on Tariffs and Trade (GATT) negotiations. Initial research focused on the environmental issues relating to agriculture and natural resources (Barrett, 1990; Markandya and Pemberton, 1990; Anderson, 1992). With the negotiations on the North American Free Trade Agreement (NAFTA), a rich body of work has been developed both in the theoretical and empirical areas with an emphasis on industrial pollution in the Mexican border area (Grossman and Krueger, 1995). With the international integration process accelerating in the late 1990s and early 2000s, this area has seen significant development in terms of methodologies and research objectives. We focus on the most relevant literature and group these papers according to their methodologies.

## 5.3.1 Environmental Kuznets Curve: the role of trade

This branch of the literature builds on the inverted-U shape hypothesis (commonly termed as the Environmental Kuznets Curve (EKC) Hypothesis, due to its resemblance to the Kuznets Curve postulated by Kuznets (1965) and used broadly in the studies of the growth and environment nexus (e.g. Grossman, 1995; Panayotou, 1993, 1997; Selden and Song, 1994; Shafik, 1994).

The basic idea of EKC is that, pollution first increases with industrialization and then decreases after the economy reaches a certain income threshold. Since trade liberalization is highly intertwined with economic growth, most empirical work includes a variable for trade liberalization or includes an interaction term of trade openness with key variables in their model of EKC testing. Most studies find that there is little evidence that trade has a detrimental effect on the environment; some studies even find that trade liberalization tends to reduce emissions of certain pollutants.

Grossman and Krueger (1995) is the first paper to examine the empirical relationship between national income and measures of environmental quality. In their specifications, per capita GDP is regarded as the combined effect of income and scale effects of economic growth, while trade intensity is included as an additional explanatory variable. Their findings suggest that $SO_2$ levels are significantly lower in cities located in countries that conduct a great deal of trade (relative to GDP). The role of trade openness on the emissions of suspended particles and dark matter[57], however, is not clear with the insignificant estimated coefficients.

Lucas et al. (1992) contribute to the testing of the trade liberalization-environment relationship by interacting trade liberalization and income growth in their model specification. Their results suggest that trade liberalization (measured in terms of Dollar's price-based measure which seeks to capture the magnitude of price distortions induced by policy) may be good for a country, with increased trade openness reducing the growth rate of manufacturing toxic intensity.

Using cross-country data for the year 1990, Frenkel and Rose (2005) address the issue of endogeneity of trade openness and income which was overlooked in previous studies. They construct an instrumental variable for trade openness by aggregating

[57] Suspended particles refer to gases and liquids suspended in the air while dark matter refers to smoke in their paper.

across a country's partners the trade flow predictions from a gravity equation and construct a set of instrumental variables for income using neoclassical growth equations. Their measures of environmental quality consist of seven indicators. Both OLS and IV results seem to support the view that trade openness reduces the tree measures of local air pollution ($SO_2$, $NO_2$ and suspended particulate matter) as well as stops further deforestation and energy depletion although the significance level varies. For the global externality Carbon Dioxide ($CO_2$), a positive sign of openness with moderate significance in OLS estimation is found (although the effect loses significance in IV estimation). They argue that this is because a global externality is unlikely to be addressed at individual country level. As for rural clean water access, they find a beneficial effect of openness in OLS estimation which disappears in IV estimation. A critique on their geographically-constructed trade share to instrument trade openness is made by Rodriguez and Rodrik (2001)[58].

Apart from the cross-country studies, there is a growing body of research on the determination of state/provincial pollution levels in individual countries. For example, examination of the role of trade openness as well as other control variables (such as technology advancement, the share of state ownership, industrial composition) is carried out by employing Chinese provincial characteristics. Peng and Bao (2006) test the Environmental Kuznets Curve using Chinese provincial data between 1996 and 2002. Trade openness is included in their specifications as a control variable. Using various emission indicators, the findings suggest that trade openness seems to be pollution reducing for most of the pollutants (COD, industrial soot, industrial dust and $SO_2$), while the effect on other pollutants (industrial waste water and industrial solid waste) remain insignificant. Another paper by Zeng and Eastin (2007) also examines

[58] Rodriguez and Rodrik (2001) argue that the geographically-determined component of trade may be correlated with other factors and that IV estimate is biased unless these factors are explicitly controlled for in the income equation.

the determinants of industrial pollution in Chinese provinces. Zeng and Eastin argue that four different channels can be identified such that increased economic integration results in overall environmental quality improvement. The impact of trade openness, FDI, export intensity and import intensity (relative to GDP) are investigated in separate specifications. Their results based on ordinary least square models with panel corrected standard errors (PCSE estimation) suggest a significantly negative relationship between economic integration and environmental pollution which holds up across alternative measures of pollution and openness.

EKC analysis itself has been criticized widely (for example, Arrow et al., 1995; Cole, 2003; Nahman and Antrobus, 2005; He, 2007) in terms of its theoretical underpinning, choice of environmental indicators and empirical interpretations. One school of criticism (Chapman and Agras, 1999; Stern, 1998; Cole, 2003 and 2004) points out that the EKC is determined by certain important variables such as energy price and trade/FDI patterns rather than growth-induced pollution abatement. In addition, the traditional EKC analysis often have some econometric issues such as ignoring simultaneity of income and emissions as well as ignoring the issue of heteroskedasticity (Cole, 2003; Stern et al., 1996) which would incur biased and inconsistent estimates (Cole, 2003). Recent studies (Cole et al., 1997; Shen, 2006; Zhang, 2008) on the EKC relation have tried to deal with the criticisms in many ways such usage of panel data, model specification, alternative pollution indicators and inclusion of other variables.

Accordingly, the research on trade liberalization and the environment done under the framework of EKC hypothesis inherits similar criticisms. Even if these issues are not serious problems with adoption of advanced econometric techniques and data, the EKC literature discussed above does not distinguish between the different mechanisms through which trade liberalization can affect the environment. Many other papers

(Grossman and Krueger, 1992, 1995; Copeland and Taylor, 1994, 1995; Antweiler et al., 2001) find it useful to decompose the impact of trade liberalization on the environment into three effects: the scale, (trade-induced) composition and technique effects; though they do not try to estimate their magnitudes individually.[59]

There are a number of reasons for examining the individual effects of trade liberalization. Firstly, trade liberalization should have different compositional effects in different countries. "A consistent relationship between additional pollution and openness to trade (across a panel of both rich and poor countries) is unlikely to be fruitful" (ACT, 2001). Secondly, the decomposition should also be stressed on the grounds of different welfare and policy implications. In the following section, we review a selection of studies which examine the different effects of trade liberalization on the environment.

### 5.3.2 ACT and the mechanisms of trade liberalization

Following Grossman and Krueger, other studies have tried to decompose trade's impact on the environment. One of the most prominent works was carried out by Antweiler, Copeland and Taylor (2001) [thereafter ACT]. To isolate and identify the mechanisms mentioned above in a more structured and theoretically solid framework, they develop a general equilibrium model to disentangle the mechanisms (scale effect, composition effect, technique effect and trade-induced composition effect) for a small open economy.

Using 1971-1995 GEMS (global environment monitoring system) data of $SO_2$

[59] Grossman and Krueger and others investigate the combined effect of scale and income using per capita income and interpreting the inverted-U shape curve as reflecting the relative strength of the two effects, see Grossman and Krueger, 1995.

concentrations recorded in different sites located in different cities in a number of countries, ACT measured the elasticities of these effects. They found that for an average country in the sample further trade openness tends to reduce $SO_2$ concentrations and it seems that freer trade is good for the environment. The authors also warn that their conclusions are based on the assumption that factor endowments and technologies of an economy will not change when trade frictions fall. Since we adopt ACT modelling, the basics of the model will be explained in details in the section of methodology.

Following ACT modelling, Cole and Elliot (2003) examined the trade-environment relationship using cross-country data for 1975 to 1995. They pay special attention to the nature of the trade-induced composition effect, while scale and income effect are not separately estimated. Their findings suggest different implications according to the pollutants and measures of pollution: the magnitude and sign of the effects vary by pollutants and measures of pollution. In summary, their results are partially supportive of ACT's empirical work by concluding that trade liberalization will reduce the pollution intensity of output but not necessarily pollution per capita (the reverse is true in the cases of $NO_x$ and $CO_2$).

He (2006b) also employs a pollution decomposition method used by Grossman and Krueger (1992; 1995) and applies an ACT type model to investigate the role of trade openness on $SO_2$, using Chinese provincial data for the period 1992 and 2003. The study's findings are relatively consistent with theoretical predictions: a positive signed scale effect and negative signed technique effect. The composition effect is counterintuitive, predicting that the increasing capital to labour ratio is beneficial for the environment. For the trade induced composition effect, He finds that it depends on the measurement of pollution. With small magnitudes, trade intensity acts as a decreasing factor for sulphur dioxide density (measured as industrial sulphur dioxide emissions divided by the surface of a province) and as an increasing factor for total industrial sulphur dioxide density.

Managi et al. (2009) address the issue of endogeneity of trade openness and income in ACT model using the instrumental variable approach (income equation and trade openness equation are used to get the fitted values of income and trade) adopted from Frankel and Rose (2005) as well as the differenced generalized method of moment (GMM) estimator. They find that the impact of trade on the environment depends on the pollutant and the country. Although trade lowers BOD emissions in both OECD and non-OECD countries, detrimental effects of trade on $SO_2$ and $CO_2$ emissions seem to occur only in non-OECD countries. They also find that the impact of trade is larger in the long term after the dynamic adjustment process.

Despite the increasing popularity for disentangling empirically the impact of trade liberalization on the environment, the ACT framework has weaknesses. It assumes that the changes of factor endowments and technology progress are exogenous to trade liberalization, though in reality trade liberalization may well bring factor movements (especially capital flows in the context of North-South trade) as well as technology spillovers and standards transfers. This limitation is especially important in a study that deals with time-series data. In addition, the model is built on the basis of many classical assumptions about market structure, for example, competitiveness and small open economy assumption with world prices taken as given. However even individual countries can have greater than proportional impact on the world market price in terms of some important goods such as oil.

The following section introduces some other models which address the issue of endogeneity to take into account the full impact of trade on the environment.

### 5.3.3 Structural models

Dean (2002) develops a theoretical Hechsher-Ohlin model with endogeneous factor supply (the environment is modelled as a productive input). Dean identifies the direct effect of trade liberalization (through emissions growth determination) and the indirect effect (through income growth determination) using a two-equation simultaneous system. Dean then analyzes the model using 1987 to 1995 Chinese provincial waste water data. Her findings confirm the detrimental direct effect of trade liberalization on the environment, but its indirect income effect turns out to be beneficial. The relative strength of the two effects changes from a detrimental effect dominance to beneficial effect dominance when other variables (for example state ownership and provincial differences) are taken into account. The author also undertook a counterfactual simulation based on the assumption that in 1991 the old exchange rate regime did not shift to the managed float exchange regime. Without such a reform, the author predicted a more rapid growth in waste water in Chinese provinces. In addition, Dean argues that China may have a comparative advantage in pollution-intensive goods because an improvement in the relative price of exports increases emissions growth significantly. This is in contradiction to other studies which conclude China has comparative advantage in producing clean goods (He, 2006b). Dean's choice of trade openness indicator and the interpretations may not be sufficiently precise to ensure such a conclusion.[60]

Inspired by Dean's model, He (2007) constructed a four-equation simultaneous system

[60] Dean uses Black Market Premium (BMP) as an indicator of trade openness which is criticized by Rodriguez and Rodrik (2001). In addition, the fact that a less distorted price regime induces more emissions growth does not necessarily imply China has a comparative advantage in pollution-intensive goods.

to capture both direct and indirect impacts of trade intensity on emissions. It is hypothesized in his model that imports and exports have different impacts on the emission situation: imported machinery and equipment are used to expand dirty goods production, while exports reflect comparative advantage. He's results suggest that the total impact of international trade on China's industrial $SO_2$ emissions is relatively small and the impacts of exports and imports have opposite signs: exports are emission-reducing, while imports (stock of imported machinery and equipment) are emission-increasing.

### 5.3.4 Miscellaneous methods

Other methods have been employed to examine the trade-environment nexus. For example, He (2006a) investigates the impact of economic growth and openness on the environment using Divisia decomposition for Chinese provincial level $SO_2$ emissions between 1991 and 2001. He's findings are consistent with international experiences: a positive signed scale effect, negative signed technique effect and inconclusive for the role of trade on China's industrial composition transformation.

Several others have modelled the impact of trade liberalization on various pollutants using CGE (Computable General Equilibrium) models (see Madrid-Aris, 1998; Beghin et al., 2002; Anderson and Strutt, 1998). These studies generate mixed results for individual countries. For example, Anderson and Strutt (1998) predict that Indonesia would benefit from GATT Uruguay Round trade reforms and APEC MFN trade provisions up to 2010 and 2020 because the detrimental scale effect is overridden by the composition effects. However, Beghin et al. (2002) analyze the impact of various trade reform scenarios in Chile on various pollutants and conclude that integration into NAFTA is relatively benign to the environment, while unilateral trade liberalization induces more adverse movements to the environment and the

MERCOSUR (a regional trade agreement concerning south American countries) simulations do not create substantial changes in pollution.

### 5.3.5 Summary

The branch of EKC-type analysis that examines the role of international trade on the environment has been criticized due to its lack of solid theoretical grounding. Compared to the EKC models, the ACT model and Dean (2002) offer some improvement by decomposing the impact of trade liberalization on the environment into various countervailing channels. In regard to cross-country analysis, nevertheless, concern arises with the ACT model and the Dean model in that the small country specifications may not be suitable for large countries. Some countries may have a lion's share of certain industries and thus have the power to influence relative world prices.

The other issues concerning the existing literature include measurement problems such as the choice and quality of trade liberalization index, environmental quality indicators and measurement of trade-induced composition effect.

Most of the existing literature proxies trade liberalization using trade intensity. While trade flows can reflect to a certain extent economic integration and trade liberalization, they are by no means the only and best measure of trade liberalization. Studies have used different measures of trade liberalization. For example, Dean uses the black market premium (BMP) to measure trade liberalization, although changes in BMP may not be induced by trade liberalization (Rodiguez and Rodik, 2001).

It is suggested that the impact of trade liberalization on the environment depends on the choice of pollutants and measures of pollution (Cole and Elliott, 2003). However, the literature has focused on using $SO_2$ emissions on the grounds that it is closely related to industrial activities and well documented. Since $SO_2$ emissions have a strong local and easily discernible effect, it may not be too surprising that most studies identify an overall beneficial nature of trade liberalization on the environment when this pollutant only is used. This may not be the case for other pollutants or environmental degradation situation.

Finally, it is often assumed the capital intensive industries are also heavier polluters. Although there is empirical evidence for the assumption (Cole and Elliott, 2003), it is potentially ambiguous since "capital intensive sectors could also be a more clean technology owner" (Dinda and Pal, 2000) and "the rise of the knowledge and high-tech industries during the last several decades obviously disrupts this assumption" (He, 2006b:2)

# 5.4 THEORETICAL FRAMEWORK

In this section, we discuss the theoretical part of work. First, the theoretical framework to model the mechanisms of trade's impact on the environment is described. Second, the choice of key indicators-trade liberalization and environmental degradation are reviewed.

## 5.4.1 Theory

As summarized in the last section, both reduced form modelling (RFM) and simultaneous equation modelling (SEM) have been employed by the existing studies in the literature. Although SEM seems attractive in the sense that it controls for the endogeneity problem better than RFM, it is not without shortcomings: 'expensive' in terms of data requirement, assumptions and estimation techniques[61].

Copeland and Taylor (2003:232-233) demonstrate that the recursive nature of their reduced form ensures the OLS estimates are unbiased and consistent. In the study we use a reduced form modelling following that of ACT to investigate the channels of how trade liberalization impacts on the environment.

The basics of ACT modelling are as follows. A small open economy produces two final goods, capital intensive dirty good X and clean good Y using two primary factors L and K. Pollution demand z, is defined as in Grossman and Krueger (1992), as the product of emission intensity e, share of dirty good X in total output as $\varphi$ , and total output S as an economy's scale, i.e. $z = e\varphi S$ . In differential form, $\hat{z} = \hat{S} + \hat{\varphi} + \hat{e}$ . The first term is the scale effect measuring the increase in pollution generated by scaling up the economy, the second term is the composition effect measuring the mix of goods all else equal and the third term is the technique effect measuring the improvement in emission intensity.

From the production side equilibrium (profit maximization given pollution tax $\tau$), the composition effect and the technique effect can be further decomposed as functions of capital abundance ($\kappa$), trade frictions ($\beta$), world relative price ($p^w$) of X and the pollution tax ($\tau$) with elasticities and pollution abatement share ($\alpha$) as parameters. So, the demand for pollution from the private sector is expressed as follows:

$$\hat{z} = \hat{S} + \varepsilon_{\varphi\kappa}\hat{\kappa} + [(1+a)\varepsilon_{\varphi p} + \varepsilon_{e,p/\tau}]\hat{\beta} + [(1+a)\varepsilon_{\varphi p} + \varepsilon_{e,p/\tau}]\hat{p}^w - [a\varepsilon_{\varphi p} + \varepsilon_{e,p/\tau}]\hat{\tau} \tag{5.1}$$

[61] Wooldridge (2003) explains that OLS estimation for a SEM-type model incurs simultaneity bias.

The government chooses a pollution tax to maximize the weighted sum[62] of consumer utilities. The optimal pollution tax is a function of country type (T) and the effective marginal damage ($\phi(p,I)$) which resembles Samuelson's rule[63]. In differential form, a decomposition of pollution supply can be expressed as

$$\hat{\tau} = \hat{T} + \varepsilon_{MD,p}\hat{\beta} + \varepsilon_{MD,p}\hat{p}^{w} + \varepsilon_{MD,I}\hat{I} \tag{5.2}$$

where MD is the marginal rate of substitution between emissions and income measuring the willingness of a consumer to pay for reduced emissions and I is real per capita income.

Combining pollution demand and supply ((5.1) and (5.2)) together yields a simple reduced form linking pollution emissions to a set of economic factors:

$$\hat{z} = \pi_1\hat{S} + \pi_2\hat{\kappa} - \pi_3\hat{I} + \pi_4\hat{\beta} + \pi_5\hat{p}^{w} - \pi_6\hat{T} \tag{5.3}$$

All the $\pi_i$ are positive. β is a measure of trade frictions, for a dirty good exporter β<1 and for a dirty good importer β>1. ACT argues that if factor endowments, world prices and country type are held constant, a fall in trade frictions will produce a scale effect, a technique effect and the trade-induced composition effect (the composition of factor endowments is not influenced by trade liberalization in their framework).

$$\frac{dz}{d\beta}\frac{\beta}{z} = \pi_1\frac{dS}{d\beta}\frac{\beta}{S} - \pi_3\frac{dI}{d\beta}\frac{\beta}{I} + \pi_4 \tag{5.4}$$

Hence the effect of trade liberalization depends on a country's comparative advantage: for a dirty good exporter, it is a possibility but not necessity that trade liberalization causes more emissions while for a dirty good importer trade liberalization would reduce emissions. In their estimation models, the trade-induced composition effect is

[62] The government assigns different weights to different consumer groups. In ACT paper, they assume that governments' behaviour vary across Communist and non-Communist countries.

[63] Samuelson rule for public goods provision: the government chooses pollution so that firms face emissions price that is equal to the sum of the marginal damages across all consumers.

conditioned on country characteristics (capital abundance and income level) which are proxied by a second order Taylor series.

$$\psi \cong \psi_0 + \psi_1 \kappa + \psi_2 \kappa^2 + \psi_3 I + \psi_4 I^2 + \psi_5 \kappa I \tag{5.5}$$

Their empirical results also show that freer trade appears to be good for the environment in an average country in the sample.

## 5.4.2 Variable selection

In order to empirically test the ACT model, we discuss variable selection in this section. We first deal with the measurement of environmental degradation in the context of Chinese provinces. Next we turn to the measurement of trade liberalization in the following two sub-sections. Variables of economic scale, capital abundance (capital intensity), income level and others are also discussed.

### 5.4.2.1 Environmental indicators

The left-hand-side variable should be a measure of environmental degradation, but this is difficult to quantify. As Grossman and Krueger (1995:353) recognize, "Environmental quality has many dimensions. ... ... Each of these dimensions of environmental quality (and others) may respond to economic growth in a different way. Therefore, a study of environment and growth should aim to be as comprehensive as possible."[64] A comprehensive set of environmental indicators is also required in the study of the linkages between trade liberalization and the environment. Copeland and Taylor (2003:223) state a list of desirable properties that a pollutant should possess for it to be relevant to their model: 1) it is a by-product of goods

[64] See also Grossman (1995) about different sensitivities from government to address the issue in respect for global and local pollutants; Arrow et al. (1995) warn that global pollutants may even increase monotonically with income.

production; 2) it is emitted in greater quantities per unit of output in some industries than others; 3) it has strong local effects; 4) it is subject to regulations because of its noxious effect on the population; 5) well-known abatement technologies are available for implementation; 6) data available for a mix of economies in terms of openness.

The environmental indicators in this study are chosen on the basis of availability, comparability and reliability. China's environmental quality records are recorded at local level as well as national level. At the provincial level, data are comparable across provinces since 1) environmental data monitoring and recording are subject to the same regulations and laws at national level and 2) production and pollution are subject to same international prices (excluding differences in trade costs). Although the reliability of Chinese data is an issue raised by many studies, the shared institutional and social settings ensure the relative credibility for cross-province studies. Our study only focuses on the pollution generated by industrial production related activities due to data availability. Three categories of pollution are available: air pollution, water pollution and solid waste pollution from industrial processes. In the following, we describe the environmental indicators along with an explanation of their anthropogenic sources and the possible hazardous nature.

### Industrial Water pollutants

#### 1) Industrial waste water emissions

One indicator is the total volume of industrial waste water emissions. It refers to the volume of waste water discharged by industrial enterprises through all their outlets, including waste water from the production process, directly cooled water, groundwater from mining wells which does not meet discharge standards and sewage from households mixed with waste water produced by industrial activities, but excluding indirectly cooled water discharged (which should be included if the discharge is not separated from waste water).

This indicator is too general in the sense that the pollutants in the same volume of industrial waste water can vary substantially across provinces and over time. Alternative measurement involves using the volumes of particular water pollutants. One error-correcting measure is to use the indicator of chemical oxygen demand which is a common test used to indirectly measure the amount of organic compounds in water.

## 2) Chemical Oxygen Demand (COD)

The presence of organic compounds in water is problematic in aquatic systems because it causes algal blooms and contaminating drinking water. COD refers to the amount of oxygen required when chemical oxidants are used to oxidize organic pollutants in water. A higher value of COD corresponds to more serious pollution by organic pollutants. There are also data on individual compounds including cyanide, petroleum, phenol, PM (particulate matter), sulphide, and volatile hydroxyl-benzene. Toxic cyanide has been used as poison throughout history. Other indicators are more or less toxic. They can be viewed as an indicator of water quality.

There are also other important water pollutants such as heavy metals, excess phosphorous and nitrates which can cause serious problems in aquatic systems and eventually in human bodies. Phosphorous is often the result of detergents entering the river networks and is associated with the use of phosphate fertilizers on agricultural land. Used in making fertilizers and pharmaceuticals, nitrates are soluble in water and contaminate soils. In this study, we focus on industrial waste water and COD, from which we draw generalizations concerning water quality.

## Air pollutants

Anthropogenic air pollution mostly originates from inefficient combustion of fuels. The available indicators in our dataset for air pollutants are industrial waste gas, $SO_2$, industrial soot and industrial dust.

### 1) Industrial waste air

Industrial waste air refers to the discharge into atmosphere of waste air containing pollutants generated from fuel burning and production processes in enterprises within a given period of time. It is calculated at standard status (273K, 101325Pa). Similar to the volume of industrial waste water, this indicator is a generic measure of the total volume of all air pollutants emitted from combustion and production processes in industrial enterprises.

### 2) $SO_2$ (Sulphur Dioxide)

$SO_2$ is the most commonly-used environmental indicator in similar studies for many reasons (see Copeland and Taylor, 2003; Cole and Elliott, 2003; He, 2006a and 2006b, 2007). Anthropogenic sources of $SO_2$ are related to fossil fuel combustion especially in electricity generation, non-ferrous ores smelting and home heating. It is believed that anthropogenic sources account for a large share of all $SO_2$ emissions (UNEP, 1991). $SO_2$ is linked to respiratory illnesses as well as acid rain problems (Lave et al., 1970). We only focus on the emissions from combustion and production in industrial activities.

### 3) Industrial Soot

Industrial soot refers to airborne particulate matters resulting from the incomplete combustion of a hydrocarbon. It is related to activities such as mining and combustion. It not only stains clothing but is also considered hazardous to the lungs and general health. In addition, it causes damage to vegetation growth. Here we use the volume of soot in smoke emitted in the process of fuel burning in the premises of enterprises.

### 4) Industrial Dust

Dust is referred to the category of solid particles with diameters less than 500 micrometers. It occurs from various sources such as soil dust lifted up by natural forces (wind, volcanic eruptions etc.) or from industrial pollutions. With its agglomerate nature, dust is especially hazardous for vulnerable humans such as children and older people and are suppressing to vegetation. We use the volume of dust emitted by production process of enterprises and suspended in the air for a given period of time, including dust from refractory material of iron and steel works, dust from coke-screening systems and sintering machines of coke plants, dust from lime kilns and dust from cement production in building material enterprises, but excluding soot and dust emitted from power plants.

Other hazardous air pollutants are unfortunately less readily available at the provincial level in China. Important air pollution absent from this study are CO, NO and $NO_2$ which are largely generated from fossil fuel combustion especially with motor vehicles. With no odour or colour, CO can cause serious toxicity of the central nervous system and heart. We don't have the information for gases that have a global effect such as $CO_2$ and CFC's, methane, nitrous oxide and tropospheric ozone.

### Solid pollutants

#### Industrial solid waste produced

In our data this refers to the total volume of solid waste, semi-solid waste and high concentration liquid residues produced by industrial enterprises from production processes, gangue, tailings, radioactive residues and other wastes, but excludes stones stripped or dug out in mining - gangue and acid or alkaline stones not included (a stone is acid or alkaline according to the PH value of the water being below 4 or above 10.5 when the stone is in, or soaked by water).

### 5.4.2.2 Indicators of trade liberalization

Defining and measuring trade liberalization is another crucial yet difficult job for the study. There are various potential indicators of trade liberalization with differing strengths and limitations.[65]

A common definition of trade liberalization emphasizes the removal or reduction in trade practices that hamper the free flow of goods and services from one economy to another. A more detailed definition views trade liberalization as "the gradual reduction in trade frictions that moves domestic prices closer to world prices" and included in trade frictions are "explicit trade barriers limiting imports or restricting exports, the sum of communication and logistical costs endemic to any real world trading relationship, and, of course, the costs of international shipment" (Copeland and Taylor, 2003:221). This definition is imperfect either, particularly when price changes are complicated by other institutional designs such as monetary and exchange rate policies.

[65] Criticisms and investigations on trade liberalization measures can be found in Rodriguez and Rodrik (2001) and Edwards (1998).

Direct measures of trade liberalization could be tariffs and non-tariff barriers. These direct measures, however, could be biased due to the coexistence of many intractable surcharges, taxes and subsides.

Another group of indices are related to price differences and exchange rate distortions. For example, Dollar's price based indices are widely adopted (Dollar, 1992; Lucas, et. al, 1992). But since such indices are dependent on the Law of One Price hypothesis and nominal exchange rate movement, they suffer limitations as pointed out by Rodriguez and Rodrik (2001). Black market premium (BMP)[66] measures exchange rate distortion and can be used to assess an economy's foreign exchange regime. It is sometimes adopted as an indicator of trade restrictiveness. For example, Harrison (1996) reports negative and significant correlations between the BMP and other indices of trade openness. Dean (1998; 2002) uses BMP to indicate the degree of trade liberalization in China. However, BMP is not an ideal indicator for the following reasons. It is closely related to a wide range of policy failures, for example, the effectiveness of regulation enforcements and other laws (Rodriguez and Rodrik, 2001). In addition, BMP cannot be captured precisely (Lardy, 1992) and varies greatly (across time and local markets in the case of Chinese provinces). Last but not least, Dean only uses the national average level of BMP for all provinces while the left-hand-side variables are in provincial level. The Sachs-Warner indicator (Sachs and Warner, 1995) is a 0-1 type indicator reflecting a country's policy stance toward trade by looking at different aspects of an economy. To proxy a wide range of policy and institutional differences, this indicator is clearly too crude. Rodriguez and Rodrik (2001): "the Sachs-Warner measure is so correlated with plausible groupings of alternative explanatory variables-macroeconomic instability, poor institutions, and location in Africa—that it is risky to draw strong inferences about the effect of

[66] The black market premium is the percent over the official exchange rate that currency is traded on the black market.

openness on growth based on its coefficient in a growth regression." Besides, 0-1 type indicators normally give ambiguous results when we change the threshold. There are studies (Edwards, 1998; Harrison, 1995) with attempt to compare different indicators of trade liberalization.

To sum up, these indicators each have their merits and flaws in measuring trade liberalization. We go back to the definition in Copeland and Taylor (2003). Because movements in domestic prices are not easily observable, the authors use trade intensity (the ratio of the sum of exports and imports to GDP) (Harrison, 1996; Copeland and Taylor, 2003) to proxy movements in trade frictions. Changes in trade volumes can reflect changes in trade regulations as well as changes in transport costs and world demands which fit in the definition well. However, trade volume variations also reflect other aspects of macroeconomic changes. When trade liberalization is accompanied by domestic reforms, the role of trade is not easily separated and studied. Hence, the question we seek to solve is actually 'what is the effect of increasing trade volume on the environment? '

In China, the degree of trade liberalization is not even across regions. Opened earlier than inland provinces, coastal provinces/municipalities have enjoyed favourable policies in export tax rebates, setting up industrial parks as well as cooperating with foreign investment. For each province, both exports and imports data are reported for each year. Imports data are recorded at the Customs for the destination province while exports are recorded for the origin province. We denote the trade openness variable as trade intensity, namely the sum of exports and imports divided by GDP.

#### 5.4.2.3 Indicators of other variables

**Scale effect** refers to the effect of economic activities and is measured by the industrial output at 1990 constant price level. Industrial output seems to be a better measure of economic scale than gross regional output in this study because all the emission levels accounted in the dataset are emitted by industrial production only. We expect that an increase in this variable (denoted by S) incurs increased pollution emissions.

**Composition effect** is a measure of economic structure. It is measured by the ratio of capital stock to employment[67] (denoted as KL). Capital stock is constructed for each province in each year adopted from Zhang et al. (2007) who use the perpetual inventory method (PIM). It should be noted that the capital stock only refers here to physical capital and does not include human capital accumulation. Employment is the sum of the employed in urban and rural areas. According to some studies, capital-abundance implies a comparative advantage in heavy-polluting industries (see Copeland and Taylor, 1994; Antweiler et al., 2001; Cole and Elliot, 2003; He, 2006b). Some studies also suggest a positive relationship between capital intensity and pollution intensity. Contradictory views argue that capital-abundance may imply a comparative advantage in high-technology green industries and thus in environmental-benign industries (see Dinda and Pal, 2000). These two contrasting views make the prediction of the coefficient sign rather difficult. For example, He (2006b) finds a negative relationship between capital intensity and industrial $SO_2$ density in Chinese provinces. We include a squared term of capital intensity in our model to account for nonlinearity.

[67] Since inter-provincial labour migration is substantial, we use the employment data rather the labour supply in constructing the composition effect. Hence it is capital intensity rather than capital abundance, although these measures are positively and highly correlated in our dataset.

**Income effect** in each province[68] is measured by the real income level; it is often referred as the technique effect although the actual income level accounts for only part of the technique effect (changes in the emission intensity). ACT exploits GNP per capita to differentiate the technique effect from the scale effect based on GDP data. A few studies (He, 2006b, 2007) use per capita GDP as a measure for income effect. We distinguish per capita GDP from real income for several reasons. Firstly, although per capita GDP and income level in a province is often positively related, they may have different influences on inhabitants' tolerance of pollution emissions. Per capita GDP often captures other influences than income itself, for example, the scale effect, the productivity level as well as FDI activities. Moreover, in our dataset, per capita GDP is highly correlated with capital intensity (>0.92). For each province in China, the income information is reported for urban (per capita annual disposable income) and rural households (per capita annual net income) respectively. We use per capita urban disposable annual income to represent a province's income level since 1) these two income levels are highly correlated (>0.93) and 2) urban disposable income relates to people who live in cities and towns where the industrial emissions data are collected[69]. In consideration of the above, we use per capita GDP (GDPPC) and income level (I) in two alternative empirical equations (see details in section 5.5.1).

We also consider other control variables. The first is a measure of productivity. Although the ACT model doesn't specifically model technological differences, we

[68] We use provincial income information to capture the differences in environmental policies and their implementation across provinces. In China, national environmental policies (basic standards) are set by the government and overseen by the environmental authorities and implemented by various government departments. Local governments and environmental authorities also have administrative power over local environmental policies and their implementation. As a result variations exist among provinces in the implementation of environmental policies. Local environmental policy can be more stringent than that set by the central government. Provinces with higher income level such as Beijing, Shanghai and Guangzhou set higher standards than others.

[69] Survey or annual data are better monitored and collected at city and town level. As for rural area, the data is not so precise given the weak environment regulatory institutions.

believe that an increase in productivity will drive down $\alpha$ (abatement cost share in producer's price) and ceteris paribus reduce emission intensities. We use output per worker to proxy this productivity (PROD) effect. Population density is another control variable. We construct population density as the ratio of population to the area of a province (POPDEN). Population growth increases the risk of environmental deterioration: demand for cultivation land and housing increases as does energy consumption. However, it is also argued by others that population growth spurs technological progress which is beneficial to the environment. Since our dataset concerns only about industrial emissions, we also expect that an increase in population density increase land prices which would deter industrial enterprises from entering. In addition, greater population density puts pressure on local authorities to use more stringent environmental regulations on industrial enterprises. To sum up, we expect a deterrent impact of population density on the emission level.

# 5.5 DATA AND ESTIMATION

This section describes empirical equations, data and definitions of the variables and choice of estimators.

## 5.5.1 Empirical specifications

The nature of panel data for Chinese provinces enables us to explore the mechanisms of trade liberalization's impact on the environment for a group of economic entities with the same general institutional settings. Economic studies on China provinces have been growing for the reasons that the variations in many aspects among provinces are prominent. Also, as the decentralization process continues, each province can be viewed as a small economic entity. Based on the choice of real income level discussed previously, we use two similar empirical equations which are analogous to ACT's reduced functional form. We use logarithmic forms of the variables (in capital cases in the model specifications below). Logarithmic transformation has many advantages in our context. It incorporates possible nonlinear relationships between the dependent and independent variables. In addition, it reduces non-normality[70] in residuals. Moreover, it makes results easier to interpret; a coefficient representing the elasticity of the dependent variable with regard to the explanatory variable. In our case, the logarithmic format also suits the theoretical ACT model which is a linear relationship between the percentage changes of the variables (see equation 3). In theory, this specification would also produce the same results for emissions density (if we divide both emissions and scale variable by land size) and for emissions intensity (if we divide both emissions and scale variable by population).

*Model A*

$$\begin{aligned}E_{it}=&\alpha+\beta_1 S_{it}+\beta_2 KL_{it}+\beta_3 KL_{it}^2\\&+\beta_4 I_{it-1}+\beta_5 O_{it}+\beta_6 O_{it}*rel.KL_{it}+\beta_7 O_{it}*rel.KL_{it}^2+\beta_8 O_{it}*rel.I_{it-1}\\&+\beta_9 O_{it}*rel.I_{it-1}^2+\beta_{10} O_{it}*rel.KL_{it}*rel.I_{it-1}+\gamma_1 POPDEN_{it}+\gamma_2 PROD_{it}+\mu_i+\delta_t+\varepsilon_{it}\end{aligned} \quad (5.6)$$

*Model B*

$$\begin{aligned}E_{it}=&\alpha+\beta_1 S_{it}+\beta_2 KL_{it}+\beta_3 KL_{it}^2+\beta_4 GDPPC_{it-1}+\beta_5 O_{it}+\beta_6 O_{it}*rel.KL_{it}+\beta_7 O_{it}*rel.KL_{it}^2\\&+\beta_8 O_{it}*rel.GDPPC_{it-1}+\beta_9 O_{it}*rel.GDPPC_{it-1}^2+\beta_{10} O_{it}*rel.KL_{it}*rel.GDPPC_{it-1}\\&+\mu_i+\delta_t+\varepsilon_{it}\end{aligned} \quad (5.7)$$

where: i refers to a province; t refers to a year; $\alpha$ is the constant term, $\beta_1$ - $\beta_{10}$ the coefficients of core variables, $\gamma_1$, $\gamma_2$ the coefficients of control variables; $\mu$ represents provincial specific effect, $\delta$ the time specific effect and $\varepsilon$ i.i.d error term. In Dean (2002), state ownership is accounted for in the estimation since stated-owned

[70] Normality of residuals is a requirement for t-statistic to be valid.

enterprises (SOEs) may be less responsive to environmental regulations if they face soft budget constraints (see Dasgupta et al., 1998; Wang and Wheeler, 1999). Due to limitation of data, we count on province dummies and time dummies to control for state ownership since SOEs are often concentrated in certain industries in certain provinces. The dependent variable **E** is an environmental indicator. **S** is the scale effect measured as industrial output in logarithmic form, **KL** the composition effect. **I** the urban disposable income and **GDPPC** per capita GDP[71] are alternative measures for the provincial income level. **O** is trade openness measure. **PROD** is labour productivity while POPDEN denotes population density. Detailed variable definitions can be found in the Appendix table A5.2.2.

Trade-induced composition effect depends on comparative advantage which is a relative concept. Hence a province's capital intensity and income level are ideally to be expressed relative to the world average (see ACT, 2001; Cole and Elliot, 2003). Relative capital intensity (rel.KL) for province i (relative to world average) at year t shall be computed as:

$$\begin{aligned}
\mathbf{rel.KL_{it}} &= \ln(\mathrm{rel.kl}_{it}) = \ln(kl_{it}/kl_{wt}) = \ln(kl_{it}/kl_{ct} * kl_{ct}/kl_{wt}) = \ln(kl_{it}/kl_{ct}) + \ln(kl_{ct}/kl_{wt}) \\
&= \ln(kl_{it}) - \ln(kl_{ct}) + \ln(kl_{ct}/kl_{wt}) = \ln(kl_{it}) - \ln(1/30 * \textstyle\sum kl_{it}) + \ln(kl_{ct}/kl_{wt}) \\
&\approx \ln(kl_{it}) - \ln(1/30 * \textstyle\sum kl_{it}) = \ln(kl_{it}/kl_{ct}) \qquad (5.8)
\end{aligned}$$

where *c* refers to China and *w* refers to the World average, *kl* is the level form of capital intensity and *KL* is the logarithmic form of capital intensity .

Although data for capital intensity at world average for each year is not in our dataset, we can leave it to the time dummies since the third term in equation 5.8 is same for

[71] We use lagged income term since the transmission of income growth into policy is considered to be slow. Antweiler et al. (1998) uses one period lagged three year moving average of GDP per capita to proxy income.

each province at time t. Hence the relative capital intensity is the provincial capital intensity ($kl_{it}$) relative to the average across provinces ($kl_{ct}$). We do the same to the relative income terms.

$$
\begin{aligned}
rel.I_{it-1} &= \ln(rel.i_{it-1}) = \ln(i_{it-1}/i_{wt-1}) = \ln(i_{it-1}/i_{ct-1} * i_{ct-1}/i_{wt-1}) = \ln(i_{it-1}/i_{ct-1}) + \ln(i_{ct-1}/i_{wt-1}) \\
&= \ln(i_{it-1}) - \ln(i_{ct-1}) + \ln(i_{ct-1}/i_{wt-1}) = \ln(i_{it-1}) - \ln(1/30 * \sum i_{it-1}) + \ln(i_{ct-1}/i_{wt-1}) \\
&\approx \ln(i_{it-1}) - \ln(1/30 * \sum i_{it-1}) = \ln(i_{it-1}/i_{ct-1}) \qquad (5.9)
\end{aligned}
$$

$$
\begin{aligned}
rel.GDPPC_{it-1} &= \ln(rel.gdppc_{it-1}) = \ln(gdppc_{it-1}/gdppc_{wt-1}) \\
&= \ln(gdppc_{it-1}/gdppc_{ct-1} * gdppc_{ct-1}/gdppc_{wt-1}) \\
&= \ln(gdppc_{it-1}/gdppc_{ct-1}) + \ln(gdppc_{ct-1}/gdppc_{wt-1}) \\
&= \ln(gdppc_{it-1}) - \ln(gdppc_{ct-1}) + \ln(gdppc_{ct-1}/gdppc_{wt-1}) \\
&= \ln(gdppc_{it-1}) - \ln(1/30 * \sum gdppc_{it-1}) + \ln(gdppc_{ct-1}/gdppc_{wt-1}) \\
&\approx \ln(gdppc_{it-1}) - \ln(1/30 * \sum gdppc_{it-1}) = \ln(gdppc_{it-1}/gdppc_{ct-1})
\end{aligned}
$$

(5.10)

where i and gdppc are level format of urban disposable income and provincial GDP per capita.

In model A we use one year lagged urban disposable income to proxy the effect caused by the changes in income level. We also include both population density and productivity as control variables. In model B we use one year lagged per capita GDP to proxy the technique effect.

One problem associated with our model specification and variable selection is multicollinearity. Although multicollinearity does not violate the basic multiple linear regression assumptions and does not reduce the predictive power of a model as whole, it affects the validity of an individual predictor. The issue of multicollinearity merits attention in this study since 1) multicollinearity is aggravated by adding interaction terms in the equation and 2) we are more interested in the decomposed effects of trade liberalization on the environment and 3) we don't have a large panel (multicollinearity issue would be attenuated with larger number of observations). A feasible solution is to centre the interaction terms. In both model A and B, we interact trade openness with relative capital intensity and relative income. Because each variable is in logarithmic form, the relative term is equivalent to subtracting an average (average across provinces for each year) from the original term. Detailed discussion of the extent of multicollinearity and how this arrangement works can be found in the appendix A5.5.

**Table 5.1 The expected signs for the coefficients**

| | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_4$ | $\beta_5$ | $\beta_6$ | $\beta_7$ | $\beta_8$ | $\beta_9$ | $\beta_{10}$ | $\gamma_1$ | $\gamma_2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| sign | + | + | - | - | ? | + | - | - | + | ? | - | - |

$\beta_1$ relates to the scale effect and is predicted to be positive; $\beta_2$ and $\beta_3$ both relate to the composition effect. We expect an increase in capital intensity would result in more pollution emissions being generated. A negative signed $\beta_3$ is possible when there is diminishing effect of capital intensity changes on pollution emissions. $\beta_4$ is the elasticity of emissions with regard to income level. For the direct impact of openness ($\beta_5$) on the level of emissions, there's no precise prediction because the trade-induced composition effect is reflected by the six openness-related terms collectively. The indirect impact of trade liberalization on the environment conditions on provincial characteristics: openness interacted with capital intensity implies that the environmental effect of trade liberalization conditions on factor endowments while openness interacted with income level implies that environmental effect of trade liberalization conditions on environmental stringency. To account for nonlinearity we also include interaction terms of openness and squared terms of capital intensity and income level as well as a three-way interaction term. If a province has a higher capital to labour ratio than the rest of the world, the impact of further trade openness is supposed to make the province dirtier (more specialized in the dirty good), other things equal. Given our log-log specification, $\beta_6$ is predicted to be positive for a factor endowment effect and $\beta_7$ to be negative to account for diminishing effect. If a province has a higher real income level (more stringent environmental regulation) than the rest of the world, the impact of further trade openness is supposed to make the province cleaner (more specialized in the clean good), other things equal. Given our log-log specification, $\beta_8$ is predicted to be negative for a pollution haven effect and $\beta_9$ to be positive to account for diminishing effect. The three way interaction term is difficult to predict. $\gamma_1$ and $\gamma_2$ are predicted to be negative.

## 5.5.2 Data description

We collected information for each province (mainland China) between1985 and 2007 to form a panel dataset. Important notes about the dataset, data sources can be found in Appendix A5.1 and A5.2.

### 5.5.2.1 Trends in pollution emissions

In Appendix A5.3 we include the basic descriptive statistics for the original data and the variables. Table A5.3.3 to table A5.3.9 present provincial emissions data every five years as well as the change in emissions over the twenty years in terms of total volume and per capita. The changes in pollution emissions are volatile across provinces and pollutants. For industrial waste water discharge (table A5.3.3), we see dramatic increases in emission levels for the rich coastal provinces (except Beijing), while other inland provinces have seen reduction (except Guangxi, Ningxia, Xinjiang and Xizang[72]). With only a few exceptions, the reverse seems to be true for emissions of COD (table A5.3.4), industrial dust (table A5.3.7) and industrial soot (table A5.3.8): the coastal provinces have mostly seen reduction while the inland provinces have seen increases. For industrial waste air (table A5.3.5), $SO_2$ (table A5.3.6) and industrial solid waste (table A5.3.9), the volume of emissions seems to increase for most provinces. Only Beijing has seen a reduction in emission levels of industrial waste air and $SO_2$ while Heilongjiang has experienced a decrease in industrial solid waste emissions. The pollution emissions per capita have similar patterns for most provinces as total pollution emissions. However, for areas such as Hainan and Tianjin, pollution per capita is much lower due to their expanded population during the past decades.

A visual examination of average trade dependence and average emissions levels is provided in figures A5.3.1-A5.3.9 which classifies the provinces into three groups according to the ranking. The geographical distribution of trade intensity is shown in figure A5.3.1. It shows that coastal provinces have the highest ratio of total trade volume to GDP while the border provinces have a medium level of trade dependence. Not surprisingly, the landlocked provinces have the lowest level of trade intensity (except Shaanxi which is landlocked but belongs to the medium level group). A glimpse at the average provincial trade volumes (figure A5.3.2) gives the impression that the distribution of trade flow is consistent with the division of three regions (eastern, central and western, see A5.1 for the classifications). The eastern provinces (except Hainan) are associated with the group of highest average trade volumes. The central region (except Jiangxi) has medium average trade volumes while most western provinces (except Xinjiang and Sichuan) have low trade volumes. However, the distribution of trade volumes seems to provide little information about the distribution

[72] Ningxia and Xizang's phenomenal growth rates in industrial waste water seem to be caused by their low initial emission levels.

of pollution emissions. Both industrial waste water discharge and industrial COD emissions seem to concentrate along the coastal regions as well as in inland provinces in proximity to main waterways such as Yangtze River and Pearl River. Gaseous emissions and solid emissions seem to concentrate on Northern China and Sichuan Basin.

### 5.5.2.2 Trends in the main economic indicators

Table A5.3.10 to table A5.3.12 describe the trends in output, capital, employment, income and trade using the arithmetic average annual growth rate between 1985 and 2007. Most provinces have experienced high gross output growth rate over the years (table A3.10). The eastern provinces have witnessed higher GDP growth rate than the central and western provinces. We also examine the growth rates for the components of GDP. As a result of industrialization, secondary and tertiary sectors have developed much faster than the primary sector in each province.

In table A5.3.11, we report the growth rates for capital and employment. Average annual growth rate for capital stock and capital inflow is also large for each province. Average growth rate of total employment has also increased for most provinces except for Tianjin which is an old industrial city. In the case of average annual income growth rate, we find similar patterns of provincial GDP growth rate. In addition, growth rate for rural income seems to be lower than urban income in all the provinces. Population growth has been dramatically large in three municipalities (Beijing, Tianjin, and Shanghai) as well as in Xinjiang and Guangdong provinces.

In terms of trade volumes, all provinces have witnessed dramatic increase in exports and imports (table A5.3.12). The eastern provinces have experienced higher increase in trade volumes in terms of exports, imports and the total volume.

#### 5.5.2.3 Correlation tables

A correlation table provides an initial investigation into the relationships between the variables. The correlation tables for model A and B are reported respectively in Appendix table A5.4.1 and A5.4.2. All the pollution emissions are positively correlated with each other. Economic scale is positively related to all the environmental variables. Capital intensity is negatively (and counter-intuitively) correlated to the environmental variables. It is also highly correlated with income and openness as well as the interaction terms with openness. Income is negatively associated with most environmental variables except for industrial air and industrial solid waste. The association between trade intensity and environmental variables depends on the type of pollutants. The interaction terms are still correlated to each other as well as other explanatory variables. We see from the correlation table that population density seems to be positively correlated with dependent variables while the reverse seems to be true with our productivity measure.

### 5.5.3 Estimator selection

In the following, we discuss the selection of estimator for our model. The discussion is based on Wooldridge (2003: chapters 13&14; 2002: chapter 10) unless otherwise specified.

#### 5.5.3.1 Fixed versus random effects estimators

Both models include a provincial specific effect. Whether this provincial specific effect is fixed or randomly drawn determines the choice of estimator. In our case, we prefer a fixed effect (FE) estimator to a random effect (RE) estimator since the random effects (generalised least squares models) relies on the crucial assumption that the provincial specific effects are uncorrelated win the explanatory variables. To statistically test whether a random effects estimator is more efficient than a fixed effects estimator, a Hausman test is often conducted under the null hypothesis that the difference in coefficients obtained from regression using the two estimators are not systematic. When the value from the chi-square distribution is too large we have to reject the null hypothesis of Hausman test that difference in coefficients are not systematic. In the cases when Hausman test value is either negative or the differenced variance matrix is not positive definite or the rank is lower than the number of the coefficients, we have to treat the test results carefully. It shows that if we include year dummies in the regression, Hausman test results are either negative or the differenced variance matrix is not positive definite. Also if we use VCE robust option, Hausman test will not be performed in STATA 10.1.

Another test to compare FE and RE results is the Sargan-Hansen Test (see table 5.2) for over-identification issue. RE estimators impose an additional orthogonal condition to the model that the unit specific effects are not correlated to other explanatory variables. In all the cases, we reject the null hypothesis that there is no over identification problem. Hence we prefer an FE estimator to a RE estimator.

**Table 5.2 Sagan-Hansen Test**

| Dep Var | | Waste Water | COD | Waste Air | $SO_2$ | Dust | Soot | Solid waste |
|---|---|---|---|---|---|---|---|---|
| Model A | Chi2 | 56.075 | 55.170 | 192.576 | 111.523 | 129.264 | 100.345 | 163.920 |
| | p-value | 0.0000 | 0.0001 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Model B | Chi2 | 70.505 | 139.410 | 226.601 | 264.071 | 261.736 | 243.645 | 108.392 |
| | p-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

### 5.5.3.2 Heteroscedasticity and autocorrelation

Next we check for heteroscedasticity and autocorrelation. Heteroscedasticity is common in panel data and has many causes. For a particular year, heteroscedasticity may rise because of the scale differences (across panel). For example, a province that emits a large amount of pollution is likely to have a larger variance of the residuals. Moreover, our provincial data is an aggregation of micro data at the city or lower level. In addition, the variation over time is also a possible cause of heteroscedasticity. We use the Breusch-Pagan/Cook-Weisberg test (see table 5.3) for heteroscedasticity. In all cases, we reject the null hypothesis of residuals homogeneity.

**Table 5.3 Breusch-Pagan/Cook-Weisberg test**

| Dep Var | | Waste Water | COD | Waste Air | $SO_2$ | DUST | SOOT | Solid Waste |
|---|---|---|---|---|---|---|---|---|
| Model A | Chi2 | 32.38 | 103.62 | 39.03 | 119.48 | 48.77 | 67.49 | 440.77 |
| | p-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| Model B | Chi2 | 26.86 | 104.73 | 23.30 | 94.01 | 87.48 | 63.98 | 444.12 |
| | p-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 0.0000 |

Autocorrelation is also very common in panel data since the errors for observations between adjacent periods will be more highly correlated. Here we only consider first-order autocorrelation (AR (1) process) and how to alleviate it. For higher orders of autocorrelation a structure of time series models has to be applied (AR, MA, or ARIMA). The test used is Wooldridge test (Drukker, 2003; Wooldridge, 2002). The table below show that we reject the null hypothesis of no first order autocorrelation for both models with all the seven dependent variables at least at 95% confidence level.

Table 5.4 Wooldridge test

| Model | Test value | Waste Water | COD | Waste Air | $SO_2$ | DUST | SOOT | Solid Waste |
|---|---|---|---|---|---|---|---|---|
| Model A | F-test | 54.143 | 7.910 | 164.819 | 4.304 | 6.856 | 41.497 | 79.361 |
| | p-value | 0.0000 | 0.0087 | 0.0000 | 0.0470 | 0.0139 | 0.0000 | 0.0000 |
| Model B | F-test | 52.189 | 6.222 | 167.158 | 4.763 | 7.123 | 28.657 | 90.038 |
| | p-value | 0.0000 | 0.0186 | 0.0000 | 0.0373 | 0.0123 | 0.0000 | 0.0000 |

### 5.5.3.3 Heteroscedasticity and autocorrelation robust estimators

The above discussion shows that both heteroscedasticity and autocorrelation exist with our panel data and empirical specifications. We have two options to deal with non i.i.d. errors. The first one still uses the OLS point estimates with a different estimator for variance-covariance matrix of the point estimator (VCE). One of the common estimators for VCE is the Newey-West estimator which is proposed by Newey and West (1987). It gives the same point estimate results for the coefficients as the FE estimator; the main difference lies in the fact that the VCE is corrected to account for both heteroscedasticity and autocorrelation. The Newey-West estimator requires that the maximum order (L) of any significant autocorrelation in the errors specified. It is suggested that $L = \sqrt[4]{N}$ can be used. For our 639 observations, one possible value for L is 5. The number of lags has little impact on the significance levels for highly significant coefficients in our specifications. In the following we only report the results with one lag.

Another option to deal with non i.i.d errors is to use a different point estimator with a specified structure of the errors. A Feasible Generalized Least Squares (FGLS) estimator performs a different estimation process for the point estimates while controlling for heteroscedasticity and autocorrelation.

Which approach to follow? Baum (2006: 142) summarizes, "although both the robust estimator of the VCE approach and FGLS estimators account for non-i.i.d disturbances, FGLS estimators place more structure on the estimation method to obtain more efficient point estimates and consistent estimators of the VCE. In contrast, the robust estimator of the VCE approach uses just the OLS point estimates and makes the estimator of the VCE robust to the non-i.i.d disturbances." However, it is suggested that FGLS should be used in a case when N (provinces) is several times larger than T (periods). We use the Newey-West estimator including time and province dummies for the main results. FGLS results are also reported for the sake of robustness check.

# 5.6 RESULTS

In the following we present the main regression results for both empirical models using the Newey-West estimator which controls for heteroscedasticity and autocorrelation. A robustness check is also provided by using a different interaction method as well as using a different estimator (FGLS). Lastly our results are compared with similar studies in the empirical literature.

## 5.6.1 Main results

### 5.6.1.1 Newey-West results with model A

Table 5.6 presents the estimation results for model A using the Newey-West estimator. After controlling for heteroscedasticity and autocorrelation, the p-values for each coefficient are enlarged since the HAC robust standard errors are greater than the usual standard errors. It means that we have consistent coefficients with those estimates from the FE estimator or the LSDV estimator, but the significance level will be downsized. In general the results turn out to be consistent with our predictions.

The coefficient for the scale effect is positive and highly significant (1% significance level) across all the seven environmental indicators. It is hence evident that about 0.5-1.0 percent more industrial pollution emissions will be generated if we simply scale up the economic activities by 1.0 percent.

The sign and significance level for the coefficient of capital intensity (KL) is also in consistency with our prediction. It is significantly positive across all the environmental indicators. In addition, the negativity of the squared term on capital intensity indicates a turning point for the specific environmental indicators, COD, $SO_2$, industrial dust and industrial soot with regard to increasing capital intensity. However the inference cannot be extended to the general environmental indicators since we find an insignificant and sometimes positive coefficient for the squared term of the capital intensity in these cases. We calculate the turning point of capital intensity (holding other variables constant) for the specific environmental indicators and find out that in each case the turning point is much higher than the maximum value of capital intensity in the dataset. It implies that an increase in capital intensity in any province would increase the emission levels during the period we are examining. The technology-reinforcing effect is suppressed by the pro-pollution intensive effect in the current capital intensities.

Our predictions for the income effect are also not rejected by the results. One period lagged urban disposable income seems to have a negative effect on the emissions of all the environmental indicators, though the significance level varies.

The effect of openness is captured by the six terms related with openness in the model. The direct impact of openness is captured by $\beta_5$. A positive $\beta_5$ in our specification reflects the comparative advantage in pollution intensive industries for a mean (hypothetic) province[73]. Conversely, a negative $\beta_5$ implies a comparative disadvantage in pollution intensive industries for a mean province. The results show that the coefficient turns out to be positive for all the environmental indicators, among which industrial waste water, COD, industrial dust as well as industrial solid waste appear to be strongly and positively related to openness per se.

The interaction terms related to openness are slightly more complicated than we expected to see, though there is supportive evidence for the predictions. The first interaction term is the product of openness and relative capital intensity. It shows that an increase in trade openness will result in rising pollution emissions for a province with relatively higher capital intensity, although this effect is not significantly positive for industrial waste water, industrial waste air and $SO_2$. The second interaction term is the product of openness and squared relative capital intensity. We only find the coefficient to be significantly negative for the emissions of industrial dust and industrial solid waste. For the interaction between openness and relative income, we find supportive evidence that a province with higher relative income will have comparative advantage in cleaner industries for a given level of trade openness. This effect is only significant in the case of COD, industrial dust, industrial soot and industrial solid waste. Similar to the interaction between openness and squared capital intensity, the interaction term between openness and squared relative income also has mixed signs and varying significance levels. For industrial dust and industrial solid waste, this effect is significantly negative. For the three way interaction term, we find

[73] A hypothetic province is a province that has the mean relative capital intensity and the mean relative income (mean relative per capita GDP if we use model B) in level form. It implies that the centred interactions terms would be equal to zero for a hypothetically "sample mean" province).

mixed and varying significance level across the environmental indicators. The coefficient is significantly negative for industrial waste water and industrial dust.

The terms with openness are not jointly equal to zero for most of the environmental indicators expect for industrial waste air and $SO_2$. Evaluated at the sample mean of level variables, the trade-induced composition effect is positive though in a much smaller magnitude than the scale effect and the income effect. For a hypothetic sample mean province, we find that trade openness alone will result in specialization in dirtier industries.

The coefficient for population density has mixed signs and is not significant in any specification, which may result from the fact that different effects of population density on pollution emissions cancel out each other. We also find that productivity measure has a significantly negative effect for all the environmental indicators.

**Table 5.6 Newey-West estimation results for model A**

| | | Waste water | COD | Waste air | $SO_2$ | Dust | Soot | Solid waste |
|---|---|---|---|---|---|---|---|---|
| S | $\beta_1$ | 1.015*** | 0.930*** | 0.807*** | 0.714*** | 0.615*** | 0.732*** | 0.497*** |
| | | (9.775) | (5.327) | (10.006) | (6.188) | (4.409) | (4.935) | (4.511) |
| KL | $\beta_2$ | 0.649*** | 1.182*** | 0.528*** | 0.676*** | 1.534*** | 1.050*** | 1.015*** |
| | | (3.670) | (3.174) | (3.012) | (3.294) | (5.566) | (4.331) | (5.672) |
| $KL^2$ | $\beta_3$ | 0.011 | -0.125** | 0.008 | -0.09*** | -0.19*** | -0.11*** | -0.000 |
| | | (0.376) | (-2.523) | (0.338) | (-2.59) | (-4.69) | (-3.05) | (-0.007) |
| I | $\beta_4$ | -0.795** | -2.996*** | -0.258 | -0.715** | -0.718* | -1.30*** | -0.83*** |
| | | (-2.345) | (-6.195) | (-1.167) | (-2.121) | (-1.653) | (-3.48) | (-2.88) |
| O | $\beta_5$ | 0.132*** | 0.248*** | 0.020 | 0.043 | 0.136* | 0.052 | 0.169*** |
| | | (3.084) | (2.655) | (0.394) | (0.840) | (1.886) | (0.856) | (3.312) |
| O*rel.KL | $\beta_6$ | 0.121 | 0.302* | 0.051 | 0.095 | 0.367*** | 0.259** | 0.189** |
| | | (1.465) | (1.702) | (0.650) | (1.147) | (2.867) | (2.273) | (2.418) |
| O*rel.$KL^2$ | $\beta_7$ | -0.003 | 0.095 | -0.018 | 0.013 | -0.15*** | -0.095 | -0.16*** |
| | | (-0.074) | (1.072) | (-0.543) | (0.341) | (-3.106) | (-1.591) | (-4.972) |
| O*rel.I | $\beta_8$ | -0.192 | -0.837*** | -0.063 | -0.200 | -0.65*** | -0.52*** | -0.46*** |
| | | (-1.327) | (-3.873) | (-0.587) | (-1.550) | (-2.98) | (-3.175) | (-3.112) |
| O*rel.$I^2$ | $\beta_9$ | -0.55*** | -0.120 | 0.279 | 0.245 | -0.772** | 0.583* | -0.217 |
| | | (-2.639) | (-0.306) | (1.522) | (1.236) | (-2.007) | (1.741) | (-1.126) |
| O*rel.KL*rel.I | $\beta_{10}$ | -0.666** | 0.038 | -0.161 | -0.115 | -0.988** | -0.106 | 0.366 |
| | | (-2.004) | (0.065) | (-0.584) | (-0.398) | (-2.085) | (-0.258) | (1.233) |
| POPDEN | $\gamma_1$ | -0.294 | 0.162 | -0.093 | 0.305 | -0.614 | -0.144 | 0.084 |
| | | (-0.721) | (0.343) | (-0.292) | (0.850) | (-1.492) | (-0.306) | (0.296) |
| PROD | $\gamma_2$ | -0.76*** | -1.04*** | -0.71*** | -0.76*** | -1.16*** | -0.99*** | -0.74*** |
| | | (-3.189) | (-2.740) | (-3.662) | (-3.537) | (-3.627) | (-3.749) | (-3.506) |
| F | | 309.792 | 33549.559 | 282.911 | 256.369 | 121.893 | 144.572 | 298.329 |
| N | | 639 | 584 | 639 | 639 | 639 | 639 | 639 |
| KL turning point | | n/a | 4.73 | n/a- | 4.89 | 3.99 | 5.0 | n/a |

*** means significant at 1%; **means significant at 5%;*means significant at 5%; t statistics are in parentheses; All equations are estimated time dummies and province dummies. We specify one lag for the Newey-West estimator.

Based on the estimates from model A with the Newey-West estimator, we calculate trade-induced elasticities for each province (with their relative capital intensity and relative income averaged over time). We plot the elasticity estimates in figures 5.1-5.7. The trade elasticities are positive though small in magnitude, which means that an increase in trade openness shifts the pollution demand curve to the right (i.e. dirty production increases). Whilst it is not plausible that all countries in the world have negative (positive) trade intensity elasticities, it is possible for Chinese provinces. For Beijing, Guangdong, Shanghai and Zhejiang, the relative income is much higher than inland provinces such as Henan, Inner Mongolia. A negative relationship between trade intensity elasticity and relative income (see figure 5.1) seems to exist across the environmental indicators: for provinces with lower relative income the trade elasticity is higher. To conserve space, the plots of trade-induced elasticities against relative capital intensity are not reported here. Based on correlation coefficients, a positive relationship between trade-induced elasticity and relative capital intensity seems to exist for all the environmental indicators except solid waste.

**Figure 5.1 Trade-induced Elasticity (industrial waste water)**

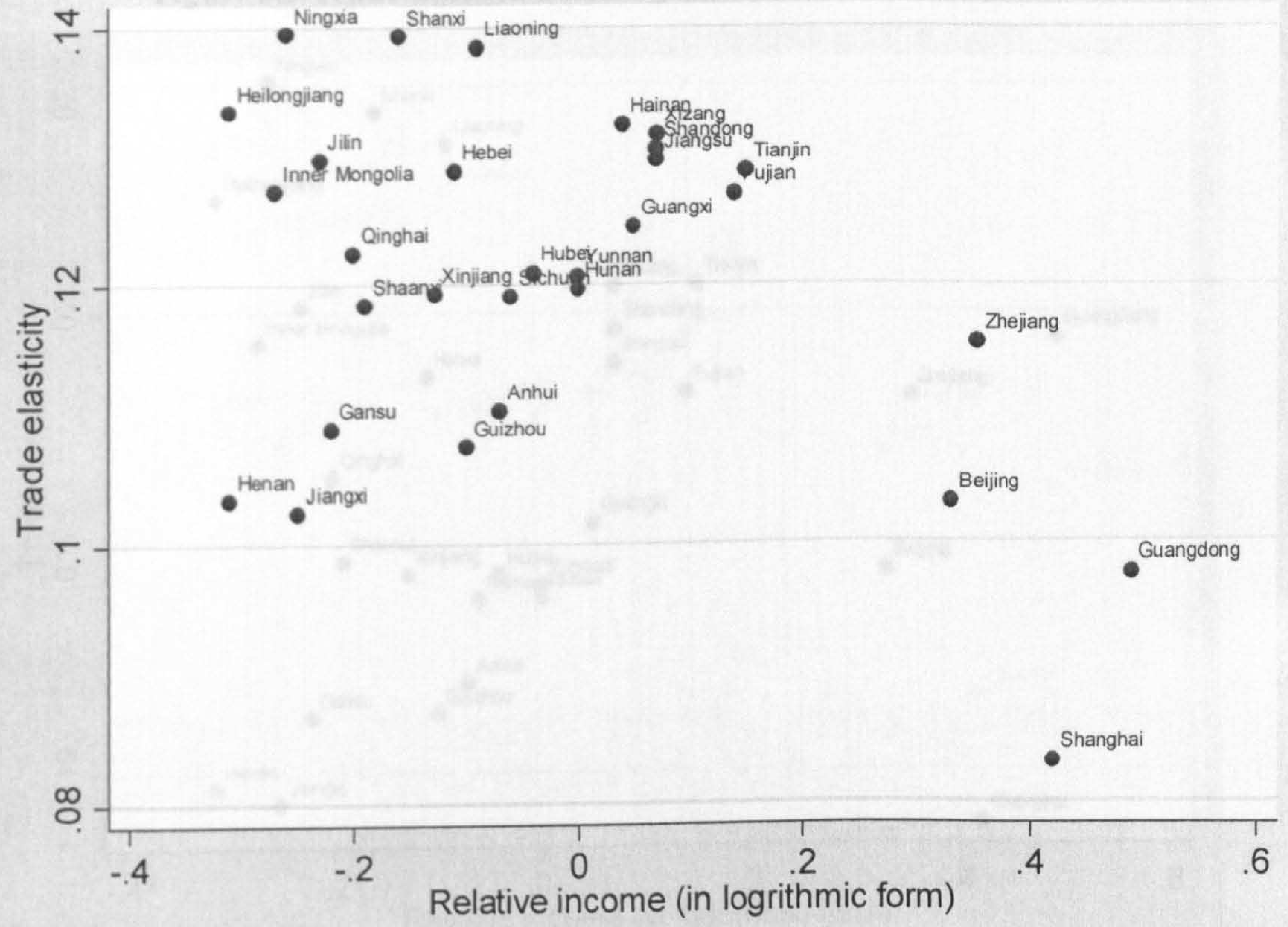



**Figure 5.2 Trade-induced Elasticity (COD)**

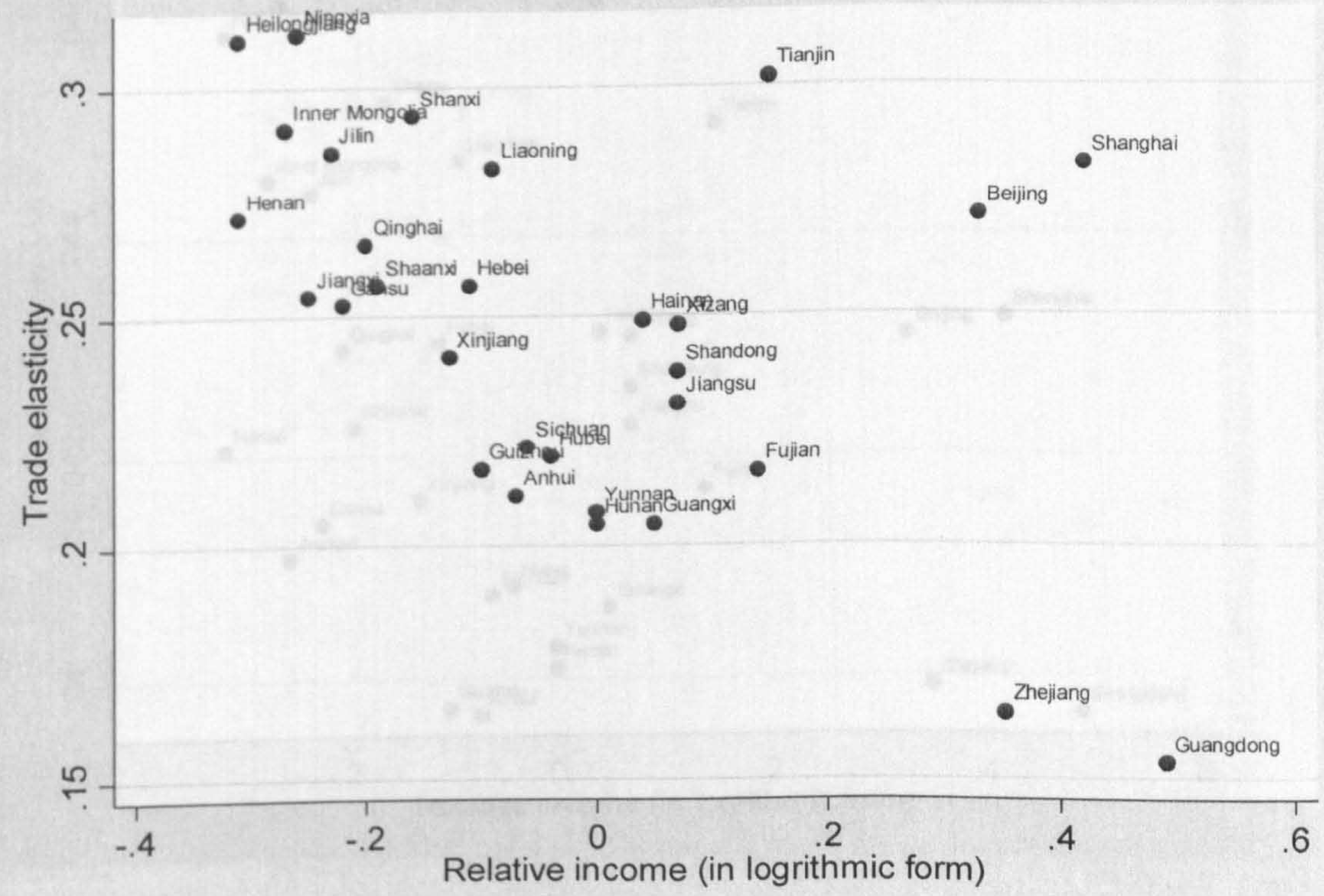


**Figure 5.3 Trade-induced Elasticity (industrial waste air)**

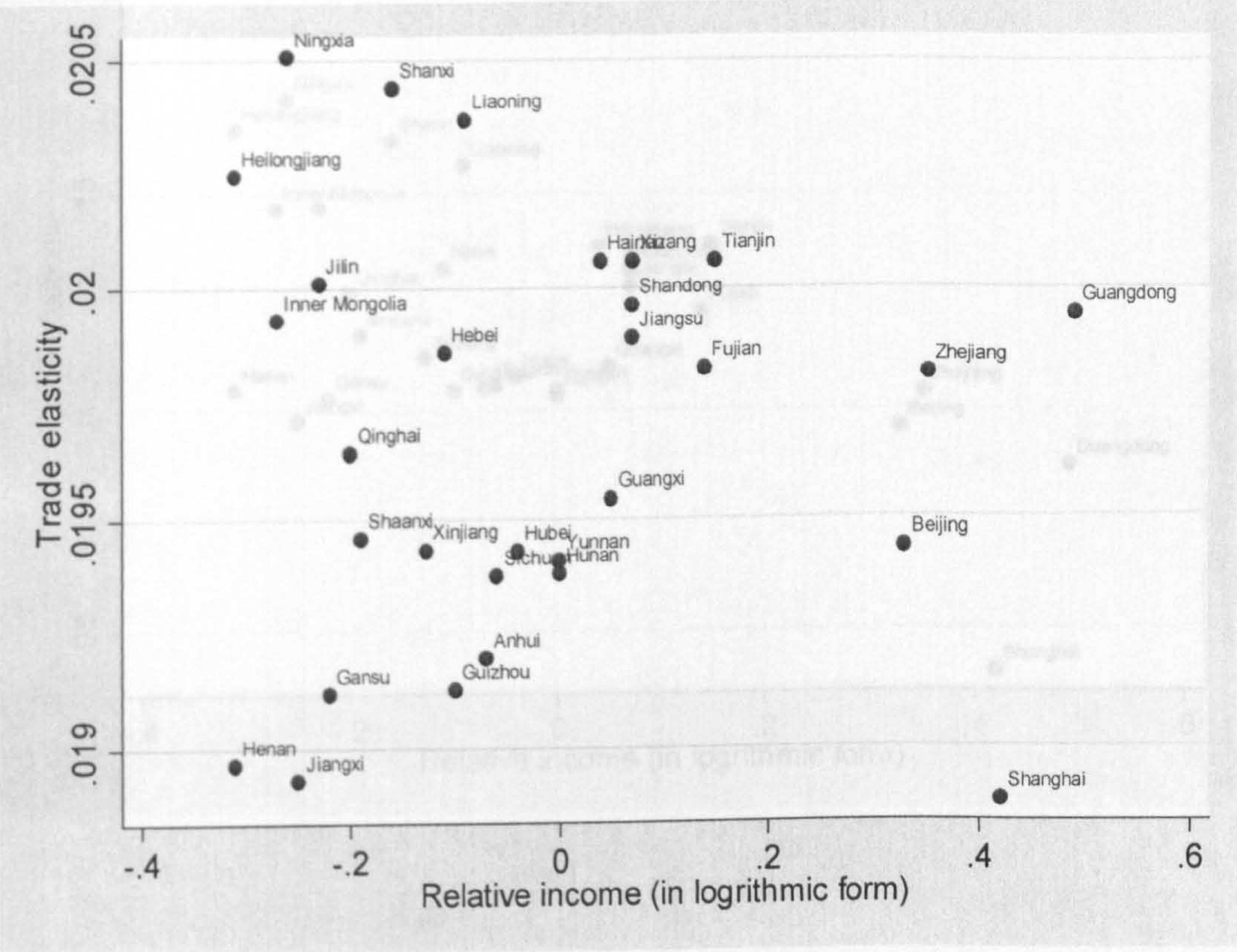



**Figure 5.4 Trade-induced Elasticity ($SO_2$)**

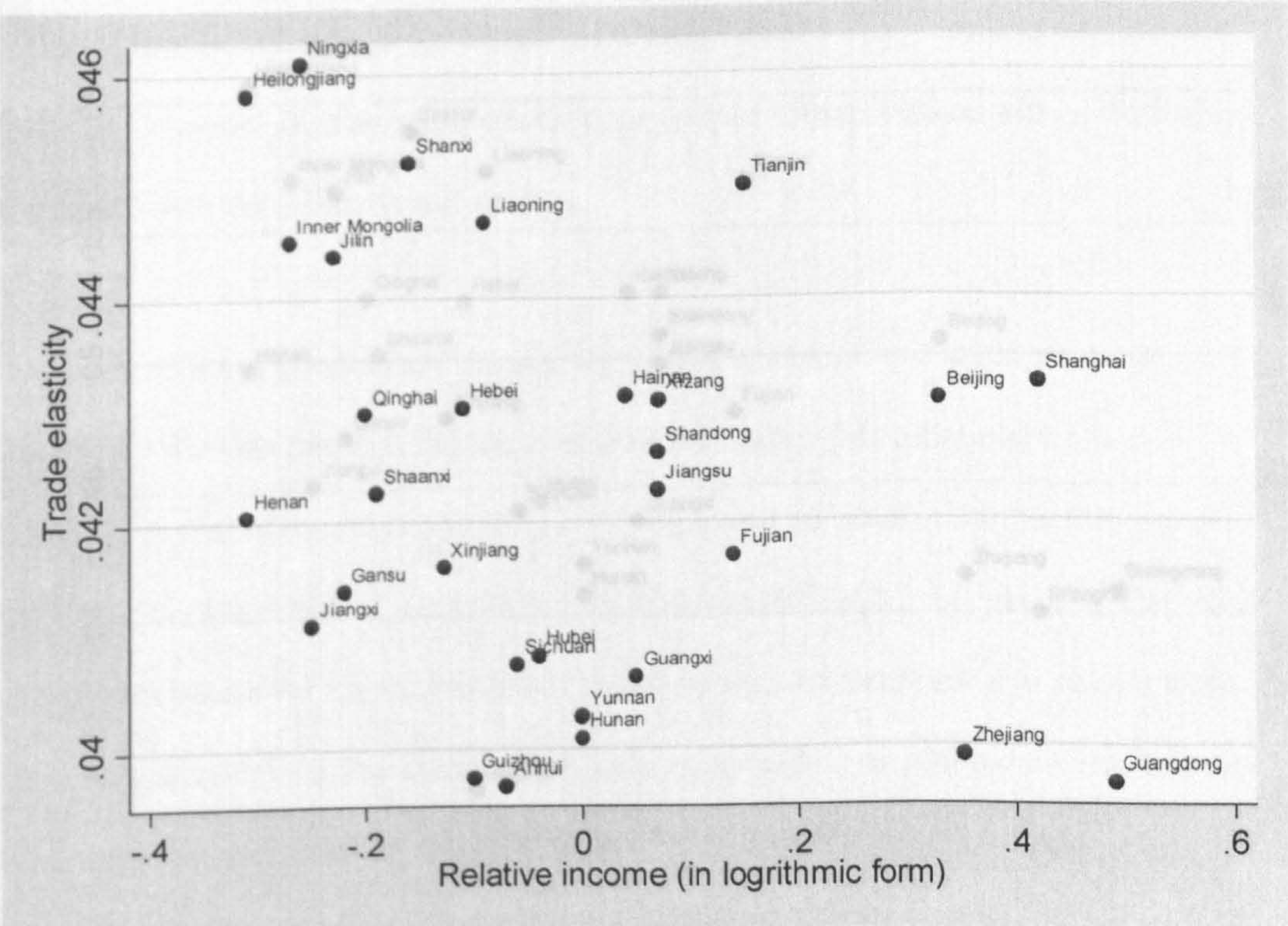


**Figure 5.5 Trade-induced Elasticity (industrial dust)**

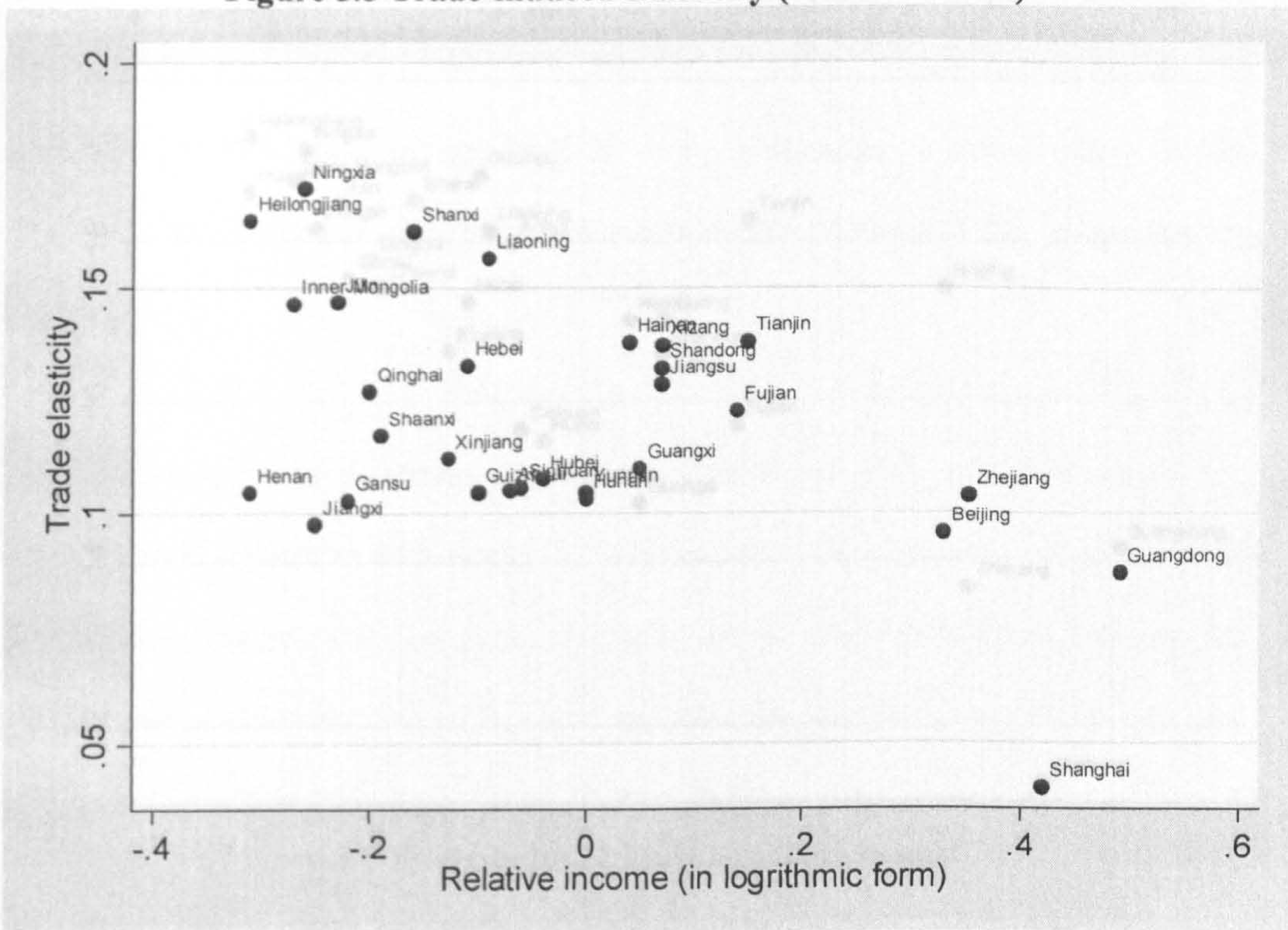



**Figure 5.6 Trade-induced Elasticity (industrial soot)**

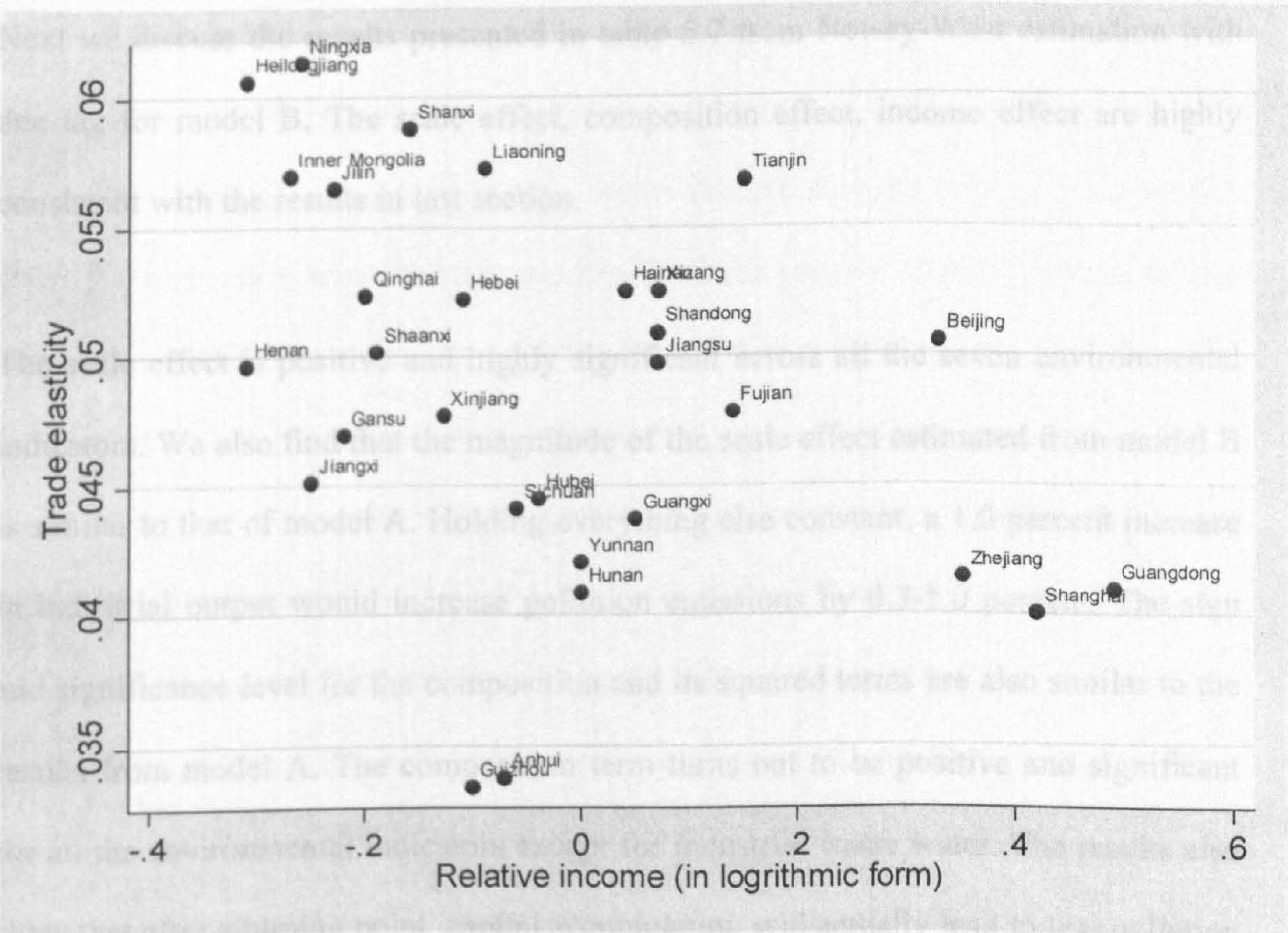
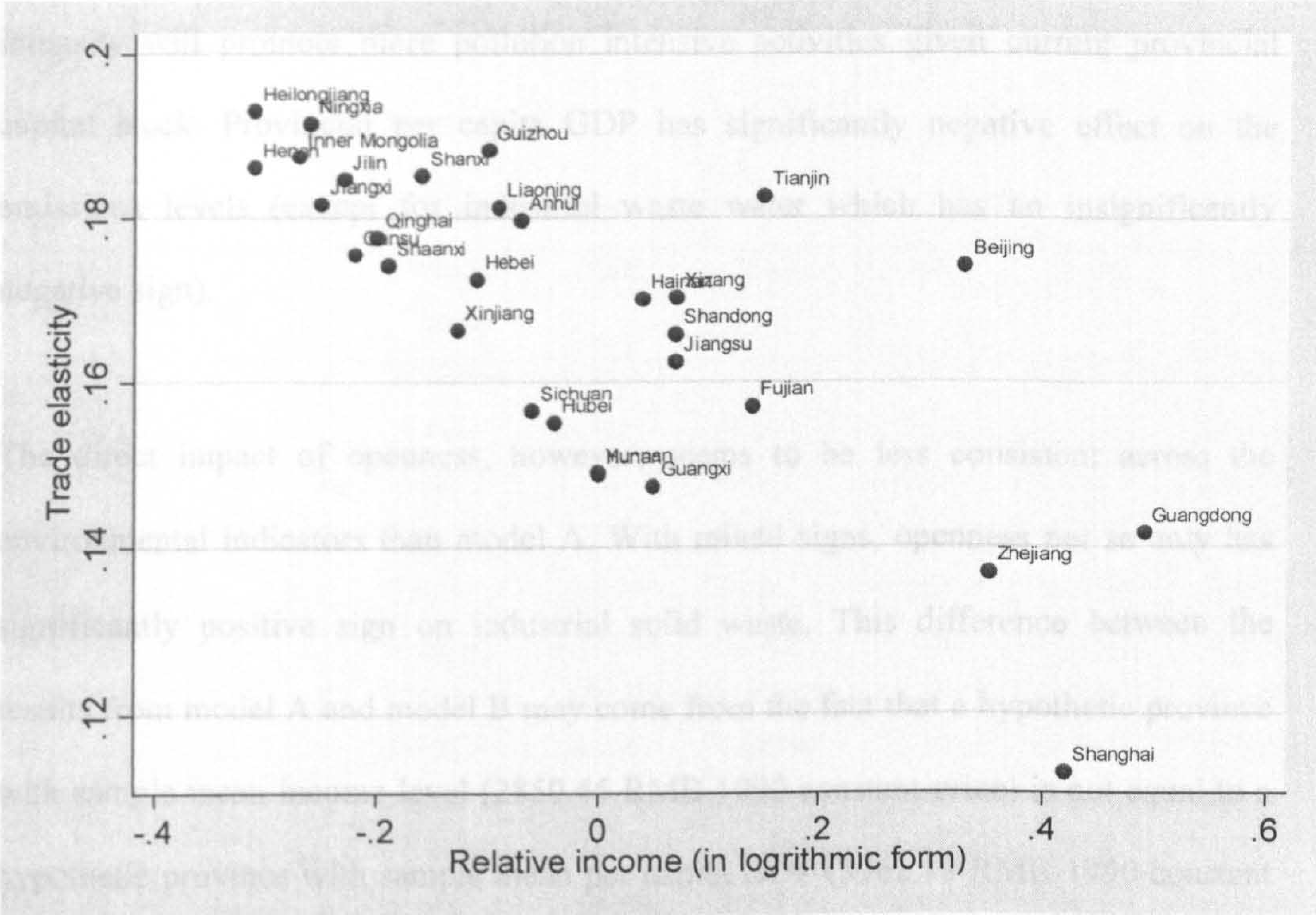


**Figure 5.7 Trade-induced Elasticity (solid waste)**




## 5.6.1.2 Newey-West results with model B

Next we discuss the results presented in table 5.7 from Newey-West estimation with one lag for model B. The scale effect, composition effect, income effect are highly consistent with the results in last section.

The scale effect is positive and highly significant across all the seven environmental indicators. We also find that the magnitude of the scale effect estimated from model B is similar to that of model A. Holding everything else constant, a 1.0 percent increase in industrial output would increase pollution emissions by 0.3-1.0 percent. The sign and significance level for the composition and its squared terms are also similar to the results from model A. The composition term turns out to be positive and significant for all the environmental indicators except for industrial waste water. The results also show that after a turning point, capital accumulation will actually lead to less pollution emissions for the specific environmental indicators. Yet the capital intensities in our dataset all lie to the left of the turning point. And we infer again an increase in capital intensity will promote more pollution intensive activities given current provincial capital stock. Provincial per capita GDP has significantly negative effect on the emissions levels (except for industrial waste water which has an insignificantly negative sign).

The direct impact of openness, however, seems to be less consistent across the environmental indicators than model A. With mixed signs, openness per se only has significantly positive sign on industrial solid waste. This difference between the results from model A and model B may come from the fact that a hypothetic province with sample mean income level (2850.45 RMB 1990 constant price) is not equal to a hypothetic province with sample mean per capita GDP (3962.19 RMB 1990 constant price). The interaction terms related to openness are again complicated though we succeed to find supportive evidence for the factor endowment effect ($\beta_6>0$) and the pollution haven effect ($\beta_8<0$). The product of openness and relative capital intensity shows that an increase in trade openness will result in rising pollution emissions for a province with higher relative capital intensity although this effect is not significant for the general indicators (industrial waste water, industrial waste air and solid waste). From the interaction term of trade openness and the squared term of relative capital intensity, we only find a possible inverted U-turn for industrial solid waste. The table also shows that an increase in trade openness will generally cause increased pollution emission for a province with a lower relative per capita GDP although the effect is not significant for industrial waste air and solid waste. The sign for the interaction between openness and the quadratic term of relative per capita GDP is mixed and insignificant. For the three way interaction term, we only find a significantly negative coefficient for industrial waste water while it is mixed in sign and insignificant for other environmental indicators. The interaction terms related to trade openness for all the dependent variables are not jointly equal to zero and hence we conclude that the trade-induced composition effect exists though on a small scale. The predicted trade-induced composition effect has mixed signs for a hypothetic sample mean province.

**Table 5.7 Newey-West estimation with model B**

| | | Waste water | COD | Waste air | $SO_2$ | Dust | Soot | Solid waste |
|---|---|---|---|---|---|---|---|---|
| S | $\beta_1$ | 0.701*** | 1.005*** | 0.733*** | 0.682*** | 0.342* | 0.578*** | 0.496*** |
| | | (6.623) | (4.864) | (8.008) | (5.791) | (1.882) | (4.087) | (4.061) |
| KL | $\beta_2$ | 0.310 | 1.541*** | 0.438** | 0.701*** | 2.105*** | 1.240*** | 0.819*** |
| | | (1.232) | (3.638) | (2.236) | (2.773) | (5.652) | (4.157) | (3.338) |
| $KL^2$ | $\beta_3$ | 0.037 | -0.098** | 0.004 | -0.067*** | -0.160*** | -0.097*** | 0.001 |
| | | (1.388) | (-2.091) | (0.186) | (-2.730) | (-4.232) | (-2.841) | (0.032) |
| GDPPC | $\beta_4$ | -0.273 | -2.704*** | -0.460** | -0.878*** | -1.819*** | -1.289*** | -0.887*** |
| | | (-0.919) | (-6.289) | (-2.419) | (-3.240) | (-3.947) | (-3.610) | (-3.610) |
| O | $\beta_5$ | 0.013 | 0.078 | -0.014 | 0.001 | 0.094 | -0.013 | 0.130** |
| | | (0.292) | (0.903) | (-0.287) | (0.017) | (1.353) | (-0.201) | (2.405) |
| O*rel.KL | $\beta_6$ | 0.058 | 0.646*** | 0.058 | 0.210* | 0.684*** | 0.476*** | 0.167 |
| | | (0.536) | (3.330) | (0.650) | (1.921) | (4.190) | (3.496) | (1.549) |
| O*rel.$KL^2$ | $\beta_7$ | 0.242*** | 0.456*** | 0.071 | 0.049 | -0.133 | -0.011 | -0.105* |
| | | (4.774) | (3.366) | (1.378) | (0.902) | (-1.512) | (-0.128) | (-1.862) |
| O*rel.GDPPC | $\beta_8$ | -0.242* | -0.925*** | -0.098 | -0.281** | -0.940*** | -0.621*** | -0.159 |
| | | (-1.950) | (-4.841) | (-1.181) | (-2.425) | (-5.842) | (-4.424) | (-1.413) |
| O*rel.$GDPPC^2$ | $\beta_9$ | 0.051 | -0.256 | 0.039 | -0.196 | -0.334 | -0.268 | -0.059 |
| | | (0.350) | (-0.998) | (0.287) | (-1.380) | (-1.402) | (-1.099) | (-0.411) |
| O*rel.KL*rel.GDPPC | $\beta_{10}$ | -0.512*** | -0.413 | -0.208 | 0.060 | 0.166 | 0.027 | -0.082 |
| | | (-3.309) | (-1.296) | (-1.511) | (0.401) | (0.720) | (0.104) | (-0.550) |
| _CONS | | 10.457*** | 28.698*** | 7.677*** | 16.246*** | 26.928*** | 20.295*** | 12.431** |
| | | (4.811) | (9.653) | (5.343) | (8.181) | (8.571) | (7.982) | (5.820) |
| F | | 320.501 | 96.701 | 322.454 | 265.652 | 125.239 | 150.409 | 318.737 |
| N | | 639 | 584 | 639 | 639 | 639 | 639 | 639 |
| KL turning point | | n/a | 7.87 | n/a | 5.25 | 6.56 | 6.37 | n/a |

*** means significant at 1%; **means significant at 5%;*means significant at 10%; t statistics are in parentheses; All equations are estimated time dummies and province dummies. We specify one lag for the Newey-West estimator.

Overall, it seems that the two models are consistent in predicting the scale effect, the composition effect, and the income effect. Five out of the seven environmental indicators, we find that the magnitude of income effect seems to be larger than that of the scale effect which is consistent with the findings in ACT (2003). However, it is difficult to compare the trade-induced composition effect since we have different "sample mean" values for income level and per capita GDP.

We also carry out regressions by including one variable or several interaction terms at a time for both models. Table A5.6.1 through to table A5.6.7 in the appendix A5.6 presents the regression results for each dependent variable in model A with the Newey-West estimator. We also do the same to model B though the tables are not attached. The coefficients for each independent variable are relatively stable across different regressions although some small differences in sign and significance level are evident.

## 5.6.2 Robustness check

In this section we discuss the sensitivity of our results to the variables and estimator in use. The examination of the results obtained by replacing the centred interaction terms with the original interaction terms is followed by a discussion based on results obtained from an FGLS estimator and a Random Effect estimator (GLS).

### 5.6.2.1 Interaction terms not centred

The following table 5.8 shows the Newey-West results with original interaction terms using the specification of model A. For the scale effect, the composition effect and the income effect, we find the coefficients are relatively consistent with those in the main results section. Some estimated turning points for capital intensity now locate within the range of current capital intensities. Consequently, an increase in capital intensity in a province with enough capital accumulation would result in less pollution emissions (for COD, $SO_2$ and industrial dust).

The direct impact of openness is obtained when both capital intensity and income (in logarithmic form) are equal to zero (which implies both capital intensity and income in level terms equal to 1). Hence $\beta_5$ no longer reflects the trade-induced composition effect for a hypothetic sample mean province. The interaction term between openness and capital intensity also seems to have a weak positive relationship with COD emissions, while the other pollutants have insignificant and sometimes negative signs (industrial soot). It also shows that an increase in openness would increase emissions in COD and $SO_2$ in a lower income province. The interaction between openness and the squared terms and the three way interaction term all have mixed signs and significance level across dependent variables. We estimate the trade-induced composition effects at sample mean. The trade-induced composition effect is significantly positive for many environmental indicators, except COD and industrial waste air. Compared to the main results, the magnitude of trade-induced composition effect is now much larger for industrial waste water, industrial waste air, $SO_2$, industrial dust and soot. Population density seems to be emissions-reducing for most pollutants. However, it shows that an increase in population density would also increase COD emissions. Productivity measure also holds as a pollution-reducing factor, except for COD emissions.

**Table 5.8 Results for model A with not centred interaction terms**

| | | Waste water | COD | Waste air | $SO_2$ | Dust | Soot | Solid waste |
|---|---|---|---|---|---|---|---|---|
| S | $\beta_1$ | 0.895*** | 0.865*** | 0.878*** | 0.570*** | 0.506*** | 0.733*** | 0.713*** |
| | | (8.743) | (4.645) | (9.158) | (4.584) | (2.986) | (4.584) | (6.294) |
| KL | $\beta_2$ | 1.045*** | 0.897** | 0.552*** | 0.555*** | 1.387*** | 1.032*** | 0.843*** |
| | | (6.169) | (2.555) | (3.384) | (2.724) | (4.921) | (4.062) | (4.496) |
| $KL^2$ | $\beta_3$ | -0.118*** | -0.205*** | 0.017 | -0.152*** | -0.353*** | -0.153*** | 0.083** |
| | | (-3.303) | (-3.225) | (0.478) | (-3.880) | (-6.661) | (-3.206) | (2.076) |
| I | $\beta_4$ | -1.100*** | -2.273*** | -0.271 | -0.225 | -0.580* | -0.860*** | -0.754*** |
| | | (-4.366) | (-5.545) | (-1.358) | (-0.928) | (-1.841) | (-2.636) | (-3.735) |
| O | $\beta_5$ | 4.954 | 32.146*** | -4.001 | 7.876** | -1.297 | -1.266 | -2.418 |
| | | (1.526) | (3.876) | (-1.085) | (2.054) | (-0.230) | (-0.225) | (-0.564) |
| O*KL | $\beta_6$ | 0.642 | 2.949** | 0.283 | 0.235 | 0.219 | -0.362 | 0.181 |
| | | (1.170) | (2.333) | (0.475) | (0.407) | (0.282) | (-0.448) | (0.262) |
| $O*KL^2$ | $\beta_7$ | -0.034 | 0.004 | 0.017 | -0.039 | -0.129*** | -0.053 | 0.030 |
| | | (-1.095) | (0.072) | (0.534) | (-1.263) | (-3.059) | (-1.304) | (0.871) |
| O*I | $\beta_8$ | -0.972 | -7.650*** | 1.192 | -2.020** | 1.037 | 0.805 | 1.112 |
| | | (-1.177) | (-3.630) | (1.267) | (-2.062) | (0.725) | (0.553) | (1.027) |
| $O*I^2$ | $\beta_9$ | 0.045 | 0.457*** | -0.087 | 0.130** | -0.109 | -0.082 | -0.101 |
| | | (0.851) | (3.393) | (-1.436) | (2.061) | (-1.189) | (-0.868) | (-1.472) |
| O*KL*I | $\beta_{10}$ | -0.047 | -0.349** | -0.025 | -0.024 | 0.027 | 0.086 | 0.001 |
| | | (-0.666) | (-2.184) | (-0.330) | (-0.331) | (0.277) | (0.829) | (0.006) |
| POPDEN | $\gamma_1$ | -0.378 | 1.021* | -0.100 | 0.358 | -0.167 | -0.278 | -0.077 |
| | | (-0.913) | (1.742) | (-0.304) | (0.850) | (-0.353) | (-0.506) | (-0.266) |
| PROD | $\gamma_2$ | -0.803*** | -0.101 | -0.751*** | -0.515** | -0.843** | -0.843*** | -0.841*** |
| | | (-3.240) | (-0.259) | (-3.873) | (-2.213) | (-2.225) | (-2.897) | (-3.767) |
| _cons | | 13.437*** | 29.673*** | 4.206** | 12.622*** | 14.739*** | 14.192*** | 9.436*** |
| | | (5.047) | (7.265) | (2.092) | (5.415) | (4.206) | (4.620) | (4.330) |
| F | | 316.273 | 97.903 | 277.556 | 252.671 | 146.146 | 153.056 | 346.655 |
| N | | 639 | 584 | 639 | 639 | 639 | 639 | 639 |
| Turning point | KL | 4.43 | 2.19 | n/a | 1.83 | 1.96 | 3.37 | n/a |
| Trade-induced Composition effect | | 2.23*** | 11.54 | -0.88** | 2.48*** | 1.05*** | 0.52*** | 0.26*** |

*** means significant at 1%; **means significant at 5%;*means significant at 10%; t statistics are in parentheses; All equations are estimated time dummies and province dummies. We specify one lag for the Newey-West estimator. Trade-induced composition effect is evaluated with capital intensity and income level at sample mean (level format) and the significance level is obtained by evaluating the overall significance of trade related variables.

Table 5.9 shows the Newey-west results with original interaction terms using the specification of model B. The scale effect, the composition effect and the income effect are relatively consistent with our main results. As in table 5.6.3, the composition effect seems to have a turning point for the specific environmental indicators.

We find a large and significantly positive coefficient for the direct impact of openness. Since the direct impact of openness does not represent the trade-induced composition effect for a hypothetic sample mean province, we need to calculate the average trade-induced composition effect based on the estimates of all the six terms related to trade openness. The interaction term between openness and capital intensity suggests that increased openness will result in more pollution emissions in a province with higher capital intensity. An inverted-U shape seems to exist only in the case of industrial dust. It also shows that an increase in openness would result in more pollution emissions if the province has lower per capita GDP. The three way interaction term seems to be mixed in sign and significance level. To make the trade-induced composition effect compatible among different model specifications, we estimate the trade-induced elasticity by using arithmetic mean of capital intensity and income in their level forms. The trade-induced composition effect is highly significant and positive.

**Table 5.9 Results for model B with not centred interaction terms**

| | | Waste water | COD | Waste air | $SO_2$ | Dust | Soot | Solid waste |
|---|---|---|---|---|---|---|---|---|
| S | $\beta_1$ | 0.752*** | 1.061*** | 0.683*** | 0.590*** | 0.221 | 0.477*** | 0.489*** |
| | | (7.606) | (4.794) | (7.165) | (4.880) | (1.287) | (3.390) | (4.309) |
| KL | $\beta_2$ | 0.811*** | 0.870** | 0.455** | 0.804*** | 2.362*** | 1.401*** | 0.481 |
| | | (3.247) | (2.168) | (2.245) | (2.772) | (5.127) | (3.850) | (1.523) |
| $KL^2$ | $\beta_3$ | -0.130*** | -0.217*** | -0.065* | -0.219*** | -0.443*** | -0.265*** | 0.029 |
| | | (-2.964) | (-3.210) | (-1.819) | (-5.381) | (-8.405) | (-5.570) | (0.599) |
| GDPPC | $\beta_4$ | -0.715** | -1.664*** | -0.271 | -0.739*** | -1.861*** | -1.105*** | -0.513* |
| | | (-2.452) | (-4.613) | (-1.316) | (-2.717) | (-3.459) | (-2.660) | (-1.709) |
| O | $\beta_5$ | 18.589*** | 47.594*** | 17.444*** | 9.720** | 6.065 | 19.493*** | 13.465*** |
| | | (4.718) | (4.037) | (4.538) | (2.275) | (0.985) | (3.467) | (3.277) |
| O*KL | $\beta_6$ | 3.753*** | 6.902*** | 2.574*** | 0.767 | 0.183 | 1.765 | 1.413 |
| | | (4.869) | (3.277) | (3.213) | (0.898) | (0.142) | (1.473) | (1.632) |
| $O*KL^2$ | $\beta_7$ | 0.126** | 0.156 | 0.079 | -0.066 | -0.182** | -0.041 | 0.049 |
| | | (2.516) | (1.466) | (1.586) | (-1.325) | (-2.323) | (-0.571) | (0.864) |
| O*GDPPC | $\beta_8$ | -4.411*** | -11.74*** | -4.439*** | -2.360** | -0.561 | -4.500*** | -3.296*** |
| | | (-4.372) | (-3.957) | (-4.570) | (-2.171) | (-0.361) | (-3.127) | (-3.121) |
| $O*GDPPC^2$ | $\beta_9$ | 0.261*** | 0.726*** | 0.282*** | 0.143** | -0.023 | 0.257*** | 0.203*** |
| | | (4.015) | (3.878) | (4.573) | (2.055) | (-0.230) | (2.770) | (2.950) |
| O*KL*GDPPC | $\beta_{10}$ | -0.437*** | -0.853*** | -0.323*** | -0.075 | 0.086 | -0.167 | -0.178 |
| | | (-4.359) | (-3.207) | (-3.183) | (-0.686) | (0.543) | (-1.100) | (-1.604) |
| _cons | | 13.568*** | 20.545 | 6.734*** | 15.695*** | 28.091*** | 19.894*** | 10.177*** |
| | | (6.494) | (.) | (4.300) | (7.112) | (7.101) | (6.439) | (3.883) |
| F | | 0.752*** | 1.061*** | 0.683*** | 0.590*** | 0.221 | 0.477*** | 0.489*** |
| | | (7.606) | (4.794) | (7.165) | (4.880) | (1.287) | (3.390) | (4.309) |
| N | | 639 | 584 | 639 | 639 | 639 | 639 | 639 |
| Turning point | KL | 3.12 | 2.00 | 3.49 | 1.84 | 2.66 | 2.64 | n/a |
| Trade-induced Composition effect | | 6.58*** | 15.72*** | 5.38*** | 3.18*** | 3.85*** | 6.88*** | 4.42*** |

*** means significant at 1%; **means significant at 5%;*means significant at 10%; t statistics are in parentheses; All equations are estimated time dummies and province dummies. We specify one lag for the Newey-West estimator. Trade-induced composition effect is evaluated with capital intensity and income level at sample mean (level format) and the significance level is obtained by evaluating the overall significance of trade related variables.

### 5.6.2.2 Results obtained from the FGLS estimator and GLS estimator

We also present regression results obtained from the FGLS estimator controlling for AR (1) and heteroscedastic disturbances. The results are presented in table 5.10 and table 5.11. The scale effect and the composition effect are relatively consistent with our previous results. However, we find the income effect (measured in urban disposable income or per capita GDP) is not consistently negative across the environmental indicators. The significance level of the income effect also varies considerably.

The direct impact of trade openness (equivalent to the trade-induced composition effect for a hypothetic sample mean province) is found to be mixed in signs and significance level. Similarly to the main results, we find that the trade-induced composition effect for a hypothetic sample mean province is much smaller than the scale, the composition and the income effect. The interaction terms provide similar evidence as before and we find traits of both FEH and PHH effects.

The random effect estimator (GLS) is less efficient than the FGLS estimator. Reported in table A5.6.8 and table A5.6.9 in the appendix, the random effect results are highly consistent with the results from the Newey-West estimator.

Table 5.10 FGLS estimation results for model A

| | | Waste water | COD | Waste air | $SO_2$ | Dust | Soot | Solid waste |
|---|---|---|---|---|---|---|---|---|
| S | $\beta_1$ | 0.454*** | 0.678*** | 0.449*** | 0.347*** | 0.345*** | 0.520*** | 0.323*** |
| | | (6.975) | (5.169) | (7.228) | (4.943) | (2.835) | (5.187) | (5.276) |
| KL | $\beta_2$ | 0.419*** | 0.409* | 0.339*** | 0.526*** | 1.032*** | 0.417** | 0.526*** |
| | | (3.974) | (1.690) | (2.821) | (4.418) | (4.718) | (2.345) | (4.147) |
| $KL^2$ | $\beta_3$ | -0.009 | -0.126*** | 0.015 | -0.051*** | -0.163*** | -0.038 | 0.006 |
| | | (-0.494) | (-3.727) | (0.917) | (-2.804) | (-4.811) | (-1.375) | (0.365) |
| I | $\beta_4$ | -0.146 | -1.251*** | 0.047 | 0.100 | -0.258 | 0.078 | -0.53*** |
| | | (-0.908) | (-4.124) | (0.331) | (0.611) | (-0.862) | (0.317) | (-3.112) |
| O | $\beta_5$ | 0.069** | -0.005 | -0.013 | 0.002 | -0.014 | -0.056 | 0.023 |
| | | (2.527) | (-0.077) | (-0.518) | (0.051) | (-0.239) | (-1.308) | (0.764) |
| O*rel.KL | $\beta_6$ | -0.002 | -0.016 | -0.028 | 0.006 | 0.105 | -0.084 | 0.115** |
| | | (-0.036) | (-0.175) | (-0.585) | (0.117) | (1.110) | (-1.100) | (2.279) |
| O*rel.$KL^2$ | $\beta_7$ | -0.061** | -0.016 | -0.065** | 0.007 | -0.152*** | -0.18*** | -0.061** |
| | | (-2.154) | (-0.318) | (-2.564) | (0.274) | (-3.275) | (-4.453) | (-2.486) |
| O*rel.I | $\beta_8$ | -0.043 | -0.452*** | -0.015 | -0.007 | -0.426*** | -0.133 | -0.33*** |
| | | (-0.545) | (-3.090) | (-0.225) | (-0.100) | (-2.819) | (-1.139) | (-4.399) |
| O*rel.$I^2$ | $\beta_9$ | -0.416*** | 0.113 | -0.070 | -0.090 | -0.353 | 0.212 | -0.270* |
| | | (-2.930) | (0.435) | (-0.540) | (-0.587) | (-1.278) | (0.958) | (-1.897) |
| O*rel.KL*rel.I | $\beta_{10}$ | -0.377* | 0.316 | 0.150 | -0.291 | -0.298 | 0.296 | 0.230 |
| | | (-1.752) | (0.805) | (0.737) | (-1.313) | (-0.696) | (0.876) | (1.099) |
| POPDEN | $\gamma_1$ | 0.351* | 0.213 | -0.298 | 0.432** | -0.585 | -0.050 | -0.014 |
| | | (1.649) | (0.591) | (-1.604) | (2.126) | (-1.525) | (-0.160) | (-0.072) |
| PROD | $\gamma_2$ | -0.324*** | -0.421* | -0.37*** | -0.811*** | -0.842*** | -0.98*** | -0.35*** |
| | | (-2.697) | (-1.783) | (-3.355) | (-6.658) | (-3.423) | (-4.814) | (-2.995) |
| _cons | | 11.540*** | 18.460*** | 3.898*** | 11.174*** | 11.174*** | 8.199*** | 9.669*** |
| | | (7.402) | (6.055) | (2.767) | (7.118) | (3.552) | (3.427) | (5.934) |
| chi2 | | 10875 | 4919 | 9737 | 9176 | 4781 | 5515 | 10052 |
| N | | 639 | 584 | 639 | 639 | 639 | 639 | 639 |
| Turning point | KL | - | 0 | - | 4.56 | 2.75 | 3.54 | - |

*** means significant at 1%; **means significant at 5%;*means significant at 10%; t statistics are in parentheses; All equations are estimated time dummies and province dummies. We specify one lag for the FGLS estimator.

**Table 5.11 FGLS estimation results for model B**

| | | Waste water | COD | Waste air | $SO_2$ | Dust | Soot | Solid waste |
|---|---|---|---|---|---|---|---|---|
| S | $\beta_1$ | 0.323*** | 0.715*** | 0.336*** | 0.230*** | 0.163 | 0.283*** | 0.270*** |
| | | (5.295) | (5.897) | (5.618) | (3.131) | (1.277) | (2.746) | (4.292) |
| KL | $\beta_2$ | 0.094 | 0.775*** | 0.401*** | 0.393** | 1.332*** | 0.603*** | 0.432*** |
| | | (0.707) | (3.196) | (3.084) | (2.572) | (5.072) | (2.806) | (3.227) |
| $KL^2$ | $\beta_3$ | 0.002 | -0.105*** | -0.007 | -0.060*** | -0.155*** | -0.053** | 0.008 |
| | | (0.121) | (-3.585) | (-0.407) | (-3.047) | (-4.780) | (-1.973) | (0.490) |
| GDPPC | $\beta_4$ | 0.207 | -1.312*** | -0.138 | -0.357** | -0.885*** | -0.589** | -0.39*** |
| | | (1.323) | (-4.522) | (-1.080) | (-2.064) | (-2.910) | (-2.369) | (-2.641) |
| O | $\beta_5$ | 0.027 | -0.069 | -0.012 | -0.003 | -0.006 | -0.063 | 0.041 |
| | | (0.954) | (-1.152) | (-0.452) | (-0.079) | (-0.099) | (-1.462) | (1.421) |
| O*rel.KL | $\beta_6$ | -0.035 | 0.259** | 0.106* | 0.082 | 0.392*** | 0.216** | 0.096 |
| | | (-0.556) | (2.181) | (1.812) | (1.178) | (3.222) | (2.128) | (1.604) |
| O*rel.$KL^2$ | $\beta_7$ | 0.148*** | 0.501*** | 0.002 | 0.056 | -0.088 | 0.091 | -0.026 |
| | | (3.281) | (5.860) | (0.060) | (1.456) | (-1.092) | (1.442) | (-0.719) |
| O*rel.GDPPC | $\beta_8$ | -0.043 | -0.433*** | -0.117** | -0.137** | -0.586*** | -0.414*** | -0.091 |
| | | (-0.619) | (-3.572) | (-2.044) | (-1.984) | (-4.716) | (-4.013) | (-1.627) |
| O*rel.$GDPPC^2$ | $\beta_9$ | 0.029 | 0.197 | -0.137* | -0.127 | -0.201 | 0.177 | -0.015 |
| | | (0.296) | (1.025) | (-1.752) | (-1.232) | (-1.080) | (1.143) | (-0.166) |
| O*KL*rel.GDPPC | $\beta_{10}$ | -0.35*** | -0.886*** | 0.013 | 0.002 | 0.021 | -0.471*** | -0.101 |
| | | (-3.141) | (-3.973) | (0.152) | (0.020) | (0.103) | (-2.717) | (-1.085) |
| _cons | | 8.743*** | 18.090*** | 7.395*** | 14.604*** | 20.191*** | 16.099*** | 9.553*** |
| | | (7.442) | (8.343) | (7.556) | (11.148) | (9.333) | (9.018) | (8.830) |
| chi2 | | 7307 | 4360 | 9997 | 10207 | 4041 | 5487 | 10772 |
| N | | 639 | 584 | 639 | 639 | 639 | 639 | 639 |
| Turning point | KL | n/a | 3.69 | n/a | 3.28 | 4.29 | 5.66 | n/a |

*** means significant at 1%; **means significant at 5%;*means significant at 10%; t statistics are in parentheses; All equations are estimated time dummies and province dummies. We specify one lag for the FGLS estimator.

#### 5.6.2.3 Endogeneity considerations

So far we have tried to tackle the problems associated with our panel data set: multicollinearity, heteroscedasticity and autocorrelation. However, we have assumed away the issue of endogeneity which may originate from omitted variables, measurement error and simultaneity. Since we only focus on a few of explanatory variables, a model specification error could happen we miss out an important variable. Ramsey's RESET test is often employed to test for omitted variables. Measurement error also exists in our specification. The endogeneity issue is associated with trade and income in this literature. Helpman(1988:6) asks "Does growth drive trade, or is there a reverse link from trade to growth?" For example, a negative effect of environmental regulation on growth together with a positive effect of growth on trade would make trade seem to be bad to the environment. Similarly, pollution emissions could have impact on income: a positive effect as income could be increased via more production and hence more pollution emissions; a negative effect as income might be reduced because of hazardous pollution problem in the area.

As reviewed in the literature section, Frankel and Rose (2005) and Managi et al. (2009) address the issue of endogeneity of trade openness and income. Antweiler et al. (2001) points out a possibility of a simultaneous determination of pollution and (current period) per capita income.

To tackle endogeneity, instrumental variable approach is a common cure. Instruments from outside the model have a problem of reliability. To examine the simultaneity of environment input (pollution emissions) and output, a structural model such as that in Dean (2002) is a good candidate.

Another possibility is to adopt dynamic panel approach which usually employs difference or system GMM (Generalized Method of Moments) (see Hansen, 1982; Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998). One problem associated with GMM estimators is that instruments from the system itself may be too many (over-identifying restrictions) (see Roodman, 2007). Like FGLS, GMM estimators prefer that units be several times larger than time periods. Also, the problem associated with proper identification of endogenous variables and exogenous variables as well as number of lags renders the credibility of estimation results. However, GMM results do not quantitatively change the sign of scale effect, composition effect and income effect although the signs for trade related variables vary considerably across specifications. Results based on GMM estimation are available upon request.

## 5.7 CONCLUSIONS

Compared with similar studies using ACT type modelling, we find our results fit in the model well even with different environmental indicators and alternative estimators. We find a significantly positive scale effect under alternative interaction methods and estimators. An inverted-U shape is found for the composition effect, although current provincial capital intensities are too low to have a strong technology reinforcing effect for some environmental indicators. A negative income effect is found under both model specifications using Newey-West estimator and is greater than the scale effect for many environmental indicators except for industrial waste water and industrial waste air. However, the negative income effect is less significant when we use the alternative FGLS estimator. The trade-induced composition effect depends on provincial characteristics in factor endowments (measured as capital intensity) and income level (measured as one period lagged urban disposable income or the per capita GDP). We do find evidence for both effects of trade liberalization on the environment (the pollution haven effect and the factor endowment effect) working against each other. We also discussed the trade-induced composition effect for a hypothetic sample mean province for each regression. The main regressions give me more consistent results for this effect: for an "average" province in our sample, trade openness seems to promote advantage in dirty industries. However, this trade-induced composition effect is smaller in magnitude, which is consistent with Antweiler et al. (2001), Copeland and Taylor (2003).

Although we succeed in decomposing the impact of trade openness on the environment into several mechanisms, it is difficult to combine them together and evaluate the overall impact. Even if we assume that an increase in trade openness increases the economic scale and income level by the same percentage, and the scale effect is outweighed by the technique effect, we still have a positive trade-induced composition effect. Whether trade openness harms the environment seems to be environmental indicator specific, provincial specific as well as time specific issue.

Another study on this topic that uses the ACT model for Chinese provinces is He (2006). Our paper differs from He (2006) in that we use a longer time period, more indicators as well as different specifications and estimators. The longer period of data enhances the strength of our model's fitness with the theory. We also check the theory against different indicators. As to the model specifications, we would argue that a logarithmic form fits the theory better. Contrary to He's findings, our results show a positive composition effect which offer evidence to the common hypothesis that higher capital intensity is associated with pollution-intensive industries. We also separate the composition effect into pro-pollution and technology-reinforcing effect. It is evident in most specifications that further capital accumulation after a turning point will promote technologies in a province and result in less pollution emissions ceteris paribus. Our specifications also enable us to extend our results for total emission volumes to emission intensity (emission per capita) and emission density (emissions per surface) if we alter our scale measure in the mean time.

There are also some limitations with this chapter. One of them relates to the difficulty to evaluate the overall impact of trade liberalization after we decompose it into the individual effects. A few studies have tried to use simultaneous equations to tackle this problem. Secondly, a deficiency lies in ACT framework itself. The model assumes that trade has no impact on factor endowments and technology; however, further trade may have impact on capital accumulation or knowledge spillovers that hastens technological progress. Another limitation is that we treat trade openness as if it is exogenous; however, trade openness (measured as trade intensity in the context) is affected by many aspects. Frenkel and Rose (2005) address the issue of endogeneity of trade openness and income by instrumentation. An ideal robustness check would incorporate addressing endogeneity.

There are also other aspects for further research, for example, how to incorporate technological spillovers in the model. The long-run impact of trade liberalization on the environment may benefit from technology advances/environment management practice transfer. Another related area is to extrapolate provincial specific characteristics from the estimation. The standards required by environmental regulations vary substantially across provinces for the following reasons: 1) Income inequality. Same as in the case of cross country differentials, the desire for a cleaner environment is presumably a normal good. This can sometimes be internalized and viewed as provincial effect. 2) Environmental absorptive capacity. Some provinces may have less population, larger land area as well as stock of natural resources than others. 3) Regulatory capability. Differences in the ability to design and enforce environmental regulations may explain some of the differences in similar developed provinces.

Most of the existing models view pollution externality as fully internalized or compensated; however, the issue of efficient regulations rises as corruption is rife in the areas of environmental monitoring and standards regulating. This topic is often investigated in the framework of regulatory efficiency and hence is not included in the chapter.

# APPENDICES TO CHAPTER FIVE

## A5.1 Explanatory notes

1. The administrative separation of Hainan Island from Guangdong to form a separate province happened in 1988. Before that, data on Hainan were not separately reported. So for 1985 and 1986, there was no comparable data for Hainan.
2. Hong Kong, Macau, Taiwan and Chongqing municipality (which was part of Sichuan province until 1997. In this analysis we still consider Chongqing as part of Sichuan).
3. We group the provinces into three groups as follows:

   **Eastern**-Beijing, Fujian, Guangdong, Hainan, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Tianjin and Zhejiang;

   **Central**-Anhui, Heilongjiang, Henan, Hubei, Hunan, Jiangxi, Jilin and Shanxi;

   **Western**-Gansu, Guangxi, Guizhou, Inner Mongolia, Ningxia, Qinghai, Shaanxi, Sichuan, Xinjiang, Xizang and Yunnan.
4. In China, economic activities are categorized into the following three strata of industry (China Statistical Yearbooks):

   Primary industry refers to agriculture, forestry, animal husbandry and fishery and services in support of these industries;

   Secondary industry refers to mining and quarrying, manufacturing, production and supply of electricity, water and gas, and construction;

   Tertiary industry refers to all economic activities not included in the primary or secondary industries.

## A5.2 Data sources and variable definitions

**Table A5.2.1 Data sources**

| Data | Source |
|---|---|
| **Industrial waste water** | China Environment Yearbooks, 1990-2000; China Statistical Yearbooks, 1986-1989; 2001-2008; COD data for the years 1987-1989 and 1991 are from the World Bank's DECRG-IE division (with data for 1990 missing) |
| **Industrial COD (chemical oxygen demand)** | |
| **Industrial waste** | |
| **Industrial $SO_2$** | |
| **Industrial soot** | |
| **Industrial dust** | |
| **Industrial Solid waste** | |
| **Total output; industrial output; price levels** | China Statistics Compilation 1949-2004; China Statistic Yearbooks 2006-2008; Chongqing Statistic Yearbook 2007 |
| **Income for urban and rural households; price levels** | |
| **Total population** | |
| **Capital stock; Capital flow; price level** | 1985-2005 from Zhang Jun et.al. 2006-2007 are calculated based on their method and data from China Statistic Yearbooks 2006-2008; Capital flow is derived from Capital Stock for each province in each year. |
| **Employment** | China Statistics Compilation 1949-2004; China Statistic Yearbooks 2006-2008 |
| **Total trade; exports; imports; exchange rate** | China Statistics Compilation 1949-2004; China Statistic Yearbooks 2006-2008 |
| **Map data for provinces** | Shapefile from CDC (Centres for Disease Control and Prevention, US)website |

Note: a few provinces have missing observations for some years (especially in early years when some inland provinces have no data for trade or FDI inflows)

Table A5.2.2 Variable definitions

| Observation definition | Observation unit | Variable | Obs | Mean | Std.Dev | Min | Max |
|---|---|---|---|---|---|---|---|
| industrial waste water discharge | 10,000 tons | Waste water | 639 | 10.84 | 1.07 | 6.42 | 12.60 |
| industrial COD discharge | Ton | COD | 584 | 11.82 | 1.24 | 6.66 | 13.98 |
| industrial waste air emissions | 100 million c. m | Waste air | 639 | 8.08 | 1.16 | 2.30 | 10.78 |
| Industrial Sulphur Dioxide emissions | Ton | $SO_2$ | 639 | 12.78 | 1.23 | 6.60 | 14.47 |
| Industrial dust emissions | Ton | DUST | 639 | 12.12 | 1.14 | 6.91 | 14.54 |
| Industrial soot emissions | Ton | SOOT | 639 | 12.31 | 1.15 | 6.84 | 14.44 |
| Solid waste disposal | 10,0000 tons | Solid waste | 639 | 7.48 | 1.23 | 0.00 | 9.84 |
| industrial output | 100 million Yuan | S | 639 | 5.86 | 1.27 | 1.23 | 8.71 |
| the ratio of capital stock to employment | 10,000 Yuan per employee | KL | 639 | 0.07 | 0.88 | -1.52 | 2.58 |
| one period lagged urban disposable | Yuan | I | 639 | 7.81 | 0.54 | 6.67 | 9.03 |
| one period lagged per capita GDP | Yuan | GDPPC | 639 | 7.99 | 0.74 | 6.46 | 10.22 |
| the ratio of (exports+imports) to GDP | N/A | O | 639 | -1.93 | 0.95 | -3.85 | 0.61 |
| GDP per employee | 100 million Yuan | PROD | 639 | -3.94 | 1.33 | -8.46 | -1.17 |
| the ratio of population to land area. | 10,000 people per $km^2$ | POPDEN | 639 | -0.45 | 0.83 | -2.60 | 2.26 |
| KL relative to the national average | | rel.KL | 639 | -0.19 | 0.58 | -1.33 | 1.38 |
| I relative to the national average | | rel.I | 639 | -0.03 | 0.23 | -0.46 | 0.65 |
| GDPPC relative to the national average | | rel.GDPPC | 639 | -0.15 | 0.51 | -1.16 | 1.30 |

Note: all the data in monetary units have been adjusted to 1990 price level using provincial specific GDP deflators

## A5.3 Descriptive Statistics and Figures

**Table A5.3.3 Trends in Industrial Waste Water**

**(Left series: in 10 thousand tons; right series: in ton per capita)**

| Province | 1985 | | 1990 | | 1995 | | 2000 | | 2005 | | Change % | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anhui | 100958 | 19.6 | 98620 | 17.4 | 87006 | 14.7 | 63106 | 10.4 | 63487 | 10.4 | -37.1 | -47.0 |
| Beijing | 38983 | 39.7 | 40641 | 37.4 | 36997 | 29.6 | 23164 | 17.0 | 12813 | 8.3 | -67.1 | -79.0 |
| Fujian | 66430 | 24.0 | 76217 | 25.1 | 66381 | 20.5 | 57617 | 16.9 | 130939 | 37.0 | 97.1 | 54.4 |
| Gansu | 41294 | 20.2 | 38375 | 17.0 | 38393 | 15.7 | 23795 | 9.3 | 16798 | 6.5 | -59.3 | -68.0 |
| Guangdong | 133314 | 23.6 | 140250 | 22.5 | 128259 | 18.9 | 114055 | 15.2 | 231568 | 25.2 | 73.7 | 6.9 |
| Guangxi | 89906 | 23.2 | 105248 | 24.8 | 96563 | 21.3 | 81571 | 17.2 | 145609 | 31.2 | 62.0 | 34.6 |
| Guizhou | 45263 | 15.2 | 34224 | 10.5 | 28206 | 8.0 | 20598 | 5.5 | 14850 | 4.0 | -67.2 | -73.9 |
| Hainan | 7064 | 11.8 | 8041 | 12.1 | 6985 | 9.7 | 7064 | 9.0 | 7428 | 9.0 | 5.2 | -24.1 |
| Hebei | 99378 | 17.9 | 99181 | 16.1 | 82825 | 12.9 | 89600 | 13.4 | 124533 | 18.2 | 25.3 | 1.5 |
| Heilongjiang | 205069 | 61.1 | 112398 | 31.7 | 69389 | 18.7 | 52644 | 13.8 | 45158 | 11.8 | -78.0 | -80.6 |
| Henan | 128056 | 16.3 | 104934 | 12.1 | 98364 | 10.8 | 109210 | 11.5 | 123476 | 13.2 | -3.6 | -19.3 |
| Hubei | 160820 | 32.3 | 162302 | 29.8 | 139938 | 24.2 | 106733 | 17.9 | 92432 | 16.2 | -42.5 | -49.9 |
| Hunan | 167512 | 29.8 | 188633 | 30.9 | 145251 | 22.7 | 112563 | 17.2 | 122440 | 19.4 | -26.9 | -35.0 |
| Inner Mongolia | 21301 | 10.6 | 26225 | 12.1 | 28239 | 12.4 | 21844 | 9.2 | 24967 | 10.5 | 17.2 | -1.0 |
| Jiangsu | 198173 | 31.9 | 233503 | 34.5 | 220184 | 31.2 | 201923 | 27.6 | 296318 | 39.6 | 49.5 | 24.3 |
| Jiangxi | 68291 | 19.5 | 77123 | 20.2 | 66880 | 16.5 | 41956 | 10.1 | 53972 | 12.5 | -21.0 | -35.7 |
| Jilin | 62847 | 27.3 | 57645 | 23.6 | 46891 | 18.4 | 37386 | 14.2 | 41189 | 15.2 | -34.5 | -44.5 |
| Liaoning | 154525 | 41.9 | 163714 | 41.5 | 140193 | 34.3 | 109044 | 26.1 | 105072 | 24.9 | -32.0 | -40.6 |
| Ningxia | 8644 | 20.8 | 8612 | 18.5 | 7813 | 15.2 | 10942 | 19.7 | 21411 | 35.9 | 147.7 | 72.3 |
| Qinghai | 8580 | 21.1 | 6865 | 15.4 | 5029 | 10.5 | 4661 | 9.0 | 7619 | 14.0 | -11.2 | -33.4 |
| Shaanxi | 43938 | 14.6 | 40168 | 12.1 | 40652 | 11.6 | 30903 | 8.5 | 42819 | 11.5 | -2.5 | -21.4 |
| Shandong | 105375 | 13.7 | 87631 | 10.4 | 95343 | 11.0 | 110324 | 12.3 | 139071 | 15.0 | 32.0 | 9.8 |
| Shanghai | 149921 | 123.2 | 133218 | 103.8 | 116116 | 89.2 | 72446 | 54.8 | 51097 | 28.7 | -65.9 | -76.7 |
| Shanxi | 45655 | 17.1 | 58430 | 20.2 | 40656 | 13.2 | 32406 | 10.0 | 32099 | 9.6 | -29.7 | -44.0 |
| Sichuan | 236830 | 23.2 | 196499 | 18.2 | 191593 | 17.2 | 201323 | 17.5 | 207475 | 18.8 | -12.4 | -18.9 |
| Tianjin | 27716 | 34.4 | 22865 | 25.9 | 21897 | 23.2 | 17604 | 17.6 | 30081 | 28.8 | 8.5 | -16.3 |
| Xinjiang | 13060 | 9.6 | 15501 | 10.1 | 19001 | 11.4 | 15365 | 8.3 | 20052 | 10.0 | 53.5 | 4.0 |
| Xizang | - | - | 129 | 0.6 | 2155 | 9.1 | 1006 | 4.0 | 991 | 3.6 | 668.2 | 504.7 |
| Yunnan | 45490 | 13.3 | 42422 | 11.4 | 48937 | 12.3 | 35117 | 8.3 | 32928 | 7.4 | -27.6 | -44.4 |
| Zhejiang | 106680 | 26.5 | 107247 | 25.3 | 102807 | 23.4 | 136433 | 29.7 | 192426 | 39.3 | 80.4 | 48.4 |

Note: for Xizang, the change in percentage is between 1990 and 2005 since we don't have observation of industrial waste water in 1985.

## Table A5.3.4 Trends in Chemical Oxygen Demand

**(Left: in tons; right: ton per 10 thousand people)**

| Province | 1985 | | 1991 | | 1995 | | 2000 | | 2005 | | Change% | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anhui | 273353 | 53.0 | 299630 | 52.2 | 310101 | 52.4 | 167503 | 27.5 | 136492 | 22.3 | -50.1 | -57.9 |
| Beijing | 71318 | 72.7 | 98285 | 89.8 | 73235 | 58.5 | 21538 | 15.8 | 10979 | 7.1 | -84.6 | -90.2 |
| Fujian | 95850 | 34.6 | 186950 | 60.7 | 218043 | 67.4 | 125676 | 36.9 | 99411 | 28.1 | 3.7 | -18.8 |
| Gansu | - | - | 60038 | 26.3 | 60533 | 24.8 | 57828 | 22.6 | 58832 | 22.7 | -2.0 | -13.7 |
| Guangdong | 39693 | 7.0 | 381480 | 60.1 | 349802 | 51.5 | 281662 | 37.6 | 291599 | 31.7 | 634.6 | 351.9 |
| Guangxi | 177351 | 45.8 | 383620 | 88.7 | 731028 | 160.9 | 281662 | 59.3 | 664388 | 142.6 | 274.6 | 211.4 |
| Guizhou | 9721 | 3.3 | 28256 | 8.5 | 44214 | 12.6 | 51508 | 13.7 | 22440 | 6.0 | 130.8 | 83.9 |
| Hainan | - | - | 62430 | 92.6 | 35600 | 49.2 | 26978 | 34.2 | 11766 | 14.2 | -81.2 | 15.3 |
| Hebei | 164697 | 29.7 | 334270 | 53.7 | 261578 | 40.6 | 492415 | 73.8 | 389338 | 56.8 | 136.4 | 91.4 |
| Heilongjiang | 421430 | 125.5 | 282940 | 79.1 | 216918 | 58.6 | 167795 | 44.1 | 136798 | 35.8 | -67.5 | -71.5 |
| Henan | 228745 | 29.2 | 389660 | 44.5 | 647305 | 71.1 | 443739 | 46.8 | 342606 | 36.5 | 49.8 | 25.3 |
| Hubei | 158865 | 31.9 | 426480 | 77.4 | 268239 | 46.5 | 266457 | 44.7 | 176733 | 31.0 | 11.2 | -3.0 |
| Hunan | 1124752 | 200.0 | 371140 | 60.2 | 314831 | 49.3 | 323588 | 49.3 | 293765 | 46.4 | -73.9 | -76.8 |
| Inner Mongolia | 72096 | 35.8 | 115240 | 52.8 | 96253 | 42.1 | 128652 | 54.2 | 154760 | 64.9 | 114.7 | 81.4 |
| Jiangsu | 523514 | 84.3 | 471130 | 68.8 | 503981 | 71.3 | 241391 | 32.9 | 337778 | 45.2 | -35.5 | -46.4 |
| Jiangxi | 149093 | 42.5 | 173360 | 44.9 | 146567 | 36.1 | 86057 | 20.7 | 111438 | 25.8 | -25.3 | -39.1 |
| Jilin | 318447 | 138.6 | 266410 | 108.3 | 288739 | 113.2 | 217201 | 82.7 | 161302 | 59.4 | -49.3 | -57.1 |
| Liaoning | 406546 | 110.2 | 476610 | 119.5 | 329342 | 80.5 | 327476 | 78.3 | 268192 | 63.5 | -34.0 | -42.3 |
| Ningxia | - | - | 52014 | 109.8 | 75741 | 147.8 | 140398 | 253.3 | 107549 | 180.5 | 106.8 | 164.4 |
| Qinghai | - | - | 4266 | 9.4 | 4036 | 8.4 | 3872 | 7.5 | 33864 | 62.4 | 693.8 | 663.7 |
| Shaanxi | - | - | 75934 | 22.6 | 119975.4 | 34.2 | 162243 | 44.5 | 149342 | 40.1 | 96.7 | 177.8 |
| Shandong | 1037215 | 134.8 | 637250 | 74.7 | 1067586 | 122.7 | 511409 | 57.0 | 356650 | 38.6 | -65.6 | -71.4 |
| Shanghai | 252835 | 207.8 | 247510 | 192.3 | 122878 | 94.4 | 69318 | 52.4 | 36610 | 20.6 | -85.5 | -90.1 |
| Shanxi | 108458 | 40.6 | 177430 | 60.3 | 81259.24 | 26.4 | 157922 | 48.6 | 168160 | 50.1 | 55.0 | 23.6 |
| Sichuan | 536009 | 52.6 | 378930 | 34.8 | 450260.6 | 40.3 | 684131 | 59.5 | 416577 | 37.8 | -22.3 | -28.1 |
| Tianjin | 214404 | 266.4 | 159170 | 175.1 | 89440 | 95.0 | 70300 | 70.2 | 59091 | 56.7 | -72.4 | -78.7 |
| Xinjiang | - | - | 88039 | 56.6 | 262494.1 | 158.0 | 100666 | 54.4 | 153286 | 76.3 | 74.1 | 134.7 |
| Xizang | - | - | 228 | 1.0 | 591.95 | 2.5 | 2720 | 10.8 | 1072 | 3.9 | 370.0 | 376.3 |
| Yunnan | 72401 | 21.2 | 195250 | 51.6 | 253049.8 | 63.4 | 177404 | 41.8 | 106941 | 24.0 | 47.7 | 13.5 |
| Zhejiang | 681353 | 169.1 | 354320 | 83.0 | 260162.5 | 59.3 | 358356 | 78.0 | 289579 | 59.1 | -57.5 | -65.0 |

Note: for Hainan, Ningxia, Qinghai, Shaanxi, Xinjiang and Xizang, there are no COD data prior to 1991 and hence the last two columns present the change between 1991 and 2005. COD data for 1990 is missing for all provinces.

## Table A5.3.5 Trends in Industrial Waste air

(Left: in 100 million $m^3$; right: 10 thousand $m^3$ per capita)

| Province | 1985 | | 1990 | | 1995 | | 2000 | | 2005 | | Change% | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anhui | 2094 | 0.4 | 2327 | 0.4 | 3559 | 0.6 | 3945 | 0.6 | 6960 | 1.1 | 232.4 | 180.0 |
| Beijing | 5921 | 6.0 | 2770 | 2.6 | 2910 | 2.3 | 3227 | 2.4 | 3532 | 2.3 | -40.3 | -62.0 |
| Fujian | 754 | 0.3 | 1347 | 0.4 | 1940 | 0.6 | 2828 | 0.8 | 6265 | 1.8 | 730.9 | 550.9 |
| Gansu | 2519 | 1.2 | 1820 | 0.8 | 2425 | 1.0 | 2800 | 1.1 | 4250 | 1.6 | 68.7 | 32.7 |
| Guangdong | 1864 | 0.3 | 3586 | 0.6 | 6476 | 1.0 | 8326 | 1.1 | 13447 | 1.5 | 621.4 | 343.8 |
| Guangxi | 906 | 0.2 | 1389 | 0.3 | 2349 | 0.5 | 4607 | 1.0 | 8339 | 1.8 | 820.4 | 665.0 |
| Guizhou | 1226 | 0.4 | 1597 | 0.5 | 2342 | 0.7 | 3882 | 1.0 | 3852 | 1.0 | 214.2 | 150.4 |
| Hainan | - | - | 80 | 0.1 | 182 | 0.3 | 434 | 0.6 | 910 | 1.1 | 1037.5 | 810.5 |
| Hebei | 3310 | 0.6 | 5669 | 0.9 | 7370 | 1.1 | 9858 | 1.5 | 26518 | 3.9 | 701.1 | 548.8 |
| Heilongjiang | 4214 | 1.3 | 4846 | 1.4 | 4224 | 1.1 | 4326 | 1.1 | 5261 | 1.4 | 24.8 | 9.7 |
| Henan | 7343 | 0.9 | 3764 | 0.4 | 6092 | 0.7 | 7436 | 0.8 | 15498 | 1.7 | 111.1 | 76.6 |
| Hubei | 2425 | 0.5 | 3416 | 0.6 | 3901 | 0.7 | 5674 | 1.0 | 9404 | 1.6 | 287.8 | 238.2 |
| Hunan | 2492 | 0.4 | 2716 | 0.4 | 3466 | 0.5 | 3569 | 0.5 | 6014 | 1.0 | 141.3 | 114.5 |
| Inner Mongolia | 1709 | 0.8 | 2952 | 1.4 | 3171 | 1.4 | 4768 | 2.0 | 12071 | 5.1 | 606.3 | 496.8 |
| Jiangsu | 3419 | 0.6 | 5046 | 0.7 | 7872 | 1.1 | 9078 | 1.2 | 20197 | 2.7 | 490.7 | 391.0 |
| Jiangxi | 1705 | 0.5 | 1659 | 0.4 | 2396 | 0.6 | 2220 | 0.5 | 4379 | 1.0 | 156.8 | 109.1 |
| Jilin | 2216 | 1.0 | 2895 | 1.2 | 3163 | 1.2 | 3082 | 1.2 | 4939 | 1.8 | 122.9 | 88.6 |
| Liaoning | 8112 | 2.2 | 8135 | 2.1 | 8498 | 2.1 | 9432 | 2.3 | 20903 | 5.0 | 157.7 | 125.2 |
| Ningxia | 237 | 0.6 | 611 | 1.3 | 932 | 1.8 | 1445 | 2.6 | 2844 | 4.8 | 1100.0 | 734.8 |
| Qinghai | 270 | 0.7 | 388 | 0.9 | 442 | 0.9 | 607 | 1.2 | 1370 | 2.5 | 407.4 | 280.3 |
| Shaanxi | 1523 | 0.5 | 1775 | 0.5 | 2378 | 0.7 | 2379 | 0.7 | 4916 | 1.3 | 222.8 | 160.5 |
| Shandong | 4292 | 0.6 | 6684 | 0.8 | 7386 | 0.8 | 12179 | 1.4 | 24129 | 2.6 | 462.2 | 367.8 |
| Shanghai | 3010 | 2.5 | 3534 | 2.8 | 4625 | 3.6 | 5755 | 4.4 | 8482 | 4.8 | 181.8 | 92.8 |
| Shanxi | 2705 | 1.0 | 4870 | 1.7 | 4790 | 1.6 | 6635 | 2.0 | 15142 | 4.5 | 459.8 | 346.1 |
| Sichuan | 4598 | 0.5 | 4996 | 0.5 | 6359 | 0.6 | 6687 | 0.6 | 11795 | 1.1 | 156.5 | 137.4 |
| Tianjin | 1711 | 2.1 | 1335 | 1.5 | 1705 | 1.8 | 1749 | 1.7 | 4602 | 4.4 | 169.0 | 107.5 |
| Xinjiang | 744 | 0.5 | 1071 | 0.7 | 1735 | 1.0 | 1944 | 1.1 | 4485 | 2.2 | 502.8 | 308.2 |
| Xizang | - | - | 6 | 0.0 | 9 | 0.0 | 15 | 0.1 | 13 | 0.0 | 116.7 | 70.6 |
| Yunnan | 1140 | 0.3 | 1559 | 0.4 | 1674 | 0.4 | 2749 | 0.6 | 5444 | 1.2 | 377.5 | 266.8 |
| Zhejiang | 1601 | 0.4 | 2537 | 0.6 | 3108 | 0.7 | 6509 | 1.4 | 13025 | 2.7 | 713.6 | 569.3 |

Note: for Hainan, there are no industrial waste air data prior to 1990 and hence the last column presents the change between 1990 and 2005 for it

## Table A5.3.6 Trends in Sulphur Dioxide

(Left: in tons; right: ton per 10 thousand people)

| Province | 1985 | | 1990 | | 1995 | | 2000 | | 2005 | | Change% | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anhui | 320000 | 62.1 | 380000 | 67.1 | 351161 | 59.3 | 350625 | 57.5 | 515000 | 84.2 | 60.9 | 35.6 |
| Beijing | 320000 | 326.2 | 340000 | 313.1 | 214899 | 171.8 | 146431 | 107.4 | 105000 | 68.3 | -67.2 | -79.1 |
| Fujian | 100000 | 36.1 | 120000 | 39.5 | 143335 | 44.3 | 214338 | 62.9 | 439000 | 124.2 | 339.0 | 243.9 |
| Gansu | 320000 | 156.8 | 360000 | 159.6 | 346682 | 142.2 | 311878 | 122.0 | 517000 | 199.3 | 61.6 | 27.1 |
| Guangdong | 290000 | 51.3 | 400000 | 64.0 | 534998 | 78.8 | 881558 | 117.6 | 1274000 | 138.6 | 339.3 | 170.2 |
| Guangxi | 360000 | 93.0 | 600000 | 141.4 | 579485 | 127.6 | 800485 | 168.5 | 975000 | 209.2 | 170.8 | 125.1 |
| Guizhou | 450000 | 151.4 | 500000 | 153.0 | 566856 | 161.6 | 642490 | 171.1 | 659000 | 176.7 | 46.4 | 16.7 |
| Hainan | - | - | 10000 | 15.1 | 24844 | 34.3 | 20178 | 25.6 | 22000 | 26.6 | 120.0 | 76.1 |
| Hebei | 630000 | 113.6 | 890000 | 144.5 | 944139 | 146.7 | 1133599 | 169.9 | 1281000 | 187.0 | 103.3 | 64.7 |
| Heilongjiang | 260000 | 77.5 | 320000 | 90.3 | 244849 | 66.2 | 221670 | 58.2 | 431000 | 112.8 | 65.8 | 45.7 |
| Henan | 370000 | 47.2 | 490000 | 56.7 | 530149 | 58.3 | 747384 | 78.8 | 1471000 | 156.8 | 297.6 | 232.6 |
| Hubei | 560000 | 112.4 | 560000 | 103.0 | 402282 | 69.7 | 508218 | 85.3 | 626000 | 109.6 | 11.8 | -2.5 |
| Hunan | 670000 | 119.2 | 550000 | 90.0 | 578562 | 90.5 | 626494 | 95.5 | 755000 | 119.3 | 12.7 | 0.2 |
| Inner Mongolia | 380000 | 188.5 | 530000 | 245.1 | 531985 | 232.9 | 506309 | 213.4 | 1296000 | 543.2 | 241.1 | 188.2 |
| Jiangsu | 760000 | 122.3 | 1000000 | 147.8 | 1044719 | 147.9 | 1140991 | 155.7 | 1312000 | 175.5 | 72.6 | 43.5 |
| Jiangxi | 550000 | 156.7 | 300000 | 78.7 | 281082 | 69.2 | 288108 | 69.4 | 555000 | 128.7 | 0.9 | -17.8 |
| Jilin | 240000 | 104.4 | 260000 | 106.5 | 201532 | 79.0 | 201688 | 76.8 | 308000 | 113.4 | 28.3 | 8.6 |
| Liaoning | 920000 | 249.4 | 970000 | 245.8 | 815876 | 199.4 | 705672 | 168.7 | 961000 | 227.7 | 4.5 | -8.7 |
| Ningxia | 100000 | 241.2 | 130000 | 279.2 | 172729 | 337.1 | 174155 | 314.2 | 302000 | 506.7 | 202.0 | 110.1 |
| Qinghai | 30000 | 73.7 | 30000 | 67.1 | 26143 | 54.4 | 20177 | 39.1 | 115000 | 211.8 | 283.3 | 187.3 |
| Shaanxi | 590000 | 196.5 | 590000 | 177.9 | 652262 | 185.7 | 553738 | 152.0 | 800000 | 215.1 | 35.6 | 9.4 |
| Shandong | 1600000 | 207.9 | 1930000 | 229.1 | 1581981 | 181.8 | 1460902 | 162.8 | 1715000 | 185.4 | 7.2 | -10.8 |
| Shanghai | 340000 | 279.4 | 420000 | 327.3 | 381454 | 293.1 | 326804 | 247.3 | 375000 | 210.9 | 10.3 | -24.5 |
| Shanxi | 470000 | 175.8 | 780000 | 269.1 | 658291 | 213.9 | 902681 | 277.9 | 1200000 | 357.7 | 155.3 | 103.5 |
| Sichuan | 1650000 | 162.0 | 1480000 | 136.9 | 1081970 | 96.9 | 1658304 | 144.2 | 1824000 | 165.7 | 10.5 | 2.3 |
| Tianjin | 220000 | 273.4 | 220000 | 248.9 | 262375 | 278.6 | 241815 | 241.5 | 241000 | 231.1 | 9.5 | -15.5 |
| Xinjiang | 130000 | 95.5 | 160000 | 104.6 | 222000 | 133.6 | 187689 | 101.5 | 348000 | 173.1 | 167.7 | 81.3 |
| Xizang | - | - | - | - | 1884 | 8.0 | 756 | 3.0 | 1000 | 3.6 | -15.7 | -54.9 |
| Yunnan | 320000 | 93.6 | 230000 | 61.7 | 258454 | 64.8 | 323853 | 76.4 | 429000 | 96.4 | 34.1 | 3.0 |
| Zhejiang | 300000 | 74.4 | 440000 | 103.8 | 413229 | 94.2 | 561847 | 122.2 | 831000 | 169.7 | 177.0 | 127.9 |

Note: for Hainan there is no $SO_2$ data prior to 1990 and hence the last column presents the change between 1990 and 2005. Similarly, for Xizang, it is between 1992 and 2005.

## Table A5.3.7 Trends in Industrial Dust

(Left: in tons; right: ton per 10 thousand people)

| Province | 1985 | | 1990 | | 1995 | | 2000 | | 2005 | | Change% | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anhui | 1190000 | 230.8 | 290000 | 51.2 | 219742 | 37.1 | 284977 | 46.8 | 462000 | 75.5 | -61.2 | -67.3 |
| Beijing | 40000 | 40.8 | 70000 | 64.5 | 62609 | 50.0 | 93681 | 68.7 | 33000 | 21.5 | -17.5 | -47.4 |
| Fujian | 320000 | 115.6 | 160000 | 52.7 | 217095 | 67.1 | 187076 | 54.9 | 193000 | 54.6 | -39.7 | -52.8 |
| Gansu | 270000 | 132.3 | 150000 | 66.5 | 122061 | 50.1 | 146347 | 57.2 | 166000 | 64.0 | -38.5 | -51.6 |
| Guangdong | 430000 | 76.0 | 420000 | 67.2 | 641727 | 94.5 | 579895 | 77.3 | 321000 | 34.9 | -25.3 | -54.1 |
| Guangxi | 320000 | 82.6 | 210000 | 49.5 | 276033 | 60.8 | 567717 | 119.5 | 556000 | 119.3 | 73.8 | 44.4 |
| Guizhou | 240000 | 80.7 | 220000 | 67.3 | 205183 | 58.5 | 406234 | 108.2 | 191000 | 51.2 | -20.4 | -36.6 |
| Hainan | - | - | 20000 | 30.2 | 14040 | 19.4 | 13470 | 17.1 | 11000 | 13.3 | -45.0 | -56.0 |
| Hebei | 800000 | 144.2 | 410000 | 66.6 | 371138 | 57.7 | 812663 | 121.8 | 713000 | 104.1 | -10.9 | -27.8 |
| Heilongjiang | 1000000 | 297.9 | 280000 | 79.0 | 134562 | 36.4 | 103853 | 27.3 | 124000 | 32.5 | -87.6 | -89.1 |
| Henan | 760000 | 96.9 | 510000 | 59.0 | 402321 | 44.2 | 817734 | 86.2 | 704000 | 75.1 | -7.4 | -22.5 |
| Hubei | 490000 | 98.4 | 310000 | 57.0 | 237561 | 41.2 | 410286 | 68.8 | 338000 | 59.2 | -31.0 | -39.8 |
| Hunan | 650000 | 115.6 | 390000 | 63.8 | 271287 | 42.4 | 639667 | 97.5 | 769000 | 121.6 | 18.3 | 5.2 |
| Inner Mongolia | 420000 | 208.3 | 150000 | 69.4 | 194861 | 85.3 | 175644 | 74.0 | 456000 | 191.1 | 8.6 | -8.3 |
| Jiangsu | 860000 | 138.4 | 480000 | 70.9 | 269509 | 38.1 | 256790 | 35.0 | 355000 | 47.5 | -58.7 | -65.7 |
| Jiangxi | 340000 | 96.9 | 340000 | 89.2 | 228823 | 56.3 | 343351 | 82.8 | 350000 | 81.2 | 2.9 | -16.2 |
| Jilin | 230000 | 100.1 | 140000 | 57.4 | 1482.65 | 0.6 | 123792 | 47.1 | 137000 | 50.4 | -40.4 | -49.6 |
| Liaoning | 920000 | 249.4 | 690000 | 174.9 | 398765 | 97.4 | 429231 | 102.6 | 453000 | 107.3 | -50.8 | -57.0 |
| Ningxia | 90000 | 217.1 | 120000 | 257.7 | 54248 | 105.9 | 132781 | 239.5 | 90000 | 151.0 | 0.0 | -30.4 |
| Qinghai | 150000 | 368.6 | 30000 | 67.1 | 34250 | 71.2 | 41658 | 80.7 | 93000 | 171.3 | -38.0 | -53.5 |
| Shaanxi | 250000 | 83.3 | 150000 | 45.2 | 243653 | 69.4 | 377237 | 103.5 | 340000 | 91.4 | 36.0 | 9.8 |
| Shandong | 710000 | 92.3 | 480000 | 57.0 | 389886 | 44.8 | 745589 | 83.1 | 373000 | 40.3 | -47.5 | -56.3 |
| Shanghai | 90000 | 74.0 | 70000 | 54.5 | 62898 | 48.3 | 26941 | 20.4 | 11000 | 6.2 | -87.8 | -91.6 |
| Shanxi | 570000 | 213.2 | 300000 | 103.5 | 220853 | 71.8 | 504133 | 155.2 | 695000 | 207.2 | 21.9 | -2.8 |
| Sichuan | 780000 | 76.6 | 740000 | 68.4 | 429956 | 38.5 | 779921 | 67.8 | 597000 | 54.2 | -23.5 | -29.2 |
| Tianjin | 70000 | 87.0 | 60000 | 67.9 | 29695 | 31.5 | 37891 | 37.8 | 19000 | 18.2 | -72.9 | -79.1 |
| Xinjiang | 180000 | 132.2 | 80000 | 52.3 | 132256 | 79.6 | 112574 | 60.9 | 173000 | 86.1 | -3.9 | -34.9 |
| Xizang | - | - | 10000 | 45.9 | 11315 | 48.0 | 2114 | 8.4 | 2000 | 7.2 | -80.0 | -84.3 |
| Yunnan | 240000 | 70.2 | 150000 | 40.2 | 178117 | 44.6 | 122818 | 29.0 | 155000 | 34.8 | -35.4 | -50.4 |
| Zhejiang | 640000 | 158.8 | 380000 | 89.7 | 187149 | 42.6 | 489627 | 106.5 | 231000 | 47.2 | -63.9 | -70.3 |

Note: for Xizang there is no industrial dust data prior to 1990 and hence the last two columns present the change between 1990 and 2005.

## Table A5.3.8 Trends in Industrial Soot

### (Left: in tons; right: ton per 10 thousand people)

| Province | 1985 | | 1990 | | 1995 | | 2000 | | 2005 | | Change% | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anhui | 550000 | 106.7 | 310000 | 54.8 | 260403 | 44.0 | 243493 | 40.0 | 253000 | 41.3 | -54.0 | -61.2 |
| Beijing | 400000 | 407.7 | 250000 | 230.2 | 124471 | 99.5 | 51842 | 38.0 | 18000 | 11.7 | -95.5 | -97.1 |
| Fujian | 110000 | 39.7 | 100000 | 32.9 | 89562 | 27.7 | 103539 | 30.4 | 118000 | 33.4 | 7.3 | -16.0 |
| Gansu | 170000 | 83.3 | 200000 | 88.7 | 178283 | 73.1 | 124768 | 48.8 | 124000 | 47.8 | -27.1 | -42.6 |
| Guangdong | 270000 | 47.7 | 220000 | 35.2 | 208113 | 30.7 | 264453 | 35.3 | 271000 | 29.5 | 0.4 | -38.3 |
| Guangxi | 270000 | 69.7 | 300000 | 70.7 | 299875 | 66.0 | 590999 | 124.4 | 538000 | 115.5 | 99.3 | 65.6 |
| Guizhou | 250000 | 84.1 | 250000 | 76.5 | 248577 | 70.9 | 342453 | 91.2 | 205000 | 55.0 | -18.0 | -34.7 |
| Hainan | - | - | 10000 | 15.1 | 12036 | 16.6 | 18078 | 22.9 | 10000 | 12.1 | 0.0 | -20.0 |
| Hebei | 690000 | 124.4 | 760000 | 123.4 | 445646 | 69.2 | 672176 | 100.7 | 560000 | 81.7 | -18.8 | -34.3 |
| Heilongjiang | 1300000 | 387.3 | 1280000 | 361.3 | 461015 | 124.6 | 409337 | 107.5 | 454000 | 118.8 | -65.1 | -69.3 |
| Henan | 620000 | 79.0 | 590000 | 68.2 | 478576 | 52.6 | 690618 | 72.8 | 857000 | 91.4 | 38.2 | 15.6 |
| Hubei | 360000 | 72.3 | 470000 | 86.4 | 191518 | 33.2 | 321461 | 53.9 | 266000 | 46.6 | -26.1 | -35.6 |
| Hunan | 450000 | 80.0 | 380000 | 62.2 | 306610 | 48.0 | 381268 | 58.1 | 453000 | 71.6 | 0.7 | -10.5 |
| Inner Mongolia | 450000 | 223.2 | 660000 | 305.2 | 396668 | 173.6 | 303292 | 127.8 | 604000 | 253.1 | 34.2 | 13.4 |
| Jiangsu | 770000 | 123.9 | 620000 | 91.6 | 540930 | 76.6 | 374737 | 51.1 | 426000 | 57.0 | -44.7 | -54.0 |
| Jiangxi | 310000 | 88.3 | 300000 | 78.7 | 280303 | 69.0 | 234059 | 56.4 | 230000 | 53.4 | -25.8 | -39.6 |
| Jilin | 770000 | 335.1 | 860000 | 352.4 | 367209 | 144.0 | 283006 | 107.7 | 327000 | 120.4 | -57.5 | -64.1 |
| Liaoning | 1060000 | 287.3 | 1050000 | 266.1 | 604840 | 147.8 | 547223 | 130.8 | 517000 | 122.5 | -51.2 | -57.4 |
| Ningxia | 90000 | 217.1 | 110000 | 236.2 | 93881 | 183.2 | 125537 | 226.5 | 102000 | 171.1 | 13.3 | -21.2 |
| Qinghai | 60000 | 147.4 | 70000 | 156.6 | 38549 | 80.1 | 63810 | 123.7 | 57000 | 105.0 | -5.0 | -28.8 |
| Shaanxi | 340000 | 113.3 | 490000 | 147.8 | 476598 | 135.7 | 371908 | 102.1 | 292000 | 78.5 | -14.1 | -30.7 |
| Shandong | 1200000 | 155.9 | 1210000 | 143.6 | 606252 | 69.7 | 543067 | 60.5 | 485000 | 52.4 | -59.6 | -66.4 |
| Shanghai | 200000 | 164.4 | 190000 | 148.1 | 133343 | 102.5 | 83153 | 62.9 | 50000 | 28.1 | -75.0 | -82.9 |
| Shanxi | 410000 | 153.4 | 810000 | 279.4 | 361509 | 117.5 | 791300 | 243.6 | 910000 | 271.2 | 122.0 | 76.9 |
| Sichuan | 930000 | 91.3 | 800000 | 74.0 | 597262 | 53.5 | 920693 | 80.1 | 765000 | 69.5 | -17.7 | -23.9 |
| Tianjin | 150000 | 186.4 | 180000 | 203.6 | 92899 | 98.6 | 112234 | 112.1 | 77000 | 73.8 | -48.7 | -60.4 |
| Xinjiang | 140000 | 102.9 | 190000 | 124.3 | 172195 | 103.6 | 84000 | 45.4 | 150000 | 74.6 | 7.1 | -27.4 |
| Xizang | - | - | - | - | 4866 | 20.7 | 1150 | 4.6 | 2000 | 7.2 | -58.9 | -65.0 |
| Yunnan | 290000 | 84.8 | 290000 | 77.7 | 161039 | 40.4 | 232566 | 54.8 | 171000 | 38.4 | -41.0 | -54.7 |
| Zhejiang | 340000 | 84.4 | 280000 | 66.1 | 146682 | 33.4 | 247096 | 53.8 | 199000 | 40.6 | -41.5 | -51.8 |

Note: for Hainan there is no industrial soot data prior to 1990 and hence the last two columns present the change between 1990 and 2005. Similarly, for Xizang, it is between 1995 and 2005.

## Table A5.3.9 Trends in Industrial Solid Waste

**(Left: in 10 thousand tons; right: ton per capita)**

| Province | 1985 | | 1990 | | 1995 | | 2000 | | 2005 | | Change% | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Anhui | 1841 | 0.4 | 2552 | 0.5 | 2749 | 0.5 | 2815 | 0.5 | 4196 | 0.7 | 127.9 | 92.0 |
| Beijing | 470 | 0.5 | 617 | 0.6 | 1068 | 0.9 | 1139 | 0.8 | 1238 | 0.8 | 163.4 | 68.0 |
| Fujian | 469 | 0.2 | 650 | 0.2 | 728 | 0.2 | 2191 | 0.6 | 3773 | 1.1 | 703.7 | 529.5 |
| Gansu | 778 | 0.4 | 1094 | 0.5 | 1432 | 0.6 | 1704 | 0.7 | 2249 | 0.9 | 189.3 | 127.6 |
| Guangdong | 1577 | 0.3 | 1678 | 0.3 | 1465 | 0.2 | 1694 | 0.2 | 2896 | 0.3 | 83.6 | 13.0 |
| Guangxi | 791 | 0.2 | 1211 | 0.3 | 1503 | 0.3 | 2108 | 0.4 | 3489 | 0.7 | 341.0 | 266.5 |
| Guizhou | 836 | 0.3 | 897 | 0.3 | 1309 | 0.4 | 2272 | 0.6 | 4854 | 1.3 | 480.6 | 362.6 |
| Hainan | - | - | 97 | 0.1 | 87 | 0.1 | 95 | 0.1 | 127 | 0.2 | 30.9 | 4.8 |
| Hebei | 3795 | 0.7 | 5162 | 0.8 | 6186 | 1.0 | 7028 | 1.1 | 16279 | 2.4 | 329.0 | 247.4 |
| Heilongjiang | 6563 | 2.0 | 3482 | 1.0 | 2681 | 0.7 | 2694 | 0.7 | 3210 | 0.8 | -51.1 | -57.0 |
| Henan | 1873 | 0.2 | 2039 | 0.2 | 2792 | 0.3 | 3625 | 0.4 | 6178 | 0.7 | 229.9 | 176.0 |
| Hubei | 1652 | 0.3 | 1799 | 0.3 | 2063 | 0.4 | 2818 | 0.5 | 3692 | 0.6 | 123.5 | 94.9 |
| Hunan | 2083 | 0.4 | 1974 | 0.3 | 1853 | 0.3 | 2355 | 0.4 | 3366 | 0.5 | 61.6 | 43.6 |
| Inner Mongolia | 1134 | 0.6 | 1912 | 0.9 | 2270 | 1.0 | 2376 | 1.0 | 7363 | 3.1 | 549.2 | 448.5 |
| Jiangsu | 1738 | 0.3 | 2200 | 0.3 | 2883 | 0.4 | 3038 | 0.4 | 5757 | 0.8 | 231.2 | 175.3 |
| Jiangxi | 2490 | 0.7 | 3199 | 0.8 | 3669 | 0.9 | 4796 | 1.2 | 7007 | 1.6 | 181.4 | 129.1 |
| Jilin | 1356 | 0.6 | 1716 | 0.7 | 1672 | 0.7 | 1604 | 0.6 | 2457 | 0.9 | 81.2 | 53.3 |
| Liaoning | 7181 | 1.9 | 7451 | 1.9 | 6920 | 1.7 | 7563 | 1.8 | 10242 | 2.4 | 42.6 | 24.7 |
| Ningxia | 203 | 0.5 | 354 | 0.8 | 397 | 0.8 | 479 | 0.9 | 719 | 1.2 | 254.2 | 146.4 |
| Qinghai | 235 | 0.6 | 256 | 0.6 | 208 | 0.4 | 337 | 0.7 | 649 | 1.2 | 176.2 | 107.0 |
| Shaanxi | 1223 | 0.4 | 1586 | 0.5 | 1870 | 0.5 | 2625 | 0.7 | 4588 | 1.2 | 275.1 | 202.7 |
| Shandong | 2747 | 0.4 | 3880 | 0.5 | 4484 | 0.5 | 5407 | 0.6 | 9175 | 1.0 | 234.0 | 177.9 |
| Shanghai | 722 | 0.6 | 1107 | 0.9 | 1368 | 1.1 | 1355 | 1.0 | 1964 | 1.1 | 172.0 | 86.1 |
| Shanxi | 2261 | 0.8 | 3196 | 1.1 | 4204 | 1.4 | 7695 | 2.4 | 11183 | 3.3 | 394.6 | 294.1 |
| Sichuan | 4972 | 0.5 | 4002 | 0.4 | 4290 | 0.4 | 6019 | 0.5 | 8198 | 0.7 | 64.9 | 52.6 |
| Tianjin | 376 | 0.5 | 419 | 0.5 | 544 | 0.6 | 470 | 0.5 | 1123 | 1.1 | 198.5 | 130.3 |
| Xinjiang | 325 | 0.2 | 389 | 0.3 | 602 | 0.4 | 718 | 0.4 | 1295 | 0.6 | 298.1 | 169.6 |
| Xizang | - | - | - | - | 0 | - | 17 | 0.1 | 8 | 0.0 | - | -57.3 |
| Yunnan | 2265 | 0.7 | 2030 | 0.5 | 2147 | 0.5 | 3187 | 0.8 | 4661 | 1.0 | 105.8 | 58.1 |
| Zhejiang | 633 | 0.2 | 848 | 0.2 | 1030 | 0.2 | 1386 | 0.3 | 2514 | 0.5 | 297.2 | 226.8 |

Note: for Hainan there is no industrial soot data prior to 1990 and hence the last two columns present the change between 1990 and 2005. Similarly, for Xizang, it is between 1995 and 2005.

Table A5.3.10 Average Growth % Gross Regional Output and Composition

| Province | GRP | Primary | Secondary | | Tertiary |
|---|---|---|---|---|---|
| | | | | Industry | |
| Anhui | 8.91 | 4.79 | 10.16 | 8.66 | 11.87 |
| Beijing | 11.21 | 2.61 | 7.11 | 6.30 | 15.45 |
| Fujian | 11.35 | 5.74 | 13.11 | 11.15 | 12.83 |
| Gansu | 9.35 | 6.69 | 9.41 | 8.28 | 11.62 |
| Guangdong | 13.29 | 4.90 | 14.74 | 13.04 | 15.24 |
| Guangxi | 9.15 | 5.78 | 11.12 | 9.27 | 11.02 |
| Guizhou | 8.30 | 3.99 | 8.60 | 7.88 | 12.45 |
| Hainan | 10.32 | 7.68 | 12.46 | 10.82 | 12.77 |
| Hebei | 10.00 | 6.17 | 10.78 | 9.45 | 12.08 |
| Heilongjiang | 6.92 | 5.32 | 6.64 | 5.79 | 9.83 |
| Henan | 9.42 | 5.01 | 11.50 | 10.18 | 10.57 |
| Hubei | 8.70 | 4.58 | 8.81 | 7.44 | 12.52 |
| Hunan | 8.36 | 4.29 | 9.27 | 8.16 | 11.47 |
| Inner Mongolia | 9.58 | 5.22 | 11.69 | 10.55 | 10.30 |
| Jiangsu | 11.45 | 4.45 | 11.86 | 10.26 | 15.49 |
| Jiangxi | 8.68 | 4.49 | 10.64 | 9.01 | 10.44 |
| Jilin | 8.94 | 6.71 | 8.93 | 7.71 | 11.55 |
| Liaoning | 8.46 | 7.09 | 7.65 | 6.78 | 11.03 |
| Ningxia | 9.63 | 5.09 | 10.88 | 9.95 | 11.01 |
| Qinghai | 8.43 | 4.27 | 9.88 | 8.83 | 8.97 |
| Shaanxi | 9.00 | 4.22 | 10.02 | 8.95 | 10.64 |
| Shandong | 11.00 | 4.79 | 12.58 | 10.84 | 13.07 |
| Shanghai | 9.60 | 2.19 | 7.65 | 6.78 | 13.20 |
| Shanxi | 8.97 | 2.80 | 9.47 | 8.73 | 10.72 |
| Sichuan | 8.11 | 4.18 | 9.04 | 8.04 | 10.59 |
| Tianjin | 9.55 | 4.02 | 8.99 | 8.02 | 11.56 |
| Xinjiang | 10.21 | 6.76 | 12.99 | 10.15 | 12.04 |
| Xizang | 7.24 | 1.95 | 11.38 | 8.07 | 9.96 |
| Yunnan | 8.67 | 4.87 | 9.27 | 8.33 | 12.18 |
| Zhejiang | 11.62 | 3.32 | 12.47 | 10.70 | 14.25 |
| Average | 9.48 | 4.80 | 10.30 | 8.94 | 11.89 |

**Table A5.3.11 Average Growth rate % Capital, employment, income and population**

| Province | Capital Stock | Capital Flow | Total EMP | Urban Income | Rural Income | POP |
|---|---|---|---|---|---|---|
| Anhui | 11.08 | 11.08 | 1.83 | 7.04 | 4.10 | 0.78 |
| Beijing | 16.5 | 15.46 | 3.19 | 8.01 | 5.17 | 2.38 |
| Fujian | 13.9 | 15.33 | 2.55 | 6.68 | 4.88 | 1.18 |
| Gansu | 11.18 | 12.72 | 1.16 | 6.92 | 4.67 | 1.14 |
| Guangdong | 15.29 | 15.79 | 3.07 | 7.01 | 4.98 | 2.41 |
| Guangxi | 13.33 | 18.45 | 1.89 | 5.51 | 3.27 | 0.96 |
| Guizhou | 9.7 | 10.1 | 2.49 | 6.09 | 3.00 | 1.09 |
| Hainan | 12.34 | 11.62 | 2.02 | 5.94 | 4.08 | 1.59 |
| Hebei | 14 | 15.41 | 1.54 | 6.27 | 3.97 | 1.03 |
| Heilongjiang | 8.49 | 8.56 | 1.18 | 4.75 | 3.20 | 0.59 |
| Henan | 13.25 | 15.24 | 2.29 | 6.39 | 3.93 | 0.81 |
| Hubei | 13.88 | 15.3 | 1.24 | 6.25 | 3.79 | 0.63 |
| Hunan | 10.79 | 12.72 | 1.46 | 5.47 | 3.36 | 0.57 |
| Inner Mongolia | 15.99 | 18.46 | 1.08 | 5.59 | 2.80 | 0.81 |
| Jiangsu | 16.45 | 15.85 | 1.28 | 7.50 | 5.38 | 0.94 |
| Jiangxi | 12.82 | 14.83 | 1.52 | 6.56 | 3.96 | 1.00 |
| Jilin | 13.17 | 15.99 | 0.83 | 6.52 | 3.60 | 0.79 |
| Liaoning | 11.94 | 13.45 | 0.74 | 6.80 | 4.24 | 0.70 |
| Ningxia | 10.48 | 11.68 | 2.58 | 5.06 | 3.69 | 1.77 |
| Qinghai | 11.05 | 12.29 | 1.99 | 4.84 | 1.98 | 1.40 |
| Shaanxi | 10.84 | 11.33 | 1.55 | 5.52 | 2.81 | 1.02 |
| Shandong | 14.84 | 15.2 | 1.89 | 6.81 | 4.88 | 0.90 |
| Shanghai | 12.9 | 12.72 | 0.61 | 7.79 | 5.51 | 2.12 |
| Shanxi | 13.55 | 15.39 | 1.36 | 6.79 | 3.99 | 1.09 |
| Sichuan | 10.68 | 12.54 | 1.1 | 5.31 | 3.75 | 0.34 |
| Tianjin | 11.74 | 12.43 | -0.12 | 6.70 | 4.67 | 1.50 |
| Xinjiang | 15.29 | 16.53 | 1.72 | 5.72 | 2.66 | 1.98 |
| Xizang | 12.11 | 12.24 | 1.61 | 2.92 | 2.02 | 1.63 |
| Yunnan | 11.19 | 14.27 | 2.03 | 5.16 | 2.39 | 1.27 |
| Zhejiang | 16.94 | 16.32 | 2.06 | 7.42 | 5.71 | 1.04 |
| Average | 12.86 | 13.98 | 1.66 | 6.18 | 3.88 | 1.18 |

Table A5.3.12 Average Growth % Total Trade, Exports and Imports

| Province | Total Trade | Exports | Imports |
|---|---|---|---|
| Anhui | 17.60 | 16.09 | 23.71 |
| Beijing | 22.69 | 19.38 | 29.89 |
| Fujian | 20.77 | 20.79 | 21.27 |
| Gansu | 22.49 | 18.66 | 41.72 |
| Guangdong | 27.42 | 26.18 | 30.71 |
| Guangxi | 14.02 | 11.85 | 21.79 |
| Guizhou | 17.75 | 19.95 | 20.73 |
| Hainan | 20.01 | 15.61 | 26.00 |
| Hebei | 14.37 | 12.90 | 23.57 |
| Heilongjiang | 16.75 | 15.55 | 16.99 |
| Henan | 15.35 | 14.70 | 21.28 |
| Hubei | 14.65 | 13.47 | 22.53 |
| Hunan | 13.86 | 12.88 | 19.89 |
| Inner Mongolia | 16.87 | 13.62 | 23.36 |
| Jiangsu | 25.74 | 24.04 | 30.76 |
| Jiangxi | 15.89 | 14.48 | 23.77 |
| Jilin | 14.48 | 10.86 | 22.70 |
| Liaoning | 11.82 | 9.35 | 22.12 |
| Ningxia | 17.93 | 19.07 | 22.53 |
| Qinghai | 17.55 | 15.24 | 51.23 |
| Shaanxi | 18.59 | 19.17 | 20.16 |
| Shandong | 16.88 | 16.40 | 30.65 |
| Shanghai | 19.00 | 17.65 | 21.75 |
| Shanxi | 19.32 | 20.56 | 22.14 |
| Sichuan | 16.26 | 15.48 | 22.71 |
| Tianjin | 18.69 | 16.01 | 27.26 |
| Xinjiang | 19.78 | 22.60 | 22.14 |
| Xizang | 30.57 | 30.44 | 52.48 |
| Yunnan | 15.87 | 15.38 | 17.54 |
| Zhejiang | 25.06 | 24.15 | 29.63 |
| Average | 18.60 | 17.42 | 26.1 |

**Figure A5.3.1 Average Provincial Trade Intensity, 1985-2007**

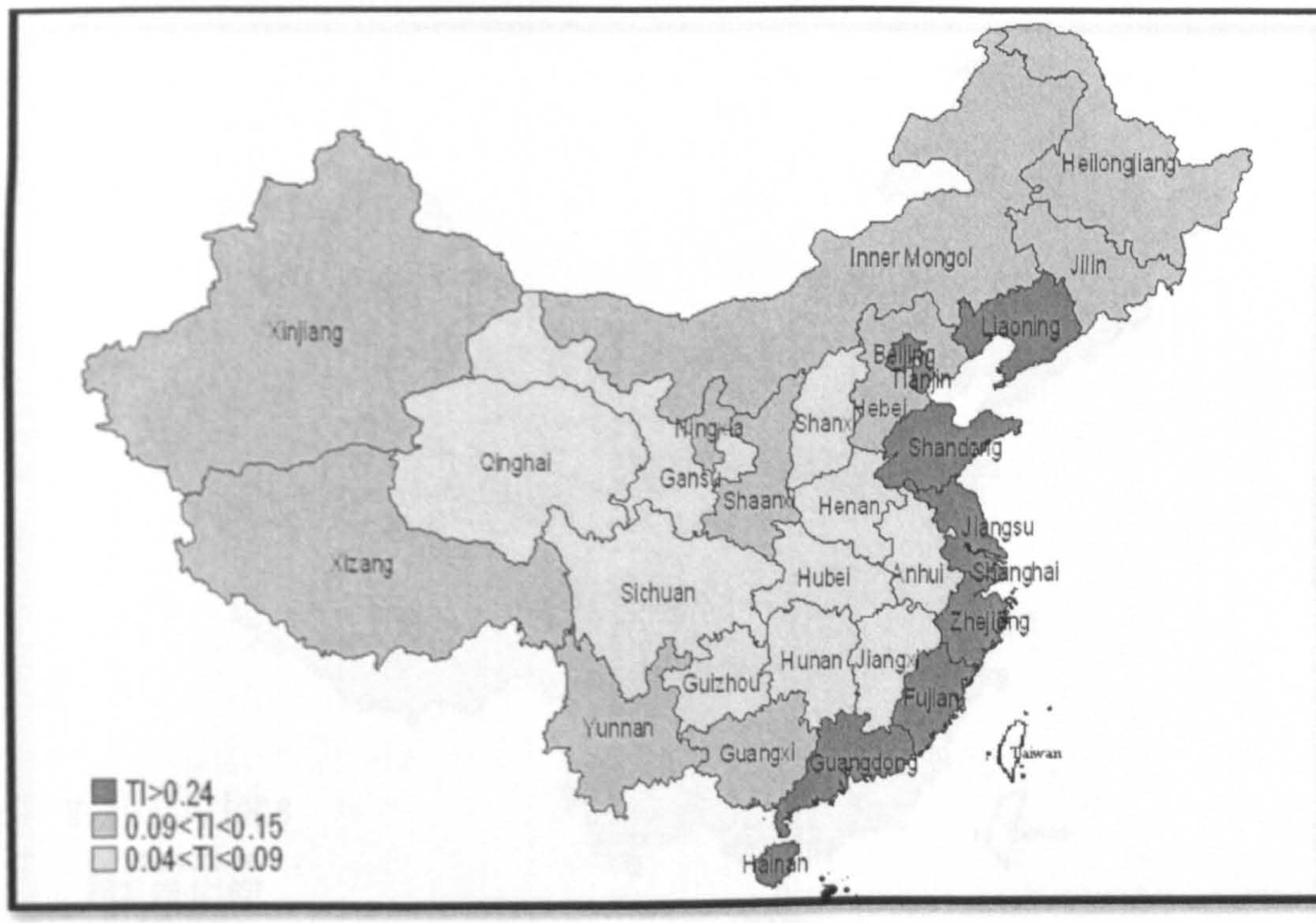



**Figure A5.3.2 Average Trade Volumes by province, 1985-2007**

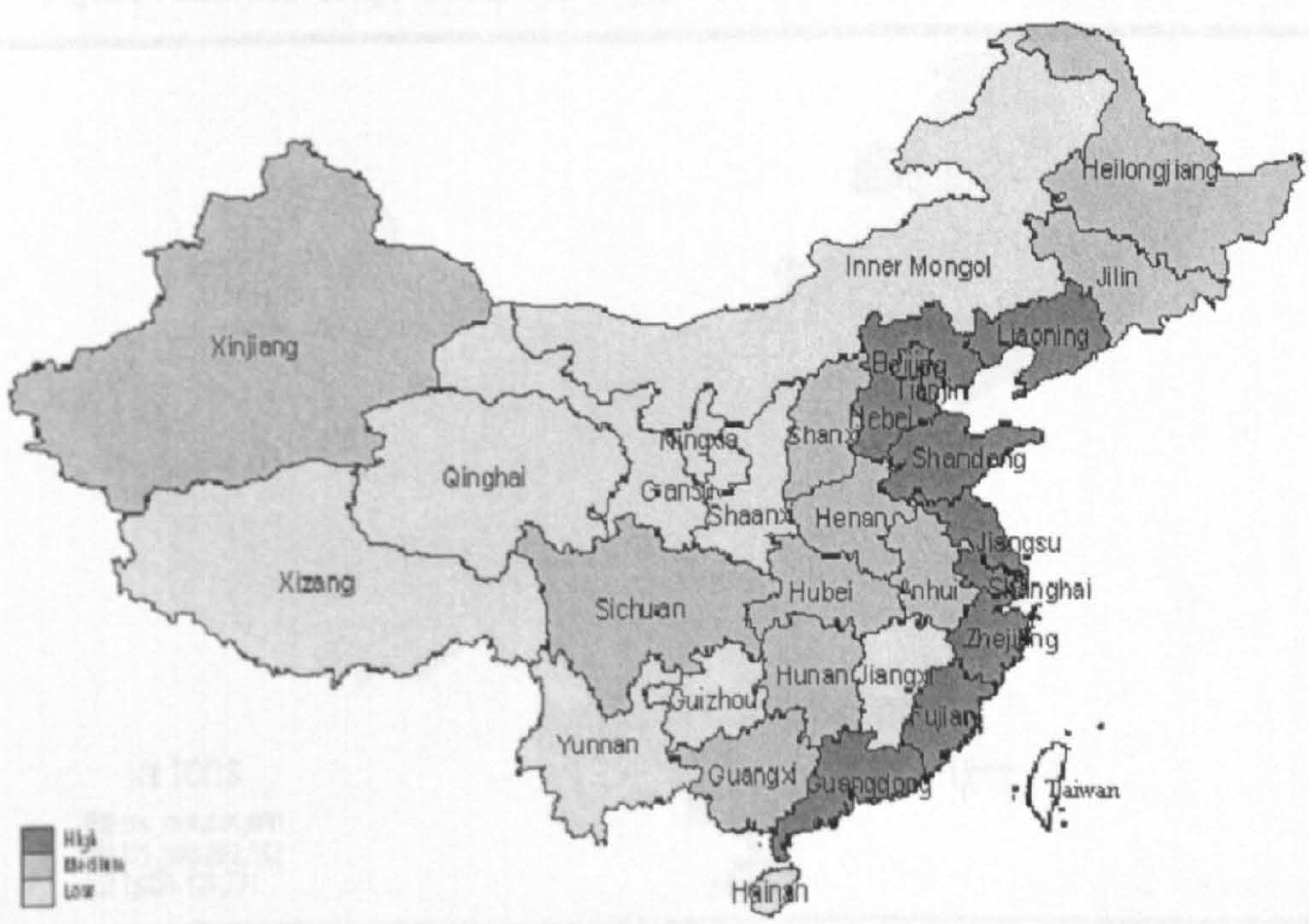


**Figure A5.3.3 Average Industrial Waste Water Discharge, 1985-2007**

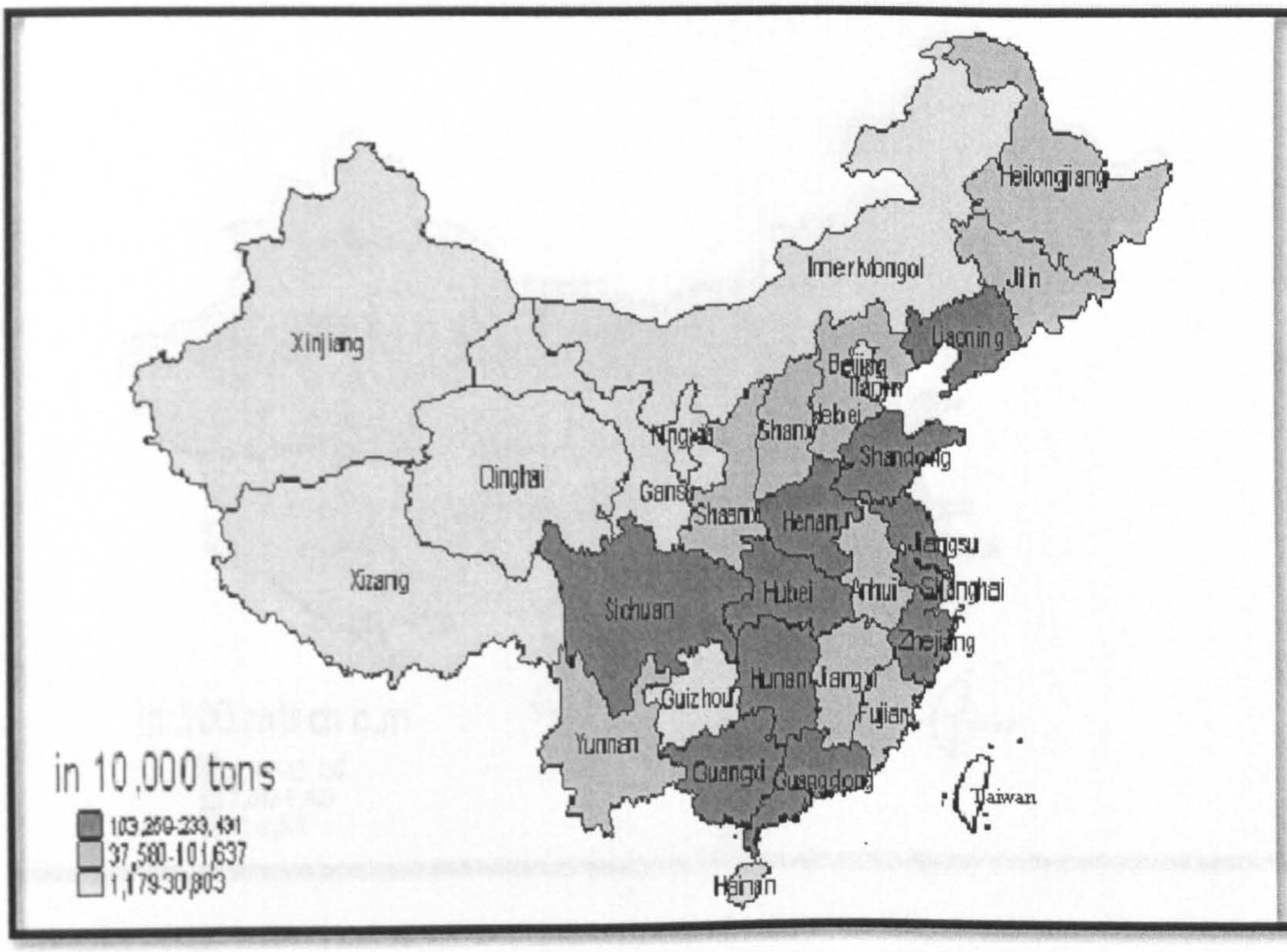



**Figure A5.3.4 Average Chemical Oxygen Demand Emissions, 1985-2007**

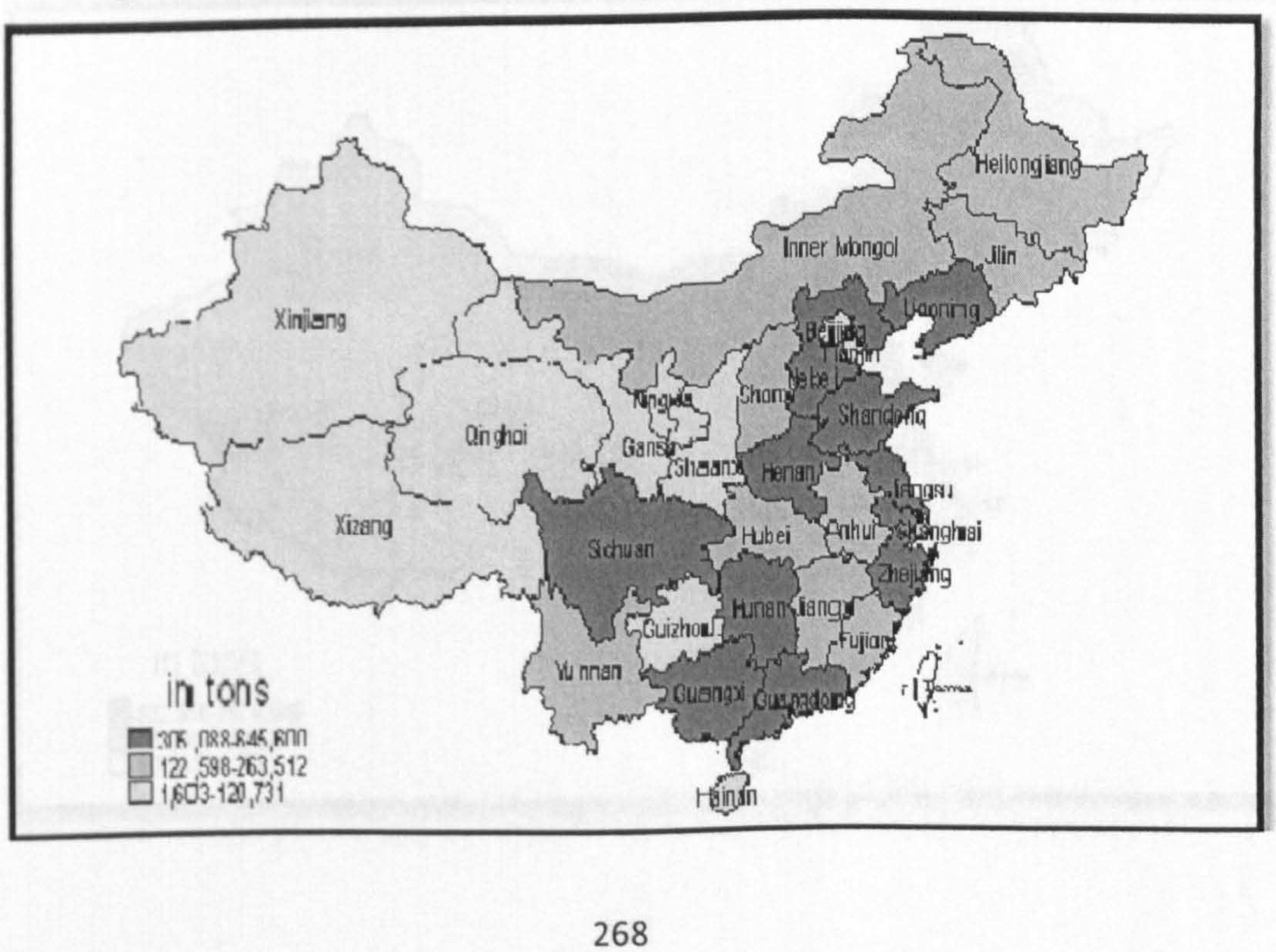


**Figure A5.3.5 Average Industrial Waste Air Emissions, 1985-2007**

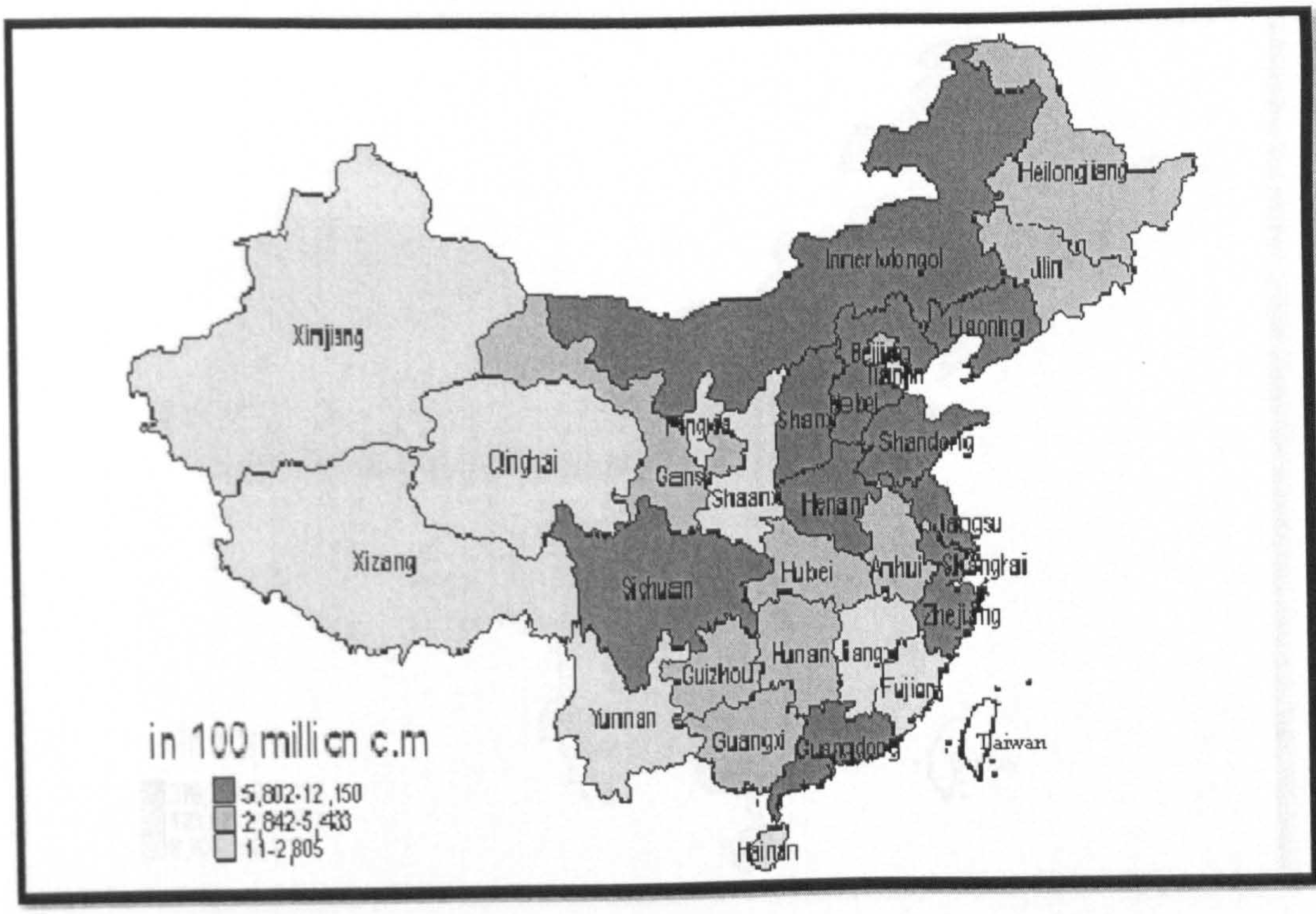



**Figure A5.3.6 Average Industrial $SO_2$ Emissions, 1985-2007**

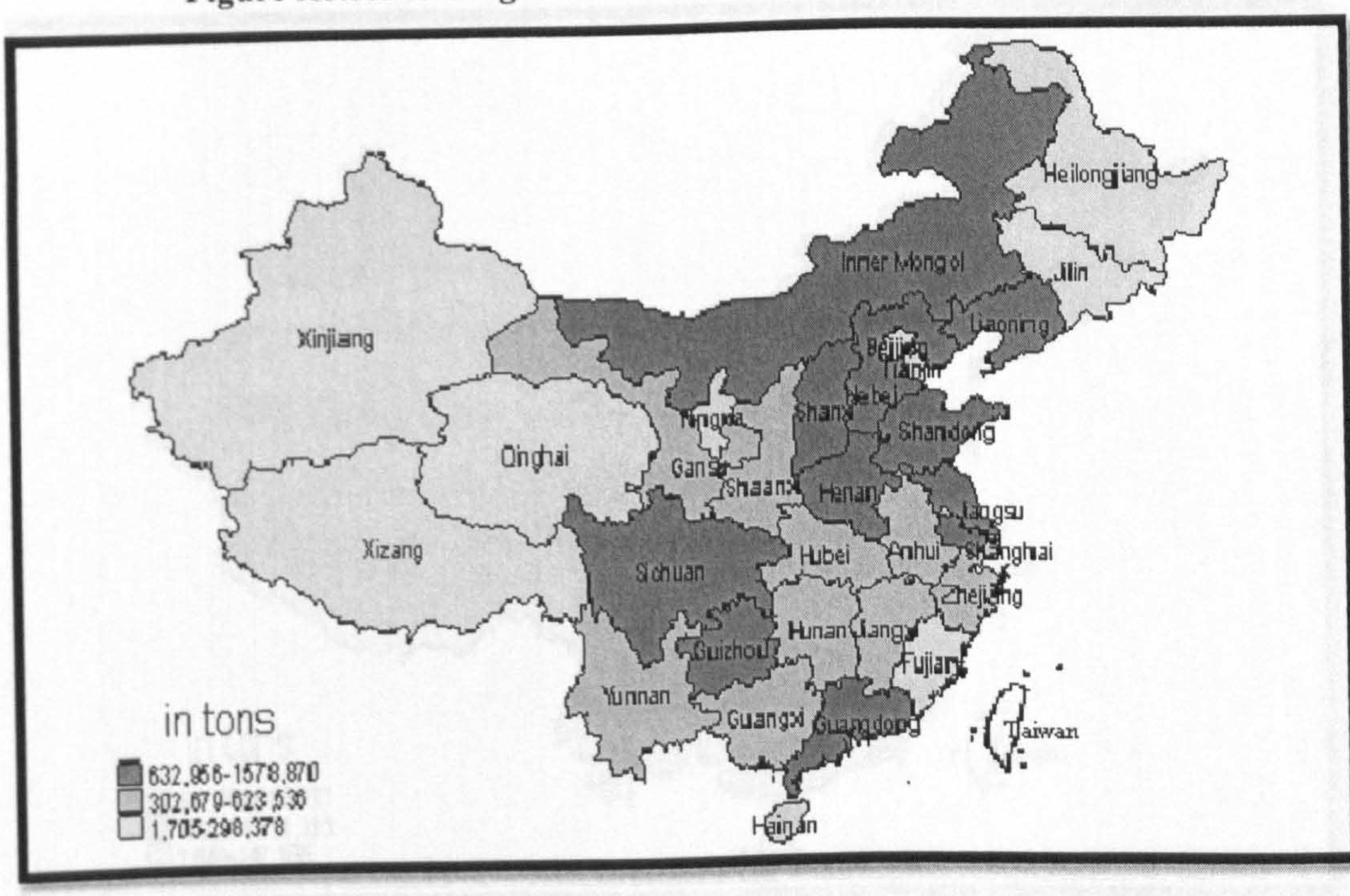


**Figure A5.3.7 Average Industrial Dust Emissions, 1985-2007**

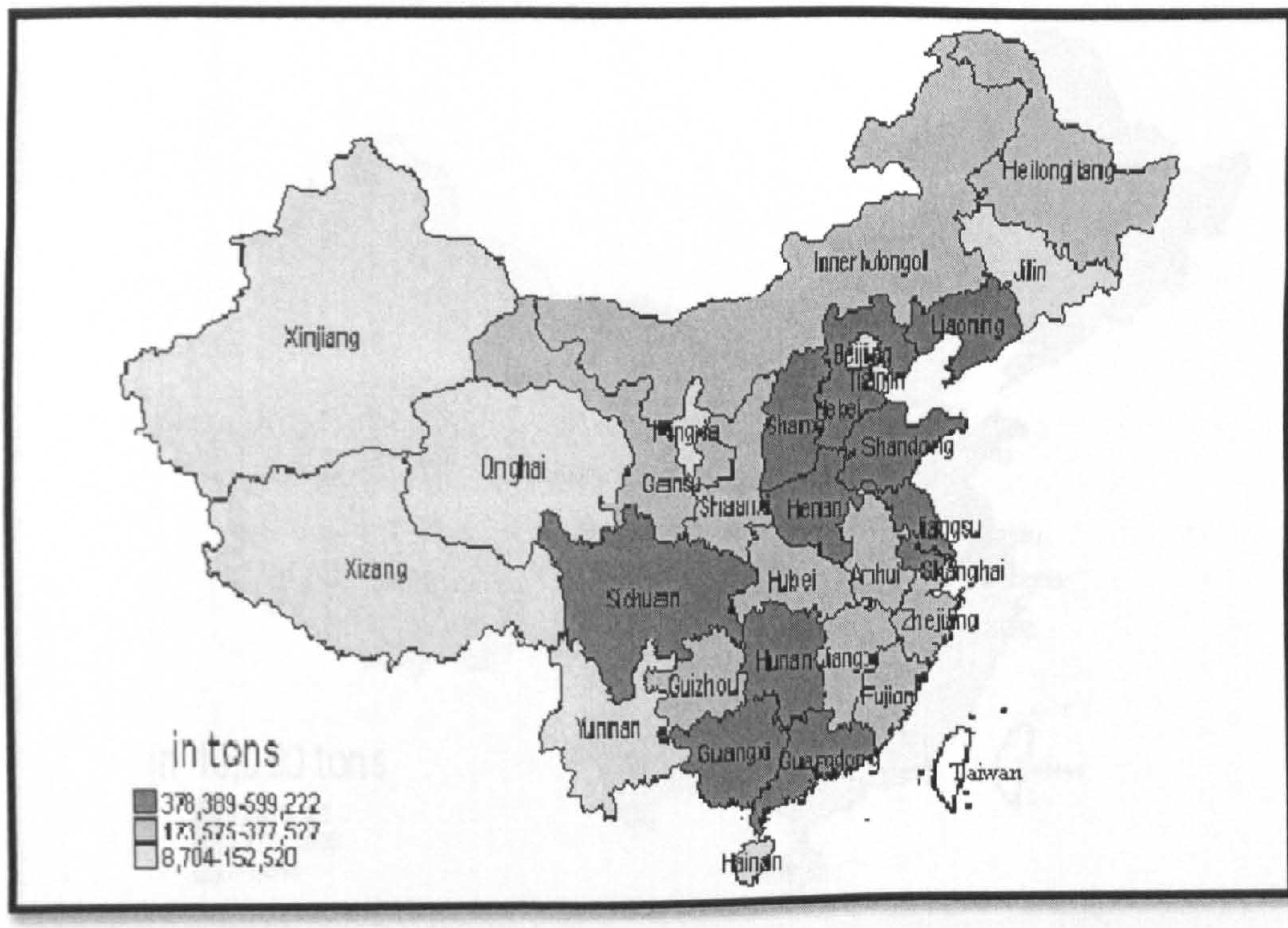



**Figure A5.3.8 Average Industrial Soot Emissions, 1985-2007**

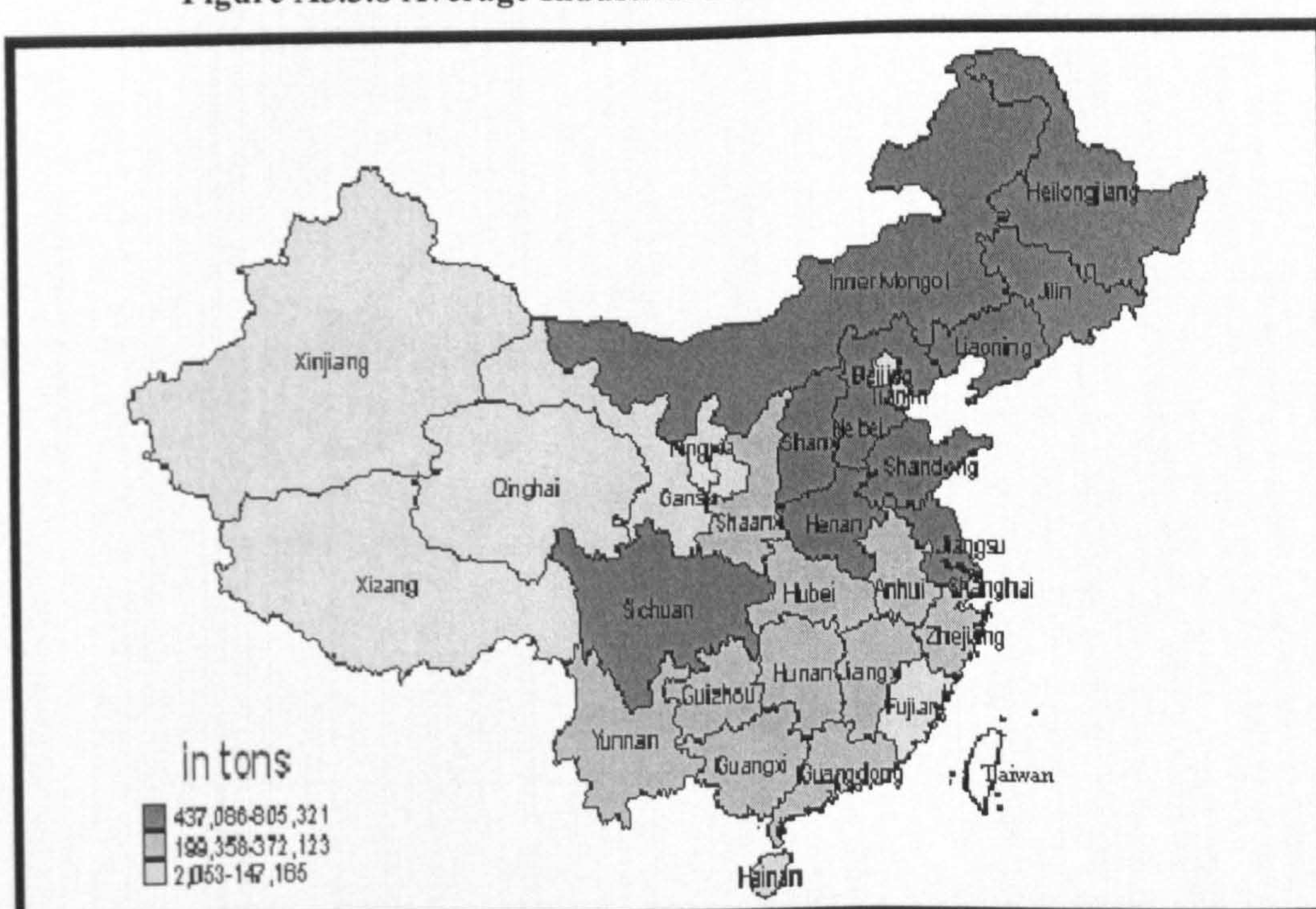
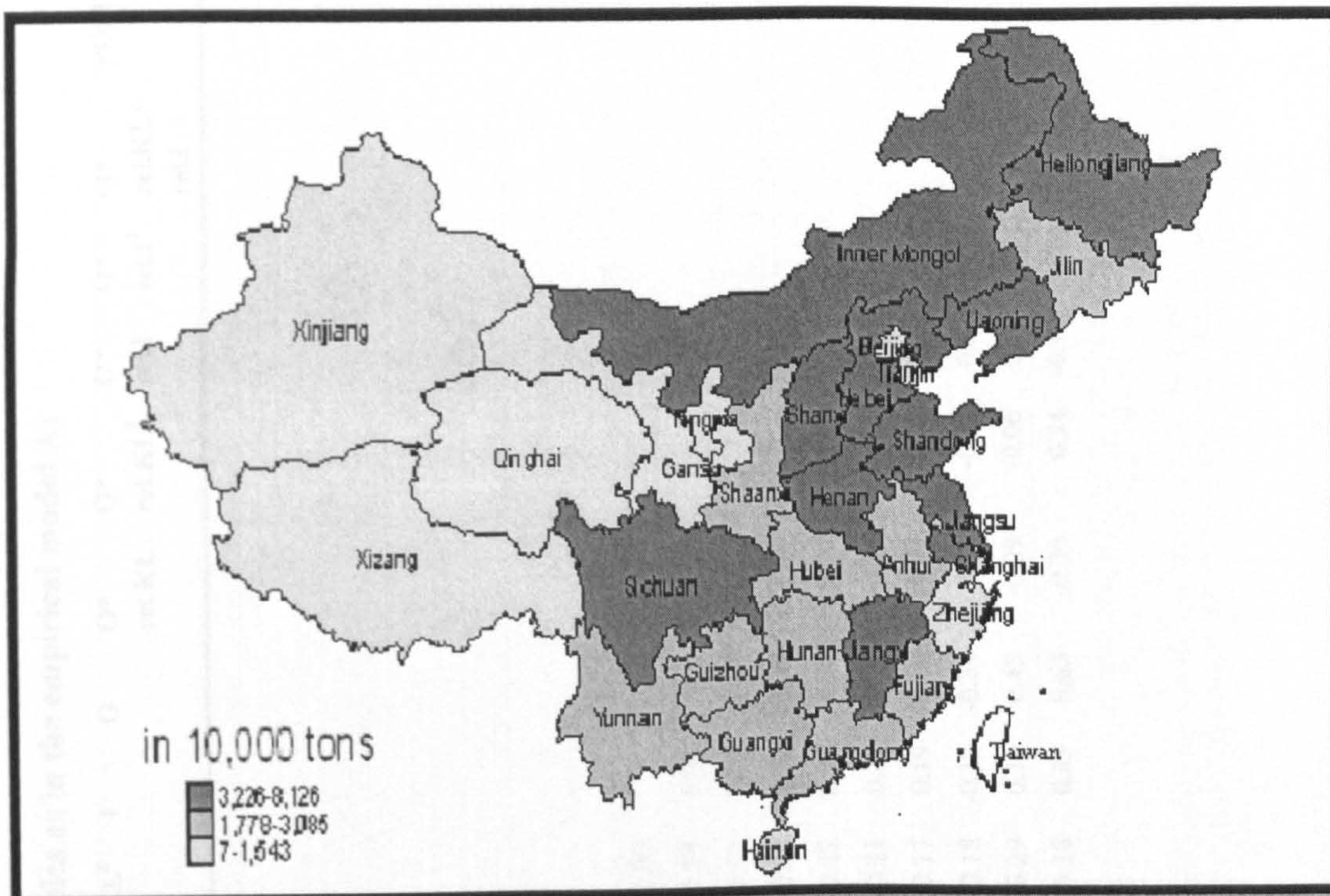


**Figure A5.3.9 Average Industrial Solid Waste Emissions, 1985-2007**



## A5.4 Correlation Tables

### Table A5.4.1 Correlation table (all the variables as in the empirical model A)

| Obs=584 | Waste water | COD | Waste air | SO2 | Dust | Soot | Solid waste | S | KL | $KL^2$ | I | O | O* rel.KL | O* rel.$KL^2$ | O* rel.I | O* rel.$I^2$ | O* rel.KL* rel.I | POPDEN | PROD |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| waste water | 1.00 | | | | | | | | | | | | | | | | | | |
| COD | 0.87 | 1.00 | | | | | | | | | | | | | | | | | |
| waste air | 0.75 | 0.68 | 1.00 | | | | | | | | | | | | | | | | |
| SO2 | 0.79 | 0.78 | 0.90 | 1.00 | | | | | | | | | | | | | | | |
| Dust | 0.75 | 0.77 | 0.69 | 0.81 | 1.00 | | | | | | | | | | | | | | |
| Soot | 0.75 | 0.80 | 0.76 | 0.88 | 0.86 | 1.00 | | | | | | | | | | | | | |
| solid waste | 0.73 | 0.69 | 0.91 | 0.89 | 0.78 | 0.84 | 1.00 | | | | | | | | | | | | |
| S | 0.77 | 0.64 | 0.89 | 0.74 | 0.57 | 0.56 | 0.77 | 1.00 | | | | | | | | | | | |
| KL | -0.17 | -0.27 | 0.20 | -0.10 | -0.35 | -0.32 | -0.02 | 0.34 | 1.00 | | | | | | | | | | |
| $KL^2$ | -0.01 | -0.21 | 0.14 | -0.03 | -0.32 | -0.23 | 0.00 | 0.19 | 0.50 | 1.00 | | | | | | | | | |
| I | -0.04 | -0.19 | 0.26 | -0.01 | -0.15 | -0.30 | 0.06 | 0.48 | 0.81 | 0.39 | 1.00 | | | | | | | | |
| O | 0.12 | 0.01 | 0.17 | -0.02 | -0.25 | -0.25 | -0.07 | 0.37 | 0.62 | 0.41 | 0.51 | 1.00 | | | | | | | |
| O*rel.KL | 0.14 | 0.12 | 0.08 | 0.21 | 0.33 | 0.22 | 0.24 | 0.01 | -0.56 | -0.18 | -0.12 | -0.60 | 1.00 | | | | | | |
| O* rel.$KL^2$ | -0.03 | 0.03 | -0.01 | -0.13 | -0.21 | -0.11 | -0.15 | 0.05 | 0.42 | 0.17 | 0.08 | 0.50 | -0.77 | 1.00 | | | | | |
| O*rel.I | -0.15 | -0.04 | 0.10 | 0.10 | 0.12 | 0.23 | 0.21 | -0.09 | -0.14 | -0.21 | -0.22 | -0.44 | 0.36 | -0.15 | 1.00 | | | | |
| O*rel.$I^2$ | 0.19 | 0.10 | 0.06 | 0.08 | 0.02 | -0.06 | 0.00 | 0.16 | 0.04 | 0.17 | 0.19 | 0.39 | -0.09 | 0.08 | -0.61 | 1.00 | | | |
| O*rel.KL*rel.I | 0.05 | 0.09 | 0.08 | 0.12 | 0.19 | 0.17 | 0.17 | 0.04 | -0.27 | -0.18 | -0.12 | -0.34 | 0.58 | -0.26 | 0.67 | -0.35 | 1.00 | | |
| POPDEN | 0.64 | 0.48 | 0.54 | 0.51 | 0.26 | 0.31 | 0.42 | 0.62 | 0.19 | 0.29 | 0.19 | 0.43 | -0.09 | -0.06 | -0.31 | 0.24 | -0.11 | 1.00 | |
| PROD | 0.07 | 0.04 | 0.43 | 0.15 | -0.10 | -0.06 | 0.18 | 0.52 | 0.72 | 0.38 | 0.65 | 0.63 | -0.36 | 0.31 | -0.12 | 0.12 | -0.18 | 0.22 | 1.00 |

Note: all the variables are in logarithmic forms.

Table A5.4.2 Correlation table (all the variables as in the empirical model B)

| Obs=584 | waste water | COD | waste air | $SO_2$ | Dust | Soot | solid waste | S | KL | $KL^2$ | GDPPC | O | O* rel.KL | O* rel.$KL^2$ | O* rel.GDPPC | O* rel.$GDPPC^2$ | O* rel.KL* rel.GDPPC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| waste water | 1.00 | | | | | | | | | | | | | | | | |
| COD | 0.87 | 1.00 | | | | | | | | | | | | | | | |
| waste air | 0.75 | 0.68 | 1.00 | | | | | | | | | | | | | | |
| $SO_2$ | 0.79 | 0.78 | 0.90 | 1.00 | | | | | | | | | | | | | |
| Dust | 0.75 | 0.77 | 0.69 | 0.81 | 1.00 | | | | | | | | | | | | |
| Soot | 0.75 | 0.80 | 0.76 | 0.88 | 0.86 | 1.00 | | | | | | | | | | | |
| solid waste | 0.73 | 0.69 | 0.91 | 0.89 | 0.78 | 0.84 | 1.00 | | | | | | | | | | |
| S | 0.77 | 0.64 | 0.89 | 0.74 | 0.57 | 0.56 | 0.77 | 1.00 | | | | | | | | | |
| KL | -0.17 | -0.27 | 0.20 | -0.10 | -0.35 | -0.32 | -0.02 | 0.34 | 1.00 | | | | | | | | |
| $KL^2$ | -0.01 | -0.21 | 0.14 | -0.03 | -0.32 | -0.23 | 0.00 | 0.19 | 0.50 | 1.00 | | | | | | | |
| GDPPC | 0.05 | -0.10 | 0.35 | 0.03 | -0.22 | -0.22 | 0.09 | 0.56 | 0.92 | 0.49 | 1.00 | | | | | | |
| O | 0.12 | 0.01 | 0.17 | -0.02 | -0.25 | -0.25 | -0.07 | 0.37 | 0.62 | 0.41 | 0.72 | 1.00 | | | | | |
| O*rel.KL | 0.14 | 0.12 | 0.08 | 0.21 | 0.33 | 0.22 | 0.24 | 0.01 | -0.56 | -0.18 | -0.45 | -0.60 | 1.00 | | | | |
| O*rel.$KL^2$ | -0.03 | 0.03 | -0.01 | -0.13 | -0.21 | -0.11 | -0.15 | 0.05 | 0.42 | 0.17 | 0.33 | 0.50 | -0.77 | 1.00 | | | |
| O*rel.GDPPC | -0.20 | -0.18 | -0.16 | 0.01 | 0.13 | 0.05 | 0.04 | -0.31 | -0.42 | -0.16 | -0.54 | -0.69 | 0.79 | -0.59 | 1.00 | | |
| O*rel.$GDPPC^2$ | 0.20 | 0.24 | 0.14 | -0.01 | -0.03 | 0.02 | 0.02 | 0.27 | 0.28 | 0.16 | 0.36 | 0.49 | -0.54 | 0.76 | -0.68 | 1.00 | |
| O*rel.KL*rel.GDPPC | -0.01 | 0.05 | -0.04 | -0.17 | -0.18 | -0.12 | -0.17 | 0.06 | 0.37 | 0.15 | 0.32 | 0.45 | -0.72 | 0.92 | -0.63 | 0.91 | 1.00 |

Note: all the variables are in logarithmic forms

## A5.5 Multicollinearity

Multicollinearity is aggravated by adding interaction terms in an econometric equation. A feasible solution without increasing sample size or dropping out interaction terms is centring the interaction terms at sample mean. Centring will sometimes increase the correlations and decrease the correlations at other times according to Jaccard and Turrisi (2003:28).

The following correlation table shows the correlation of variables for model A. The interaction terms are highly correlated with the individual terms. For example, the correlation between the interaction of openness and composition and the interaction of openness composition and income seems to be extremely high. After centring, multicollinearity is greatly reduced. For the variables in model B, centring reduces the correlation between the interaction terms and their individual terms; however, the correlation between the interaction terms seems to be strengthened after centring.

Table A5.5.1 Multicollinearity issue for model A

| (obs=639) | S | KL | $KL^2$ | I | POPDEN | PROD | O | O*KL | O*$KL^2$ | O*I | O*$I^2$ | O *KL*I | O *rel.KL | O *rel.$KL^2$ | O *rel.I | O *rel.$I^2$ | O *rel.KL *rel.I |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| O*KL | -0.21 | -0.82 | 0.04 | -0.66 | 0.06 | -0.54 | -0.59 | 1.00 | | | | | | | | | |
| O*$KL^2$ | 0.26 | 0.34 | -0.34 | 0.33 | 0.17 | 0.38 | 0.48 | -0.35 | 1.00 | | | | | | | | |
| O*I | 0.34 | 0.55 | 0.37 | 0.40 | 0.44 | 0.58 | -0.43 | -0.27 | 0.40 | 1.00 | | | | | | | |
| O*$I^2$ | 0.30 | 0.46 | 0.39 | 0.29 | 0.44 | 0.51 | 0.38 | -0.16 | 0.35 | 0.99 | 1.00 | | | | | | |
| O*KL*I | -0.20 | -0.82 | 0.02 | -0.64 | 0.08 | -0.53 | -0.34 | 1.00 | -0.30 | -0.26 | -0.15 | 1.00 | | | | | |
| O*rel.KL | 0.01 | -0.54 | -0.12 | -0.10 | -0.10 | -0.34 | -0.59 | | | | | | 1.00 | | | | |
| O*rel.$KL^2$ | 0.05 | 0.39 | 0.14 | 0.06 | -0.06 | 0.29 | 0.48 | | | | | | -0.75 | 1.00 | | | |
| O*rel.I | -0.08 | -0.11 | -0.19 | -0.18 | -0.31 | -0.10 | -0.43 | | | | | | 0.35 | -0.15 | 1.00 | | |
| O*rel.$I^2$ | 0.15 | 0.03 | 0.16 | 0.16 | 0.23 | 0.11 | 0.38 | | | | | | -0.09 | 0.08 | -0.60 | 1.00 | |
| O*rel.KL*rel.I | 0.04 | -0.26 | -0.16 | -0.10 | -0.11 | -0.18 | -0.34 | | | | | | 0.58 | -0.25 | 0.66 | -0.37 | 1.00 |

Table A5.5.2 Multicollinearity issue for model B

| obs=639 | S | KL | KL² | GDPPC | O | O *KL | O *KL² | O *GDPPC | O *GDPPC² | O* KL* GDPPC | O* rel.KL | O* rel.KL² | O* rel.GDPPC | O* rel.GDPPC² | O* rel.KL* rel.GDPPC |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| O*KL | -0.21 | -0.82 | 0.04 | -0.70 | -0.38 | 1.00 | | | | | | | | | |
| O*KL² | 0.26 | 0.34 | -0.34 | 0.40 | 0.44 | -0.35 | 1.00 | | | | | | | | |
| O*GDPPC | 0.33 | 0.53 | 0.39 | 0.62 | 0.99 | -0.24 | 0.39 | 1.00 | | | | | | | |
| O*GDPPC² | 0.26 | 0.41 | 0.41 | 0.49 | 0.94 | -0.08 | 0.34 | 0.98 | 1.00 | | | | | | |
| O*KL*GDPPC | -0.20 | -0.82 | 0.02 | -0.69 | -0.36 | 1.00 | -0.28 | -0.21 | -0.06 | 1.00 | | | | | |
| O*rel.KL | 0.01 | -0.54 | -0.12 | -0.43 | -0.59 | | | | | | 1.00 | | | | |
| O*rel.KL² | 0.05 | 0.39 | 0.14 | 0.30 | 0.48 | | | | | | -0.75 | 1.00 | | | |
| O*rel.GDPPC | -0.30 | -0.40 | -0.11 | -0.53 | -0.68 | | | | | | 0.78 | -0.57 | 1.00 | | |
| O*rel.GDPPC² | 0.26 | 0.25 | 0.14 | 0.33 | 0.48 | | | | | | -0.52 | 0.75 | -0.66 | 1.00 | |
| O*rel.KL*rel.GDPPC | 0.05 | 0.33 | 0.13 | 0.29 | 0.44 | | | | | | -0.70 | 0.91 | -0.61 | 0.90 | 1.00 |

It is argued that correlation maybe not a good way to detect multicollinearity in a model. Some authors have suggested computing tolerance indices of multicollinearity. The variance inflation factor (VIF) is one of the indices which measure the severity of multicollinearity. Mathematically, $VIF(?_i) = \frac{1}{1-R_i^2}$, which is a component part of the sampling variances of the OLS slope estimator for the $i^{th}$ independent variable. $R_i^2$ is the R-squared obtained by regressing the $i^{th}$ independent variable on the other independent variables. A higher value of $R_i^2$ increases the sampling variance and implies that the $i^{th}$ independent variable is more correlated with other independent variables. (Wooldridge, 2003: 97). As a rule of thumb, a variable whose VIF is greater than 10 (some researchers suggest a lower value) indicate a possibility that it could be considered as a linear combination of other independent variables. For our datasets, it shows that the models with the original interaction terms suffer greatly from the violation of the condition. If we use centred interaction terms, the VIF values are much *smaller. Also model B has a* greater mean VIF (27.09) than model A (8.82).

The correlation of economic variables is unavoidable. As long as the correlation is not too high, the regression results are viewed as credible. In fact, we do not see much of the multicollinearity problem addressed in current empirical research work. However, in some models, the issue of multicollinearity is so severe that it affects the validity of the coefficients for individual regressors. Since we are more interested in the mechanisms of how trade liberalization affects environment, caution should be taken whenever we interpret the coefficient results of the interaction terms. The introduction of the interaction terms in the model also aggravates the issue as we just have shown. There are a few ways to reduce multicollinearity. Based on the current panel, the feasible solutions are: 1. centring the interaction terms at sample means; 2. drop some of the interaction terms; 3.

Check if other proxies for composition effect exists (for example, energy intensity) and are better indicators.

## A5.6 Robustness Check

**Table A5.6.1 Results for industrial waste water**

| Specification | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| S | 0.789*** | 0.750*** | 0.726*** | 0.764*** | 0.764*** | 0.829*** | 0.829*** | 1.015*** |
| | (-10.186) | (-9.087) | (-8.71) | (-9.387) | (-9.321) | (-10.397) | (-10.064) | (-9.775) |
| KL | | 0.098 | 0.139 | 0.263** | 0.263** | 0.462* | 0.462** | 0.649*** |
| | | (-1.208) | (-1.445) | (-2.658) | (-2.683) | (-2.551) | (-2.641) | (-3.67) |
| $KL^2$ | | | -0.024 | -0.001 | -0.007 | -0.018 | -0.018 | 0.011 |
| | | | (-1.148) | (-0.055) | (-0.340) | (-0.720) | (-0.715) | -0.376 |
| I | | | | -0.620** | -0.733*** | -0.962** | -0.962** | -0.795* |
| | | | | (-3.102) | (-3.744) | (-2.821) | (-2.883) | (-2.345) |
| O | | | | | 0.098* | 0.112** | 0.112** | 0.132** |
| | | | | | (-2.306) | (-2.62) | (-2.612) | (-3.084) |
| O*rel.KL | | | | | | 0.128 | 0.128 | 0.121 |
| | | | | | | -1.529 | -1.528 | -1.465 |
| $O*rel.KL^2$ | | | | | | (-0.007) | (-0.007) | (-0.003) |
| | | | | | | (-0.171) | (-0.171) | (-0.074) |
| O*rel.I | | | | | | -0.271 | -0.271 | -0.192 |
| | | | | | | (-1.840) | (-1.858) | (-1.327) |
| $O*rel.I^2$ | | | | | | -0.713** | -0.713** | -0.546** |
| | | | | | | (-3.205) | (-3.203) | (-2.639) |
| O*rel.KL*rel.I | | | | | | -0.67 | -0.67 | -0.666* |
| | | | | | | (-1.920) | (-1.928) | (-2.004) |
| POPDEN | | | | | | | -0.001 | -0.294 |
| | | | | | | | (-0.00.) | (-0.72.) |
| PROD | | | | | | | | -0.757** |
| | | | | | | | | (-3.189) |
| _cons | 7.358*** | 7.730*** | 7.952*** | 12.240*** | 13.329*** | 14.689*** | 14.685*** | 10.719*** |
| | (-17.966) | (-15.373) | (-14.658) | (-8.301) | (-9.177) | (-5.99) | (-5.516) | (-3.354) |
| F | 328 | 323 | 344 | 310 | 987 | 370 | 5689 | 318 |
| N | 639 | 639 | 639 | 639 | 639 | 639 | 639 | 639 |

Note: model A using Newey-West estimator; for all the following tables, province and time dummies are included; t-statistics are in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%

**Table A5.6.2 Results for COD**

| Specification | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| S | 0.609*** | 0.708*** | 0.567*** | 0.652*** | 0.662*** | 0.712*** | 0.678*** | 0.930*** |
| | (-3.535) | (-3.663) | (-3.34) | (-3.982) | (-4.191) | (-4.329) | (-4.117) | (-5.327) |
| KL | | -0.253 | 0.039 | 0.351 | 0.343 | 0.838* | 0.918* | 1.182** |
| | | (-1.203) | (-0.169) | (-1.704) | (-1.697) | (-2.421) | (-2.535) | (-3.174) |
| $KL^2$ | | | -0.17*** | -0.12** | -0.129*** | -0.152** | -0.164*** | -0.125* |
| | | | (-5.273) | (-3.484) | (-3.896) | (-3.279) | (-3.357) | (-2.523) |
| I | | | | -1.63** | -1.873*** | -3.12*** | -3.203*** | -2.99*** |
| | | | | (-4.702) | (-5.096) | (-6.430) | (-6.352) | (-6.195) |
| O | | | | | 0.205* | 0.213* | 0.221* | 0.248** |
| | | | | | (-2.293) | (-2.305) | (-2.375) | (-2.655) |
| O*rel.KL | | | | | | 0.29 | 0.303 | 0.302 |
| | | | | | | (-1.6) | (-1.658) | (-1.702) |
| O*rel.$KL^2$ | | | | | | 0.091 | 0.088 | 0.095 |
| | | | | | | (-1.002) | (-0.978) | (-1.072) |
| O*rel.I | | | | | | -0.89*** | -0.93*** | -0.84** |
| | | | | | | (-3.978) | (-4.039) | (-3.873) |
| O*rel.$I^2$ | | | | | | -0.341 | -0.343 | -0.12 |
| | | | | | | (-0.862) | (-0.870) | (-0.306) |
| O*rel.KL*rel.I | | | | | | 0.013 | 0.042 | 0.038 |
| | | | | | | (-0.022) | (-0.07) | (-0.065) |
| POPDEN | | | | | | | 0.55 | 0.162 |
| | | | | | | | (1.17) | (0.34) |
| PROD | | | | | | | | -1.037** |
| | | | | | | | | (-2.740) |
| _cons | 9.256 | 8.309 | 9.699 | 21.224 | 23.497*** | 32.533 | 35.224*** | 30.012 |
| | (.) | (.) | (.) | (.) | -7.7 | (.) | -7.677 | (.) |
| F | 1289.593 | 2183.69 | 1004.507 | 10631.56 | 93.458 | 46495.81 | 101.228 | 33549.56 |
| N | 584 | 584 | 584 | 584 | 584 | 584 | 584 | 584 |

Note: model A using Newey-West estimator; for all the following tables, province and time dummies are included; t-statistics are in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%

**Table A5.6.3 Results for industrial waste air**

| Specification | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| S | 0.709*** | 0.649*** | 0.626*** | 0.632*** | 0.632*** | 0.642*** | 0.632*** | 0.807*** |
| | (-10.787) | (-9.297) | (-8.877) | (-8.918) | (-8.911) | (-8.794) | (-8.58) | (-10.006) |
| KL | | 0.151* | 0.190* | 0.210** | 0.210** | 0.328* | 0.354* | 0.528** |
| | | (-2.139) | (-2.403) | (-2.589) | (-2.589) | (-1.994) | (-2.054) | (-3.012) |
| $KL^2$ | | | -0.023 | -0.019 | -0.019 | -0.016 | -0.02 | 0.008 |
| | | | (-1.700) | (-1.318) | (-1.221) | (-0.676) | (-0.822) | (-0.338) |
| I | | | | -0.098 | -0.082 | -0.387 | -0.414 | -0.258 |
| | | | | (-0.647) | (-0.523) | (-1.785) | (-1.862) | (-1.167) |
| O | | | | | -0.013 | -0.001 | 0.002 | 0.02 |
| | | | | | (-0.283) | (-0.018) | (-0.035) | (-0.394) |
| O*rel.KL | | | | | | 0.053 | 0.058 | 0.051 |
| | | | | | | (-0.66) | (-0.711) | (-0.65) |
| O*rel.$KL^2$ | | | | | | -0.021 | -0.022 | -0.018 |
| | | | | | | (-0.593) | (-0.618) | (-0.543) |
| O*rel.I | | | | | | -0.127 | -0.137 | -0.063 |
| | | | | | | (-1.167) | (-1.245) | (-0.587) |
| O*rel.I2 | | | | | | 0.122 | 0.122 | 0.279 |
| | | | | | | (-0.642) | (-0.643) | (-1.522) |
| O*rel.KL*rel.I | | | | | | -0.173 | -0.165 | -0.161 |
| | | | | | | (-0.595) | (-0.565) | (-0.584) |
| POPDEN | | | | | | | 0.181 | -0.093 |
| | | | | | | | (0.57) | (-0.29) |
| PROD | | | | | | | | -0.708*** |
| | | | | | | | | (-3.662) |
| _cons | 3.986*** | 4.556*** | 4.773*** | 5.448*** | 5.299*** | 7.430*** | 8.314*** | 4.604* |
| | (-11.633) | (-10.64) | (-10.472) | (-4.822) | (-4.291) | (-4.414) | (-3.806) | (-2.011) |
| F | 291 | 288 | 290 | 283 | 5226 | 286 | 284 | 286 |
| N | 639 | 639 | 639 | 639 | 639 | 639 | 639 | 639 |

Note: model A using Newey-West estimator; for all the following tables, province and time dummies are included; t-statistics are in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%

**Table A5.6.4 Results for $SO_2$**

| Specification | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| S | 0.621*** | 0.615*** | 0.519*** | 0.540*** | 0.540*** | 0.560*** | 0.527*** | 0.714*** |
| | (-6.89) | (-6.174) | (-5.591) | (-5.654) | (-5.65) | (-5.664) | (-5.028) | (-6.188) |
| KL | | 0.016 | 0.177* | 0.246** | 0.246** | 0.404* | 0.488* | 0.676** |
| | | (-0.19) | (-1.967) | (-2.597) | (-2.596) | (-1.9920 | (-2.401) | (-3.294) |
| $KL^2$ | | | -0.094*** | -0.081*** | -0.081*** | -0.085*** | -0.098*** | -0.069** |
| | | | (-5.860) | (-5.488) | (-5.307) | (-3.545) | (-3.781) | (-2.594) |
| I | | | | -0.345 | -0.348 | -0.793* | -0.883* | -0.715* |
| | | | | (-1.926) | (-1.860) | (-2.264) | (-2.578) | (-2.121) |
| O | | | | | 0.003 | 0.014 | 0.023 | 0.043 |
| | | | | | (-0.06) | (-0.275) | (-0.448) | (-0.84) |
| O*rel.KL | | | | | | 0.087 | 0.102 | 0.095 |
| | | | | | | (-0.992) | (-1.175) | (-1.147) |
| O*rel.$KL^2$ | | | | | | 0.012 | 0.009 | 0.013 |
| | | | | | | (-0.294) | (-0.222) | (-0.341) |
| O*rel.I | | | | | | -0.245 | -0.280* | -0.2 |
| | | | | | | (-1.776) | (-2.102) | (-1.550) |
| O*rel.$I^2$ | | | | | | 0.075 | 0.077 | 0.245 |
| | | | | | | (-0.374) | (-0.376) | (-1.236) |
| O*rel.KL*rel.I | | | | | | -0.148 | -0.119 | -0.115 |
| | | | | | | (-0.494) | (-0.395) | (-0.398) |
| POPDEN | | | | | | | 0.598* | 0.305 |
| | | | | | | | (1.76) | (0.85) |
| PROD | | | | | | | | -0.760*** |
| | | | | | | | | (-3.537) |
| _cons | 9.382*** | 9.442*** | 10.323*** | 12.709*** | 12.740*** | 15.875*** | 18.797*** | 14.815*** |
| | (-20.159) | (-16.056) | (-18.202) | (-9.762) | (-8.948) | (-6.111) | (-7.47) | (-5.312) |
| F | 242 | 233 | 273 | 229 | 411 | 221 | 11967 | 239 |
| N | 639 | 639 | 639 | 639 | 639 | 639 | 639 | 639 |

Note: model A using Newey-West estimator; for all the following tables, province and time dummies are included; t-statistics are in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%

**Table A5.6.5 Results for industrial dust**

| Specification | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| S | 0.461*** | 0.429** | 0.203 | 0.191 | 0.191 | 0.319** | 0.329** | 0.615** |
| | (-3.704) | (-3.218) | (-1.727) | (-1.657) | (-1.661) | (-2.751) | (-2.749) | (-4.409) |
| KL | | 0.082 | 0.464*** | 0.424** | 0.424** | 1.271*** | 1.248*** | 1.534** |
| | | (-0.668) | (-3.572) | (-3.144) | (-3.141) | (-4.752) | (-4.516) | (-5.566) |
| $KL^2$ | | | -0.222*** | -0.229*** | -0.232*** | -0.240*** | -0.236*** | -0.19*** |
| | | | (-8.719) | (-7.836) | (-7.693) | (-5.666) | (-5.509) | (-4.690) |
| I | | | | 0.195 | 0.15 | -0.999* | -0.974* | -0.718 |
| | | | | (-0.605) | (-0.486) | (-2.290) | (-2.145) | (-1.653) |
| O | | | | | 0.039 | 0.109 | 0.106 | 0.136 |
| | | | | | (-0.51) | (-1.493) | (-1.451) | (-1.886) |
| O*rel.KL | | | | | | 0.383** | 0.378** | 0.367** |
| | | | | | | (-2.712) | (-2.656) | (-2.867) |
| O*rel.$KL^2$ | | | | | | -0.160** | -0.159** | -0.152** |
| | | | | | | (-3.126) | (-3.104) | (-3.106) |
| O*rel.I | | | | | | -0.784*** | -0.774*** | -0.653** |
| | | | | | | (-3.411) | (-3.318) | (-2.982) |
| O*rel.$I^2$ | | | | | | -1.029* | -1.029* | -0.772* |
| | | | | | | (-2.491) | (-2.492) | (-2.007) |
| O*rel.KL*rel.I | | | | | | -0.987* | -0.995* | -0.988* |
| | | | | | | (-2.055) | (-2.076) | (-2.085) |
| POPDEN | | | | | | | -0.166 | -0.614 |
| | | | | | | | (-0.41) | (-1.49) |
| PROD | | | | | | | | -1.16** |
| | | | | | | | | (-3.627) |
| _cons | 10.689*** | 10.997*** | 13.087*** | 11.737*** | 12.169*** | 19.937*** | 19.127*** | 13.051* |
| | (-16.533) | (-13.949) | (-18.228) | (-4.958) | (-5.401) | (-6.097) | (-4.598) | (-3.086) |
| F | 65.8 | 60.9 | 106 | 91.6 | 502 | 145 | 5768 | 120 |
| N | 639 | 639 | 639 | 639 | 639 | 639 | 639 | 639 |

Note: model A using Newey-West estimator; for all the following tables, province and time dummies are included; t-statistics are in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%

**Table A5.6.6 Results for industrial soot**

| Specification | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| S | 0.530*** | 0.599*** | 0.445*** | 0.458*** | 0.458*** | 0.499*** | 0.486*** | 0.732*** |
| | -4.558 | -4.462 | -3.983 | -3.972 | -3.963 | -4.079 | -3.681 | -4.935 |
| KL | | -0.176 | 0.084 | 0.128 | 0.128 | 0.770*** | 0.804*** | 1.050*** |
| | | (-1.384) | -0.657 | -0.91 | -0.907 | -3.389 | -3.461 | -4.331 |
| $KL^2$ | | | -0.151*** | -0.143*** | -0.141*** | -0.138*** | -0.143*** | -0.105** |
| | | | (-6.482) | (-6.094) | (-5.880) | (-3.926) | (-4.015) | (-3.054) |
| I | | | | -0.221 | -0.184 | -1.484*** | -1.520*** | -1.300*** |
| | | | | (-0.709) | (-0.583) | (-3.800) | (-4.034) | (-3.479) |
| O | | | | | -0.032 | 0.022 | 0.026 | 0.052 |
| | | | | | (-0.525) | (-0.369) | (-0.434) | (-0.856) |
| O*rel.KL | | | | | | 0.262* | 0.268* | 0.259* |
| | | | | | | (-2.238) | (-2.284) | (-2.273) |
| O*rel.$KL^2$ | | | | | | -0.1 | -0.101 | -0.095 |
| | | | | | | (-1.585) | (-1.604) | (-1.591) |
| O*rel.I | | | | | | -0.612*** | -0.627*** | -0.522** |
| | | | | | | (-3.441) | (-3.582) | (-3.175) |
| O*rel.$I^2$ | | | | | | 0.361 | 0.362 | 0.583 |
| | | | | | | (-1.005) | (-1.002) | (-1.741) |
| O*rel.KL*rel.I | | | | | | -0.123 | -0.111 | -0.106 |
| | | | | | | (-0.285) | (-0.260) | (-0.258) |
| POPDEN | | | | | | | 0.242 | -0.144 |
| | | | | | | | (0.55) | (-0.31) |
| PROD | | | | | | | | -0.998*** |
| | | | | | | | | (-3.749) |
| _cons | 10.101*** | 9.434*** | 10.857*** | 12.385*** | 12.031*** | 21.287*** | 22.468*** | 17.237** |
| | (-17.272) | (-11.447) | (-15.213) | (-5.606) | (-5.357) | (-7.541) | (-7.487) | (-5.194) |
| F | 133 | 125 | 154 | 139 | 694 | 141 | 16242 | 142 |
| N | 639 | 639 | 639 | 639 | 639 | 639 | 639 | 639 |

Note: model A using Newey-West estimator; for all the following tables, province and time dummies are included; t-statistics are in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%

**Table A5.6.7 Results for industrial solid waste**

| Specification | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| S | 0.376*** | 0.319** | 0.288* | 0.289* | 0.288* | 0.335** | 0.314** | 0.497*** |
| | (-3.319) | (-2.817) | (-2.45) | (-2.47) | (-2.489) | (-3.195) | (-2.943) | (-4.511) |
| KL | | 0.145 | 0.197* | 0.199* | 0.199* | 0.781*** | 0.833*** | 1.015*** |
| | | (-1.791) | (-2.327) | (-2.081) | (-2.115) | (-4.602) | (-4.707) | (-5.672) |
| $KL^2$ | | | -0.031* | -0.03 | -0.036* | -0.021 | -0.029 | 0 |
| | | | (-2.222) | (-1.824) | (-1.988) | (-0.844) | (-1.110) | (-0.007) |
| I | | | | -0.012 | -0.125 | -0.941*** | -0.997*** | -0.833** |
| | | | | (-0.056) | (-0.616) | (-3.472) | (-3.652) | (-2.877) |
| O | | | | | 0.098 | 0.144** | 0.149** | 0.169*** |
| | | | | | (-1.889) | (-2.759) | (-2.843) | (-3.312) |
| O*rel.KL | | | | | | 0.186* | 0.196* | 0.189* |
| | | | | | | (-2.413) | (-2.525) | (-2.418) |
| O*rel.$KL^2$ | | | | | | -0.164*** | -0.166*** | -0.162*** |
| | | | | | | (-4.725) | (-4.792) | (-4.972) |
| O*rel.I | | | | | | -0.512*** | -0.534*** | -0.456** |
| | | | | | | (-3.607) | (-3.786) | (-3.112) |
| O*rel.$I^2$ | | | | | | -0.383 | -0.382 | -0.217 |
| | | | | | | (-1.879) | (-1.890) | (-1.126) |
| O*rel.KL*rel.I | | | | | | 0.344 | 0.362 | 0.366 |
| | | | | | | (-1.124) | (-1.205) | (-1.233) |
| POPDEN | | | | | | | 0.371 | 0.084 |
| | | | | | | | (1.32) | (0.30) |
| PROD | | | | | | | | -0.742*** |
| | | | | | | | | (-3.506) |
| _cons | 5.756*** | 6.302*** | 6.590*** | 6.671*** | 7.762*** | 13.502*** | 15.314*** | 11.426*** |
| | (-9.524) | (-9.772) | (-9.542) | (-3.986) | (-4.607) | (-6.297) | (-6.216) | (-3.991) |
| F | 354 | 365 | 354 | 344 | 335 | 300 | 27030 | 286 |
| N | 639 | 639 | 639 | 639 | 639 | 639 | 639 | 639 |

Note: model A using Newey-West estimator; for all the following tables, province and time dummies are included; t-statistics are in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%

**Table A5.6.8 Random Effects estimation results for model A**

| | Waste water | COD | Waste air | $SO_2$ | Dust | Soot | Solid waste |
|---|---|---|---|---|---|---|---|
| S | 1.015*** | 0.930*** | 0.807*** | 0.714*** | 0.615*** | 0.732*** | 0.497*** |
| | (-12.021) | (-6.526) | (-12.288) | (-7.58) | (-4.886) | (-5.796) | (-5.551) |
| KL | 0.649*** | 1.182*** | 0.528*** | 0.676*** | 1.534*** | 1.050*** | 1.015*** |
| | (-4.475) | (-3.761) | (-3.707) | (-3.878) | (-6.272) | (-5.178) | (-6.492) |
| $KL^2$ | 0.011 | -0.125*** | 0.008 | -0.069*** | -0.192*** | -0.105*** | 0 |
| | (-0.464) | (-3.075) | (-0.416) | (-3.103) | (-5.628) | (-3.731) | (-0.008) |
| I | -0.795*** | -2.996*** | -0.258 | -0.715** | -0.718* | -1.300*** | -0.833*** |
| | (-2.922) | (-7.354) | (-1.401) | (-2.573) | (-1.942) | (-4.219) | (-3.493) |
| O | 0.132*** | 0.248*** | 0.02 | 0.043 | 0.136** | 0.052 | 0.169*** |
| | (-3.766) | (-3.009) | (-0.488) | (-0.94) | (-2.117) | (-1.012) | (-3.567) |
| O*rel.KL | 0.121* | 0.302** | 0.051 | 0.095 | 0.367*** | 0.259*** | 0.189*** |
| | (-1.796) | (-2.052) | (-0.8) | (-1.342) | (-3.276) | (-2.699) | (-2.788) |
| O*rel.$KL^2$ | -0.003 | 0.095 | -0.018 | 0.013 | -0.152*** | -0.095* | -0.162*** |
| | (-0.095) | (-1.342) | (-0.673) | (-0.423) | (-3.707) | (-1.944) | (-6.117) |
| O*rel.I | -0.192 | -0.837*** | -0.063 | -0.200* | -0.653*** | -0.522*** | -0.456*** |
| | (-1.640) | (-4.528) | (-0.696) | (-1.779) | (-3.568) | (-3.652) | -3.499) |
| O*rel.$I^2$ | -0.546*** | -0.12 | 0.279* | 0.245 | -0.772** | 0.583** | -0.217 |
| | (-3.256) | (-0.358) | (-1.824) | (-1.42) | (-2.340) | (-2.046) | (-1.275) |
| O*rel.KL*rel.I | -0.666** | 0.038 | -0.161 | -0.115 | -0.988** | -0.106 | 0.366 |
| | (-2.481) | (-0.077) | (-0.705) | (-0.467) | (-2.496) | (-0.299) | (-1.415) |
| POPDEN | -0.294 | 0.162 | -0.093 | 0.305 | -0.614* | -0.144 | 0.084 |
| | (-0.912) | (-0.395) | (-0.367) | (-1.066) | (-1.802) | (-0.378) | (-0.355) |
| PROD | -0.757*** | -1.037*** | -0.708*** | -0.760*** | -1.159*** | -0.998*** | -0.742*** |
| | (-3.878) | (-3.068) | (-4.374) | (-4.126) | (-4.123) | (-4.380) | (-4.139) |
| _cons | 10.719*** | 30.834*** | 4.604** | 14.815*** | 13.051*** | 17.237*** | 11.426*** |
| | (-4.14) | (-7.89) | (-2.425) | (-6.384) | (-3.584) | (-6.092) | (-4.81) |
| Chi2 | 27812.66 | 7037.699 | 25742.04 | 21367.9 | 10625.58 | 12853.19 | 26656.72 |
| N | 639 | 584 | 639 | 639 | 639 | 639 | 639 |

Note: model A using Random Effect estimator; for all the following tables, province and time dummies are included; robust z-statistics are in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%

**Table A5.6.9 Random Effects estimation results for model B**

| | Waste water | COD | Waste air | $SO_2$ | Dust | Soot | Solid waste |
|---|---|---|---|---|---|---|---|
| S | 0.701*** | 1.005*** | 0.733*** | 0.682*** | 0.342** | 0.578*** | 0.496*** |
| | (-8.073) | (-5.779) | (-9.74) | (-6.676) | (-2.108) | (-4.602) | (-4.855) |
| KL | 0.31 | 1.541*** | 0.438*** | 0.701*** | 2.105*** | 1.240*** | 0.819*** |
| | (-1.514) | (-4.45) | (-2.759) | (-3.218) | (-6.737) | (-4.956) | (-3.56) |
| $KL^2$ | 0.037* | -0.098*** | 0.004 | -0.067*** | -0.160*** | -0.097*** | 0.001 |
| | (-1.748) | (-2.617) | (-0.232) | (-3.250) | (-5.137) | (-3.471) | (-0.036) |
| GDPPC | -0.273 | -2.704*** | -0.460*** | -0.878*** | -1.819*** | -1.289*** | -0.887*** |
| | (-1.133) | (-7.388) | (-2.923) | (-3.727) | (-4.765) | (-4.234) | (-3.918) |
| O | 0.013 | 0.078 | -0.014 | 0.001 | 0.094 | -0.013 | 0.130*** |
| | (-0.362) | (-1.032) | (-0.357) | (-0.019) | (-1.589) | (-0.238) | (-2.576) |
| O*rel.KL | 0.058 | 0.646*** | 0.058 | 0.210** | 0.684*** | 0.476*** | 0.167* |
| | (-0.656) | (-4.037) | (-0.803) | (-2.231) | (-4.844) | (-4.108) | (-1.669) |
| $O*rel.KL^2$ | 0.242*** | 0.456*** | 0.071* | 0.049 | -0.133* | -0.011 | -0.105** |
| | (-5.775) | (-4.18) | (-1.668) | (-1.077) | (-1.768) | (-0.150) | (-2.128) |
| O*rel.GDPPC | -0.242** | -0.925*** | -0.098 | -0.281*** | -0.940*** | -0.621*** | -0.159 |
| | (-2.417) | (-5.741) | (-1.446) | (-2.848) | (-6.670) | (-5.245) | (-1.516) |
| $O*rel.GDPPC^2$ | 0.051 | -0.256 | 0.039 | -0.196 | -0.334* | -0.268 | -0.059 |
| | (-0.427) | (-1.187) | (-0.341) | (-1.626) | (-1.677) | (-1.304) | (-0.467) |
| O*rel.KL*rel.GDPPC | -0.512*** | -0.413 | -0.208* | 0.06 | 0.166 | 0.027 | -0.082 |
| | (-4.044) | (-1.584) | (-1.784) | (-0.473) | (-0.862) | (0.123) | (-0.630) |
| _cons | 10.457*** | 27.602*** | 7.677*** | 16.246*** | 26.928*** | 20.295*** | 12.431*** |
| | (-5.965) | (-10.847) | (-6.572) | (-9.427) | (-10.34) | (-9.502) | (-6.34) |
| Chi2 | 28492.06 | 7106.704 | 28322.61 | 20789.82 | 10021.76 | 12953.35 | 27856.41 |
| N | 639 | 584 | 639 | 639 | 639 | 639 | 639 |

Notes only for model B using Random Effect estimator; for all the following tables, province and time dummies are included; robust z-statistics are in parentheses. *** means significant at 1%; **means significant at 5%;*means significant at 10%

# CHAPTER SIX

# CONCLUSIONS

This thesis examines the relationship between trade and the environment, both the trade pattern (competitiveness) consequences of environmental regulations and the environmental consequences of trade and trade liberalization. For four separate empirical studies, different datasets and methodologies are employed to give a broad picture of trade liberalization and the environment in China. In this last chapter, we provide a summary of main findings, contributions, limitations and policy implications. Finally, a few possible extensions for further research are briefly discussed.

## 6.1 SUMMARY OF RESULTS

In chapter two we examine whether "Dirty Industry Migration" phenomenon due to North-South environmental regulatory gap actually happens for China and five selected developed countries (i.e. the US, Japan, Germany, the UK and France) using trade data from 100 countries (as a representative of world trading bloc) between 1976 and 2004. After a critical review of alternative measures of revealed comparative advantage (RCA), we choose Balassa's original RCA and normalized RCA (the preferred one) indices developed by Yu et al. (2009). We define 'dirtiness' for 28 ISIC 3-digit manufacturing industries using emissions information from IPPS dataset. Our results show that China has little revealed comparative advantage in dirty industries. The evolution of NRCA also shows that China's revealed comparative advantage in dirty industries have actually declined over the years. In the case of the industrial countries, little evidence is found that dirty industries in these countries have lost revealed comparative advantage. To sum up, our results show that 'Dirty Industry

Migration' may not be a decisive and systematic trend. Chapter two does not offer support for a strong-form of the pollution haven hypothesis (PHH). However, this does not rule out a weak-form of PHH that environmental stringency has negative impact on trade performance/specialization.

Chapter three then carries on the task of examining and quantifying the role of environmental stringency in the determination of trade performance/specialization. Given a lack of internationally comparable data on environmental stringency, we confine our study to cross-industry regression analysis using Chinese data only. Environmental stringency is proxied by two cost-based measures: the ratio of pollution abatement operating costs to value added (ENV1) and the ratio of payroll to environmental protection staff to value added (ENV2). For trade performance/specialization, we select three measures: a Trade Specialization Index (TSI), the Michaely and Net Exports scaled by value added (Netva). Two samples are constructed according to data availability. Controlling for unobserved heterogeneity, we find a significant and negative impact from environmental stringency on trade specialization/performance. We also find some evidence that dirtier industries tend to be more affected by increasing environmental stringency. In terms of other control variables, we find less consistent results for the impact of human capital intensity and physical capital intensity across trade variables and samples. The absence of comprehensive environmental stringency information at the industry level constrains the robustness of the findings.

The research focus turns to the environmental consequences of trade liberalization in chapters four and five. To address the weaknesses in the literature of pollution content in trade, chapter four adopts an Environmental Input-Output analysis to evaluate the overall effect of trade. Two contributions are made. First, we distinguish domestic intermediate inputs from imported intermediate inputs using an import proportionality assumption and obtain consistent results. Second, we differentiate 'actual' from 'potential' pollution content in trade using alternatively common technology and heterogeneous technology assumptions. The results show that trade allows China to 'save' on air pollution ($CO_2$, $SO_2$, $NO_x$) by exporting cleaner goods and importing dirtier goods that would be dirtier to produce at home. This is despite a huge trade surplus. This is a type of 'gain' from trade for China. However, China is actually exporting more air pollution and its exports structure is more pollution intensive than its imports given the more efficient technologies actually used abroad to produce these goods.

Chapter five carries out an econometric analysis of the impact of trade liberalization on the environment. Following a few recent studies, we decompose the overall impact into distinctive channels: the scale, technique and trade-induced composition effects. We use a long time period panel of Chinese provincial data between 1985 and 2007. The results provide evidence in line with expectation from the related theory: an increase in economic activities will increase pollution levels, while an increase in income levels tends to generate stricter environmental regulations and reduce pollution levels. The trade-induced composition effect depends on provincial characteristics and evidences for a PHH effect and a FEH effect are found. We also calculate the trade elastiticities for individual provinces and find that under current conditions (factor endowments and income levels) further trade openness tends to shift the composition of production to slightly more pollution intensive industries. Chapter five makes a few changes to the existing model specifications (and underlying assumptions), for example, using log-log type of specifications, including a variable of squared capital intensity measure, and using different income measures. The regression results are reasonably robust across different environmental indicators, across different model specifications and across different estimation methods.

The findings of this thesis also have important policy implications. Firstly, the evidence that China has a revealed comparative advantage in cleaner industries and the evidence that environmental stringency matters more for dirtier industries indicate that an overall strengthening in environmental stringency may cause less pain to China than to a country with a revealed comparative advantage in dirtier goods. However, whether international harmonization of environmental standards should be pursued or not needs to be carefully examined given the existence of technology gaps and regulatory differences between developed countries and China.

Secondly, further trade tends to help clear China's air; however, the energy efficiency and technologies in China are lagging behind those of advance countries. China is richly endowed with coal which renders the price of coal (in energy content term) much lower than other energy types. The need to increase energy efficiency and adopt alternative energy seems crucial for China to clean up its environment and also to reduce global air emissions.

Lastly, inland provinces would be made dirtier with capital inflows in the short run. The increases in economic activities and capital intensity are detrimental to the environment, without the long run and offsetting effect from income growth (which encourages the strengthening of environmental regulations). To develop inland provinces, more capital is being directed by the central governments to boost industries (especially the manufacturing). At least in the short run, the environment will be negatively affected in inland provinces. Whether and when this trend will be reversed depends on income growth and implementation of environmental regulations.

## 6.2 FUTURE RESEARCH

Future research on trade liberalization and the environment in China can be summarized into two directions: to extend content and research scope. We can extend the current analysis to incorporate more recent, accurate and disaggregate data which would allow the adoption of more sophisticated econometric techniques. For example, chapter two can be extended to include trade flows after 2004 to examine the changing patterns of trade specialization in more recent years. We can also investigate at finer industrial level (ISIC 4-digit) trade flows, which in turn would provide more detailed information on industry migration.

A more recent, up-to-date I-O table for China is expected to be published soon, which could be employed to analyze the economy structure and the pollution content in trade and production. To investigate the impact of environmental policy on competitiveness (as we do in chapter three), we can employ firm-level data on economic response to environmental regulations (currently industrial level regulatory stringency is easier to obtain than that of firm-level). To tackle the problems of autocorrelation and endogeneity in the regression analysis (as in chapters three and five), a dynamic panel approach using difference and system GMM (Generalized Method of Moments) estimations is a possible alternative to current techniques, although data requirements will be much more demanding.

There is scope for further and substantive research. For example, we only study pollution as if it stays 'local'; however pollutants are mobile via different media (water flows, wind etc). One strand of research examines transboundary pollution. Transboundary pollution, especially air pollution, has been regarded as a grave environmental challenge in North-East Asia (especially between China and Japan).

Merrifield (1988) uses a general equilibrium model to analyze transnational pollution, particularly transnational pollution between the US and Canada. He concludes that only tight pollution abatement standards can reduce transnational pollution. Another related topic is waste (hazardous) trade. Although buying hazardous waste from abroad is illegal in China, quite a few small family enterprises in coastal provinces still carry out great deal of such trade.

Further, the differences between urban and rural industries in environmental compliance are largely ignored in research. China's pollution levy system and environmental monitoring work relatively well in the urban areas, but faces a grave challenge in the rural areas because of intertwined interest between local governments and TVEs (Township and Village Enterprises). Rural industries are also relatively dispersed and there relatively little demand for cleaner environment in rural areas. During the 1990s, the environmental problems created by TVEs attracted the attention of Beijing (Ma and Ortonalo, 2000). However, the environmental impact of rural industrial development has not received sufficient examination, probably due to data limitations.

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