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The Pollution Effects of Mergers and Acquisitions: Asymmetry, Disaggregation, and Multilateralism

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The pollution effects of mergers and acquisitions: asymmetry, disaggregation, and multilateralism

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WORK IN PROGRESS

Abstract

This paper studies the impact of cross-border Mergers and Acquisitions (M&As) on Carbon Dioxide emissions. Carbon Dioxide is the main anthropogenic greenhouse gas. A global problem that requires a multilateral solution. To take this into account we introduce an institutional variable, which captures the degree of international commitment to decrease and control the degradation of the environment. We test three hypotheses and find: (i) Asymmetry: the development level of the target country determines the direction of the effect of M&As on CO_2 emissions; (ii) Sector-specific impact: pollution intensive sectors have an impact on CO_2 emissions, whereas other sectors do not; (iii) Multilateralism: multilateral agreements are important to reduce CO_2 emissions.

JEL classification: F23; Q55; Q56.

Keywords: Carbon Dioxide Emission; Mergers and Acquisitions; Foreign Direct Investment; Institution; Environment.

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1 Introduction

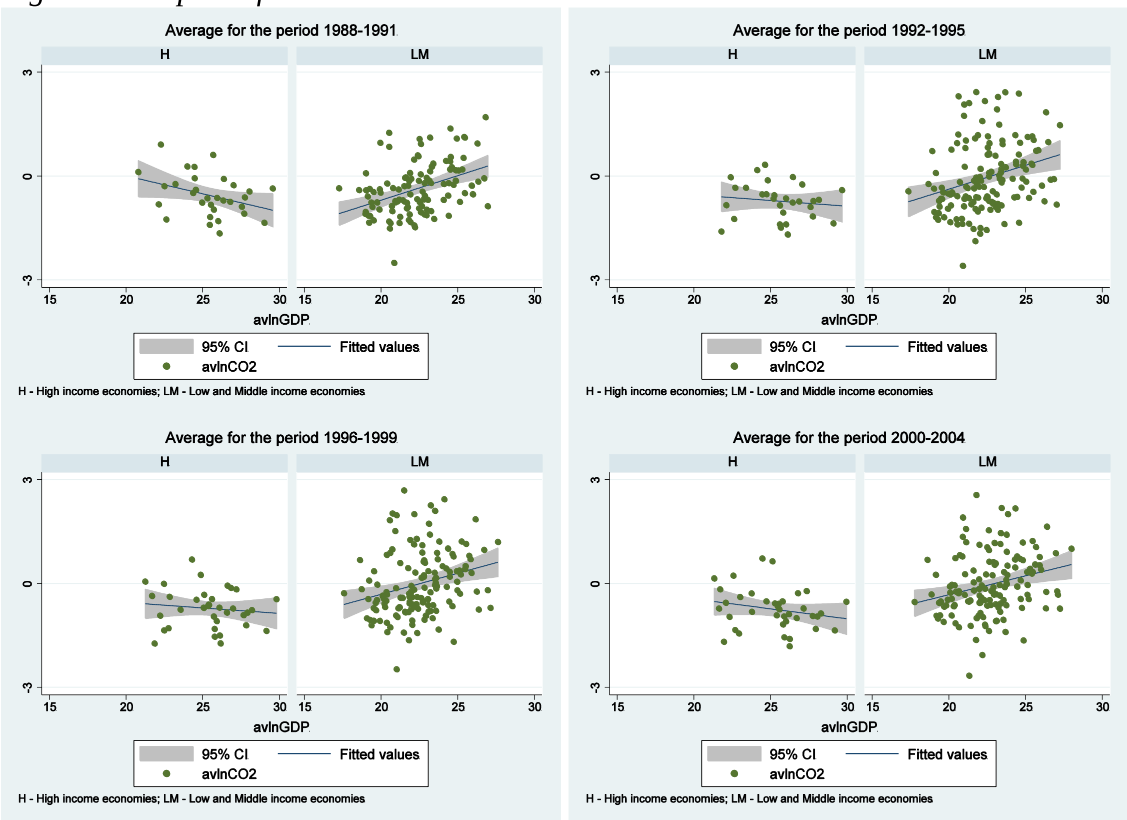
The increase in pollution emission challenges researchers to assess its causes, which frequently have an economic origin. Trade, growth, foreign direct investment, among other economic factors, affect the environment. Economists analyzed each of these different factors individually. Less attention (if any) is given to Cross-Border Mergers and Acquisitions (henceforth M&As). There are at least two reasons to consider these flows separately. First, it constitutes the biggest share of total FDI (Brakman et al., 2008) and is the main driving force of the recent increase in foreign direct investment (Unctad, 2006). Second, the effect of M&As and Greenfield Investments on the environment is not necessarily the same. Greenfield investments involve the construction of new production facilities, making the implementation of more up-to-date (and perhaps cleaner) technologies easier. M&As, on the other hand, may involve the extensive use of current technology and production facilities. But it can also imply the adoption of cleaner techniques from the acquiring firm.

To uncover the effect that M&As can have on pollution emissions, we need to consider a possible asymmetry with respect to the development level of both target and acquirer countries. Developed countries are associated with higher environmental standards, which influences the technology adopted by firms. Also, a disaggregation of the data regarding the target sector is necessary. Sectors that pollute more are expected to have a more substantial impact on the environment than sectors that do not pollute. Analyzing all sectors together may jeopardize the significance of the results.

Carbon Dioxide is the main anthropogenic greenhouse gas. The biggest concern with the increase of CO_2 emissions is global warming. Because of its global effect the solution rests upon the collaboration among countries. Therefore, in the past years many countries committed themselves to multilateral agreements to decrease and control the degradation of the environment. The participation in these agreements is another factor that determines CO_2 emissions, and should be controlled for to examine the impact of M&As on the environment.

The trade-off between environmental preservation and economic growth is non-deniable. But, even this common-sense relation can be the origin of long debates. If we consider only emissions of Carbon Dioxide we find that economic growth has a different impact on the amount of emissions, depending on the development level of the countries. By separating the countries in High income and Low or Middle income (World Bank historical classification), Figure 1 shows that for different group of years, there is (if any) a negative relation between CO_2 emissions given the GDP for high income countries, but a positive relation for low and medium income countries.

Figure 1 – Impact of Economic Growth on Carbon Dioxide Emissions



Source: Data for Carbon Dioxide emission and GDP (constant 2000 dollars) are from the World Bank, WDI.

There are at least two distinct explanations for the negative relation between CO_2 emissions and GDP for high income countries. First, the use of cleaner technologies by more developed countries. Second, developed countries are relocating dirty industries towards developing countries (either through trade or FDI).

Among the current research, a main topic is whether a closed economy (both in terms of trade and FDI) is preferred from an environmental point of view. Our objective in this paper is to focus on the impact of M&As on Carbon Dioxide emissions. If it affects the environment, then which direction prevails: do acquirer firms bring cleaner technology to their target firms, or do they take advantage of weaker pollution policy in the target country to use (perhaps) cheaper and dirtier technology?

Most of the related papers (discussed in section 2) have explored the interconnection between FDI and the environment, but no consensus has so far been reached. We take this literature in consideration, as well as the literature on the impact of trade on the environment. Our main contribution is threefold. First, we make a sectoral disaggregation of the M&As, second, we separate both target and acquirer countries with respect to their income classification (World Bank[1]), and finally we consider the impact of a multilateral institutional variable.

We test three hypotheses. In regard the income classification of the countries, we explore a possible asymmetric relationship. Considering that, in general, developed countries face stricter environmental policy; it is expected that multinationals from developed countries adopt cleaner technologies than the ones from developing countries. Therefore, we test the following hypothesis:

Hypothesis 1: *Asymmetry*
M&As from a high income country (acquiring country) reduce CO_2 emissions.

For the disaggregation of the data in sectors, we analyze whether all sectors have an impact on CO_2 emissions, or only a few of them. We separate the data on M&As in four sectors (see section 2 and appendix A for details) to test our second hypothesis:

Hypothesis 2: *Sector-specific impact*
M&As in non-polluting sectors[2] do not affect CO_2 emissions.

[1] http://siteresources.worldbank.org/DATASTATISTICS/Resources/OGHIST.xls
[2] Non-polluting sectors will be: Agriculture and Mining; Construction and Services and zero pollution intensive manufacturing sectors.

Finally, since CO_2 emission is a global problem (in the sense that the emission of every country will have an impact on the world as a whole) multilateral agreement is the most effective way to persuade countries to decrease their emission level. Therefore, we propose an institutional index, which varies from 0 to 10, where 0 means that a country does not participate[3] in any of the major multilateral agreements, and 10 if it participates in all of them (see section 2 and appendix B for details). This gives rise to our final hypothesis:

Hypothesis 3: *Multilateralism*
Multilateral agreements are an important instrument to decrease CO_2 emissions.

To test these three hypotheses, we consider a panel of more than 100 target countries, in the period 1988-2004. Our model specification considers both the theoretical and empirical literature in the field. Therefore, the next section of this paper gives an overview of the literature, and the motivation of our hypotheses. In Section 3 we present the empirical model specification. Section 4 describes the data base and presents some descriptive statistics. Section 5 covers the estimation results and robustness checks, and finally Section 6 concludes.

2 Theoretical framework and motivation

2a Motivation and contribution

Recent theory on M&As (Neary, 2007) shows that acquirers are the most efficient firms among its competitors. This result has further been supported by the empirical literature (Brakman et al., 2008). Additionally, they pursue more innovation activities as compared to uni-national firms (Dunning, 1996; Cantwell and Janne, 1999; Gerybadze and Reger, 1999; Johansson and Loof, 2006). This suggests that multinationals have a capacity to improve, which makes them more likely to undergo innovative ways to reduce costs (by reducing waste, for example), and to create higher quality and cleaner products and process.

[3] Participation means that the country has signed and ratified the agreement.

Porter and van der Linde (1995) show that innovation can lead to a decrease in pollution and a simultaneous increase in competitiveness, which they name as a win-win situation. The authors describe case examples of different ways through which companies can increase competitiveness by becoming more environment-friendly. This can be achieved because high emissions are frequently the result of inefficient use of the resources, which leads to extra handling, storage and disposal activities. By eliminating costly materials, reducing disposal costs for the user, making better use of materials in the process, and recycling, for example the firm will achieve the win-win situation.

Nonetheless, as the argument from Porter and van der Linde (1995) goes, it is the environmental standards faced by the companies that will trigger innovation in cleaner product or processes. The authors refer to stricter environmental standards as "innovation offsets" because it stimulates innovation that reduces pollution emissions. Therefore, when firms are exposed to a stricter environmental regulation, they will have an incentive to search for ways to reduce their pollution emissions. The actual introduction of cleaner technologies will depend on their resource capacity. These two characteristics (strict environmental policy and financial resources) characterize firms active in M&As from developed countries.

Two elements from the abovementioned literature motivate the hypothesis of asymmetry. First, since firms from developed countries face stricter environmental regulation we expect them to adopt cleaner technologies. Second, we expect active firms in M&As to be more prone to innovate in technologies to reduce pollution. These two facts together suggest our first hypothesis of an asymmetry between high income countries and low-middle income countries with respect to the impact of M&As on air pollution. To be more specific, we expect M&As from developed countries to decrease air pollution in the target country, holding everything else constant. Nonetheless, we do not expect this effect from M&As originating from developing countries.

Moreover, the same literature also motivates the investigation of the impact of M&As in pollution, since active firms in M&As are more efficient firms, and therefore have more financial capacity to invest and innovate in new technologies. However, they need an "innovation offset", such as rising environmental costs, to stimulate them to invest in cleaner technologies. Off course, this is only relevant for firms which are pollution intensive. This motivates the sector disaggregation of our data.

Table 1 – Sector disaggregation

Sector Group	Representative sectors
A – Agriculture and Mining	Agriculture; Forestry; Fishing and Mining
C – Construction and Services	Construction; Transportation; Communications; Electric, Gas and Sanitary Services, Wholesale Trade; Retail Trade; Finance; Insurance; Real Estate; Services; Public Administration
P –Pollution Intensive	Petroleum refining and related industries; Primary Metal Industries; Food and kindred products; Textile mill products; Furniture and fixtures; Stone, clay and concrete products; Fabricated metal products
Z – Zero Pollution Intensive	Apparel and other finished products made from fabrics and similar materials; Leather and leather products

Note: a) Pollution intensity is defined as the ratio of kilograms of Carbon Monoxide Emission over the value of output, from the Industrial Pollution Projection System (Hettige et al., 1995). b) Representative sectors in groups *P*, and *Z* are based on 2 digit code classification. They are listed as representative because many of the 4 digit SIC code under them belong to one of these groups. For the exact disaggregation, see Appendix A.

To the best of our knowledge, the sectoral distinction in M&As has not yet been analyzed empirically to measure the impact on air pollution. Nevertheless, such a study would contribute in disentangling which target sectors of M&As have an impact on the environment. We disaggregate manufacturing sectors in pollution intensive, and zero pollution intensive, along with agriculture and mining; and services and construction (Table 1 above presents a few representative sectors that fall under these categories, while Appendix A provides the complete disaggregation).

The above disaggregation of the sectors allows us to analyze the possibility of spill-over effects. If we find a negative impact of M&As in sectors not intensive in pollution in CO_2 emission, then we would have an indication for a spill-over effect, a fact present in the literature (see Albornoz et al., 2009 for a recent paper on this matter). That is, when an M&A occur in a target sector which is zero pollution intensive, this firm may demand their suppliers to provide a clean product or process. In this way, even firms that do not pollute would have a positive impact on the environment.

Table 2 – Major Multilateral Environmental Agreements

Agreements	Year	Main details
1 – Aarhus Convention	1998	Convention on access to information, public participation in decision-making and access to justice in environmental matters.
2 – Bio-Safety Protocol	2000	International treaty governing the movements of living modified organisms resulting from modern biotechnology from one country to another.
3 – Convention on Biological Diversity	1992	The objectives are the conservation of biological diversity, the sustainable use of its components and the fair and equitable sharing of the benefits arising out of the utilization of genetic resources.
4 – Covenant on Civil and Political Rights	1966	Agreement on civil and political rights of individuals and nations.
5 – Convention to Combat Desertification	1994	Convention to combat desertification and mitigate the effects of drought in countries experiencing serious drought and/or desertification.
6 – Covenant on Economic, Social, and Cultural Rights	1966	Agreement on economic, social, and cultural rights of individuals and nations.
7 – Convention on International Trade in Endangered Species of Wild Fauna and Flora (CITES)	1975	Agreement to ensure that international trade in specimens of wild animals and plants does not threaten their survival.
8 – Kyoto Protocol	1997	The major feature of the Kyoto Protocol is that it sets binding targets for 37 industrialized countries and the European community for reducing greenhouse gas emissions.
9 – Stockholm Convention	2001	Convention on persistent organic pollutants to protect human health and the environment from chemicals that remain intact in the environment for long periods.
10 – United Nations Framework Convention on Climate Change (UNFCC)	1992	The convention ultimate objective is to stabilize greenhouse gas concentrations at a level that would prevent dangerous anthropogenic interference with the climate system.

The motivation for the Multilateralism hypothesis is the global nature of the problem imposed by high CO_2 emissions. To take that into account we propose an institutional index. It involves the number, out of 10 major multilateral agreements, that the target country has signed and ratified. To construct this index we counted the number of agreements that a particular country participated in each year, from 1988 until 2004 (see Appendix B for details). Table 2 gives an overall description of these agreements. The agreements are considered as the 10 major environmental multilateral agreements by the Earth Trends, World Resources Institute.

We expect that countries participating in a higher number of multilateral agreements to be more active in implementing measures that decrease environmental degradation. This is particularly important for CO_2 emissions, since what matters is the total emission by all countries.

2b Theoretical framework

To the best of our knowledge there are no papers that try to assess the impact of M&As on the environment, but a few analyze it for Foreign Direct Investment as a whole[4]. Jorgenson (2007a) investigates the impact of FDI dependence (FDI over GDP) in the manufacturing sector on CO_2 and organic water pollutants emissions in less developed countries. Using panel regression analyses covering the period 1975-2000, the author's finding indicates that FDI dependence in manufacturing has a positive impact in CO_2 (and water pollutants) emission in less developed countries.

Bao et al. (2008) adopt a quadratic relation to measure the impact of FDI in pollution emission[5] in China. Their argument is that initially, multinationals have a "scale" effect in the target country, which leads to a rise in pollution. As the number of multinationals increases in this target country, the demand for stricter environmental regulation goes up. This pushes multinationals to adopt cleaner technologies, with spill-overs to domestic firms as well. Based on data from 29 provinces in the period 1992-2004, the authors find support for an inverted-U curve relationship between FDI and pollution emission. Thus, initially, multinationals would have a negative impact on the environment, and after a threshold has been reached, the impact would be positive.

[4] Most of the papers that explore the link between the environment and FDI focus on the pollution-haven hypothesis, that is, they measure the impact of environmental regulation on the attraction of FDI (Eskeland and Harrison, 1997; Wheeler, 2001; Smarzynska and Wei, 2001).

[5] The authors use five different indicators of pollution emission: industrial polluted water emissions; chemical oxygen demand in industrial water pollution; sulfur dioxide emissions; industrial smoke emissions and industrial solid wastes.

Liang (2006) also estimates the impact of FDI on pollution emission in China, but using as an indicator for the pollutant, sulfur dioxide. The author considers more than 260 cities from 1996 to 2003 and estimates the model using an instrumental variable approach. The results generally show that more FDI decreases SO_2 emissions.

Jorgenson (2007) tests whether FDI as a proportion of total GDP in the primary sector increases CO_2 emissions from agriculture production in less developed countries. The motivation is based on the hypothesis that foreign firms in the agriculture sector use more chemicals and machinery in order to increase productivity. His results, using data from 1980 and 1999, indicate that FDI dependence in agriculture increases CO_2 emissions in developing countries.

Antweiler et al. (2001), while paying more attention to the impact of trade on the environment, have also considered the role of FDI. The authors use the ratio of inward stock of FDI to the overall capital stock and in addition interact this variable with a categorical variable of GDP per capita. In general they find that the link between FDI intensity and pollution level is positive but small.

Furthermore, the papers that deal with the impact of trade on the environment also bring important insight to our research question. More importantly, we believe that the literature on FDI and trade should not be separated. If there is an indication that both factors can affect pollution emission, than they should be included together in any empirical model that tries to understand the determinants of pollution emission. For this reason, we will also control for trade variables in our empirical model specification.

From a theoretical point of view, the "pollution havens" models of international trade are the reference of supporters of the idea that poorer countries are harmed with trade because of their weaker environmental regulation. However, these models base on the assumption that environmental regulation is an essential production cost. Once factor endowment is also considered, the results may actually reverse. Poorer countries may specialize in cleaner goods if they have a relative abundance in factors used intensively in the production of clean goods.

Therefore, the impact of trade on the environment is not so obvious. Briefly stating, two mechanisms will determine the overall result: relative factor endowment abundance and environmental regulation. To measure the impact of trade on the environment, we need to take both mechanisms into account. What is more commonly done in the empirical literature is to measure the impact of trade openness on pollution.

Harbaugh et al. (2000) consider the impact of trade openness, among other variables, in SO_2 concentration. Their finding is a negative and significant impact. Antweiler et al. (2001) use the same polluter, but consider the effect of trade due to factor endowment abundance, in addition to the trade openness variable. They find similar results as Harbaugh et al. (2000) for trade openness.

Frankel and Rose (2005) assess the impact of trade on the environment, taking as a dependent variable different environmental measures, among them CO_2 emissions. This measure was the only one to result in a positive and significant coefficient of trade openness. The authors conclude that this could be a consequence of the pure global externality of CO_2 emissions, leading to a free-rider problem. Countries do not attempt to reduce their emissions for fear of loss in competitiveness.

These recent papers obtained different results for the impact of trade openness on the environment. Considering the paper from Frankel and Rose (2005) who estimated their model for seven different measures of environmental degradation, these results are not necessarily conflicting with one another. It is possible that trade has a different effect on CO_2 emissions than on other environmental variables, as the authors suggest.

3 Data and empirical model

3a Mergers and Acquisitions

Data for M&As comes from Thomson Financial Investment Bank. To collect the data, we considered every deal with status completed, as only M&As that have actually taken place can potentially have an impact on the environment. For the same reason, we considered the “effective date” of transaction instead of the “announced date”.

The collection of the data for this criteria resulted in 90,081 M&As for the period 1988 until 2004. From this, 49,516 (55% of the total) did not have the value of the deal. Table 3 below shows the division of the data with the four sectors considered in this study, and the corresponding number of deals with missing value. Three things stand out from this table. First, the majority of the M&As observed in this period were in the sector "Construction and Services", corresponding to more than half of all transactions. Second, the sector that we would be more concerned with, "Pollution Intensive" is the second most important target of M&As, representing 32.2% of the deals in the period. Finally, regarding the problem of missing values, although this frequency is high, there is not much difference with respect to the sectors. The sector with the least missing values of the deal is "Agriculture and Mining" (41.6%) and the one with the most missing values is "Pollution Intensive" (57.4%).

Table 3 – Number of M&As disaggregated by sector; 1988-2004

Sector	Total deals		Observations without value	
	Frequency	% of total frequency	Frequency	% of total sector
Agriculture and Mining	5,164	5.7	2,146	41.6
Construction and Service	48,671	54.0	26,872	55.2
Pollution intensive	29,005	32.2	16,635	57.4
Zero pollution intensive	7,241	8.0	3,863	53.3
Total	90,081	100	49,516	55.0

Table 3 shows the sectoral distribution of M&As in terms of number of M&As. Nevertheless, for our purpose, the value of the transactions is a better indication of the "size" of this investment for the target country, and will be our primary control variable for M&As. Therefore, in table 4 we show summary statistics for the value of the deal, disaggregated by sectors. Again, "Construction and Services" received the majority of M&As (58%), followed by "Pollution intensive" (30%). Additionally, also in terms of values, sector "Pollution intensive" embodies a significant part of all M&As. Comparing the percentage from total, in terms of number (third column from Table 3) and values (last column from Table 4), we find that, for all sectors, there is no substantial difference.

Table 4 – Value of M&As: summary statistics

	Value of M&As (constant 2005 US dollars, millions)				
Sector	Mean	Standard deviation	Maximum value	Sum	% of total value
Agriculture and Mining	159	1,174	56,444	480,062	6.7
Construction and Service	189	1,862	229,216	4,130,581	58.0
Pollution intensive	173	913	47,414	2,136,794	30.0
Zero pollution intensive	112	519	12,399	379,589	5.3
Total	176	1,498	229,216	7,127,026	100

Another noteworthy disaggregation is in terms of the development status from both acquirer and target countries. Considering the value of the deals[6], table 5 shows that 87% of all M&As are from developed countries, who take-over another firm from a developed country. The predominance of M&As from developed to developed countries occurs for all sectors analyzed. Nonetheless, Construction and Services is the main sector responsible for this, alone it corresponds to 50% of all M&As.

Table 5 – Percentage of value of M&As disaggregated by sector and by development status of both acquirer and target countries; 1988 - 2004

Target sector/ Income classification	Percentage of total value of M&As				
Acquiring country	High		Low or Middle		
Target country	High	Low or Middle	High	Low or Middle	Total
Agriculture and Mining	4.7	1.2	0.2	0.6	6.7
Construction and Service	50.1	5.6	0.8	1.4	58.0
Pollution intensive	26.7	2.0	0.8	0.6	30.0
Zero pollution intensive	5.1	0.1	0.1	0.0	5.3
Total	86.5	9.0	1.8	2.6	100

Considering the sector "Pollution intensive", M&As from developed to developed countries represent 26.7% of all M&As, from developed to developing countries this number is 2%. When the acquiring country is a developing country, then if the target is a developed country, the value of M&As in "Pollution intensive" sectors represents 0.8% of all M&As, and 0.6% if the target is another developing country. Thus, these figures show that M&As in manufacturing sectors that pollute, represent a significant fraction of all M&As only when both target and acquiring countries are developed.

[6] Appendix C, Table C1, shows a similar (to Table 5) table considering the number of deals.

Additionally, this fraction is considerably smaller, when developing countries are one of the players.

Finally, since our primary variable will be the value of M&As, it is important to check whether there are some data characteristics with more missing values then the others. We already showed that this was not the case for the target sectors of the deals. Additionally, we check the percentage of missing data for the 18 years considered in our analysis. Table C2 in Appendix C presents these results. It shows that the amount of missing data is more or less constant throughout the time. The average is 54.8%. The year with least missing data was 1988, with 49.4% of the M&As for that year not having the value of the deal. The year with most missing data was 1991, with 60% of missing values.

The only concern we have by using the value of M&As, as our control variable of M&As, is that there are some important players, both as target and acquirers, that have a large amount of missing data for the value of transactions.[7] On the other hand, the correlation between the value of the transaction (or number) and the percentage of missing data by country (both for target or acquirer) is very close to zero. In other words, it is not the case that more active countries in M&As have more complete data, nor the other way around.

3b Additional control variables

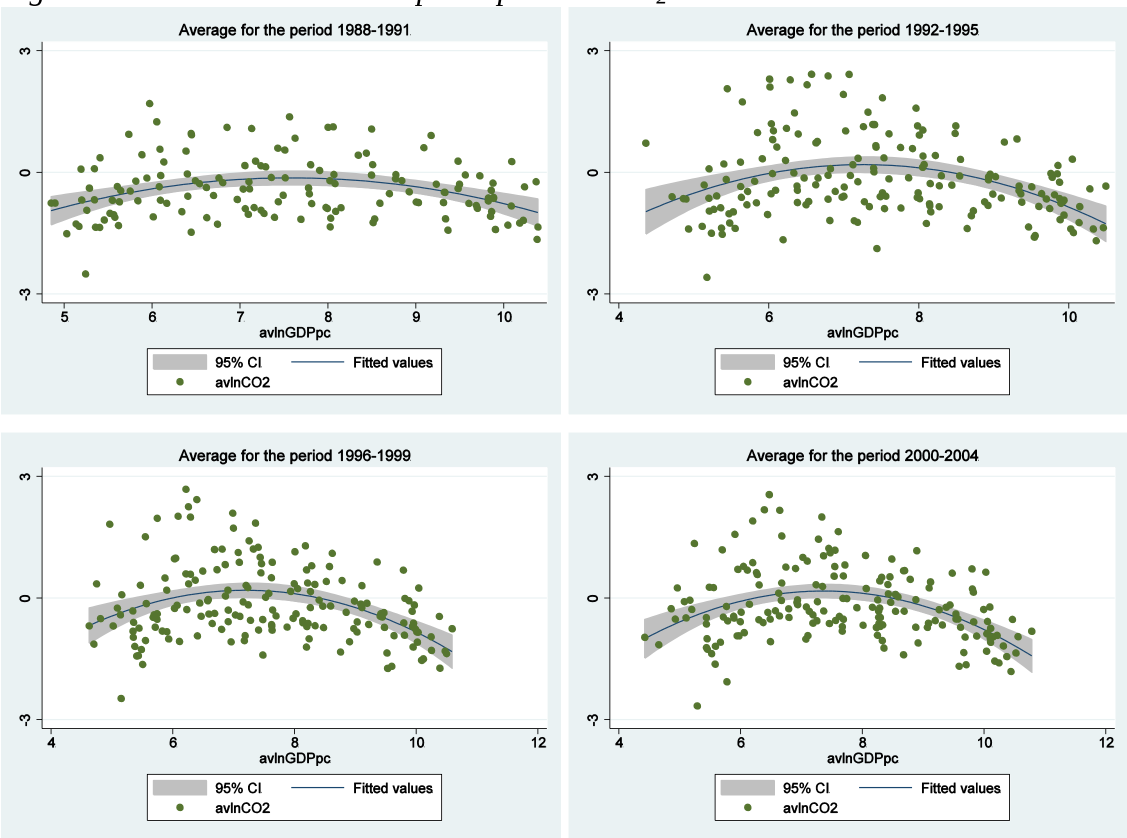
From the empirical literature, common control variables are: GDP, urban population, GDP per capita and GDP per capita squared. The inclusion of the first two variables is straightforward. The higher the GDP, the higher the demand for goods and services, and therefore more pollution is expected. In regard urbanization, many “dirty” activities (e.g. transport, production) take place in urban regions, causing higher emissions.

The inclusion of a quadratic effect of GDP per capita on pollution is not so clear-cut. The motivation is the “Kuznets curve”, named after Simon Kuznets, who in a 1995 paper showed that income inequality rises for lower economic development and

[7] In appendix C, we provide a more detailed descriptive analysis of the percentage of missing value by both target and acquirer countries.

decreases for higher economic development. Grossman and Krueger (1993) were the first to present similar evidence, but considering pollution in place of income inequality. The quadratic relationship between pollution and income per capita is now called the "Environmental Kuznets curve".

Figure 2 – Kuznets curve: GDP per capita and CO_2 emissions



Source: Data for Carbon Dioxide emissions and GDP per capita (constant 2000 dollars) are from the World Bank, WDI.

If we were to consider the impact of GDP per capita alone on CO_2 emissions, then indeed a quadratic relation would be a good approximation, as Figure 2 illustrates for four different groups of years. Nevertheless, this relation does not necessarily hold when other factors are taken into account. The empirical support for an Environmental Kuznets curve is mixed (see Stern, 2003 and Harbaugh et al., 2000 for a discussion on this issue and Frankel and Rose, 2005 for empirical findings of no environmental Kuznets curve for CO_2 emissions).

Additionally, we take into consideration that the impact of growth on the environment can be separated in three channels: scale, technique and composition effect (see Copeland and Taylor, 2003). The scale effect represents the impact on the environment due to greater economic activity. We take the GDP as a measure for this effect. The composition effect refers to changes in the mix of economic activity, for example, specialization in cleaner or dirtier goods. The capital to labor ratio is a usual proxy for the composition effect, and it is taken to reflect the production of dirty and clean goods, respectively. The problem with this measure is data availability. Therefore, we consider instead the value added of manufacturing as a percentage of the GDP. Finally, the technique effect concerns the use of a cleaner or dirtier technology. It is common in the literature to take GDP per capita as a proxy for this. We propose the inclusion of a more direct measure of this effect, which is the percentage of electricity production from "dirty" sources.

The 2000 Report from the Department of Energy and the Environmental Protection Agency (both located in Washington D.C.), shows that Coal and Petroleum have the highest Carbon Dioxide Emissions per kWh of electricity generation compared to other sources of electricity generation in the United States, for the years 1998 and 1999. Marland and Boden (2001) present more general statistics, which points out to the higher CO_2 emission rate of Coal and Petroleum Combustion. The reason for this is the ratio of Hydrogen to Carbon, which differs in each fuel. Taking, therefore, oil and coal as the fuels that most emit CO_2 per unit of energy; we used World Bank's data on electricity production from different sources as a percentage from the total, and added the percentage originating from Coal and Petroleum. This is what we called "dirty" electricity, which is a measure of the technique effect.

Other control variables we consider are: the share of manufacturing exports, the share of manufacturing imports, trade openness and an multilateral institutional variable. The definition, sources and availability of the variables are provided in Appendix D. Finally, the variables GDP, trade openness, GDP per capita and M&As[8] are taken in their logarithmic form to correct for excessive skewness. In Appendix E we present the

[8] Since there are many zero values of M&As, to take the log of this variable we added 100 thousand dollars to all data.

skewness measure of all relevant control variables and CO_2 emissions. When there was a gain in terms of reduction of skewness we considered the logarithmic form.

3c Empirical model

To test our hypotheses, we consider a Panel Data model, as described below:

$$CO_{2,it} = \alpha_i + X'_{it}\beta + \varepsilon_{it}\,, \tag{1}$$

where *i* is an index for country and *t* for time. α_i is a variable that captures unobserved heterogeneity for country *i*, and ε_{it} is an error term.

Our dependent variable is Carbon Dioxide (CO_2) emissions (in log). We chose this variable for three main reasons. First, the data coverage of CO_2 emissions is available on an annual base from the World Bank for many countries, whereas other important air polluters, such as SO_2 and NO_x have much more limited coverage. Second, some authors (see Hoffman et al., 2005, for an example) argue that Carbon Dioxide is a good proxy to measure pollution levels. Third, CO_2 is the major anthropogenic greenhouse gas causing global warming. It has, therefore, a global effect such as a rise in global temperatures. Other air pollutants (see Box 1) have a more local effect, such as acid rain and bad air quality. This distinction implies that their determinants could differ.

Box 1 Local air pollutants

Air pollutants emitted by local sources can bring local problems related to health and the environment. Common air polluters causing local problems are: Ozone (O_3), Particulate matter (PM), Carbon Monoxide (CO), Nitrogen Oxides (NO_x), Sulfur Dioxide (SO_2), and Lead (Pb)

Below we separate health from environmental effects by listing the common air pollutants responsible for them. Additionally, we give a few examples of the specific problems caused by each of the air pollutants.

Health effects
- Ozone: can cause respiratory related problems.
- Particulate matter: fine particles can get deep into the lungs and cause serious health problems.
- Carbon Monoxide: can cause cardiovascular and central nervous system problems by reducing oxygen delivery to the body's organs and tissues. Additionally CO contributes to the formation of smog which may cause respiratory problems.

- Nitrogen Oxides: can cause damage to lung tissue and reduction in lung function.
- Sulfur Dioxide: sensitive groups such as people with asthma who are active outdoors, children, the elderly and people with heart or lung disease may suffer from respiratory illness and aggravate existing heart disease when the air contains high levels of SO_2.
- Lead: can have neurological effects in children and cardiovascular effects in adults.

Environmental effects
- Ozone: can have detrimental effects on plants (e.g. interfering with the ability of sensitive plants to produce and store food) and ecosystems (reduction in forest growth and crop yields)
- Particulate matter: fine particles can cause visibility reduction and acid rain.
- Nitrogen Oxides: can cause reduction in visibility and acid rain, fog, snow or dry particles.
- Sulfur Dioxide: can cause reduction in visibility and acid rain, fog, snow or dry particles.
- Lead: can lead to losses in biodiversity, decreased growth and reproductive rates in plants and animals, and neurological effects in vertebrates.

Note: One member of the NO_x, Nitrous Oxide (N_2O) is also a greenhouse gas, so additionally to local effects it also has global effects.
Source: Environmental Protection Agency. 2008: What are the six common air pollutants? http://www.epa.gov/air/urbanair/index.html. Washington DC: U.S. Environmental Protection Agency.

Given our hypotheses, we disaggregate our control variables (X_{it}) in four groups, as below:

$$CO_{2,it} = \alpha_i + C_{it}^{'}\pi + M_{it}^{'}\delta + M^{*'}_{it}\delta^{*} + I_{it}^{'}\gamma + \varepsilon_{it}, \qquad (2)$$

where M_{it} encompasses M&As from four sectors, separated by the development level of the acquirer country, leading to eight variables. M^{*}_{it} is the interaction of M_{it} and the development status of the target country (1 if target is a High income economy, and 0 otherwise). Therefore, it also consists of eight variables. I_{it} is the multilateral institutional variable. The final group, represented by C_{it}, covers the remaining control variables.

The eight variables that form M_{it} are individually represented by $M_{k,j,i,t}$, where k = {A,C,P,Z) is an index for the target sector of the M&A (see Table 1) and j = {DC,LDC} stands for the development level of the acquirer country, either developed (DC) or least developed (LDC). Using this notation, $M_{P,DC,i,t}$, for example, stands for cross-border mergers and acquisitions in the Pollution Intensive sector from developed countries (acquiring country).

Considering the interaction terms in a similar way, we can evaluate the impact of M&As from developed/developing countries to developed/developing countries. To make things more clear, consider, as an example, the estimation result for M&As in the Pollution Intensive sector from developed countries. This would result in a parameter $\delta_{P,DC}$ and $\delta_{P,DC}{}^{*}$ (interaction term):

$$M_{P,DC,i,t}{}'\delta_{P,DC} + M_{P,DC,i,t}{}^{*'}\delta_{P,DC}{}^{*} \tag{3}$$

We should interpret the result as follows: $\delta_{P,DC}$ measures the impact of M&As in Pollution Intensive sector from developed countries to developing countries; and $\delta_{P,DC} + \delta_{P,DC}{}^{*}$ measures the impact of M&As in the same sector from developed countries to developed countries. This approach enables us to test the asymmetry and the sector-specific impact hypotheses.

The variables of trade openness and multilateral agreements are also interacted with the development level of the target country. For the first variable, we want to check the impact of trade on the environment due to the pollution-haven hypothesis. Given the effect of trade on CO_2 emissions via the specialization in capital intensive goods (controlled by the variables percentage of exports and imports of manufactures), the trade openness variables measure the pollution-haven hypothesis. Therefore, we test whether trade openness has a positive effect on CO_2 emissions when the target is least developed (lax environmental regulation) and negative when the target is developed (strict environmental regulation), as established in the pollution-haven models.

The reason for interacting the multilateral agreements with the development level of the target country is that richer countries are more likely to demand environment-friendly policy. Hence, we want to check whether a global agreement is less important for developed than developing countries in helping to reduce CO_2 emissions.

4 Results

4a Main results

Our first estimation results consider the four sectors presented before, but it turned out that only variables of Pollution Intensive sector were significant. Therefore, we proceeded in steps to remove the non-significant sectors. Appendix F presents these initial results. Model 1_F considers all four sectors, 2_F removes the sector Construction and Services, 3_F removes additionally the Zero Pollution Intensive sector and 4_F also removes sector Agriculture and Mining. These sectors did not present a significant result in all models we tested, therefore, apart from the results in Appendix F, we do not include them in the estimations we discuss here. Nonetheless, these findings confirm our Sector-specific impact hypothesis. Indeed, only M&As in manufacturing sectors with a positive intensity of pollution have an impact on CO_2 emissions.

Regarding the estimation procedure, we used a Hausman test to choose between a Random and a Fixed Effect Model. The traditional Hausman test produced a non-positive definite differenced covariance matrix for all of the models tested. Hence, we considered instead the covariance matrix based on a common estimate of the disturbance matrix. This generated the sigmamore and sigmaless option. The former specifies that the covariance matrix uses the estimated disturbance variance from the random effect estimator; and the latter from the fixed effect estimator. For details on these options for the Hausman test, see the online help file of stata[9], which additionally recommends the use of these options when comparing fixed-effects and random-effects models.

Our first results, presented in Appendix F, also show that a quadratic form for GDP per capita is not statistically significant. Hence, although we tested both specifications, we present in the next tables GDP per capita without the squared term, since only GDP per capita alone is statistically significant.

In Table 6 we present our main findings. Model 1 includes only GDP per capita as a proxy for the technique effect, whereas model 2 also considers dirty electricity. Model 3

[9] http://www.stata.com/help.cgi?hausman

considers both these variables, and it replaces GDP by total population as a measure for the scale effect. Overall we find that the scale and the composition effect are important in explaining CO_2 emissions.

Table 6 – Fixed effect model for Carbon Dioxide Emissions; Endogenous variable is ln(CO_2); Value of M&As is ln($M_{P,j,i,t}$+0.1), with j = {DC,LDC}.

	(1)		(2)		(3)	
	coefficient		*coefficient*		*coefficient*	
Institution	-0.012		-0.016	**	-0.016	**
Institution*D_{DC}	0.009		0.018		0.018	
Ln($M_{P,DC}$)	0.003		0.004	*	0.004	*
Ln($M_{P,LDC}$)	0.005	**	0.006	**	0.006	**
Ln($M_{P,DC}$)*D_{DC}	-0.010	**	-0.012	**	-0.012	**
Ln($M_{P,LDC}$)*D_{DC}	-0.007	**	-0.007	***	-0.007	***
Ln(GDP)	1.519	***	1.625	***		
Ln(population)					1.625	***
Urban population (% total)	0.010		0.006		0.006	
Manufacturing (% GDP)	0.013	***	0.011	***	0.011	***
Manufactures X (% exports)	-0.001		-0.001		-0.001	
Manufactures M (% imports)	-0.002		-0.001		-0.001	
Ln(trade openness)	0.076		0.092	*	0.092	*
Ln(trade openness)*D_{DC}	-0.027		-0.040	**	-0.040	**
Ln(GDPpc)	-0.915	***	-0.963	***	0.662	***
Dirty electricity			0.005	***	0.005	***
Intercept	-13.248	***	-15.460	***	-15.460	***
# of observations	1,555		1,357		1,357	
# of groups	136		113		113	
Within R-square	0.604		0.634		0.634	
F-statistics	26.81	***	38.38	***	38.38	***
Hausman test	n.p.d.		n.p.d.		n.p.d.	
Hausman test, sigmamore	81.52	***	68.47	***	68.47	***
Hausman test, sigmaless	85.29	***	71.34	***	71.34	***

Notes: The dependent variable is Carbon Dioxide Emissions. Manufactures X = exports of manufactures. Manufactures M = imports of manufactures. D_{DC} = dummy for development level of the target country; it takes the value of 1 if the target country is a Developed country and 0 otherwise. GDPpc = GDP per capita. n.p.d = not positive definite. To obtain the significance levels we considered robust estimates of the standard errors, to take into account possible heteroskedasticity and serial correlation of the error terms. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

The technique effect is also statistically significant. Model 1 and 2 show that higher GDP per capita of a country results in less CO_2 emissions. Our preferred model between these two is number 2, since it has a higher explanatory power than model 1 and the inclusion of the variable dirty electricity was statistically significant. Our finding indicates that a unit increase in the percentage of electricity coming from dirty sources increases CO_2 emissions by 0.5%.

Model 3 replaces GDP by Total Population as the scale variable. Therefore, Models 2 and 3 are essentially similar. Nevertheless, we consider Model 3 to show the importance of the choice of the scale variable. Using GDP as the scale variable (Model 2) implies a negative coefficient for GDP per capita, whereas the opposite is true if we choose Total Population (Model 3). Although this seems trivial from an econometric perspective, its implication is fundamental. Authors that consider Total Population as the scale effect (e.g. Jorgenson, 2007) conclude that economic development (as measured by GDP per capita) is bad for the environment. Considering GDP the conclusion is reversed.

A significant part of pollution has its origin in the production side of the economy. Therefore, the scale variable should not restrict to a measure of the demand side, such as Total Population. For this reason, we consider GDP as a better measure of the scale effect. Comparing Model 2 and 3, we prefer again number 2. Hence, we restrict the discussion of the results below to this Model.

We do not find evidence for the factor endowment hypothesis. Both exports of manufacturing as imports of manufacturing were not statistically significant. Trade openness instead was significant. The more open a developing country is the higher its CO_2 emissions. This is also the case for developed countries, but it is not as strong, as we can see by adding the coefficient of the interaction term.

For the three hypotheses from Section 1, our findings were as follow:

Empirical support for Multilateralism:
Multilateral agreements are an important instrument in reducing CO_2 emissions in both developed and developing countries.
The results for the institution variable shows that we have support for the Multilateralism hypothesis. The increase in participation in multilateral agreements leads to a reduction in CO_2 emissions. Each additional multilateral agreement that a

country participates in decreases CO_2 emissions by 1.6%. Moreover, there is no significant difference between developed and developing countries.

Empirical finding for the Asymmetry hypothesis:

We did not find support for the Asymmetry hypothesis as stated in Section 1. Instead, we found another Asymmetry, with respect to the target sector of the M&As. Using the notation from section 3c, our Asymmetry findings can be grouped in two:

Pollution increases if target is from a least developed country

Our findings show that M&As to least developed countries increases CO_2 emissions in those countries. A 1% increase in M&As from Developed Countries to Least Developed Countries in sector Positive-Intensity-Pollution implies an increase of 0.004% in CO_2 emissions. When the acquiring country is instead a Least Developing Country, the impact is stronger, of 0.006%.

Therefore, regardless of the acquiring country development status, firms that merge or acquire a firm from a least developed country contribute to CO_2 emissions in those countries. This finding suggests that acquiring firms tend to take advantage of the laxer environmental regulation of least developed countries. This could occur by adopting dirtier technologies, sending old technologies from the acquiring firm to the target firm, or by using the full capacity of production of the firm.

Pollution decreases if target is from a developed country

Our findings show that M&As to developed countries decreases CO_2 emissions in those countries. A 1% increase in M&As from Developed Countries to Developed Countries in sector Positive-Intensity-Pollution implies a decrease of 0.008% in CO_2 emissions. When the acquiring country is instead a Least Developing Country, the impact is weaker, of 0.001%.

Again, the results have the same direction for both developed and least developed acquiring country. These results suggest that firms that merge or acquire a firm from a developed country have to adjust to their stricter environmental regulation. By doing that the multinational firm contributes to the decrease in CO_2 emissions in the target country. Nonetheless, we notice that this effect is stronger when the acquiring country is also from a developed country.

The empirical results for the Asymmetry hypothesis show that only part of our argument from section 2 holds. There we wrote about our expectations of a decrease in CO_2 emissions with M&As from developed countries. Nonetheless, this only takes place when the target country is a developed country. In other words, the destination country of the M&As is what matters, and not the origin. This makes sense once we take into account that most M&As do not result in new production plants, but they use instead the facilities of the target firm. Therefore, the "innovation offset" has to be substantial in order to motivate the firms to adopt cleaner technologies. When this innovation offset is not present, as in least developed countries, the acquiring firm actually takes advantage of the laxer regulation and pollutes more.

Hence, the Asymmetry hypothesis from Section 1 should be re-written as:

Hypothesis 1A: *Target Country Asymmetry*

(i) M&As to a high income country (target country) reduce CO_2 emissions.

(ii) M&As to a low or middle income country (target country) increase CO_2 emissions.

Support for the Sector-Specific hypothesis:

Only M&As on Pollution Intensive sectors affect pollution levels

As we pointed out in the beginning of this Section, our findings show that only M&As in manufacturing sectors with a strictly positive intensity of pollution have an effect on the pollution levels of the target country. Agriculture, Mining, Construction, Service and Manufacturing Sectors with an intensity of pollution equal to zero, have no effect. These sectors represent approximately 70% of all M&As observed between 1988-2004 (see Table 5).

4b Robustness check

Five sector disaggregation

In the main results the disaggregation of manufacturing sectors considered as polluting any manufacturing sector with a positive intensity of pollution, even if this index was very low. As a robustness check we test for a possible difference between polluting sectors with respect to the impact on CO_2 emissions. For that, we disaggregate manufacturing sectors in three sectors according to their pollution intensity. Table 7 describes this disaggregation (see Appendix A for details).

Table 7 – Sector disaggregation; 5 sectors

Sector Group	Representative sectors
A – Agriculture and Mining	Agriculture; Forestry; Fishing and Mining
C – Construction and Services	Construction; Transportation; Communications; Electric, Gas and Sanitary Services, Wholesale Trade; Retail Trade; Finance; Insurance; Real Estate; Services; Public Administration
H – High Pollution Intensive	Petroleum refining and related industries; Primary Metal Industries
M – Medium Pollution Intensive	Food and kindred products; Textile mill products; Furniture and fixtures; Stone, clay and concrete products; Fabricated metal products
Z – Zero Pollution Intensive	Apparel and other finished products made from fabrics and similar materials; Leather and leather products

Note: Representative sectors in groups *P*, M and *Z* are based on 2 digit code classification. They are listed as representative because many of the 4 digit SIC code under them belong to one of these groups. For the exact disaggregation, see Appendix A.

Table 8 presents the results using this five sector disaggregation. Once again, we only report the results of manufacturing sectors Medium Pollution Intensive and High Pollution Intensive, since coefficients for the other sectors were not statistically significant. The only difference between the results from Model 4 (Table 8) and Model 2 (Table 6) is the disaggregation of the Pollution Intensive sector in Medium and High Pollution Intensive sectors. Overall, this disaggregation confirmed our findings from Model 2.

Regarding the Multilateralism hypothesis, there is no reason for the results to change with a further disaggregation of the data. Indeed, the hypothesis is supported by these robustness results.

Table 8 – Fixed effect model for Carbon Dioxide Emissions; Endogenous variable is $ln(CO_2)$; Value of M&As is $ln(M_{k,j,i,t}+0.1)$, with k = {H,M} and j = {DC,LDC}.

	(4)				
	coefficient			*coefficient*	
Institution	-0.016	**	Ln(GDP)	1.627	***
Institution*D_I	0.018		Urban population (% total)	0.006	
$Ln(M_{H,DC})$	0.001		Manufacturing (% GDP)	0.012	***
$Ln(M_{M,DC})$	0.004	*	Manufactures X (% exports)	-0.001	
$Ln(M_{H,LDC})$	0.005	**	Manufactures M (% imports)	-0.001	
$Ln(M_{M,LDC})$	0.004	*	Ln(trade openness)	0.096	*
$Ln(M_{H,DC})*D_I$	-0.005	*	Ln(trade openness)*D_I	-0.056	**
$Ln(M_{M,DC})*D_I$	-0.009	**	Ln(GDPpc)	-0.967	***
$Ln(M_{H,LDC})*D_I$	-0.006	**	Dirty electricity	0.005	***
$Ln(M_{M,LDC})*D_I$	-0.006	*	Intercept	-15.467	***
# of observations	1,357				
# of groups	113				
Within R-square	0.64				
F-statistics	35.44	***			
Hausman test	n.p.d.				
Hausman test, sigmamore	82.45	***			
Hausman test, sigmaless	86.62	***			

Notes: The dependent variable is Carbon Dioxide Emissions. Manufactures X = exports of manufactures. Manufactures M = imports of manufactures. D_I = dummy for development level of the target country; it takes the value of 1 if the target country is a Developed country and 0 otherwise. GDPpc = GDP per capita. n.p.d = not positive definite. To obtain the significance levels we considered robust estimates of the standard errors, to take into account possible heteroskedasticity and serial correlation of the error terms. ***, **, * indicate significance at 1%, 5% and 10%, respectively.

The Sector-specific impact hypothesis is also supported by the results. Now we have further support that sectors with a positive intensity of pollution are the only relevant sectors in analyzing the impact of M&As on CO_2 emissions. This is the case for Medium and High Pollution Intensive, showing that further disaggregation of the data does not add much to the analysis.

Finally, we find support for the *Target Country Asymmetry* Hypothesis. For both Medium and High Pollution Intensive sectors, we find that: (i) M&As to low or middle income countries increases CO_2 emissions in those countries, regardless of the acquiring country; (ii) M&As to high income countries decreases CO_2 emissions in those countries, regardless of the acquiring country.

5 Conclusion

This paper looks into the impact of Cross-Border Mergers and Acquisitions and Multilateral Agreements in Carbon Dioxide emissions. Using data from 1988 until 2004 for more than 100 target countries, we make three contributions to the empirical literature on the driving forces of pollution emissions. First, we show that only M&As in manufacturing sectors with a positive intensity of pollution have an impact on CO_2 emissions. Second, we find that there is an Asymmetry with respect to the target country development level. Third, we propose an Institutional variable for Multilateral Agreement, and show that Multilateral Agreements are important to reduce pollution.

The three findings have an important policy implication. Our institutional variable measures the participation of countries in ten major environmental multilateral agreements. We found that the participation of countries in those agreements has a significant impact on CO_2 emissions reduction. Therefore, the increase in the number of participating members in these agreements, particularly countries with a high emission of Carbon Dioxide, should be part of the solution to revert the increasing trend of CO_2 emissions.

Our empirical results indicate that if the United States, for example, would have participated on 5 instead of 4 agreements in 2004, it would have led to a decrease in CO_2 emissions by $9.6*10^7$ metric tons. This amount is approximately the same as the total emissions of Greece or Vietnam in 2004. In this same year the United States alone emitted $6.0*10^9$ metric tons of carbon dioxide, approximately 22% of the world's emission.

Foreign Direct Investment is a driving force analyzed in the empirical literature on the determinants of pollution emissions. Considering M&As, which is the main part of FDI, we showed that only a few sectors are relevant in the analysis. Sectors such as Agriculture, Mining, Construction and Services should be excluded from empirical papers on CO_2 emissions. In addition, not every manufacturing sector affects pollution if M&As occur, as M&As in sectors with a zero intensity of pollution do not have an impact on CO_2 emissions. In terms of policy implication, this result suggests a focus on policy. Local authorities concerned with the environmental impact of M&As could impose conditions to acquiring firms in critical sectors, that is, manufacturing sectors with a positive intensity of pollution.

In particular, our findings suggest that least developed countries should be the ones more concerned by the increase in pollution that M&As could bring to their countries. Acquiring firms, from both developed and developing countries, take advantage of the laxer environmental regulation in those countries, and pollute more. We found robust evidence of an Asymmetry with respect to the Target countries. Table 9 summarizes these results.

Table 9 – Impact on pollution of Mergers and Acquisitions

	Non-polluting sectors		Pollution Intensive sector	
Income classification	Acquirer		Acquirer	
Target	High	Low or Middle	High	Low or Middle
High	0	0	- -	-
Low or Middle	0	0	+	+ +

Firms active in M&As are more likely to innovate and adopt cleaner technologies. In spite of that, the results summarized in Table 9 show that if a target country has a lax environmental regulation, as in least developed countries, the outcome of M&As (in polluting sectors) will be an increase in pollution. On the other hand, developed countries, with their stricter environmental regulation offer an innovation offset for firms to become cleaner. Acquiring firms, regardless of the development level of their country will contribute to a decrease in the pollution if the target is from a developed country. This finding suggests that not only multilateral agreements are important, but local regulation and enforcement are the ultimate objective of these agreements.

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Appendix A: Sector disaggregation

Sector Agriculture and Mining:

SIC 01, 02, 07, 08, 09 (Agriculture, forestry and fisheries); SIC 10, 12, 13, 14 (Mineral industries).

Sector Construction and Services:

SIC 15, 16, 17 (Construction industries); SIC 40, 41, 42, 43, 44, 45, 46, 47, 48, 49) (Transportation, communication and utilities); SIC 50, 51 (Wholesale trade); SIC 52, 53, 54, 55, 56, 57, 58, 59 (Retail trade); SIC 60, 61, 62, 63, 64, 65, 67 (Finance, insurance and real state); SIC 70, 72, 73, 75, 76, 78, 79, 80, 81, 82, 83, 84, 86, 87, 88, 89 (Service industries); SIC 91, 92, 93, 94, 95, 96, 97, 99 (Public administration).

Sector Pollution Intensive and Zero Pollution Intensive:

SIC 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39 (manufacturing).

Giving the degree of pollution intensity of the subsectors (on a four digit SIC code classification), we separate the sectors with a positive intensity of pollution from the ones with a zero intensity of pollution. To classify the sectors on their pollution intensity we based on data from the Industrial Pollution Projection System (IPPS) elaborated by Hettige et al. (1995)[10]. We ordered the sectors based on their Carbon Monoxide (CO) pollution intensity. Sectors with a pollution intensity equal to zero were included in the group Zero Pollution Intensive, and with positive pollution intensity in the group Pollution Intensive.

With this criteria we obtained the following division based on a four digit SIC code classification:

[10] The measure of emission is divided by the total output of the firm, leading to the sectoral "emission intensities", as we use here. For more detail on the estimation of these emission intensities, see Hettige et al. (1995).

Sector Zero Pollution Intensive:

SIC 2021, 2045, 2053, 2068, 2097, 2098, 2241, 2252, 2254, 2273, 2311, 2323, 2325, 2326, 2329, 2331, 2335, 2337, 2342, 2353, 2361, 2369, 2371, 2381, 2384, 2385, 2386, 2387, 2389, 2391, 2393, 2394, 2395, 2397, 2399, 2411,, 2448, 2449, 2451, 2452, 2514, 2591, 2656, 2657, 2673, 2674, 2675, 2676, 2677, 2678, 2741, 2761, 2796, 2835, 2836, 3052, 3061, 3082, 3083, 3084, 3085, 3086, 3087, 3088, 3131, 3142, 3143, 3144, 3149, 3151, 3171, 3172, 3199, 3262, 3263, 3363, 3364 3365, 3366, 3412, 3425, 3442, 3448, 3451, 3466, 3491, 3492, 3498, 3533, 3534, 3536, 3537, 3543, 3545, 3546, 3547, 3548, 3549, 3552, 3553, 3556, 3565, 3571, 3572, 3575, 3577, 3578, 3581, 3586, 3593, 3594, 3596, 3613, 3625, 3635, 3644, 3645, 3646, 3652, 3663, 3669, 3671, 3676, 3677, 3678, 3695, 3716, 3799, 3812, 3821, 3824, 3826, 3827, 3829, 3841, 3843, 3844, 3845, 3873, 3915, 3942, 3944, 3953, 3955, 3961, 3965.

Sector Pollution Intensive:

Medium Pollution Intensive

SIC 2011, 2013, 2015, 2022, 2023, 2024, 2026, 2032, 2033, 2034, 2035, 2037, 2038, 2041, 2043, 2044, 2046, 2047, 2048, 2051, 2052, 2062, 2064, 2074, 2075, 2076, 2077, 2079, 2082, 2083, 2084, 2085, 2086, 2087, 2091, 2092, 2095, 2096, 2099, 2131, 2141, 2221, 2231, 2251, 2253, 2257, 2258, 2259, 2261, 2262, 2269, 2281, 2282, 2284, 2295, 2297, 2298, 2299, 2322, 2339, 2341, 2392, 2396, 2431, 2434, 2439, 2441, 2491, 2493, 2511, 2512, 2515, 2517, 2519, 2521, 2522, 2531, 2541, 2542, 2599, 2652, 2653, 2655, 2671, 2672, 2679, 2711, 2721, 2731, 2732, 2752, 2754, 2759, 2771, 2782, 2789, 2791, 2813, 2819, 2821, 2833, 2834, 2841, 2842, 2843, 2844, 2851, 2874, 2875, 2879, 2891, 2893, 2952, 2992, 3011, 3021, 3053, 3069, 3081, 3089, 3111, 3161, 3211, 3229, 3231, 3253, 3255, 3259, 3261, 3264, 3269, 3271, 3272, 3273, 3275, 3281, 3291, 3292, 3295, 3297, 3299, 3316, 3317, 3351, 3353, 3354, 3355, 3356, 3357, 3398, 3399, 3411, 3421, 3423, 3429, 3431, 3432, 3433, 3441, 3443, 3444, 3446, 3449, 3452, 3462, 3463, 3465, 3469, 3471, 3479, 3483, 3484, 3489, 3494, 3495, 3496, 3497, 3499, 3511, 3519, 3523, 3524, 3531, 3532, 3535, 3541, 3542, 3544, 3554, 3555, 3561, 3562, 3563, 3564, 3566, 3567, 3568, 3569, 3579, 3582, 3585, 3589, 3599, 3612, 3621, 3629, 3631, 3632, 3633, 3634, 3639, 3641, 3643, 3647, 3648, 3651, 3661, 3672, 3674, 3675, 3679, 3691, 3692, 3694, 3699, 3711, 3713, 3714, 3715, 3721, 3724, 3728, 3731, 3732, 3743, 3751, 3761, 3764, 3769, 3792, 3822, 3823, 3825, 3842, 3851, 3861, 3911, 3914, 3931, 3949, 3951, 3952, 3991, 3993, 3995, 3999.

High Pollution Intensive

SIC 2061, 2063, 2211, 2421, 2426, 2429, 2435, 2436, 2499, 2611, 2621, 2631, 2812, 2816, 2824, 2861, 2865, 2869, 2873, 2892, 2899, 2911, 2951, 2999, 3221, 3241, 3251, 3274, 3296, 3312, 3313, 3315, 3321, 3322, 3324, 3325, 3334, 3339, 3341, 3369, 3493, 3559, 3592, 3624, 3795.

Above, under the Pollution Intensive sector we additionally present the classification used for our robustness check. Using the ordered sectors based on their Carbon Monoxide (CO) pollution intensity, sectors with a pollution intensity over the 90 percentile were classified as High Pollution Intensive. Sectors with zero intensity of pollution were again classified as Zero Pollution Intensive. The remaining sectors were classified as Medium Pollution Intensive.

Furthermore, we used this classification for all target countries. For that we assumed that the same sectors are high/medium/zero pollution intensive in the United States (source of data from the IPPS) and all other countries. This assumption is common in the literature (e.g. Eskeland and Harrison, 1997), and it rests on the fact that proportionally the pollution intensity among the sectors within a country is the same. Therefore, it still allows countries to be more or less environmental friendly. Although in practice these indices would differ per country, it is quite acceptable that some sectors are the most polluting sectors everywhere (such as petroleum refining and primary metal industries). Similarly for Zero Pollution Intensive, we expect that textile manufacturing, for example, will have one of the lowest intensity of pollution in every country.

Appendix B: Construction of variable “institution”

We created a variable that captures the institutional level of 155 countries of the world with respect to the environment. We considered data from the Earth Trends, World

Resources Institute[11], which provides data on the year of ratification of 10 major multilateral agreements. With this information, we constructed a new dataset with the number of agreements ratified by each country from 1988 until 2005. This gave us an index from 0 (no agreements ratified) until 10 (all major agreements ratified) for each country between 1988-2005. The advantage of this dataset is twofold. First, it comprises a wide range of countries and years. Second, we include in one index, the participation or not in 10 major multilateral agreements. This dataset is available upon request.

Appendix C: Additional data description

Table C1 – Percentage of number of M&As by development status of target and acquirer countries; 1988 - 2004

Target sector/ Income classification	Percentage of total number of M&As				
Acquiring country	High		Low or Middle		
Target country	High	Low or Middle	High	Low or Middle	Total
Agriculture and Mining	3.4	1.7	0.2	0.5	5.7
Construction and Service	42.5	7.6	1.5	2.5	54.0
Positive-intensity-pollution	24.5	5.5	0.7	1.5	32.2
Zero-intensity-pollution	7.0	0.7	0.1	0.2	8.0
Total	77.3	15.5	2.6	4.6	100

Table C2 – Data per year: missing value of the deal

Year	Number of M&As	Number of deals without the value	% from year
1988	1,758	869	49.4
1989	2,724	1,391	51.1
1990	3,062	1,541	50.3
1991	3,530	2,117	60.0
1992	3,260	1,901	58.3
1993	3,477	2,004	57.6
1994	4,361	2,507	57.5
1995	5,277	3,127	59.3
1996	5,653	3,155	55.8
1997	6,276	3,355	53.5
1998	7,334	3,982	54.3
1999	8,501	4,733	55.7

[11] World Resources Institute. 2005 EarthTrends: Multilateral Environmental Agreements. Available at http://earthtrends.wri.org/pdf_library/data_tables/gov3_2005.pdf. Washington DC: World Resources Institute.

2000	9,828	5,492	55.9
2001	7,486	4,102	54.8
2002	5,548	2,922	52.7
2003	5,591	2,976	53.2
2004	6,415	3,342	52.1

C1 Missing values by target and acquirer countries

In the main text we showed that the existence of the value of M&As is random in regard sectors and years of the deals. Nonetheless, one potential concern is that some countries appear to have more missing data than other. Figure C1 below plots the percentage of missing value for each country, when in the position of target, and Figure C2 similarly when they are in the position of acquirers. Both graphs show on the horizontal axis the value of the deals, in log. A few countries call attention for their high percentage of missing values, among them, Austria (82% when target; 78% when acquirer) and Germany (75% when target; 77% when acquirer).

Figure C1 – Missing value, by target country

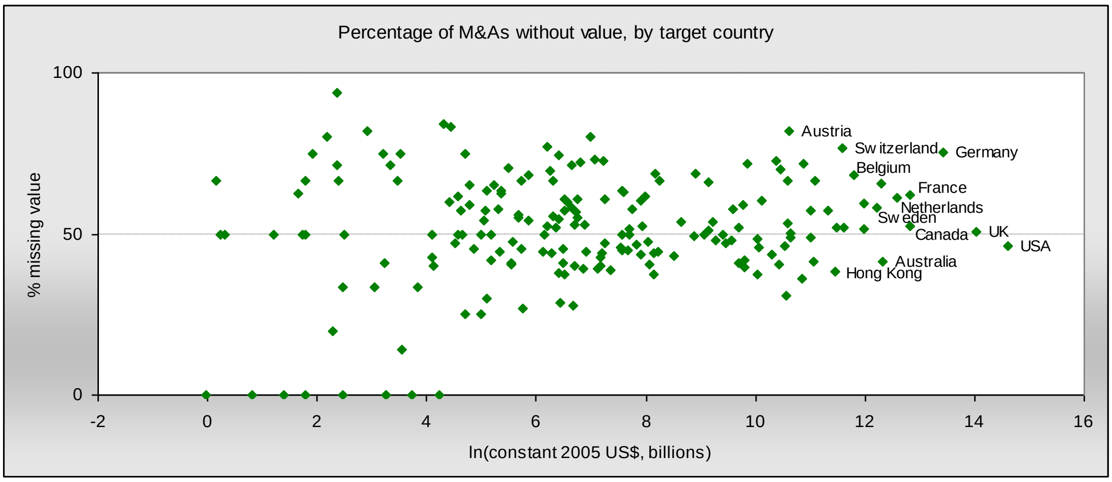
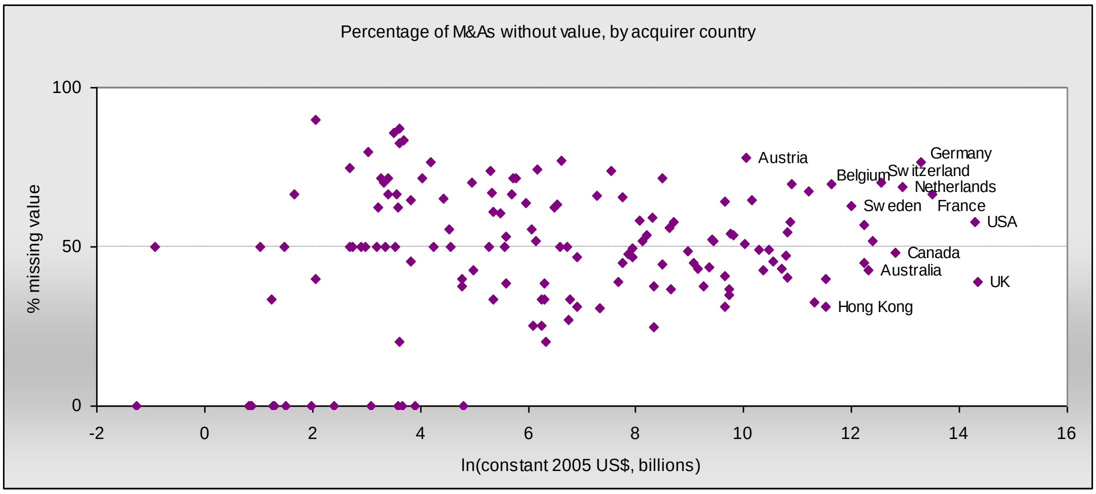


Figure C2 – Missing value, by acquirer country



One thing that immediately stands out when comparing the missing value for countries in the position of target and acquirer is that these values are very similar for every country. In other words, countries that have more missing value when in the position of acquirer also have more missing value when in the position of target. To check for the validity of this statement, we computed the correlation between the percentage of missing value for target and acquirer countries. Considering only countries which had more than 10 M&As (both as target and as acquirer) for the whole period, the correlation was of 0.57; and taking instead only countries which had more than 100 M&As, the correlation was of striking 0.9.

Table C3 – Missing value: countries are either in the position of targets or of acquirers

Income classification	Target			Acquirer		
	No. M&As	No. missing values	% missing values	No. M&As	No. missing values	% missing values
High	77,522	43,028	55.5	90,510	50,084	55.3
Middle or Low	20,415	10,734	52.6	7,427	3,678	49.5
Total	97,937	53,762	54.9	44,175	53,762	54.9

Finally, grouping the countries by their income classification, developing countries (either as target or as acquirer) have relatively less missing data, although this difference is not so substantial, especially when we compare them in the position of target. This is what Table C3 shows.

Appendix D: Data sources

Variable	*Definition*	*Source*	*Period*
CO_2	Emissions (metric tons)	World Bank	1988-2004
M&As flows		Thomson Financial Investment Banking	1988-2004
Population (total)	Number of residents	World Bank	1988-2004
GDP	Constant 2000 US$	World Bank	1988-2004
Manufacturing	Value added (% of GDP)	World Bank	1988-2004
Urban	Urban population (% of total)	World Bank	1988-2004
Manufactures exports	(% of merchandise exports)	World Bank	1988-2004
Manufactures imports	(% of merchandise imports)	World Bank	1988-2004
GDP per capita	Constant 2000 US$	World Bank	1988-2004
Dirty electricity	Electricity production from coal and oil sources (% of total)	World Bank	1988-2004
Institution	Index of participation in major multilateral agreements (0 – 10)	World Resources Institute	1988-2004

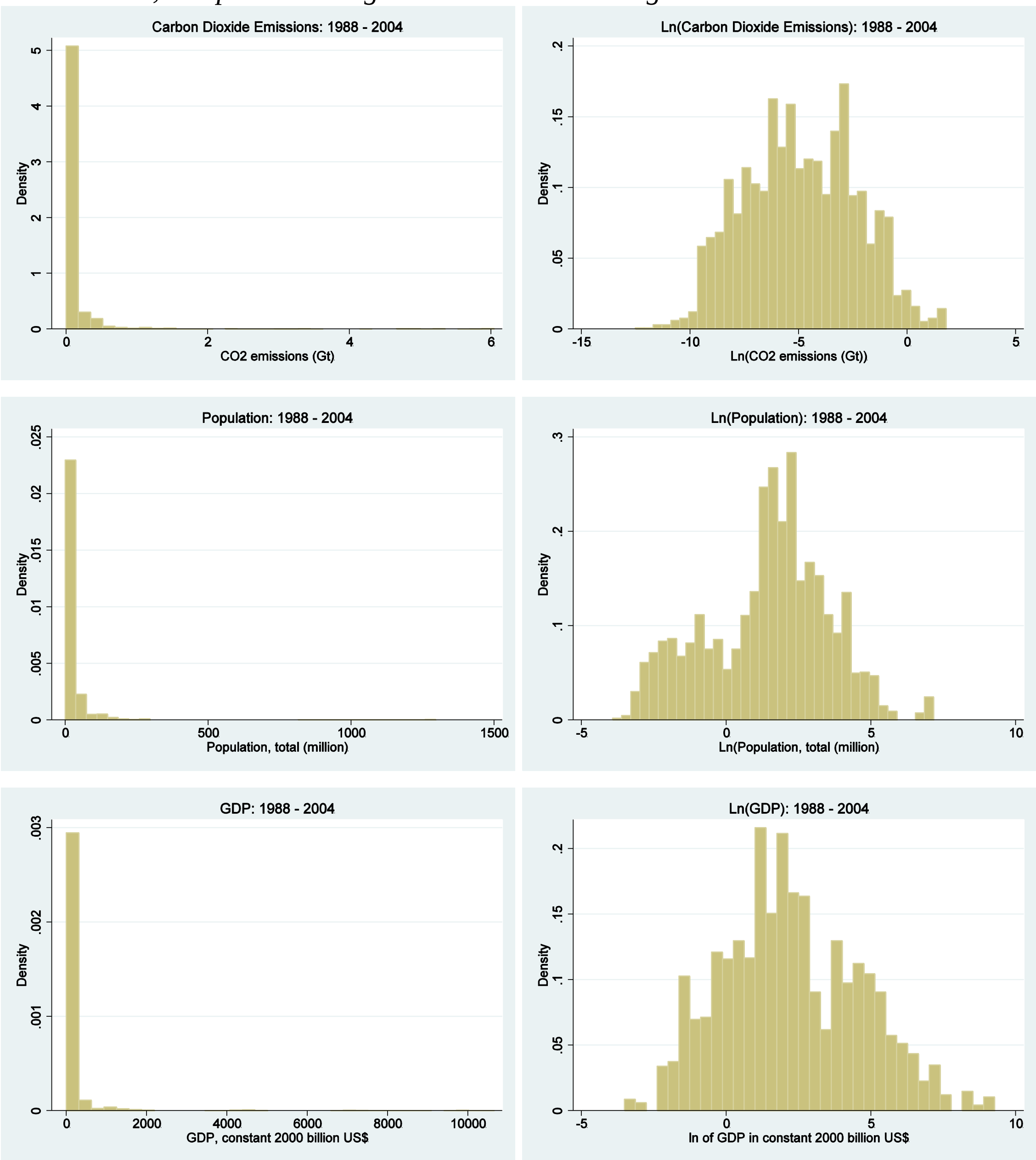
Appendix E: Skewness

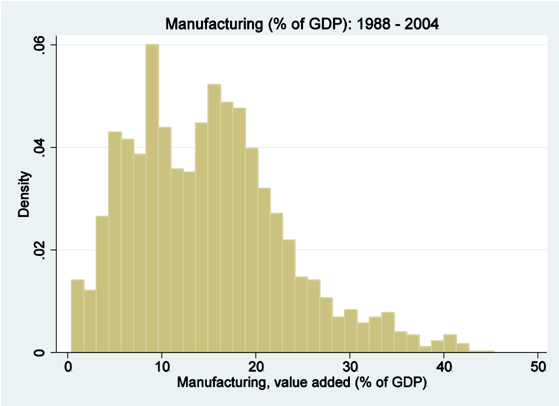
Table E1 – Summary statistics (1988 – 2004)

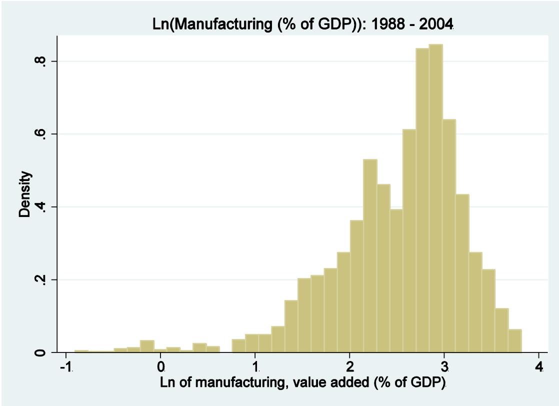
	Mean	Median	Standard Deviation	Skewness; variable in natural units	Skewness; variable in ln
CO_2 (metric tons)	$1.2*10^8$	$7.6*10^6$	$4.93*10^8$	8.6	0.0
Population	$2.9*10^7$	$5.3*10^6$	$1.1*10^8$	8.7	-0.2
GDP	$1.6*10^{11}$	$7.6*10^9$	$7.5*10^{11}$	9.5	0.3
Manufacturing	14.9	14.4	8.2	0.7	-1.1
Urban	53.5	53.4	24.5	0.1	-0.9
Manufactures exports	45.8	43.6	31.4	0.1	-2.3
Manufactures imports	68.9	70.5	11.0	-0.7	-1.5
Dirty electricity	38.9	32.6	33.5	0.5	-1.6
GDPpc	5,772.0	1,708.1	8,482.8	2.0	0.1
Trade openness	83.5	72.7	47.1	1.5	-0.7

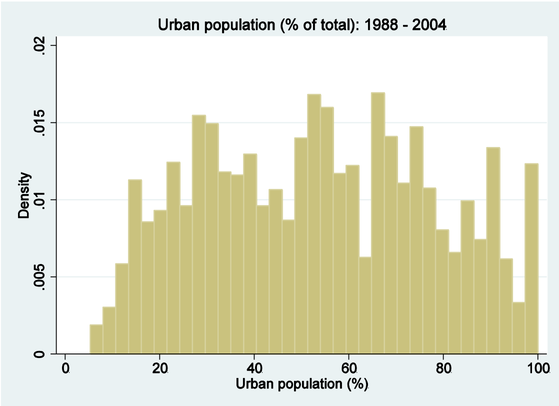
The decision of taking the independent and dependent variables in their natural or logarithmic form was based on their skewness measure. For that we analyzed basic statistics of the variables, as well as a visual comparison of the variables histograms when using its natural and logarithmic form. Table E1 presents the descriptive statistics, and Figure E1 gives the histogram for the relevant variables.

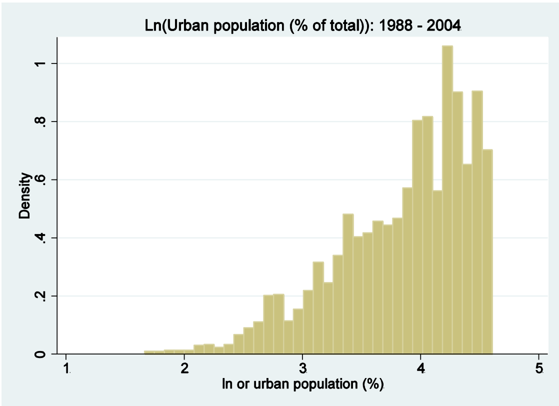
Figure E1 – Selected variables – histograms; Graphs on the left show variables in natural units; Graphs on the right show variables in logarithm.

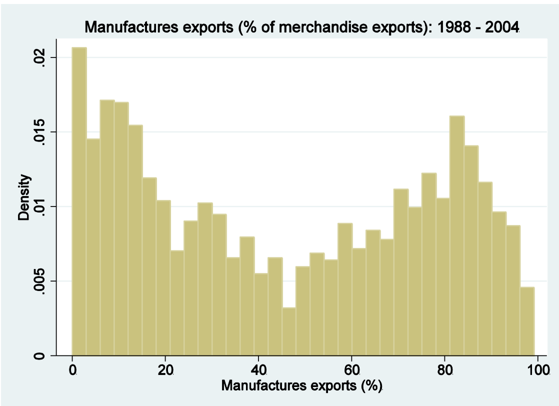



Manufacturing (% of GDP): 1988 - 2004
Density
0 .02 .04 .06
0 10 20 30 40 50
Manufacturing, value added (% of GDP)

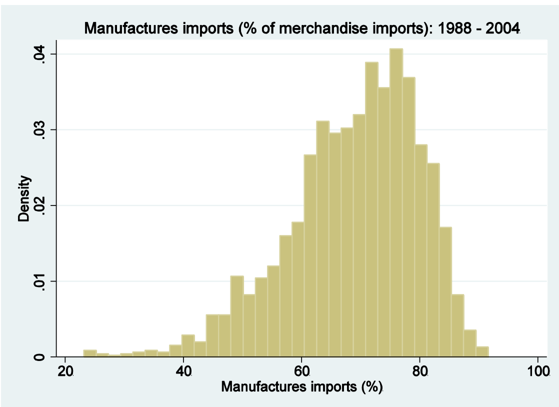

Ln(Manufacturing (% of GDP)): 1988 - 2004
Density
0 .2 .4 .6 .8
-1 0 1 2 3 4
Ln of manufacturing, value added (% of GDP)

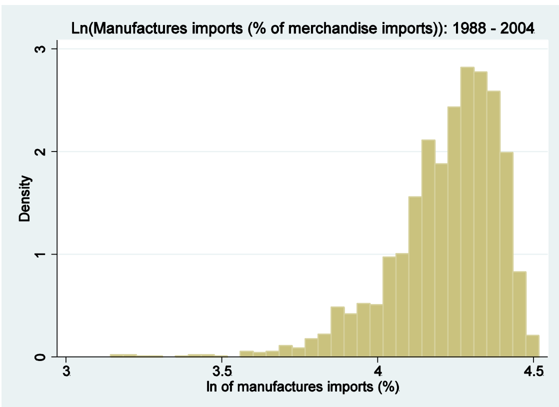

Urban population (% of total): 1988 - 2004
Density
0 .005 .01 .015 .02
0 20 40 60 80 100
Urban population (%)

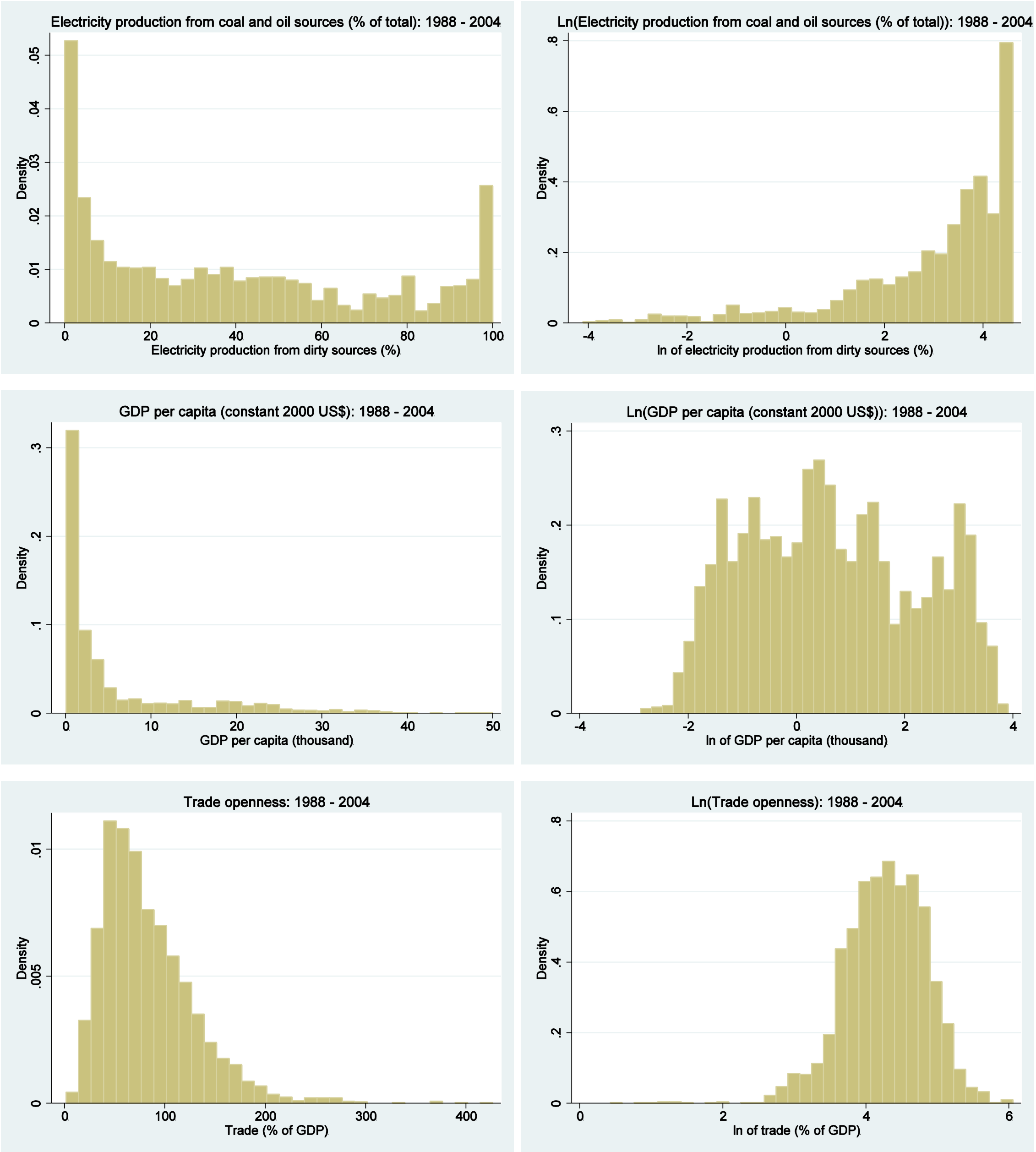

Ln(Urban population (% of total)): 1988 - 2004
Density
0 .2 .4 .6 .8 1
1 2 3 4 5
ln or urban population (%)


Manufactures exports (% of merchandise exports): 1988 - 2004
Density
0 .005 .01 .015 .02
0 20 40 60 80 100
Manufactures exports (%)


Ln(Manufactures exports (% of merchandise exports)): 1988 - 2004
Density
0 .2 .4 .6 .8 1
-10 -5 0 5
ln of manufactures exports (%)


Manufactures imports (% of merchandise imports): 1988 - 2004
Density
0 .01 .02 .03 .04
20 40 60 80 100
Manufactures imports (%)


Ln(Manufactures imports (% of merchandise imports)): 1988 - 2004
Density
0 1 2 3
3 3.5 4 4.5
ln of manufactures imports (%)


Electricity production from coal and oil sources (% of total): 1988 - 2004
Density
Electricity production from dirty sources (%)
Ln(Electricity production from coal and oil sources (% of total)): 1988 - 2004
Density
ln of electricity production from dirty sources (%)
GDP per capita (constant 2000 US$): 1988 - 2004
Density
GDP per capita (thousand)
Ln(GDP per capita (constant 2000 US$)): 1988 - 2004
Density
ln of GDP per capita (thousand)
Trade openness: 1988 - 2004
Density
Trade (% of GDP)
Ln(Trade openness): 1988 - 2004
Density
ln of trade (% of GDP)

Appendix F: Additional results

Table F1 – Fixed effect model for Carbon Dioxide Emissions; Endogenous variable is $ln(CO_2)$; Value of M&As is $ln(M_{k,j,i,t}+0.1)$, with k = {A,C,P,Z} and j = {DC,LDC}.

	(1_F)		(2_F)		(3_F)		(4_F)	
	coefficient		*coefficient*		*coefficient*		*Coefficient*	
Institution	-0.013	*	-0.012		-0.012		-0.012	
Institution* D_{DC}	0.009		0.007		0.007		0.007	
$Ln(M_{A,DC})$	-0.000		-0.000		0.000			
$Ln(M_{C,DC})$	0.001							
$Ln(M_{P,DC})$	0.003		0.003		0.003		0.003	
$Ln(M_{Z,DC})$	-0.001		-0.001					
$Ln(M_{A,LDC})$	0.002		0.002		0.002			
$Ln(M_{C,LDC})$	0.001							
$Ln(M_{P,LDC})$	0.004	**	0.005	**	0.005	**	0.005	**
$Ln(M_{Z,LDC})$	0.002		0.004					
$Ln(M_{A,DC})*D_{DC}$	0.001		0.001		0.001			
$Ln(M_{C,DC})*D_{DC}$	-0.006							
$Ln(M_{P,DC})*D_{DC}$	-0.008		-0.010	**	-0.011	**	-0.011	**
$Ln(M_{Z,DC})*D_{DC}$	0.000		-0.001					
$Ln(M_{A,LDC})*D_{DC}$	0.001		0.000		0.000			
$Ln(M_{C,LDC})*D_{DC}$	-0.005							
$Ln(M_{P,LDC})*D_{DC}$	-0.006	**	-0.007	***	-0.008	***	-0.008	**
$Ln(M_{Z,LDC})*D_{DC}$	-0.000		-0.004					
Ln(GDP)	1.539	***	1.528	***	1.527	***	1.527	***
Urban population (%)	0.009		0.009		0.009		0.009	
Manufacturing (% GDP)	0.014	***	0.014	***	0.014	***	0.014	***
Manufactures X (% X)	-0.001		-0.001		-0.001		-0.001	
Manufactures M (% M)	-0.002		-0.002		-0.002		-0.002	
Ln(trade openness)	0.080	*	0.077		0.076		0.077	
Ln(trade openness)* D_{DC}	-0.035		-0.033		-0.025		-0.027	
Ln(GDPpc)	-1.124	*	-1.089	*	-1.082	*	-1.079	*
$Ln(GDPpc)^2$	0.013		0.011		0.011		0.011	
Intercept	-12.852	***	-12.743	***	-12.783	***	-12.812	***
# of observations	1,555		1,555		1,555		1,555	
# of groups	136		136		136		136	
Within R-square	0.605		0.604		0.604		0.604	
F-statistics	22.92	***	24.28	***	25.73	***	29.12	***
Hausman test	n.p.d.		n.p.d.		n.d.p.		n.p.d.	
Hausman test, sigmamore	104.36	***	101.28	***	93.84	***	89.88	***
Hausman test, sigmaless	110.11	***	106.83	***	98.71	***	94.52	***

Notes: The dependent variable is Carbon Dioxide Emissions. Manufactures X = exports of manufactures. Manufactures M = imports of manufactures. D_{DC} = dummy for development level of the target country; it takes the value of 1 if the target country is a Developed country and 0 otherwise. GDPpc = GDP per capita. n.p.d = not positive definite. To obtain the significance levels we considered robust estimates of the standard errors, to take into account possible heteroskedasticity and serial correlation of the error terms. ***, **, * indicate significance at 1%, 5% and 10%, respectively.